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# The Effects of Market Uncertainty on Financial Performance and Economic Activity Using SVAR and Kalman Filter Approaches

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**ABSTRACT**

This paper aims to establish the impact of market risk on the performance of the financial markets and the level of economic activity. It explores the impact of uncertainty shocks in the S&P 500 index which represents general market sentiment and the yield interest rate which is an indicator of economic activity using the VIX. Some of the significant findings are based on Impulse Response Functions which are within the SVAR model and with the use of Kalman Filter to eliminate noise and seasonality. The results show negative findings between the VIX and the S&P 500 index, which clearly illustrate that a one-percentage-point rise in the VIX results in a decrease in the value of the S&P 500 index by 0. 37%. In the same way, the yield interest rate weakens sharply, which is evidence of a decrease in activity within the economy. Thus, these results emphasize the significance of market risks on numerous financial and economic parameters while stressing the significance of risk management.

**ملخص**

تهدف هذه الورقة البحثية إلى بيان أثر مخاطر السوق على أداء الأسواق المالية ومستوى النشاط الاقتصادي.إذ نستعرض تأثير صدمات عدم اليقين في مؤشر S&P 500 الذي يمثل المزاج العام للسوق، إضافة إلى سعر الفائدة على العوائد الذي يُعد مؤشرا على النشاط الاقتصادي، وذلك باستخدام مؤشر VIX. وتستند بعض النتائج المهمة إلى دوال الاستجابة للصدمة ضمن نموذج SVAR، مع توظيف مرشح كالمان لإزالة الضوضاء والتقلبات الموسمية. وقد أظهرت النتائج وجود علاقة سلبية بين مؤشر VIX ومؤشر S&P 500، حيث تبيّن أن ارتفاع مؤشر VIX بمقدار نقطة مئوية واحدة يؤدي إلى انخفاض قيمة مؤشر S&P 500 بنسبة 0.37%. وبالمثل، يتراجع معدل

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العائد بشكل ملحوظ، وهو ما يُعد دليلا على تراجع النشاط الاقتصادي. وعليه، تؤكد هذه النتائج على أهمية مخاطر السوق وتأثيرها في العديد من المعايير المالية والاقتصادية، مع التشديد على ضرورة إدارة المخاطر.

## RÉSUMÉ

Cet article vise à établir l'impact du risque de marché sur la performance des marchés financiers et le niveau d'activité économique. Il explore l'impact des chocs d'incertitude sur l'indice S&P 500, qui représente le sentiment général du marché, et sur le taux d'intérêt, qui est un indicateur de l'activité économique, à l'aide du VIX. Certaines des conclusions importantes sont basées sur les fonctions de réponse impulsionnelle qui font partie du modèle SVAR et sur l'utilisation du filtre de Kalman pour éliminer le bruit et la saisonnalité. Les résultats montrent une corrélation négative entre le VIX et l'indice S&P 500, ce qui illustre clairement qu'une hausse d'un point de pourcentage du VIX entraîne une baisse de 0,37 % de la valeur de l'indice S&P 500. De la même manière, le taux d'intérêt des rendements s'affaiblit fortement, ce qui témoigne d'un ralentissement de l'activité économique. Ces résultats soulignent donc l'importance des risques de marché sur de nombreux paramètres financiers et économiques, tout en mettant l'accent sur l'importance de la gestion des risques.

**Keywords:** Market Uncertainty, Financial Market, Structural Vector Auto regression, Kalman Filter, Volatility Index (VIX)

**JEL Classification:** C32, E44, G12, G17, C58

## 1 Introduction

Financial markets have undergone significant transformations over the past few decades due to globalization, technological advancements, and increased financial product complexity (Brunnermeier et al., 2021). These changes have led to heightened market volatility, making it crucial for researchers and policymakers to understand how uncertainty affects financial stability and economic performance (Elsayed & Helmi, 2021; Lean & Tan, 2011). One key indicator that has emerged in this context is the Volatility Index (VIX), often referred to as the 'fear gauge' due to its ability to capture market sentiment and future volatility expectations (Koshoev, 2024). While existing research has extensively explored the impact of market volatility on financial turbulence (Bhowmik & Wang, 2020; Pomfret, 1997), the present research is the first to employ SVAR models augmented with Kalman filters to navigate the difficulties of noise elimination and the identification of structural shifts, especially during extraordinary events such as the COVID-19 outbreak.

Existing literature has primarily relied on traditional econometric models such as Vector Autoregressive (VAR) models to analyze market volatility's impact on financial indicators. However, these methods often fail to account for time-varying uncertainty and structural breaks that significantly influence market behavior, particularly during extreme events like the COVID-19 pandemic. This study addresses this limitation by integrating Structural Vector Autoregression (SVAR) models with the Kalman Filter, an advanced signal-processing technique that effectively removes noise and identifies hidden patterns in financial time series data. By combining these methodologies, we provide a more refined and accurate assessment of how market uncertainty affects financial markets and economic indicators.

The Kalman Filter is a recursive algorithm that updates the estimated score of the unobservable state of a state-space model, assuming a normal distribution of disturbances and an initial state vector (Khodarahmi & Maihami, 2023; Woodward, 2004). This forms the maximum likelihood function of the model by decomposing prediction errors. Let it represent a time series of n observed elements linked to the unobserved vector ξt. The state-space model is defined as follows:

$$y_t = H_t \xi_t + x_t + w_t \dots\dots\dots\dots.\dots. \quad (1)$$

$$\xi_t = F_t \xi_{t-1} + c_t + B_t v_t \dots\dots\dots\dots.. \quad (2)$$

Equation 1 is defined as the measurement equation, where $H_t$ is an nxr matrix, $x_t$ is a kx1 vector, and $w_t$ is an error with $E(w_t) = 0$ and $VAR(w_t) = R_t$. The unobserved state is modeled as a Markov process called the transition equation (expression 2), where $F_t$ is an rxr matrix, $c_t$ is an rx1 vector, $_t$ is an mxg matrix, and $v_t$ is a gx1 error with $E(v_t) = 0$ and $VAR(v_t) = Q_t$. In the period $\mathrm{t} = 1$ :

$$\widehat{\xi_1} = F_1 \widehat{\xi_0} + c_1 + B_1 v_1 \dots\dots\dots\dots.\dots\dots \quad (3)$$

Given the normality of the error, the conditional mean and variance concerning the information at time $\mathrm{t} = 0$ are, respectively:

$$\widehat{\xi_{1|0}} = F_1\widehat{\xi_0} + c_1 \quad P_{1|0} = F_1 P_0 F_1^T + B_1 Q_1 B_1^T \dots\dots\dots\dots\dots\dots \quad (4)$$

Let the system of equations be defined for the distribution of $\xi_1$ conditional on $y_1$

$$\xi_1 = \widehat{\xi_{1|0}} + \left(\xi_1 - \widehat{\xi_{1|0}}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (5)$$

$$y_1 = H_1\widehat{\xi_{1|0}} + x_1 + H_1\left(\xi_1 - \widehat{\xi_{1|0}}\right) + w_1 \dots\dots\dots\dots\dots\dots \quad (6)$$

Therefore, the vector $\begin{bmatrix} \hat{\xi}_1 \\ y_1 \end{bmatrix}$ has a normal distribution with mean and variance:

$$E\begin{bmatrix} \widehat{\xi_1} \\ y_1 \end{bmatrix} = \begin{bmatrix} \widehat{\xi_{1|0}} \\ H_1 \frac{\xi_{1|0}}{} + x_1 \end{bmatrix} \dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (7)$$

$$V\begin{bmatrix} \widehat{\xi_1} \\ y_1 \end{bmatrix} = \begin{bmatrix} P_{1|0} & P_{1|0}H_1^l \\ H_1 P_{1|0} & H_1 P_{1|0} H_1^l + R_1 \end{bmatrix} \dots\dots\dots \quad (8)$$

Applying the conditional distribution of the multivariate normal for the case of $\widehat{\xi_1}$ conditional to the specific value of $y_1$, we have the respective mean and variance:

$$\widehat{\xi_1} = \widehat{\xi_{1|0}} + P_{1|0}H_1^l S_1^{-1}\left(y_1 - H_1\widehat{\xi_{1|0}} - x_1\right) \dots\dots\dots\dots\dots\dots \quad (9)$$

$$P_1 = P_{1|0} - P_{1|0}H_1^l S_1^{-1} H_1 P_{1|0} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (10)$$

Where $S_1 = H_1 P_{1|0} H_1^l + R_1$. Iteratively for all t $= 2,3 \dots$ T is the Kalman filter. $\hat{\xi}_{t-1}$ is the estimation of $\xi_{t-1}$ based on the observations of $y_{t-1}$

The mean and variance conditional to the information at time t-1 are, respectively:

$$\hat{\xi}_{t|t-1} = F_t\hat{\xi}_{t-1} + c_t \dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (11)$$

$$P_{t|t-1} = F_t P_{t-1} F_t^T + B_t Q_t B_T^T \dots\dots\dots\dots\dots \quad (12)$$

Now, the estimation is updated:

$$\hat{\xi}_t = \hat{\xi}_{t|t-1} + P_{t|t-1}H_1^T S_t^{-1}\left(y_t - H_t\hat{\xi}_{t|t-1} - x_t\right) \dots\dots\dots\dots\dots \quad (13)$$

$$P_t = P_{t|t-1} - P_{t|t-1}H_1^T S_t^{-1} P_{t|t-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (14)$$

Donde $P_t = P_{t|t-1} - P_{t|t-1} H_1^T S_t^{-1} P_{t|t-1}$, Now, the same can be constructed for the period $\mathrm{t} + 1$ :

$$\hat{\xi}_{t+1|t} = (F_{t+1} - K_t H_t)\hat{\xi}_{t|t-1} + K_t y_t + (c_{t+1} - K_t x_t) \dots\dots\dots\dots\dots \quad (15)$$

$$P_{t+1|t} = F_{t+1}(P_{t|t-1} - P_{t|t-1} H_1^T S_t^{-1} P_{t|t-1}) F_{t+1}^T + B_{t+1} Q_{t+1} B_{t+1}^T \dots\dots\dots (16)$$

Where

$$K_t = F_{t+1} P_{t|t-1} H_1^T S_t^{-1}$$

In this paper, the Kalman filter is utilized to obtain a smooth version of the main variables. The algorithm is applied to the VIX index, the SP500 index, and the yield interest rate. Consequently, the daily noise of the variables can be extracted and their reaction to shocks analyzed.

On the other hand, to analyze the impact of a variable on a set of others, the Vector Autoregressive (VAR) model is one of the most widely used econometric tools, especially in time series analysis. Another type of the VAR model is the so called Structural VAR (SVAR) encompasses specific structural conditions. As brought in by Sims (1980), SVAR has been used in major analysis in applied macroeconomic research including but not limited to the works of Babajani Baboli (2022) and Angeletos et al. (2020). The primary outcome of this model is the analysis of impulse response functions, which provide a quantitative measure of the effect of one variable on others.

The initial step involves identifying the set of endogenous variables (Cao et al., 2020). In this study, aimed at understanding how the VIX impacts key financial variables in the global market, the chosen endogenous variables include the VIX index, the S&P 500 index, and the yield interest rate (Wang et al., 2022).

The rationale for including these variables is anchored on the premise that a shock to the VIX index augments the volatility in the financial market hence reducing the market capitalization of large firms and in the process impacting the S&P 500 index. When the S&P 500 is stagnant, a decline in the yield interest rate will be seen. Therefore, the model is developed with the purpose of making the effect of the VIX index measurable in terms of the overall financial system (Wang et al., 2022).

The specification of the general Vector Autoregressive (VAR) model is:

$$\begin{bmatrix} i_t \\ sp500_t \\ yied_t \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ \phi_{21} & \phi_{22} & \phi_{23} \\ \phi_{31} & \phi_{32} & \phi_{33} \end{bmatrix} \begin{bmatrix} i_{t-1} \\ sp500_{t-1} \\ yied_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix} \dots\dots\dots\dots.. \quad (17)$$

Where the stability conditions for this Vector Autoregressive (VAR) model with a 3x3 coefficient matrix $\mathbf{\Phi}$ are given by the roots of the characteristic equation:

$$\mathrm{Det}(\mathbf{I} - \mathbf{\Phi} z) = 0 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. \quad (18)$$

Expanding this expression for a $3 \times 3$ matrix:

$$\mathrm{Det}\left(\begin{bmatrix} 1-\phi_{11}z & -\phi_{12}z & -\phi_{13}z \\ -\phi_{21}z & 1-\phi_{22}z & -\phi_{23}z \\ -\phi_{31}z & -\phi_{32}z & 1-\phi_{33}z \end{bmatrix}\right) = 0 \dots\dots\dots\dots\dots\dots\dots. \quad (19)$$

This leads to the characteristic equation:

$$(1-\phi_{11}z)(1-\phi_{22}z)(1-\phi_{33}z) - (\phi_{12}z)(\phi_{23}z)(\phi_{31}z) - (\phi_{13}z)(\phi_{21}z)(\phi_{32}z) = 0 \dots (20)$$

The stability of the VAR model is ensured when all the roots (eigenvalues) of this characteristic equation satisfy $|\lambda_i| < 1$, where $\lambda_i$ represents each eigenvalue.

The current study expresses the model in terms of vectors and matrices for practical reasons. In this context, the vector y of endogenous variables is defined.

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \epsilon_t$$
$$u_t \sim (0, \Sigma_u)$$

where $y_t$ is the vector of endogenous variables consists of the VIX index, the SP500 index, and the yield interest rate.

$$y_t = \left(i_t, sp500_t, \text{ yied }_t\right)'$$

$A_i s$ are $(4 \times 4)$ coefficient matrices and $u_t = (u_{1t}, \cdots, u_{4t})'$ is an error term. Under the condition that the vector of errors $u_t$ has a normal distribution with mean zero and a positive covariance matrix.

The impulse response function for the VAR with variables $y_t = \left(i_t, \text{sp}\,500_{t_t}, \text{ yied }_t\right)'$ is given by:

$$\Delta y_t = \Phi_1 \Delta y_{t-1} + \Phi_2 \Delta y_{t-2} + \cdots + \Phi_h \Delta y_{t-h} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (21)$$

where:

- $\Delta y_t$ is the vector of changes in the variables at time $t$,
- $\Phi_1, \Phi_2, \ldots, \Phi_h$ are the coefficient matrices for each lag,
- $\Delta y_{t-1}, \Delta y_{t-2}, \ldots, \Delta y_{t-h}$ are the lagged changes in the variables, and
- $\varepsilon_t$ is the vector of error terms.

The current study is anchored on the macroeconomic risk and returns theory with the VIX as an indicator of market sentiment and risk aversion. Thus, by analyzing how the VIX affects equity, the S&P 500 as well as bond yields in this work, the understanding of how macroeconomic uncertainty impacts financial stability is advanced. The current study proposes a new method by combining the CUSUM test with the SVAR and Kalman Filter techniques. The advantage of incorporating the CUSUM test is that it makes it possible to identify structural breaks in the time series data. This step is important in identifying trends in market risk and how it affect the financial performance of organizations. This superimposes robustness to the analysis since it ensures that the results are adaptive to possible changes like the data structure over time.

This paper contributes to the literature in several ways. First, it enhances our understanding of the transmission mechanisms through which market uncertainty propagates to financial performance and economic activity. Second, it introduces a novel methodological framework that improves volatility estimation and identifies structural breaks in financial data using the CUSUM test. Third, by analyzing the VIX index, S&P 500 index, and yield interest rates, this study provides empirical insights into how uncertainty shocks influence financial market stability and economic conditions.

The methodological approach employed in this study is well-suited to the research objectives. The SVAR model allows us to capture the interdependencies among key financial variables while imposing theoretical constraints that help identify the causal effects of uncertainty shocks. Meanwhile, the Kalman Filter ensures that the analysis is not distorted by short-term fluctuations, allowing us to extract the true underlying impact of market uncertainty. This methodological advancement enables us to offer more precise policy recommendations for investors, financial regulators, and policymakers seeking to mitigate the adverse effects of market volatility (Furqani & Mulyany, 2009).

By addressing these gaps, this study provides a comprehensive and data-driven understanding of how market uncertainty influences financial markets and economic activity. The findings hold important implications for risk management strategies, monetary policy, and financial market stability, particularly in times of heightened uncertainty.

## 2 Literature Review

### *2.1 Introduction to Volatility and the VIX*

Volatility plays a central role in financial markets as it reflects uncertainty and influences investors' decisions (Dhingra et al., 2024). The Volatility Index (VIX) has emerged as the most popular indicator of market expectations regarding future price fluctuations (Reisizadeh et al., 2025). Unlike historical volatility measures that are based on past market movements, the VIX measures anticipated future volatility using the implied volatility of put and call options on the S&P 500 Index (Dotsis, 2024). High VIX values typically signal a high level of expected volatility, often associated with a bear market, while low VIX values indicate lower volatility expectations. The VIX is also used in contrarian investment strategies (Wang et al., 2024).

The VIX's influence is not limited to domestic markets but extends to global markets as well. Altinkeski et al. (2024) found that the VIX impacts global stock markets, particularly during extreme market conditions. This demonstrates how volatility affects both developed and emerging markets (Altinkeski et al., 2024). Their study employed a Quantile-on-Quantile spillover analysis, which revealed a non-linear relationship between VIX and stock returns, where low VIX levels are associated with high returns and high VIX levels correlate with low returns.

## 2.2 *Volatility as a Factor Affecting Financial Markets*

Volatility has been extensively studied concerning financial markets, with numerous research contributions in this area. Adrangi et al. (2019) explored the reactions of major equity markets to changes in the VIX in a dynamic context. Their findings show a decline in stock prices as VIX rises, particularly during periods of heightened investor fear and risk aversion (Adrangi et al., 2019). This aligns with the findings of Altinkeski et al. (2024), who concluded that movements in the VIX affect both developed and emerging markets. Their quantile analysis shows that negative spillovers are most pronounced during periods of market stress, reinforcing the VIX's role as a leading indicator of market sentiment.

However, there are limitations in these studies when it comes to explaining how structural breaks in volatility data impact such outcomes. Studies that overlook structural shifts are likely to produce skewed empirical evidence, as noted by Adrangi et al. (2019). To address this, the present study utilizes the CUSUM test to detect structural breaks in volatility data.

In addition, Qadan et al. (2023) reviewed the relationship between volatility in treasury yields and macroeconomic variables, finding that higher volatility in yields is linked to reduced economic activity, including lower industrial production and employment (Qadan et al., 2023). However, their approach did not incorporate noise reduction techniques, such as the Kalman Filter, which could have provided more accurate estimations by filtering out unnecessary noise in time-series data.

## 2.3 *Volatility and Its Relation to Advanced Financial Instruments*

Derivatives, Exchange Traded Funds (ETFs), and commodity futures have had a significant impact on market volatility in the modern financial world (Yadav et al., 2024). Arunanondchai et al. (2020) argue that while these instruments provide ways to manage risk, they also add an additional layer of risk during volatile periods. As the use of these instruments has increased, so has the need for investors to better understand the dynamics of volatility (Arunanondchai et al., 2020).

The emergence of derivative markets, in particular, has heightened the importance of the VIX as a tool for measuring market sentiment. The VIX becomes more relevant in a financial environment dominated by complex hedging strategies by providing insights into future price movements derived from options trading (Aliu et al., 2024). However, these instruments can create liquidity risks, as large trading orders or sudden market shifts may lead to sharp increases in implied volatility.

### *2.4 Modern Techniques in Volatility Prediction*

As financial markets evolve, so do the methods used to forecast volatility. Adrangi et al. (2019) used traditional models, which often fail to capture the complexity of market dynamics, especially during periods of high volatility (Adrangi et al., 2019). Recent research, however, has introduced the use of machine learning and AI to improve the accuracy of VIX movement forecasts.

For instance, Altinkeski et al. (2024) argue that machine-learning models can detect patterns in VIX movements that are not captured by traditional econometric models. These methods are particularly effective in predicting market behavior during volatile periods (Altinkeski et al., 2024). Although this is a relatively new area of study, it offers promising strategies for market participants to better manage risks.

Despite these advancements, many studies continue to rely on conventional statistical approaches, such as SVAR models, which may not fully capture the complexities of modern financial markets. To address these limitations, this study will apply the CUSUM test for detecting structural breaks, along with the Kalman Filter for noise reduction, providing a more comprehensive understanding of volatility patterns.

### *2.5 Addressing Gaps in Existing Research*

While VIX-related research has garnered significant attention, many gaps remain unaddressed. Previous studies have focused extensively on volatility data but have often failed to consider structural breaks, as seen in Adrangi et al. (2019) and Qadan et al. (2023). Ignoring these breaks can lead to inaccurate conclusions, as market environments and volatility patterns shift over time.

Additionally, few studies have incorporated noise reduction techniques in their analysis of volatility. By using the Kalman Filter, this study aims to remove the random fluctuations in time-series data that obscure the true relationship between VIX, stock prices, and yield rates. This approach offers a significant improvement over previous research, which has primarily relied on standard econometric models.

Finally, the role of high-risk financial instruments in increasing market volatility has not been adequately explored. While Arunanondchai et al. (2020) provide useful insights into this area, further investigation is needed to understand how these instruments influence volatility during periods of market stress. The current study contributes to the literature by examining how the introduction of these instruments has affected volatility in both the pre-COVID and post-COVID periods.

### *2.6 Theoretical Foundation*

#### *2.6.1 Market Sentiment and Investor Behaviour*

The first of the theories that form the basis of the interaction between the VIX and the S&P 500 is the aspect of market sentiment. As per this theory, VIX reflects the average of the sentiments that are felt by the market participants which may be on a scale of extreme optimism to extreme fear (Kitonyi et al., 2023). An increase of the VIX means that investors anticipate future volatility to be higher and this is normally linked with uncertainty regarding the future economic environment. This increases uncertainty and investors’ risk aversion and consequently reduces their investment in risky assets like equities.

Therefore, the increase in the value of VIX leads to a decrease in the value of the S&P index 500 (Vergili & Çelik, 2023). This link is anchored on the theory of risk aversion whereby investors will require a higher risk premium when investing in risky securities or will move their money to safer assets such as bonds, or cash which will trigger the selling of equities. This flight to safety is represented by the subsequent decline in the S&P 500.

#### *2.6.2 Macroeconomic Theory and Interest Rates*

Concerning the relationship between the VIX and yield interest rates, analysis can be done through the characteristics of the macroeconomic theory (Cochrane, 2024). Yield interest rates depend on various aspects such as; expected inflation, monetary policy as well and general economic conditions (Moore, 2023). When the VIX goes up, the market becomes volatile and the expectation of a lower growth of the economy or even a downturn is expected.

Expectations theory of the term structure of interest rates suggests that when investors are expecting a recession, they also expect central banks to lower interest rates to boost the economy (Conard, 2023). This expectation of future rate cuts results in a reduction in long-term interest rates as evidenced by low yields. Hence, more often than not, the VIX going up leads to a decrease in yield interest rates because the market expects central banks to ease their monetary policies to counterbalance the increased risk.

#### *2.6.3 The Risk-Return Trade-off*

The second theory that applies to this study is the risk-return trade-off which is a key part of the modern portfolio theory (Barroso & Maio, 2024). As per this theory, risk and return are directly proportional to each other, meaning the higher the level of risk an investor is willing to undertake the higher will be the level of return expected by him (Jeffers et al., 2024). Since VIX measures the expected volatility in the market if the VIX rises then it means there is an expectation of high volatility and this makes the risk of holding equities to be perceived as high.

In turn, investors require a higher rate of return for bearing this extra risk or they can simply avoid equities and therefore the S&P 500 (Mladjenovic, 2024). On the other hand, risk-free assets like government securities are more desirable and hence their yields decline with an increase in demand (Bogołębska et al., 2024). This dynamic shows the negative correlation between the VIX and the S&P 500 as well as yield interest rates.

With these theoretical perspectives in place, this study offers a sound basis for conceptualizing the observed correlations between market volatility (as evidenced by the VIX), equity performance (S&P 500), and bonds (yield interest rates). The rise in the VIX exerts a positive effect that activates market sentiment and macroeconomic expectation which in turn results to discernible reductions in both the S&P 500 and yield interest rates. Besides, these theoretical grounds also explain the empirical relationships investigated in this study as well as further enrich the overall significance of the research findings to the subsequent literature.

### *2.7 Hypothesis*

It is pertinent to state the hypotheses that this study aims to test before diving into the technicalities of the econometric models. These hypotheses are based on the theoretical framework discussed earlier and are intended to test the dynamic interactions between market uncertainty (VIX index), market returns (S&P 500 index), and economic activity (yield interest rates).

*Hypothesis 1:* A positive change in the value of VIX will lead to a negative change in the value of the S&P 500.

This hypothesis has been derived from the theory of market sentiment and risk aversion. If the VIX rises, it gives a signal of higher expected volatility and thus fear, which makes investors offload risky investments such as equities hence a negative relationship between the VIX and the S&P 500 index.

*Hypothesis 2:* Based on the VIX index, it will be observed that if there is a positive shock in the VIX index then yield interest rates will fall.

Based on the macroeconomic theory, a rise in the market volatility (as measured by the VIX) may indicate future recession, and thus lead to an anticipation of future reductions in interest rates by central banks. This results in a decrease in yield on long-term interest rates due to a shift in demand towards safer assets.

*Hypothesis 3:* The impact of a VIX shock on the S&P 500 and yield interest rates will be higher in periods of high market risk.

This hypothesis seeks to find out whether, in a situation of increased uncertainty such as during economic and geo-political instabilities, VIX, S&P 500 and yield interest rates will be more correlated because of high risk aversion by investors. These hypotheses are going to be tested by using the Structural Vector Auto Regression (SVAR) model and, the Kalman Filter to filter the time series data. The SVAR model allows one to assess the impact of the shocks to the VIX on S&P 500 and yield interest rates and the Kalman Filter ensures that all noise and seasonality effects have been accounted for.

## 3 Methodology

### *3.1 Data Collection and Processing*

The data set in this study is daily data of the VIX index, S&P 500 index, and yield interest rate. The data was collected from the public domain, which includes Yahoo Finance and the Federal Reserve. The data analyzed in the paper ranges from 1/2/2014 to 12/6/2023, which allows us to examine the market changes during various economic circumstances. The analysis was conducted using MATLAB, incorporating the 'dlm' package for applying the Kalman filter.

### *3.2 Kalman Filter Application*

The application of the Kalman filter algorithm, which recursively estimates the state of a state-space model unobserved components, was used to decompose the time series data and filter out the noise and seasonality effects from the financial variables. The first step is to smooth outgoing variables using the 'dlm' package to apply the Kalman filter to the three-time series. The Kalman filter is an algorithm that predicts how a system behaves in certain conditions. It uses estimated data to minimize uncertainties and improve the accuracy of current state estimates, even with noise or incomplete data (Urrea & Agramonte, 2021).

The Kalman filter operates through two primary steps. In the prediction step, a new state estimate is forecasted through a mathematical model and past estimates, incorporating model uncertainties and errors. In the update step, this predicted state is compared with the resulting data, and the estimate is corrected to achieve greater accuracy, considering the uncertainty in the new data (Khodarahmi & Maihami, 2023). At First, local-level analysis and smoothing techniques are used. This method is most applicable for time series analysis, including the VIX, a measure of the stock market's volatility, and the S&P 500. The Kalman filter continuously refines the estimates by integrating new observations, minimizing the impact of random fluctuations (Wang et al., 2022). Hence, the Kalman filter utilizes the prediction and update steps where the new state estimate is predicted based on a mathematical model and previous estimates. This method reduces the uncertainties in the results even if the data is noisy or incomplete as compared to the previous method.

### *3.3 Utilization of SVAR*

In the present study, the SVAR model was used to analyze the effects of market uncertainty proxied by the VIX index on the S&P 500 index and yield interest rate. The SVAR model makes it possible to use impulse response functions, which measure the responses of different variables (for example, S&P 500 and yield interest rate) for shocks in other variables (for instance, VIX) while controlling their cross-section dependence.

The choice of these variables is grounded on the assumption that a shock to the VIX index raises uncertainty in the financial US markets, which in turn declines the S&P 500 index and decreases the yield interest rate. Once the SVAR model has been estimated, the IRF can be calculated to visualize the impact of shocks over time (Braun & Brüggemann, 2023).

### *3.4 Data and Lag Structure*

In time series analysis, there is a need to choose the right lag structure, as it determines the relationship between variables. Therefore the following three information criteria were used to assess the number of lags for the Structural Vector Autoregression (SVAR) model; Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQC), and Schwarz Information Criterion (SIC).

AIC (Akaike Information Criterion) normally leads to the selection of models with more lag variables as these models can capture more dynamic linkages but with the disadvantage of overfitting. SIC (Schwarz Information Criterion) often indicates fewer lags, stressing on the model parsimony and no overfitting. HQC (Hannan-Quinn Criterion) is another model selection criterion that lies between AIC and SIC, seeking a better balance between model complexity and model fit.

### *3.5 Robustness Testing*

To ensure that the results are robust, the researchers also estimate the SVAR model using two more specifications; with a shorter lag length of 2 lags and a longer lag length of 4 lags. The IRFs for these different lag lengths showed very little significant variation, thus supporting the stability of the findings.

The researchers of the current study also adjusted the time period for data analysis by considering the longer and the shorter periods to check whether there were any differences. The IRFs over these different time horizons kept the same direction and statistical significance of the responses, which added more credibility to the results. Last of all, the current study conducted the Portmanteau test to test for the autocorrelation in the residual of the SVAR model.

### *3.6 CUSUM Analysis: The Segmentation of Data*

Besides the main analysis, a CUSUM test was conducted in a bid to determine whether there were any structural breaks in the VIX data over the period under consideration. CUSUM tests revealed a structural shift in September 2019, though the COVID-19 crisis starting from January 2020 could also have impacted the results. Based on this finding, the data was split into two periods: pre-COVID-19 and post-COVID-19 or pre-2020 and post-2020.

In the primary study, how the VIX, S&P 500, and yield interest rates are associated is investigated using the Kalman filter and SVAR model; however, the split VIX data was visually examined to identify changes in the behavior of market volatility before and after the structural break. This additional analysis is intended to give a better understanding of how market uncertainty changed in these two different periods.

## 4 Results

This section presents a detailed analysis of the results. The first step involves smoothing the outgoing variables using the 'dlm' package to apply the Kalman filter to the three-time series. The three graphs illustrate the original versus the smoothed versions of the time series, providing a clear visual representation of the data refinement process and the effectiveness of the Kalman filter in smoothing the time series.

Figure 1 shows the results of the smoothing of the VIX time series. The volatility in the VIX index itself is recognizable. The COVID-19 period around 2020, when there was increased volatility in the market, also stands out.

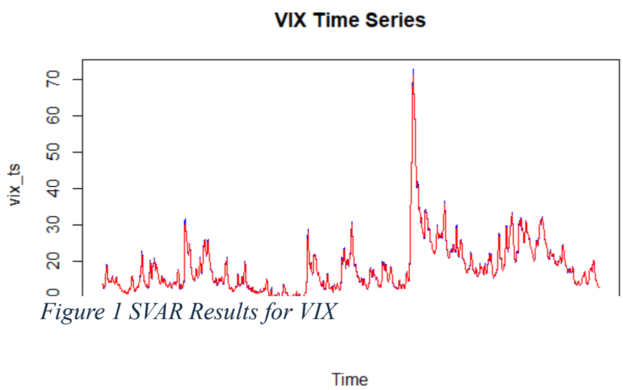


*Figure 1 SVAR Results for VIX*

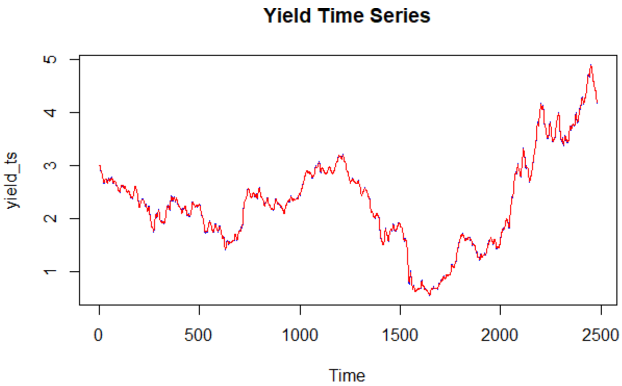


Figure 2 also shows the performance of the S&P 500 in the smoothed version. It shows the performance of the S&P 500 against the VIX. The

*Figure 2 SVAR results for S&P 500*

VIX behaves dynamically concerning the market trend. Thus, stronger price drops in a shorter time frame can be recognized as a stronger swing on the VIX.

Figure 3 ultimately shows the development of yields over the period under review. Here, too, the relationship between the market development can be better recognized. The smoothing here shows the falling yield rates,

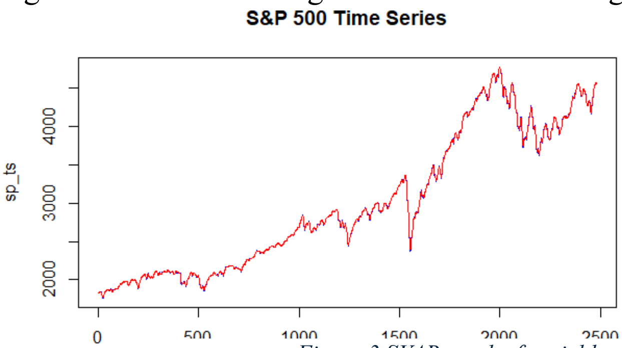


*Figure 3 SVAR results for yield*

particularly in the period of the coronavirus pandemic, as well as smaller declines in the period from 2022. An impulse response function (IRF) in the context of econometrics and time series analysis describes how a variable responds to the change in another variable over time after a shock or impulse has occurred (Iwanaga et al., 2021). In the specific context of explaining the VIX on the S&P 500, the impulse response function allows us to analyze how shocks in expected market volatility (measured by the VIX) affect the value of the S&P 500 over time (Megaritis et al., 2021)

For each variable (VIX, SP 500, and Yield), there is a pair of plots: The first plot displays the original time series in blue, and the second plot illustrates the corresponding smoothed time series in red. In the shown figure 4, it can be observed that a 1 percent shock on the VIX index leads to a negative deviation of the SP 500 index by 0.002 percent in the first days and around 0.01 percent in the next 19 days. Therefore, there is evidence that when there is a shock in the volatility index, the financial market declines, expressed by the contraction in the

SP 500 index. In addition, Figure 5 demonstrates how a positive shock on the VIX index negatively affects the interest rate yield.

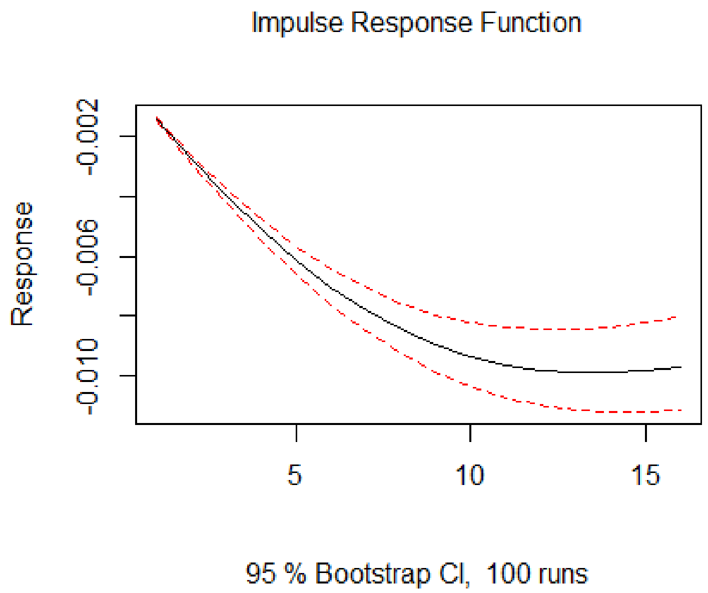


*Figure 4 The impact of a shock in VIX on the SP500*

In addition to the VIX, the IRF on the return rates can be shown in Figure 5. The analysis shows that a 1 percent shock causes the market to fluctuate by up to 0.010 to 0.020 basis points over a period of up to 16 days. Positive effects in the VIX due to full volatility thus lead to a negative return development of the S&P 500.

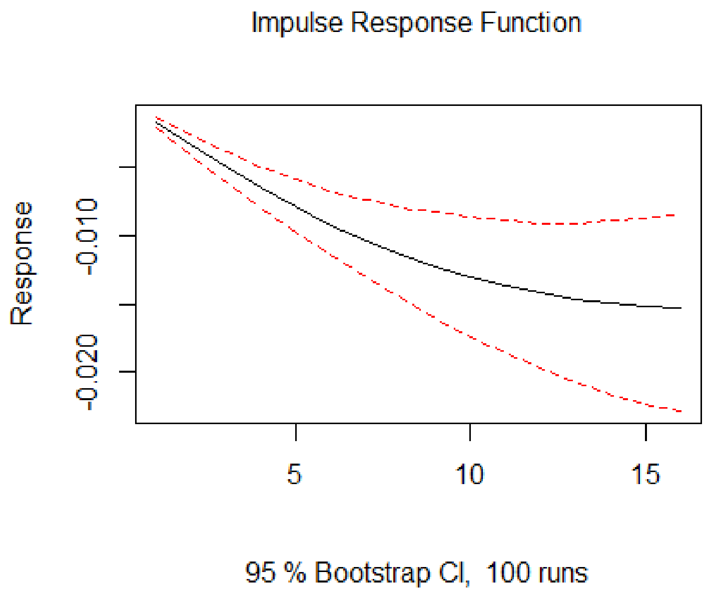


*Figure 5The impact of a shock in VIX on the Yield interest*

### *4.1*

The impulse response function is used to summarize the main results, with key findings presented in Figures 4 and 5. Figure 4 illustrates the effect of a 1% shock in the VIX index on the S&P 500 index, showing how the financial market responds to increased uncertainty. Similarly, Figure 5 demonstrates the impact of a 1% shock in the VIX index on the yield interest rate, revealing how the real economy reacts to an uncertainty shock.

In the initial phase, a mathematical filter in R called Kalman filter from the 'dlm' package is used to filter the three time series. This approach is used in an effort to identify a shifting trend of the variables while at the same time excluding other factors such as noise and seasonality. The strength of the Kalman filter is in its ability to work when there is uncertainty or noise in the measurements, which is adjusted with updates as more data is obtained (Welch, 2021).

Figure 4 investigates the impact of uncertainty on the financial markets; a 1% shock in the VIX index causes an S&P 500 index's first-moment deviation of 0. 0.002%, and then steadily rising to around 0. 01% in the course of the next 19 days. From this evidence, it is clear that an increase in uncertainty leads to a decrease in the market value of large firms in USA thus meaning a volatility shock causes a reduction in the size of the financial market. In addition, Figure 5 presents the real economy's reaction to uncertainty shocks with empirical evidence. As seen in the graph, positive shock in the VIX index has a negative effect on the yield interest rate implying that increased uncertainty leads to a slower growth rate of activity (Tiwari et al., 2021).

### *4.2 Robustness Testing*

The results from the robustness tests did not show significant changes in the impulse response function, confirming the robustness of the findings. In the first experiment, the lags of variables in the VAR model were modified according to the criteria illustrated in the table below, which shows the criteria used for selecting the optimal number of lags.:

**Table 1: Selection Criteria for Lag**

| Criteria | Optimal Lag |
|---|---|
| AIC(n) | 10 |
| HQ(n) | 10 |
| SC(n) | 4 |
| FPE(n) | 10 |

Various lag lengths, ranging from 1 to 10 lags, and the results are summarized in the table below:

**Table 2: Lag Information Criteria**

| Lag Length | AIC | HQC | SIC |
|---|---|---|---|
| 1 | -2.507 | -2.506 | -2.505 |
| 2 | -2.653 | -2.651 | -2.648 |

| | | | |
|---|---|---|---|
| 3 | -2.657 | -2.655 | -2.651 |
| 4 | -2.620 | -2.619 | -2.617 |

Based on these results, the lag length of 3 lags was chosen for the main analysis as it minimizes the AIC, HQC, and SIC, providing a balance between capturing the underlying dynamics and maintaining model simplicity.

Information criteria were utilized to determine the optimal number of lags for the VAR model. The table below illustrates the different criteria used and the corresponding selected number of lags for each case. Based on these criteria, the number of lags in the main model was adjusted, and the impulse response functions were generated. Notably, the results showed minimal significant changes, reaffirming the robustness of the findings.

**Table 3: Portmanteau Test asymptotic**

| Test | Chi-squared | p-value |
|---|---|---|
| Portmanteau Test | 513 | 2.2 |

The p-value from the Portmanteau test is greater than 0.05, indicating that the null hypothesis of no autocorrelation cannot be rejected, confirming the adequacy of the model's lag structure.

### *4.3 CUSUM Analysis:*

The CUSUM test was also applied to VIX data and that also depicted a significant structural break around the early part of 2020. To further test this, VIX was split into Pre-2020 and Post-2020 datasets to compare the performance of the model on the two different timeframes. Figure X displays the CUSUM plots for structural shift and Figure Y displays VIX for both periods.

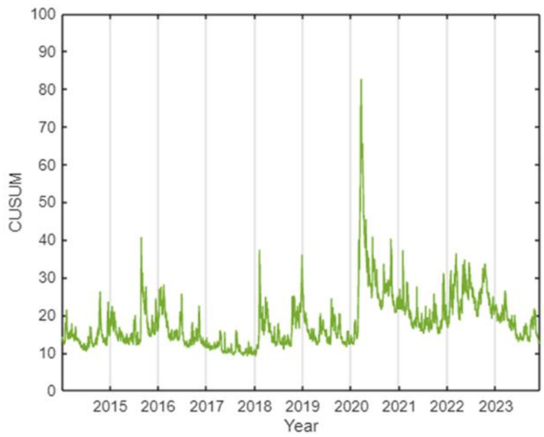


*Figure 6 CUSUM graph with spike between 2020-2021*

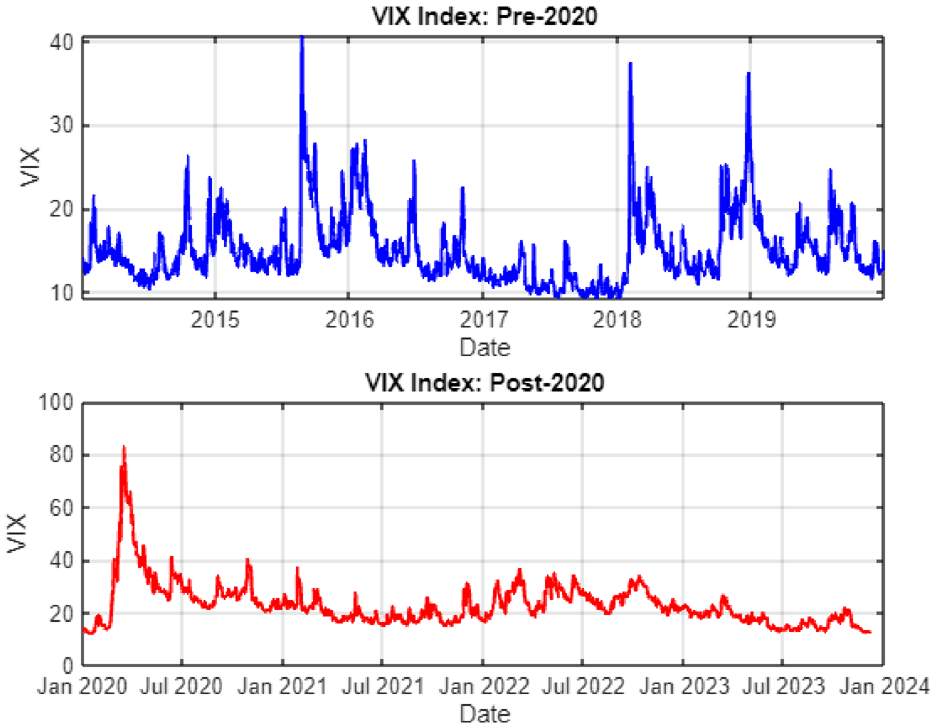


*Figure 7 CUSUM plot for pre and post 2020 VIX dataset*

The CUSUM plot for the Pre-2020 VIX dataset showcases that the levels of volatility remained constant and did not deviate much from the mean value. Any present would be in a small range, which is characteristic of the market without significant and persistent shifts in its structure. This implies that the market was operating under normalcy before the occurrence of the pandemic.

The CUSUM plot of the on the other hand for the Post-2020 VIX indicates a steep upward movement. This is seen to have a meaning of a rise in volatility levels which is in line with the market uncertainty and the general anxiety of the investors after the emergence of COVID-19. The plot shows deviations from the baseline, which proves that the market had more intense and more frequent volatility surges. This is in light of the volatility that was evident in the financial markets especially during and after the pandemic period due to fluctuations in the investor’s attitude.

The comparison of the two figures also means that there has been a structural change at around early 2020 from a stable to a volatile environment. The differences in the plots illustrate how the COVID 19 changed the market from a stable environment to a volatile and uncertain environment. Although the primary concern of this paper is the correlation between the VIX, S&P 500, and yield interest rates, this additional test shows how the volatility of the market evolves. Such visualizations enhance the primary outcomes and provide a wider perspective of the market's reaction to external factors.

## 5 Discussion

The empirical results of the existing research show that the positive change in the VIX index which reflects the market volatility and investors' attitudes has negative impacts on the S&P 500 index and yield interest rates. These findings support the theoretical postulations of market sentiment and risk aversion whereby increased market volatility leads to decreased investment in risky securities such as equities hence lower prices (Gong et al., 2024). At the same time, the expectation of a weaker economic outlook due to higher uncertainty leads to lower long-term interest rates as investors demand safer assets hence lowering yields (Blanchard, 2023).

This is in line with the market sentiment theory which postulates that the behaviour of investors is anchored on perceived risk and uncertainty. When the VIX increases, meaning that there is an increase in the expected volatility, the market sells equities and moves to bonds thus decreasing the S&P 500 and yield interest rates (Akin & Akin, 2024). The risk-return tradeoff also supports these results, where investors require higher returns for bearing risk during periods of high risk, resulting in a lower equity price when such returns are not achievable.

In line with the literature on market uncertainty and its effects on financial markets, results support and expand upon the prior research. For instance, Qadan et al. (2023) study that develops a VIX-style measure for Treasury yields also shows that uncertainty harms economic activity such as a decline in industrial production and increased unemployment (Qadan et al., 2023). These findings are supported by the current study where it is shown that shocks to the VIX lead to a decline in both the financial market performance as measured by S&P 500 and economic indicators in the form of yield interest rates.

Adrangi et al. (2019) look at how the VIX affects the major equity markets, and the authors conclude that the major equity markets' volatility is highly responsive to structural changes to the VIX. As expected, we also find a negative response of the S&P 500 to a VIX shock, which supports this view (Adrangi et al., 2019). Yet, this analysis is carried further in the current study by using the Kalman Filter to smooth the data and detect structural breaks, which gives a more detailed picture of how these relationships change and what happens during periods of increased market instability, including the COVID-19 crisis. Overall, these findings underscore the critical impact of market volatility on both financial markets and economic indicators, highlighting the importance of effective risk management strategies to mitigate the adverse effects of uncertainty.

## 6 Implications

The economic relevance of the current results is based on the consequences of the results for market actions and policies. The fact that the S&P 500 index exhibits a strong negative response to VIX shocks indicates that market participants are very sensitive to changes in perceived risk which has implications for investors and policymakers(Akin & Akin, 2024). These insights may be useful to investors who might want to change their portfolio to avoid high risks during periods of high volatility, to policymakers who may want to work on ways of ensuring that the financial markets do not become too volatile (Adrangi et al., 2023).

To the policymakers, the observed decline in yield interest rates after the VIX shock shows that markets are linked and interdependent. Based on this relationship, it is recommended that central banks should pay attention to the variables that reflect market sentiment such as the VIX while making decisions on the appropriate monetary policy to adopt (Poloz, 2024). Policies that can be taken ahead of time include changing the interest rates or coming up with liquidity measures to offset the impacts of increasing uncertainty not only in the financial markets but also in the economy (Trythall, 2024).

Altogether, the existing research adds to the global knowledge about the effects of market risk, as captured by the VIX, on financial and economic indices (Szczygielski et al., 2023). In this case, by comparing the results with the studies done by other scholars, the researchers can establish the stability of the relationship between the VIX, S&P 500, and yield interest rates while at the same time using the Kalman filter and structural break analysis to get additional insights. In light of these findings, investors, financial analysts, and policymakers can benefit from this study, especially in terms of risk management of high-volatility markets.

## 7 Conclusion

Market volatility is operationalized using the VIX index and the effect of this on financial markets and economic performance is investigated. It employs sophisticated econometric methods like the Structural Vector Autoregression (SVAR) model and the Kalman Filter to examine the connection between market attitude and risk aversion. As the findings of the study depict, the S&P 500 has a negative response to the positive shock in the VIX index, which means that the financial market shrinks. Likewise, yield interest rates reduce with an increase in uncertainty due to expectations of a slowdown in economic activity. The study also validates the fact that investors pull out their money from equities during periods of uncertainty hence affecting the stock prices and the economy. These findings imply that investors and policymakers should include market sentiment indicators in their investment decisions and should pay attention to these indicators when making decisions.

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