Analyzing VIX and Inflation using Vector Autoregressive Methods

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Introduction

Motivation

The COVID-19 pandemic played an impactful role on society, inducing social quarantine and resounding consequences at a global economic level. Due to the pandemic, in 2020, inflation surged primarily due to problems like backlogs of work orders for goods and services caused by supply chain issues amongst others. To deal with this inflationary surge, at each meeting from March 2022 to May 2023, the FOMC (Federal Open Market Committee) raised the target range for the federal funds rate. The initial increase was 25 basis points, but subsequent moves were larger, including increasing the target range by 75 basis points at each of the June, July, September, and November 2022 meetings. As the market anticipated an end to rate hikes and expectations of Fed rate cuts grew, the stock market soared in 2023. There is a very strong relationship between the performance of the stock market and the CBOE VIX (Chicago Board Operations Exchange Volatility Index), or simply, the VIX index.

The VIX Index is a calculation designed to produce a measure of the 30-day expected volatility of the U.S. stock market, derived from real-time, mid-quote prices of S&P 500® Index (SPX℠) call and put options. It is essentially a metric that gauges whether investors are scared with respect to the stock market. Upon conducting research it was discovered that there is a complex relationship between VIX and inflation. Furthermore, deeper investigation revealed that the VIX index is largely influenced by market-implied inflation.

Objective

The primary objective of this paper is to explore the relationship between VIX and market-implied inflation under the scope of certain external factors. These include three exogenous variables: the federal funds rate, unemployment rate, and GDP (Gross Domestic Product). According to the research conducted, these macroeconomic variables are chosen due to their significant impact on both VIX prices and inflation. It is important to note that instead of performing a deep dive into structural breaks like the 2008 Financial Crisis and the 2020 Covid Pandemic, they are put under control, so the relationship between VIX and inflation can be accurately explored.

Literature Review

A wide range of sources were considered while evaluating the complex relationship between VIX and inflation. A paper published by Soper (2017) indicates a significant inverse relationship between VIX and, particularly, the 5-year breakeven inflation, which holds mainly during the recent financial crisis and the post-crisis periods. Another study by Burger (2014) found that VIX had a positive effect on inflation in the next period in South Africa, and as market volatility increased, its effect also increased. However, there was also contradictory evidence found in Canada, where research by Saryal (2007) yielded that inflation had a negative impact on stock market volatility, although it was less economically significant. There was also documentation of potential bidirectional causality between VIX and inflation in the paper by Schwert (1989). In this literature, evidence was found that inflation volatility can help predict VIX volatility but stronger evidence that financial asset volatility helps to predict future inflation volatility was also found, suggesting bidirectional causality.

Several resources also supported the notion that certain macroeconomic factors affect both VIX and inflation. A paper by Vähämaa, Sami, and Äijö (2011) investigated the impact of the Fed's monetary policy on the VIX Index and found that the Fed's policy decisions significantly affected stock market uncertainty. Particularly, following the FOMC meeting, implied volatility decreased. However, the federal funds rate surprises were positively related to market uncertainty. Another macroeconomic factor significantly related to the VIX index is the unemployment rate. Recent research by Łukasz and Keller (2020) found that out of 80 macroeconomic variables, the unemployment rate had the greatest impact on the VIX index levels. Furthermore, additional recent research by Bevilacqua, Morelli, and

Tunaru (2019) found a connection between GDP and stock market volatility. The paper analyzes the role of macroeconomic and financial determinants in explaining stock market volatilities in the U.S. market. In particular, positive implied volatility is driven more by variables such as inflation and GDP. Other factors were also shown to impact VIX and inflation. There was a study conducted by Canorea (2018) on the relationship between the VIX index and industrial metals which suggested that the CRB (Commodity Research Bureau) index and the VIX index shared a long-term negative correlation which further improved over the longer horizon. However, this variable was omitted from this study so as to focus primarily on macroeconomic factors.

Noteworthy research was also required in order to determine the appropriate economic models for modeling VIX and inflation. While investigating stock return volatility in emerging equity markets, Rizwan and Khan (2007) used EGARCH (Exponential Generalized AutoRegressive Conditional Heteroskedasticity) and VAR (Vector AutoRegressive) methods and found a positive relationship between stock volatility and inflation with asymmetric variance. When the same EGARCH technique was used to find the relationship between inflation and a market index similar to the S&P 500 as a proxy for market returns in Nigeria by Sokpo, Iorember, and Usar, there was no relationship found but also no asymmetry in volatility. This essentially meant that good news had the same impact as bad news. Similar research in Nigeria using the QGARCH (Quadratic Generalized AutoRegressive Conditional Heteroskedasticity) model by Yaya and Shittu (2010) found a negative correlation between inflation and conditional market volatility. In Kenya, researchers Olweny and Omondi (2011) also used EGARCH and TGARCH (Threshold Generalized AutoRegressive Conditional Heteroskedasticity) models to check the effect of inflation volatility (not level inflation) on market volatility. Their results yielded symmetrical returns but asymmetric variance.

This comprehensive literature review substantiated the initial notions on the theory of a relationship between VIX and inflation, probing further investigation.

Data

A wide list of reliable data sources were used to collect data and have been summarized in a succinct list below:

- VIX: FactSet
- Consumer Price Index: Federal Reserve Economic Data
- Federal Funds Rate: Federal Reserve Economic Data
- Unemployment Rate: Federal Reserve Economic Data
- Monthly Real GDP Index: S&P Global

Note: Official GDP quarterly statistics were not used. S&P Global Index data was used because it provides monthly data. The Consumer Price Index is used as a measure of inflation.

Data Preparation

Time Period Selection

The monthly historical data spanning from January 1, 1992, to January 1, 2024, which encompasses variables such as VIX price and monthly inflation—calculated based on the not seasonally adjusted Consumer Price Index (CPI) for all urban consumers in the U.S.—identifies three distinct patterns of structural breaks, which correspond to significant economic disruptions: the Asian Crisis of 1997, the Financial Crisis of 2008, and the COVID-19 pandemic in 2020.

Three criteria were essential in selecting the appropriate time period for further analysis. First, the data sample must include the most recent observations to accurately reflect the current state of financial markets and the macroeconomic environment, while ensuring a large enough sample size to validate potential asymptotic inferences. Second, beyond the initial criterion, the optimal sample should exhibit a minimal number of structural breaks to reduce analytical interference. Third, the macroeconomic environment and financial markets should remain stable and normal throughout the chosen period to mitigate the risk of anomalies in the sample. In light of these considerations, the dataset selected encompasses data post-2000, specifically including the two most recent structural breaks. The dataset comprises monthly historical data from January 1, 2020, to January 1, 2024, with a total of 289 data points.

Structural Breaks

The binary variables were employed to control for the structural breaks stemming from significant economic disruptions within the sample, namely the Financial Crisis of 2008 and the COVID-19 pandemic in 2020. The influence of the economic disruptions on key variables of interest—VIX Price and Monthly Inflation—was evident in the graphical data, revealing a delayed effect. The determination of the onset of these shocks utilized the US Business Cycle Expansions and Contractions data, based on the Unemployment Rate, as a reference point. Data from the National Bureau of Economic Research (2024) highlights three recessions that encapsulate the negative impact of the 2008 Financial Crisis and the COVID-19 pandemic on the economy. These recessions spanned from March 2001 to November 2001, December 2007 to June 2009, and February 2020 to April 2020, respectively. To manage the impact of structural breaks on analytical inferences, three binary variables were defined, assigned a value of 1 during the identified recession periods and 0 otherwise, corresponding to the dates of observed data.

Stationarity Test and Variable Transformation

Given the expected presence of higher-order autocorrelation, the Augmented Dickey-Fuller Test was employed on all variables—VIX Price, Monthly Inflation, Federal Funds Rate, Unemployment Rate, and S&P Monthly Real GDP Index—to assess the stationarity of each time series. As demonstrated by the outputs of the ADF test on VIX Price, Monthly Inflation, and Federal Funds Rate, the p-values were 0.000, 0.014, and 0.005, respectively. At a 5% significance level, the null hypothesis, which posits the presence of a unit root in each of these series, is not statistically significant and is therefore rejected. Meanwhile, the ADF test yielded p-values of 0.153 and 0.987 for the

Unemployment Rate and S&P Monthly Real GDP Index, respectively. Since these p-values exceed the 5% significance level, transformations of the Unemployment Rate and S&P Monthly Real GDP Index were necessitated, as the statistical evidence failed to reject the null hypothesis of a unit root's presence.

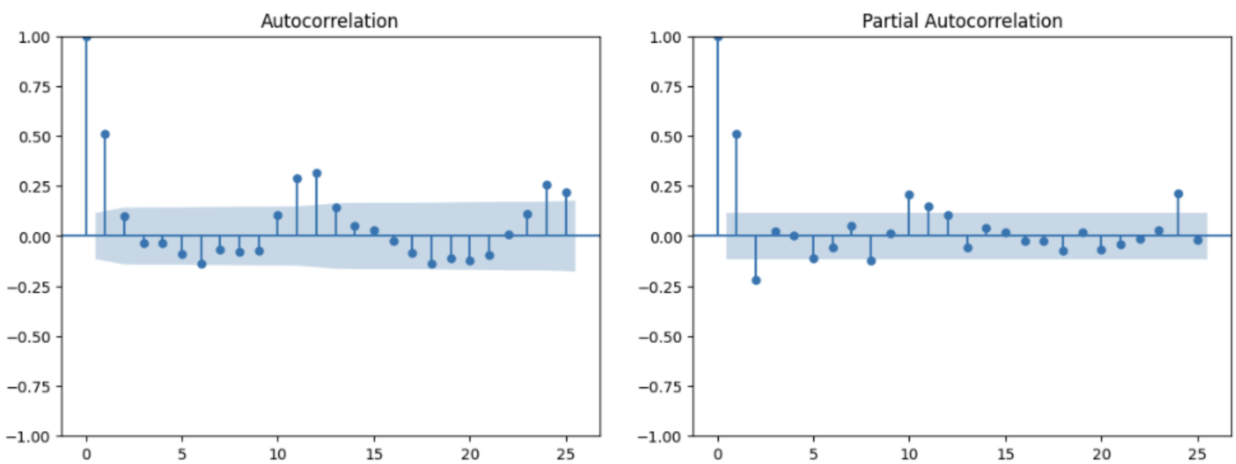
Firstly, the first difference technique was applied to the Unemployment Rate. As indicated by the graph, the first difference of the Unemployment Rate demonstrates a mean-reverting level, implying stationarity. Consequently, the Augmented Dickey-Fuller (ADF) test was reapplied, yielding a p-value of 0.000, which confirms the stationarity of the first difference of the Unemployment Rate.

Secondly, although the individual values of the S&P Monthly Real GDP Index are indexed based on actual real GDP data, and therefore the numerical values do not represent the actual monthly real GDP amounts, the growth rates of these numerical values do correspond to the actual real GDP growth rates. In response to this, the percentage difference—rather than the first difference in absolute terms—was employed for the S&P Monthly Real GDP Index. This approach was validated by a p-value of 0.000 in the output of the ADF test, confirming that the percentage difference of the S&P Monthly Real GDP Index, or the monthly growth rate of real GDP, is stationary.

In summary, following the data preparation stage, the dataset prepared for future analysis encompasses monthly historical data from January 1, 2020, to January 1, 2024, totaling 289 data points. The primary variables of interest are VIX Price and Monthly Inflation. The model also incorporates the Federal Funds Rate, the First Difference of the Unemployment Rate, and the monthly growth rate of real GDP as exogenous factors. The stationarity of all listed variables has been confirmed at the 5% significance level by the Augmented Dickey-Fuller (ADF) test.

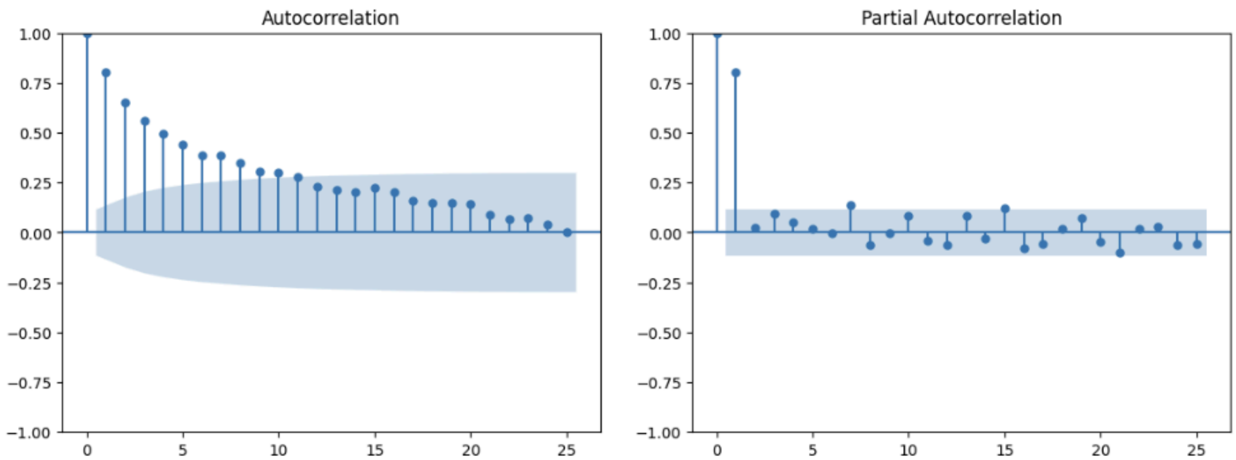
Model Selection

ACF and PACF of Primary Variables and Candidate Models



The Autocorrelation Function (ACF) graph for Monthly Inflation exhibits significant correlations at lag 1 and, to a lesser extent, at lag 2. Beyond this point, there is a sharp decline in correlation, indicating a truncation after lag 2. This pattern in the ACF graph is indicative of a potential Moving Average component of order 2 (MA(2)) within the Monthly Inflation series.

Conversely, the pattern observed in the Partial Autocorrelation Function (PACF) plot does not conform to a definitive geometric decay, as it lacks a gradual, exponential decrease across the lags. The PACF graph shows a pronounced spike at lag 1 followed by fluctuations around the zero line, suggesting the presence of an Autoregressive component of order 1 (AR(1)) in the Monthly Inflation time series.



The Autocorrelation Function (ACF) graph for the VIX Price exhibits a gradual decrease in correlation as the lag increases, illustrating a geometric decay characteristic of an Autoregressive (AR) process. Concurrently, the Partial Autocorrelation Function (PACF) graph displays a significant correlation at lag 1 followed by a sharp cutoff. Collectively, these patterns observed in the ACF and PACF correlograms align with the typical properties of an AR process, suggesting a potential model selection of AR(1).

The focus of this study is to capture the interactions between Monthly Inflation and VIX Price, interactions that have been substantiated by prior research, highlighting their importance. In consideration of the Autoregressive (AR) properties exhibited by VIX Price and the hybrid Autoregressive and Moving Average (ARMA) characteristics displayed by Monthly Inflation, and in order to answer the pivotal research question, "Do Monthly Inflation or VIX Price contribute to forecasting each other?", three multivariate time series models have been identified as potential candidates: the Vector Autoregressive Model with Exogenous Variables (VARX), the Vector Moving Average Model with Exogenous Variables (VMAX), and the Vector Autoregressive Moving Average Model with Exogenous Variables (VARMAX). These models have been strategically selected to explore the dynamic interplay and potential predictive capacities between the two variables.

Model Selection

To determine the model with the most robust predictive capabilities, an initial step involves selecting the optimal lag for each model type. Subsequently, the in-sample Root Mean Square Error (RMSE) and out-of-sample RMSE produced by each model, employing their respective optimal lags, are compared. For the purpose of generating RMSE, the dataset is partitioned into two segments: the training data, which encompasses the period from January 1, 2000, to June 1, 2023, consisting of 282 observations, and the testing data, spanning from July 1, 2023, to January 1, 2024, which includes 7 observations.

To evaluate the efficacy of models within three distinct categories — VARX(p), VMAX(q), and VARMAX(p, q) — it is imperative to first identify the optimal lag for each type, thereby facilitating the development of a comprehensive list of candidate models. The selection of the optimal lag is informed by three key metrics: the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Likelihood Ratio Test. While these measures typically converge on the same lag number, discrepancies occasionally arise among the results they yield. In instances of such discrepancies, the lag that results in the lowest in-sample and out-of-sample Root Mean Square Error (RMSE) is chosen as the optimal lag, as this metric directly reflects the minimal prediction error the model can achieve. Furthermore, the impact of including binary variables and the decision to treat all variables as endogenous, or to designate variables other than key variables as exogenous, is rigorously evaluated through an iterative modeling process to determine whether these adjustments lead to a reduction in RMSE. The models being tested include VARX(2) and VAR(2) with or without binary variables to control structural breaks, VMAX(2) and VMAX(1) with binary variables, and VARMAX(1,1) and VARMAX(1,2) with binary variables.

Given the limited size of the testing dataset, which includes only seven observations, the in-sample Root Mean Square Error (RMSE) has been prioritized as the primary criterion for model selection. This prioritization is due to the inherent limitations in assessing out-of-sample predictive accuracy with such a small sample size. Analysis of the in-sample performance reveals that VAR and VARX models generally exhibit superior predictive power, as evidenced by their lower RMSE values for both VIX Price and Monthly Inflation, compared to VMAX and VARMAX models.

Although VAR and VARX models generally exhibit higher out-of-sample RMSE than VMAX and VARMAX models, the VARX(2) model with binary variables demonstrates a unique balance: it yields a marginally higher out-of-sample RMSE yet achieves the lowest in-sample RMSE for the critical variables examined, namely VIX Price and Monthly Inflation. Consequently, the VARX(2) model incorporating binary variables is deemed the most suitable for our analysis, demonstrating strong in-sample accuracy with reasonable out-of-sample predictive performance.

Results

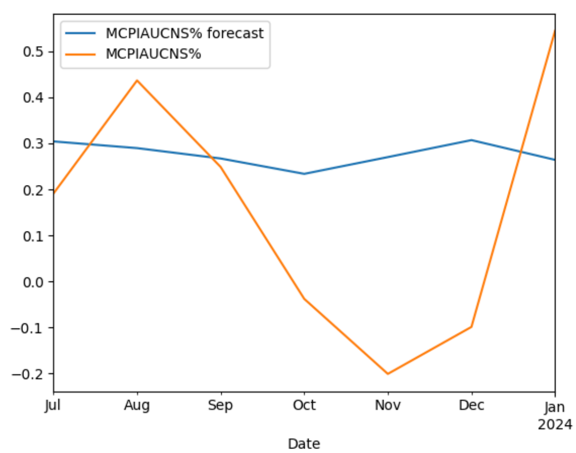
Granger Causality and Stability

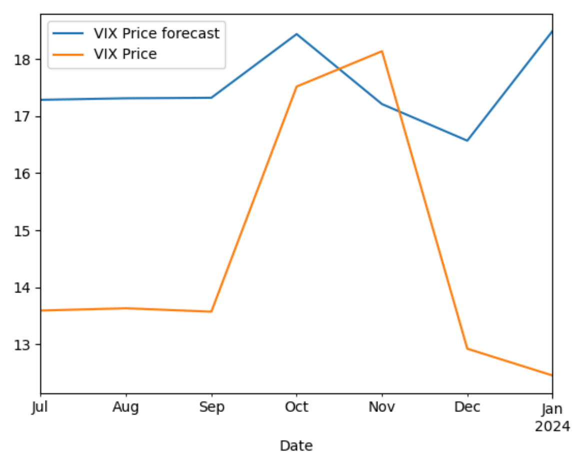
A critical step in the analysis was ensuring the stability of the VAR models, which was confirmed through the examination of the roots of the characteristic polynomial associated with each VAR system. All models displayed roots lying inside the unit circle, confirming that the processes are stable and do not exhibit explosive behavior. This stability implies that the models are well-specified and suitable for forecasting and further analysis.

Granger causality tests were conducted to determine if any of the included variables could predict future values of the other variables, a fundamental aspect of forecasting and policy analysis. Contrary to expectations and existing literature, the tests revealed no significant Granger causality between inflation and VIX. This result was robust across various model specifications and lag structures. This absence of Granger causality implies that past values of inflation do not provide statistically significant information for predicting future values of the VIX conditional on the exogenous variables in our model. Similarly, past values of VIX do not help in forecasting the future values of inflation.

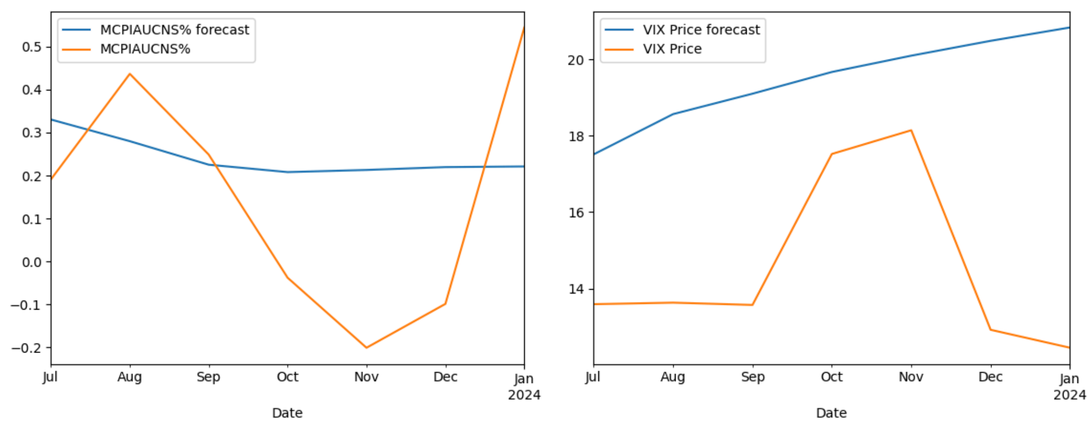
The findings that no Granger causality exists in any direction among the variables studied is surprising, given the theoretical and empirical literature suggesting relationships. Several potential explanations can be posited for these unexpected results. First, the absence of Granger causality does not imply no causality; rather, it suggests that the past values of these variables are not useful for forecasting the future values in the context of a VAR model. It is possible that nonlinear relationships or relationships manifesting over non-standard lag structures could exist, which are not captured by the framework of a VAR model. Second, the model's inability to detect relationships might also be a consequence of the granularity of the data. Monthly data might mask variations and dynamics that could be more apparent in higher-frequency (e.g., daily or weekly) data. Additionally, external shocks or structural breaks not accounted for in the model could distort the interdependencies among the variables.

Forecasting



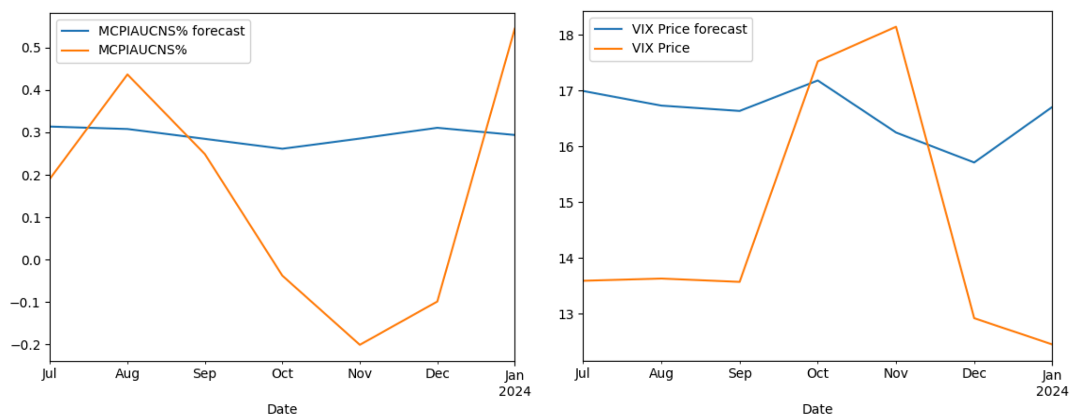


The forecasting performance of this model is scrutinized without the inclusion of dummy variables for major economic recessions, namely the Asian Crisis of 1997, the Financial Crisis of 2008, and the COVID-19 pandemic of 2020. The model was trained on data from January 1, 2000, to June 1, 2023, and was subsequently tested on data from July 2023 to January 2024. The forecasting evaluation was based on the out-of-sample root mean square error (RMSE), averaging 1.9649 across the two variables of interest—VIX and inflation. This RMSE, while indicating the model's capability to predict the general trend in both series, suggests a limitation in the precision of capturing significant fluctuations at specific peaks and troughs. Overall, the results imply that while the VAR model with exogenous variables can provide valuable insights into the general movement of inflation and VIX, its predictive accuracy diminishes during periods of significant economic turmoil, possibly due to the absence of recession-specific controls. We later incorporate these dummy variables for economic downturns with the hope of enhancing model robustness and predictive precision during volatile periods.



Notably, one model within our investigation utilized an all-endogenous approach without any dummy variables to account for significant economic downturns (results above). This particular model yielded an out-of-sample average RMSE of 2.844, indicating a relatively poorer performance compared to other models that categorized these variables differently. Like the previous model, it also captures the trend of inflation while being unable to predict significant downturns. Unlike the previous model, it is unable to capture any of the features of the VIX price data, displaying a concave function that consistently overestimates the real values.

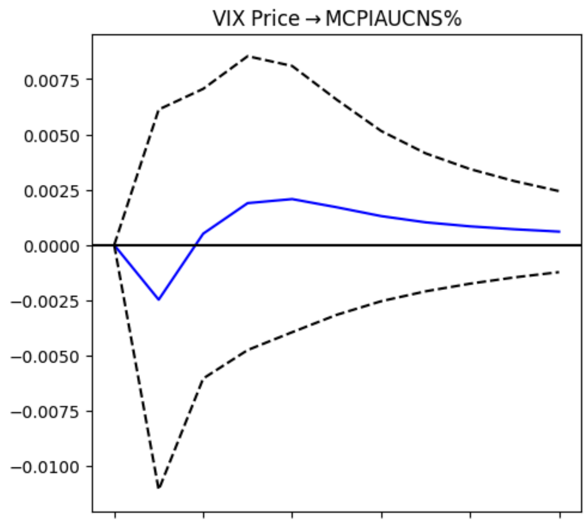
This outcome serves as a crucial learning point in econometric model building, underscoring that the inclusion of numerous variables without careful consideration of their roles and interdependencies can lead to models that not only perform suboptimally but are also prone to overfitting. Overfitting occurs when a model is excessively complex, capturing noise rather than the underlying relationship in the data, which is exacerbated by not accounting for structural breaks or regime shifts such as economic recessions. Consequently, this reinforces the idea that model selection is not merely about integrating an extensive array of variables but requires iterative refinement and validation to ensure robustness. Thus, the endeavor to model economic phenomena must be approached with meticulous design and thoughtful selection of variables to truly capture the dynamics at play.

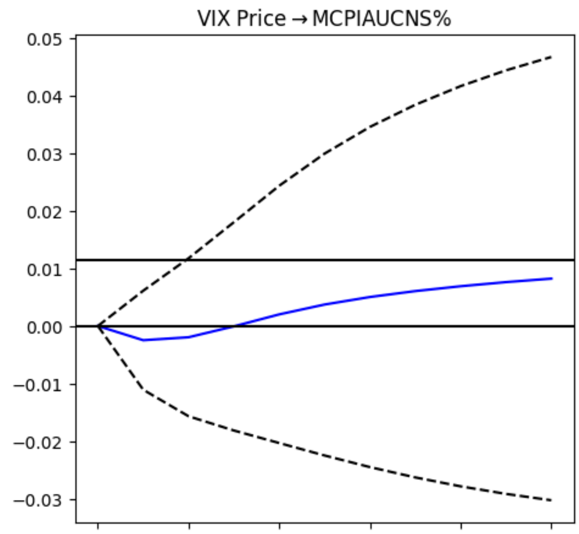


Overall, our best-performing model was our VAR(2) with exogenous variables and structural breaks for recessions. Our analysis revealed that this model achieved an out-of-sample average RMSE of 1.6104. This performance is particularly noteworthy as it significantly outstripped the forecasting capabilities of all other evaluated VAR models. This model not only handled the baseline variability in the VIX but also effectively adjusted for the extreme volatility during marked recessionary periods. It showed enhanced accuracy in predicting monthly VIX prices, thereby providing a robust tool for understanding market dynamics under different economic scenarios. These findings underscore the value of incorporating both continuous economic variables and discrete structural shifts in forecasting models. Due to these results, this model will form the basis of our impulse response analysis.

Impulse Responses

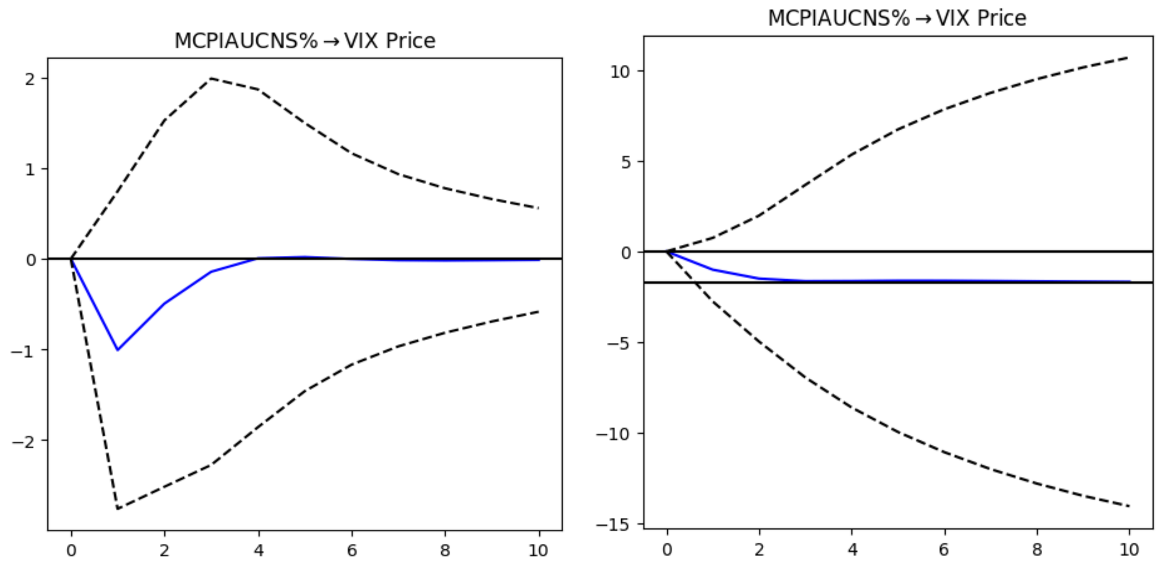
VIX to Monthly inflation





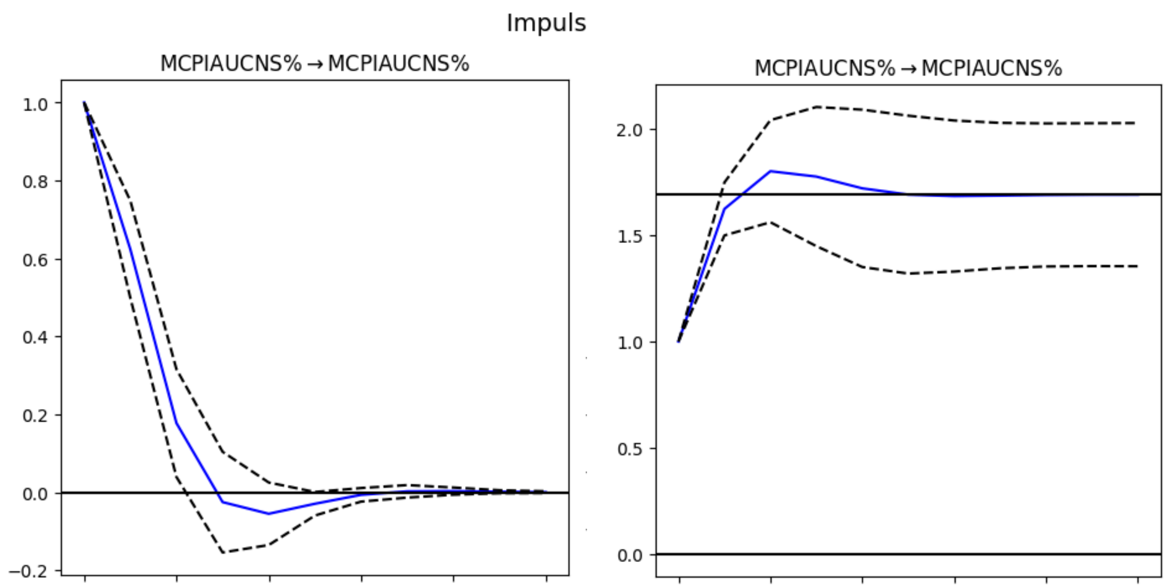
In our analysis, we observed intriguing patterns in the impulse response functions. Initially, a shock in VIX leads to a decrease in inflation, but this is followed by a series of diminishing positive shocks, which ultimately taper off towards zero. Specifically, the cumulative impulse response after 10 periods indicates a net positive effect of the VIX on inflation. However, the 95% confidence error bands encompass zero throughout the analysis period, suggesting that the observed effects are statistically indistinguishable from zero. This outcome implies that while the data hints at potential inflationary impacts from market volatility as measured by the VIX, the effects are not statistically significant, and the null hypothesis of zero effect cannot be rejected. These findings underscore the complexities and uncertainties inherent in modeling the economic predictors of inflation.

Monthly inflation to VIX



Our findings revealed an initial negative shock in VIX following an inflation shock. However, unlike the impulse response function depicting the influence of VIX on inflation, subsequent periods do not exhibit any positive shocks that would counterbalance the initial negative impact. The cumulative impulse response function further illustrates a persistent negative effect over ten periods, tending towards an asymptotic value. The 95% confidence error bands encompass zero throughout the timeline, implying that the observed effects are statistically indistinguishable from zero. This outcome suggests that while inflation influences VIX in the short run, the long-term effect is inconclusive, failing to reject the null hypothesis of a zero net impact between these variables.

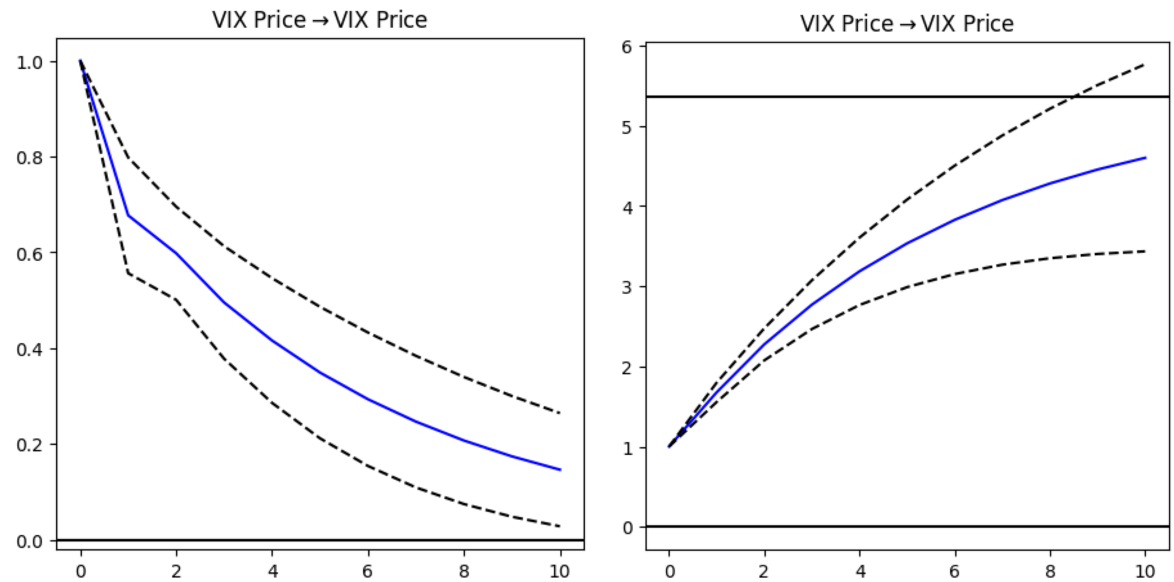
Monthly inflation to self



The results from our VAR analysis indicate that an initial positive shock to inflation tends to dissipate quickly—a phenomenon evidenced by the rapid decay of the impulse response function, which after an initial spike, declines sharply, briefly dips into negative territory, and eventually stabilizes near zero. This temporal pattern is statistically significant, as the 95% confidence error bands range from 1.35 to approximately 2, consistently above zero across all periods analyzed. Consequently, we reject the null hypothesis that the inflation shock has no effect, confirming that these shocks do influence inflation but the effects are short-lived and the cumulative impact remains positive.

The rapid decay of the inflation shock's influence could be primarily attributed to the monetary policy interventions by the Federal Reserve. In our model, the federal funds rate, an exogenous variable, plays a crucial role as it represents the primary tool through which the Federal Reserve manages the money supply and influences inflationary pressures. The observed pattern in the impulse response function suggests that the Federal Reserve's responsive adjustments to the federal funds rate effectively counteract inflationary shocks. This aligns with the monetary policy framework where the Federal Reserve actively uses interest rate adjustments to achieve its inflation targets. This proactive stance by the Federal Reserve likely explains why the inflation shocks do not continue over an extended period, underscoring the efficacy of monetary policy in stabilizing inflationary fluctuations in the short term.

<u>VIX price to self</u>



` The IRFs indicate a significant and sustained positive response of the VIX to an initial shock, which persists for over a year. This is in contrast to the IRF for inflation, where the effect of shocks decays relatively quickly. The cumulative IRF further supports these findings, showing a net positive effect with the 95% confidence error bands ranging from 3 to approximately 6, and not encompassing zero at any point during the analysis period. This allows us to confidently reject the null hypothesis that VIX shocks have no effect. These results underscore the substantial impact that large shocks have on market volatility, as measured by the VIX.

The persistence of the effects of shocks to the VIX can be largely attributed to the behavioral responses of investors to uncertainty and risk. The VIX, often called the "fear index," measures the market's expectation of volatility and is highly sensitive to investor sentiment. The slow decay observed in the response of the VIX to its shocks suggests a difficulty in calming investor fears, which tend to linger even in the absence of further negative triggers. This persistence is likely due to the risk-averse nature of investors, who are slow to adjust their expectations following periods of high volatility. The cumulative effect of this slow adjustment process is a prolonged period of elevated volatility, reflecting the market's hesitance to stabilize in the face of uncertainty. These findings highlight the challenges in managing investor sentiment and underscore the importance of considering psychological factors in financial market dynamics.

Side Note on Standard Errors

We opted to compute the impulse response functions' 95% confidence interval error bands via asymptotic standard errors. This decision was primarily driven by several considerations highlighted in the literature. Firstly, asymptotic methods are less resource-intensive compared to Monte Carlo or bootstrap methods, which is particularly advantageous in models where computational simplicity and efficiency are desired. While it is acknowledged that asymptotic standard errors might sometimes be misleading as suggested by Benkwitz, Lütkepohl, and Neumann (2000), the consensus in the literature, such as findings from Killian & Chang (2000) and Fachin & Bravetti (1996), indicates that the performance of these methods often compares favorably to alternatives, particularly when resource constraints are factored in.

Moreover, although Monte Carlo methods provide a robust alternative, they still require an asymptotic justification, making them not entirely independent of the asymptotic approach. Also, modifications to improve Monte Carlo methods' performance can substantially increase their complexity and resource needs. Bayesian methods, as discussed by Sims and Zha (1999), represent another alternative but are beyond the scope of the methods considered in this analysis due to different underlying assumptions and computational demands. Thus, while recognizing the potential limitations of asymptotic standard errors, their use in this analysis was deemed appropriate given the comparative advantage in terms of computational efficiency and the mixed empirical evidence regarding the superiority of alternative methods. This approach allowed for a balance between analytical rigor and practical feasibility, aligning with the scope and resources available for this research.

Conclusion and Improvements

We picked this topic due to the lack of direct examination of bidirectional causality between inflation and market volatility in the existing literature. Our research was motivated by the premise that understanding the interplay between economic variables like inflation and market indicators such as the VIX could enhance predictive models and guide policy decisions. Throughout this study, we utilized multiple Vector Autoregression (VAR) models with exogenous variables including the federal funds rate, the growth rate of S&P Global's real GDP index, and the unemployment rate, aiming to capture a nuanced view of the dynamics at play. Our findings, however, indicate a surprising absence of Granger causality between inflation and VIX across various model specifications and lag structures. This lack of causality suggests that, within the context of our VAR models, past values of these variables do not serve as reliable predictors for the future values of the other, under the conditions tested. This result contradicts expectations based on previous theoretical and empirical studies, which hinted at potential interactions between these variables.

Several factors could explain this unexpected outcome. First, the linear nature of VAR models may be insufficient to capture complex, possibly nonlinear interactions between market volatility and inflation. The granularity of the monthly data used might also obscure finer dynamics that could become apparent with higher-frequency data. Moreover, potential external shocks or structural changes, not accounted for in our models, could disrupt the expected relationships. The lack of observed Granger causality challenges some conventional economic theories and suggests that further research, perhaps incorporating different methodologies or data frequencies, is necessary to fully understand the dynamics between these economic indicators. This study contributes to the ongoing debate on the predictability of economic variables and their interrelationships, highlighting the complexity and the need for nuanced approaches in economic forecasting and analysis.

The impulse response analyses offered intriguing insights. The response of VIX to shocks in inflation and vice versa showed no significant long-term effects, as indicated by the confidence intervals encompassing zero. However, this does not negate the possibility of short-lived effects or effects that manifest under different conditions or in untested models. Notably, the response of VIX to its own shocks showed a significant and sustained positive response, underscoring the sensitivity of market volatility to its own past values and highlighting the importance of investor psychology in financial market dynamics.

In conclusion, while our models did not reveal the expected bidirectional causality between inflation and VIX, they illuminated the complexity of economic interactions and the limitations of current modeling approaches. This study underlines the necessity for continuous refinement of econometric models, consideration of nonlinear dynamics, higher data resolution, and the inclusion of potentially omitted variables. The pursuit of these enhancements could lead to more precise and insightful models, thereby contributing to a deeper understanding of economic phenomena and aiding in more effective policy formulation.

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