THE UNIVERSITY OF CHICAGO

The Asymmetric Impacts of Economic Policy Uncertainty on the Different Types of Stock's Volatility

By

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Abstract[1]

This study investigates the impacts of the Economic Policy Uncertainty Index on the different types of stocks' volatility. We use the standard VAR models between the EPU index and the GARCH volatility of each stock index (large-cap growth, large-cap value, small-cap growth, and small-cap value stocks). We analyze their impulse response functions, especially the responses and accumulated responses of the GARCH volatility of each stock index to the EPU index innovation. The empirical results show that the EPU index influences the volatility of value stocks more than that of growth stocks for both large-cap and small-cap stocks. In addition, small-cap value stocks are affected by the EPU index the most.

Keywords: uncertainty, risk, economic policy uncertainty, volatility, news, large-cap and small-cap stock, value and growth stock, time series, GARCH, vector autoregression, impulse response function

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1. Introduction

Volatility is significant for risk management because higher volatility is usually associated with higher risk. In addition, uncertainty is crucial to economic agents in the financial market. The price of an asset is affected by information in the market (Fama, 1970). If investors can predict the future quite well, they can make better economic decisions. However, uncertainty hinders them from making confident decisions. Uncertainty about whether or not the Federal Reserve decreases the interest rate next month can affect their investment plan. Uncertainty about how wars in another continent affect the price of their assets can influence their financial decision-making. However, uncertainty is unpredictable and impossible to calculate it (Knight, 1921; Keynes, 1937; Hayek, 1979; Greenspan, 2004).

Although uncertainty is conceptually impossible to quantify and calculate, it influences the financial market. Thus, economists have used another measurement as a proxy for uncertainty (Pindyck, 1986; Ferderer, 1993; Goldberg, 1993; Episcopos, 1995; Campa and Goldberg, 1995; Leahy and Whited, 1996; Poon and Granger, 2003; Gerlach, 2006; Baum et al., 2008; Stockhammer, 2010) and attempted to quantify uncertainty.

Using text analysis, Baker et al. (2013) introduce the Economic Policy Uncertainty (EPU) index. The EPU index is mainly based on the frequency of policy-related words from the U.S. 10 large newspapers.[2] Because of the immeasurability of uncertainty, it has gained significant attention from investors and researchers in the last decade. They have tested whether this index can help explain activities, such as volatility, in the financial market. A few researchers have shown that there is a strong and positive correlation between them, so the EPU index helps to

[2] USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the WSJ

predict stock market volatility (Baker et al., 2013; Antonakakis et al., 2013; Kang and Ratti, 2013; Brogaard and Detzel, 2015; Liu and Zhang, 2015; Arouri et al., 2016; Pástor and Veronesi, 2017; Amengual and Xiu, 2018; Ma et al., 2020; Raunig, 2021; Białkowski et al., 2022). They have found that a higher economic policy uncertainty index leads to increases in the stock market's volatility.

Nevertheless, while the literature on the relationship between the EPU index and the stock market is growing, there has been a discrepancy in the impacts of the EPU index on the different types of stocks. Aboura and Arisoy (2016) show that portfolios containing small-cap value stocks have significant and negative uncertainty betas, and the EPU index most affects small-cap value stocks. On the contrary, other research papers suggest that the EPU index most influences small-cap growth stocks (Hu et al., 2018; Luo and Zhang, 2020; Paule-Vianez et al., 2023). These mixed results require us to explore the impacts of the EPU index on the different types of stocks further. Hence, in this paper, we discuss how the economic policy uncertainty index affects different types of stocks. This study differs from the previous relevant studies in that it focuses on stock volatility. In contrast, the previous literature documents mainly discuss stock returns to explore the impacts of economic policy uncertainty on the different types of stocks.

The remaining part of the paper has the following structure. First, we review previous relevant studies in Section 2. Subsequently, we discuss the data and methodology in Section 3. Then, we provide empirical analysis in Section 4. Finally, we share this study's limitation and future direction and conclude in Section 5.

2. Literature Review

Considering that the EPU index attempts to measure the level of uncertainty, and it is a news-based index, and this paper aims to examine the impacts of the EPU index and the volatility of growth/value stocks, it is necessary to review the previous works of the relationship between uncertainty and volatility, how news influences the volatility of a stock, and how the EPU index affects volatility, as wells as the volatility of different types of stocks. Hence, in this section, we review 1) the relationship between uncertainty, risk, and volatility, 2) how news affects volatility, 3) the EPU index and stock volatility, and 4) different types of stocks.

2.1. Uncertainty, Risk, and Volatility

The relationship between uncertainty, risk, and volatility in the literature is quite complicated. Volatility describes the size and speed of price change. People say when a security is more volatile than usual, it is riskier, which may be because the beta of the Capital Asset Pricing Model (Sharpe, 1964) or Value-at-Risk measures volatility for risk.[3] Engle (2004) suggests that volatility over a future period should be considered a risk. On the contrary, Poon and Granger (2003) argue that volatility is not the same as risk. Instead, they claim that when volatility is interpreted as uncertainty, it is helpful for many investment decisions.

Volatility can be used to measure either risk or uncertainty. Then, what is the difference between risk and uncertainty? Economists have put efforts into telling the difference between uncertainty and risk. In his book *Risk, Uncertainty and Profit*, Knight (1921) distinguishes uncertainty from risk. The outcome of risk is unknown, but the probability distribution governing that outcome is known and calculable. In contrast, both the outcome and the probability

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[3] Manganelli and Engle (2001) summarize the different types of risk in the literature: credit risk, operational risk, liquidity risk, market risk. In this study, we refer to market risk which “estimates the uncertainty of future earnings, due to the changes in market conditions.”

distribution of uncertainty are unknown, immeasurable, and impossible to calculate with previous information. Keynes (1937) and Hayek (1979) also support Knightian uncertainty and make distinctions between uncertainty and risk. Keynes (1937) says risk can be measured and quantified, but uncertainty cannot be easily quantified or predicted. Hayek (1979) argues that risk can be assessed through prices, but uncertainty is the unpredictability of future events that cannot be known in advance or fully quantified. Greenspan(2004) agrees with Knightian uncertainty and suggests that, in practice, it may be best to consider a continuum ranging from well-defined risks to the truly unknown.

Because of the immeasurability of uncertainty, post-Keynesian researchers have used many indexes, such as the stock market volatility, as a proxy for uncertainty in the financial market. [4] However, uncertainty also influences the financial market because the financial market is affected by information (Fama, 1970; Pierce and Roley, 1984; Mitchell and Mulherin, 1994); Berry and Howe, 1994). Thus, the impact of uncertainty on the financial market has been extensively researched; one of the topics is how political uncertainty impacts the financial market.

Bernanke (1983) claims that firms lessen investment and hiring in the period in which uncertainty is pervasive. Bittlingmayer (1998) argues that political turbulence and uncertainty may simultaneously increase volatility. Julio and Yook (2010) argue that political uncertainty due to national elections can lead firms to reduce investment expenditures. Durnev (2010) also shows that election uncertainty due to election outcomes and policy changes can influence corporate investment and reduce company performance. Handley and Limao (2012) argue that

[4] Pindyck(1986), Episcopos(1995), Leahy and Whited(1996), Poon and Granger(2003), Baum et al.(2008), Stockhammer(2010) use stock volatility as a proxy for uncertainty in the financial market. Goldberg(1993), Campa and Goldberg(1995), Stockhammer(2010) use exchange rate volatility as the proxy. Gerlach(2006) use stock and bond volatility as the proxy

trade policy uncertainty delays corporate investment and firm entry into international trade. Pastor and Veronesi (2012) develop a general equilibrium model explaining the theoretical relationship between the business cycle, policy uncertainty, and stock market volatility. They claim that political uncertainty is associated with low stock prices and high return volatility.

2.2.News and Stock market

News and the stock market are closely related. The stock price of a firm represents its current market value. News and market situations affect the rise and fall of the stock price. Many researchers have attempted to show their relationship. According to the efficient market hypothesis, all information is already reflected in prices, and the price of security only responds to unexpected announcements, or news (Fama, 1970). Pierce and Roley (1984) show that new information about monetary policy (e.g., the CPI and the Federal Reserve's discount rate) significantly influences stock prices. In particular, money announcement surprises have a significantly negative impact on stock prices. Mitchell and Mulherin (1994) analyze the impact of public information on the stock market activity and show that the number of Dow Jones announcements and market activity are directly related. However, there is no significant difference between days having macroeconomic announcements in trading volume or market returns. In other words, anticipated macroeconomic announcements do not specifically affect trading volume or market returns more, which can support the efficient market hypothesis (Fama 1970). They also share the difficulty of connecting volatility with the number of news announcements. Berry and Howe (1994) suggest slightly different results from those of Mitchell and Mulherin (1994). They show that public information and trading volume have a positive, moderate relationship. However, the relationship between public information and price volatility is insignificant, which is similar to Mitchell and Mulherin (1994).

Stock market activity responds to new information, yet the impact of news on volatility is insignificant, according to Mitchell and Mulherin (1994) and Berry and Howe (1994). However, later studies further investigate whether macroeconomic news can influence stock volatility, and the research using the VIX index for volatility claims that the impact of policy-related news on the volatility of stocks is statistically significant, unlike Berry and Howe (1994) and Mitchell and Mulherin (1994) who do not use the VIX index.[5] Kearney and Lombra (2004) show that the response of the VIX index to policy-related news (especially employment, but not inflation) is positive and statistically significant. Chen and Clements (2007) and Vähämaa and Äijö (2011) show that the VIX index tends to plummet around US monetary policy announcements. Kurov (2009) shows that the effect of monetary news on sentiment (the VIX index) is greater in a bear market than in a bull market. Gospondinov and Jamali (2012) show that surprise changes in the Fed target rate significantly increase implied volatility. Onan et al. (2014) show that macroeconomic announcements can affect stock volatility. Thus, using the VIX index, many studies have shown that the impact of policy-related news on volatility is significant.

2.3. Economic Policy Uncertainty and Stock Market

Baker et al. (2013) develop the economic policy uncertainty index based on text analysis for countries worldwide. However, as many economists suggest, uncertainty is generally regarded as unknown information that cannot be quantitatively measured. As a result, the index gained considerable attention. Numerous empirical research papers have investigated whether the EPU index can help untangle the complex relationship between uncertainty and volatility and forecast the activity of the stock market better, while each research uses diverse quantitative

[5] The Volatility Index (VIX) was launched by the Chicago Board Options Exchange in January 1993. Berry and Howe (1994) and Mitchell and Mulherin (1994) do not use the VIX for volatility.

methods and data (Baker et al., 2013; Antonakakis et al., 2013; Kang and Ratti, 2013; Brogaard and Detzel, 2015; Liu and Zhang, 2015; Arouri et al., 2016; Amengual and Xiu, 2018; Ma et al., 2020; Raunig, 2021).

Baker et al. (2013) establish that the EPU index and the VIX have a correlation of 0.58, and they often move together. However, given that their correlation is 0.58, they also show individual variation. To understand their distinct movements further, Antonakakis et al. (2013) show that the EPU index, US stock market returns, and volatility have time-varying correlations using a DCC-GARCH model. They also reveal that the EPU index has a consistently negative correlation with stock market returns and a positive correlation with the stock market's volatility. Kang and Ratti (2013) use a structural VAR analysis and reach a similar conclusion to Antonakakis et al. (2013). Using a standard generalized method of moments (GMM), Brogaard and Detzel (2015) show a positive correlation between the EPU index and the volatility of market returns and acknowledge that the EPU index is an economically important risk factor in asset pricing. Arouri et al. (2016) show that an increase in the EPU index significantly reduces stock returns, and this effect is more substantial when volatility is extremely high. Furthermore, while previous research focuses on increases in the EPU index leading to increases in stock market volatility, Amengual and Xiu (2018) use two-factor volatility models and show that sudden declines in market volatility are highly correlated with the resolution of policy uncertainty. Using a causal graph, Raunig (2021) shows that economic policy uncertainty is an instantaneous cause of stock market volatility.

In addition, research examines whether EPU helps predict stock market volatility. Liu and Zhang (2015) use a heterogeneous autoregressive RV (HAR-RV) model with the daily realized volatility of the S&P 500 and added the EPU index to the model. Their in-sample findings show that higher EPU leads to increases in stock market volatility. Their out-of-sample evidence suggests that including EPU as an additional variable into the existing volatility prediction models significantly improve forecasting accuracy.

Moreover, research explores whether the EPU index for US impacts the volatility of international stock markets. Ma et al. (2020) use a Fourier transformation and show the spillover effects of the EPU index for the US on the realized volatilities of the stock markets in G7 countries.

Many of them show that the EPU Index has a positive correlation with stock market volatility and a negative correlation with market returns. In other words, increases in the EPU Index can lead to increases in stock market volatility and decreases in market returns. Nevertheless, researchers observed a weird phenomenon in September 2016 that contradicts the previous results. Since then, the EPU index has a negative correlation with VIX. In other words, while the EPU index increases, VIX tends to decrease.

Pástor and Veronesi (2017) suggest a plausible hypothesis to solve this contradiction. According to them, this phenomenon occurs because political signals have weakened after the 2016 election.[6] They hypothesize that the new administration's political signals were complex for investors to interpret because they were full of reversals and contradictions. Inconsistent news like these examples makes investors respond less to them. The weakened political signals contribute to weakening the relationship between EPU and market volatility: *Market Volatility = f([Political Uncertainty] x [Precision of Political Signals])*. As a result, high uncertainty and low volatility happened.

[6] Veronesi and Pástor (2017): "political news arrives in the form of political signals that are informative about what the government will do in the future. Political signals are observed by rational investors who use them to update their beliefs about the government's future policy decisions. Stock prices respond to political signals. This response is stronger when political uncertainty—uncertainty about future government actions—is larger."

Indeed, this hypothesis is insightful, and Białkowski et al. (2022) quantitatively support Pástor and Veronesi (2017) by introducing Qindex as a measure of the quality of political signals. An increase in Qindex by one standard deviation (18.31) weakens the relationship between the EPU index and log(VIX) by approximately 54%. Thus, low-quality political signals weaken the relationship between market volatility and economic policy uncertainty.

Although Pástor and Veronesi (2017) and Białkowski et al. (2022) explain why the phenomenon occurs and uphold the previous results that an increase in the EPU index leads to increases in the volatility of the stock market, a few research papers, one of which is even before September 2016, partly challenge the previous results.

Using a bootstrap panel causality test, Chang et al. (2015) investigate the causal link between policy uncertainty and stock prices in seven OECD countries.[7] They conclude that stock prices do not necessarily fall when the EPU index increases because three out of the seven countries do not have evidence of the unidirectional causal leading hypothesis. Kundu and Paul (2022) consider how stock market returns and volatility respond to the EPU index under heterogeneous market conditions (the bearish and bullish markets). Using a two-regime Markov-switching VAR model for G7 countries, they show that the influences of EPU on the returns and volatility are significant in the bear market but not in the bull market. Asgharian et al. (2023) suggest a result contradicting the previous research. Previous empirical research does not include risk aversion in their investigations of the relationship between the EPU index and stock market volatility. However, risk aversion is a significant factor when dealing with market sentiment, so they include it into the relationship between the EPU index and stock market volatility. They show that the EPU index does not provide useful information for predicting monthly stock

[7] Canada, France, Germany, Italy, Spain, UK, and US

market volatility when they consider risk aversion. These results imply that this literature is still growing and requires researchers to test the relationship between uncertainty, volatility, and news with more diverse variables within different market situations.

2.4. Market-cap, Value / Growth Stock, and Volatility

In the financial market, volatility can vary among different types of stocks. A firm's size matters because it is related to its financial stability. Large companies are generally more mature and tend to be considered stable than small companies. Thus, large-cap stocks tend to be less volatile than small-cap stocks (Cheung and Lilian, 1992).

Furthermore, the type of stock is a significant consideration. [8] Extensive empirical research has been conducted on value and growth investing, yet the views on the volatility of these stocks are diverse. Some research suggests that value stocks may carry more risk (Fama and French, 1992). Conversely, using risk indicators, Chan and Lakonishok (2004) find that growth stocks are riskier than value stocks, and value stocks suffer less severely than growth stocks during the downturn of the economy.

The impacts of the economic policy uncertainty on growth/value stocks are asymmetric. Aboura and Arisoy (2016) analyze the differential sensitivity of portfolios that contain different types of stocks (large-cap value stocks, large-cap growth stocks, small-cap value stocks, and small-cap growth stocks) to aggregate uncertainty. They show that portfolios that contain small and value stocks have significant and negative uncertainty betas, and the EPU index most affects small-cap value stocks. On the contrary, other research papers suggest that the EPU index most influences small-cap growth stocks (Hu et al., 2018; Luo and Zhang, 2020; Paule-Vianez et al.,

[8] Although stocks can be categorized in many ways, such as income, value/growth, common and preferred, cyclical and non-cyclical, defensive, IPO, ESG, etc.), this study focuses on the difference between value and growth stocks.

2023). Hu et al. (2018) use ARMA and GARCH models and show that the market index containing small-cap growth stocks is more sensitive to economic policy uncertainty shocks. Luo and Zhang (2020), who conduct cross-sectional tests, find that young stocks, small stocks, and growth stocks are more sensitive to the EPU index. Using quantile regression, Paule-Vianez et al. (2023) also show that the EPU index has the strongest correlation with small-cap growth stocks.

3. Data and Methods

3.1. Data

In this study, we use the Economic Policy Uncertainty (EPU) Index introduced by Baker et al. (2013) to quantify the level of uncertainty.[9] We use Russell 1000 Growth Index and Russell 1000 Value Index for large-cap growth/value stocks and Russell 2000 Growth Index and Russell 2000 Value Index for small-cap growth/value stocks from September 2000 to March 2024.

A. Economic Policy Uncertainty Index

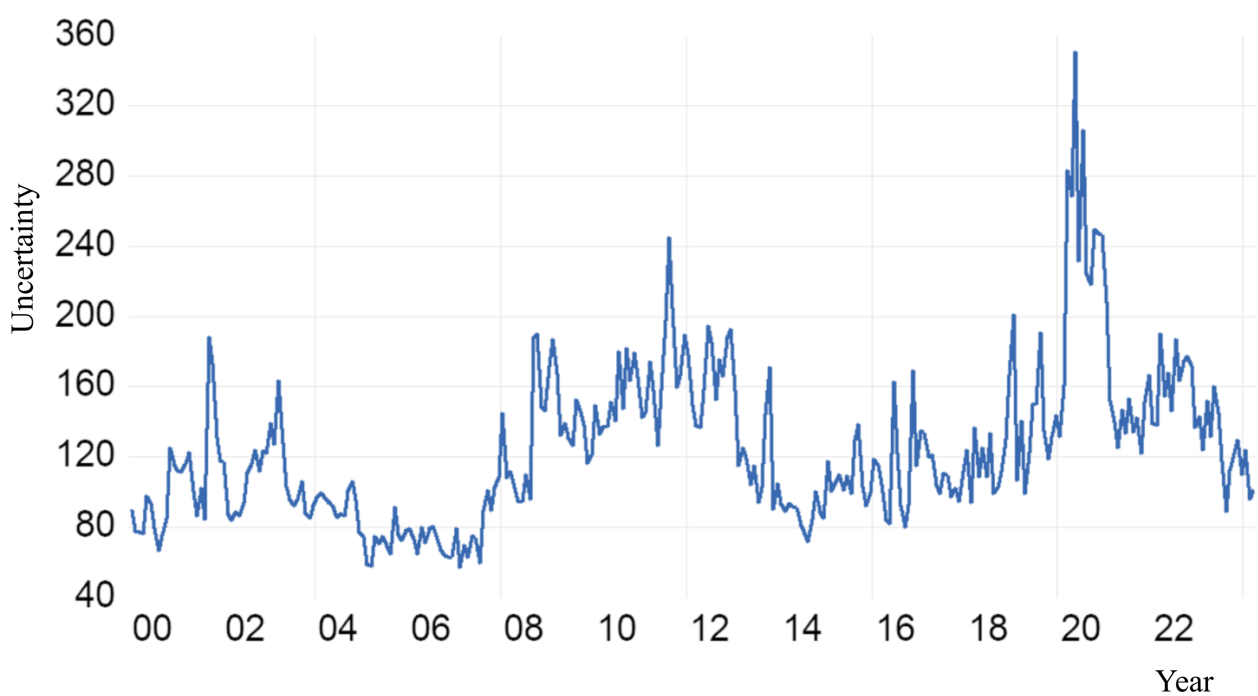
The EPU index mainly relies on the frequency of the articles, including policy-related terms from 10 large U.S. newspapers (e.g., the Washington Post and New York Times).[10] The level of the EPU index is proportional to the number of news including uncertainty policy-related terms. To construct the index, Baker et al. (2013) search for articles including terms in all three categories: uncertainty (‘uncertainty,’ ‘uncertain’), economic (‘economic,’ ‘economy’), policy (‘federal reserve,’ ‘congress,’ ‘legislation,’ ‘white house,’ ‘regulation,’ ‘tax,’ ‘deficit,’ etc.) and

[9] We downloaded the data from FRED of the St. Louis Fed.
[10] The EPU index is based on three weighted factors: the frequency of the articles, including policy-related terms, the number and revenue impact of federal tax code provisions set to expire in future years, and the extent of disagreement among economic forecasters over future government purchases and future inflation.

count the frequency of the terms.[11] Then, they scale the raw count by the total number of articles in the same newspaper and month.

The EPU index has daily, weekly, and monthly data. In this study, we use monthly data because Baker et al. (2013) find the monthly EPU index has the highest correlation with other variables, such as the VIX index.

<Figure 1> The Economic Policy Uncertainty Index for US



It is not intuitive that we measure the level of uncertainty by counting the number of articles containing the word 'uncertainty.' Nevertheless, as shown in Figure 1, the index surprisingly captures the significant events in the past, such as 9.11 in 2001, the Gulf War 2 in 2003, the U.S. elections, the financial crisis from 2008 to 2011, the Brexit announcement in

[11] The EPU index has ten sub-categorical indices: (1) economic policy uncertainty, (2) monetary policy, (3) fiscal policy, (4) government spending, (5) health care, (6) national security, (7) entitlements program, (8) regulation, (9) trade policy, and (10) sovereign debt, currency crisis.

2016, COVID-19 in 2020, Russian invasion of Ukraine war in 2022, etc. The index spikes when the events that can lead to geopolitical, monetary-policy, or trade-policy uncertainty happen.

B. Stock Indexes

Market capitalization is the market value of a company's outstanding shares of stock. Generally, large-cap corporations have market capitalizations of $10 billion or greater. Mid-cap companies have a market capitalization between $2 billion and $10 billion, and small-cap companies have between $250 million and $2 billion.

Value stocks are shares of companies traded at low prices due to being relatively undervalued compared to their current earnings, book value, or cash flow dividends per share (Basu, 1977; Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994; Blume, 1980; Rozeff, 1984; Bauman et al, 1998). They have low stock prices because of expected low growth rates in the future or excessive price declines due to negative news. Conversely, growth stocks are shares of companies expected to have a growth rate in business performance or profits higher than the average market growth over time. Stocks that have the potential to benefit from future new products and technologies also fall under growth stocks.

Given that this study aims to compare value stocks and growth stocks, we use the Russell 1000 Growth Index for large-cap growth stocks and the Russell 1000 Value Index for large-cap value stocks.[12] We use the Russell 2000 Growth Index for small-cap growth stocks and the Russell 2000 Value Index for small-cap value stocks.[13] To track these four indexes, we use

[12] The Russell 1000 Growth Index measures the performance of Russell 1000 companies with higher price-to-value ratios and higher forecasted growth values. The Russell 1000 Value Index measures the performance of Russell 1000 companies with lower PBR ratios and lower forecasted growth values.
[13] The Russell 2000 Growth Index measures the performance of Russell 2000 companies with higher price-to-value ratios and higher forecasted growth values. The Russell 2000 Value Index measures the performance of Russell 2000 companies with lower PBR ratios and lower forecasted growth values.

iShares Russell ETFs from Yahoo Finance. The sample period of our data is from September 2000 to March 2024 because the data has existed since September 2000.

To explore how the EPU index impacts the volatility of these indexes, we generate the time-varying conditional volatility of each index. We first calculate the rate of return of each stock index by using the rate of return formula: $r_j = \frac{P_{t+1} - P_t}{P_t}$, where r_j is the return on an index j, P_t is the price of the index at time t, and P_{t+1} is the price of the index at time $t + 1$.

We then create each time-varying conditional volatility series. Conditional volatility is the standard deviation of the unpredictable part of the series. To create it, we use a GARCH (1,1) model (Generalized Autoregressive Conditional Heteroskedastic) (Bollerslev ,1986), which is a generalized model of an ARCH (Autoregressive Conditional Heteroskedasticity) model (Engle, 1982). A GARCH model captures the time-varying volatility: $h_t = \sigma^2(1 - \alpha - \beta) + \alpha {\varepsilon_{t-1}}^2 + \beta h_{t-1}$, where $\sigma^2 =$ a constant, unconditional variance, ε represent news or returns at time $t - 1$, h represents forecast at time $t - 1$, and $\alpha + \beta \leq 1$.[14] The α coefficient captures the effects of shocks in the earlier periods, and the β coefficient shows the long term influences on volatility.

We construct GARCH (1,1) models for the four indexes and generate the GARCH variance series. The total number of the observations is 283. Table 1 highlights the descriptive statistics of the EPU index and the time-varying conditional volatility of the four stock indexes from September 2000 to March 2024.

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[14] If $\alpha + \beta < 1$, $E\left({h_t}^k\right) \to \sigma^2$ ($\because E\left({h_t}^k\right) = \sigma^2 + (\alpha + \beta)^{k-1}(h_{t+1} - \sigma^2)$.)

Table 1. Descriptive statistics of the EPU index and the time-varying conditional volatility of the stock indexes. Period: 2000 M09 – 2024 M03.

	EPU	**R1000G_vol**	**R1000V_vol**	**R2000G_vol**	**R2000V_vol**
Mean	125.5102	0.002682	0.002165	0.004172	0.003528
Median	117.2366	0.001810	0.001499	0.003323	0.002724
Maximum	350.4598	0.014790	0.015931	0.018418	0.029694
Minimum	57.20262	0.000659	0.000676	0.001788	0.001686
Std. Dev.	44.30043	0.002473	0.002122	0.002598	0.002762
Skewness	1.365187	2.384188	3.433479	2.342315	4.963394
Kurtosis	6.213182	9.525333	17.52694	9.705599	37.61528
Jarque-Bera	209.6496	770.2007	3044.457	788.9900	15290.95
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	35519.39	0.758965	0.612825	1.180662	0.998506
Sum Sq. Dev	553432.9	0.001724	0.001270	0.001904	0.002151
Observations	283	283	283	283	283

The table lists the summary statistics for our variables. EPU is the economic policy uncertainty index. R1000G_vol is the time-varying volatility of the Russell 1000 Growth Index. R1000V_vol is the time-varying volatility of the Russell 1000 Value Index. R2000G_vol is the time-varying volatility of the Russell 2000 Growth Index. R2000V_vol is the time-varying volatility of the Russell 2000 Value Index.

After generating the time-varying conditional volatility of each index, we perform the Augmented Dickey-Fuller (ADF) test to check if the independent (the EPU index) and the dependent variables (the conditional volatility of each index) are stationary (Said and Fuller, 1984). The null hypothesis of the ADF test is that the time series has a unit root. If we reject the null hypothesis, time series does not have a unit root, implying it is stationary.[15] If we fail to reject the null hypothesis, it is non-stationary. If variables are unit roots, we need to work with differenced series because regressing one unit root process on another unit root process can lead to a spurious regression—a model that shows misleading statistical evidence of a linear relationship. Hence, the ADF test is necessary before regressing one series on another. Table 2 reports the result of augmented Dickey-Fuller (ADF) tests. We reject the null hypothesis at the 1% level for all the variables, signifying that all the variables are stationary.

Table 2. Result of the augmented Dickey-Fuller (ADF) test.

Variables	t-statistic	prob
R1000G_vol	-4.491998	0.0003 ***
R1000V_vol	-4.869160	0.0001 ***
R2000G_vol	-6.042484	0.0000 ***
R2000V	-8.136763	0.0000 ***
EPU	-4.147927	0.0010 ***

*** denotes significance at 1%

Lastly, before establishing VAR models between the EPU index and the time-varying conditional volatility of each index, we perform the Granger causality test to check the relationship between the dependent and independent variables (Granger, 1969). The test's two assumptions are that the future cannot cause the past, and A causes B if we can better predict B "using all available information than if the information apart from B had been used (Granger 1969, 428)." While the test does not explain the true causal relationship between two variables, it helps validate the internal validity of a VAR model and determine the order of variables in a

[15] To check their stationarities, we also check their inverse roots of AR characteristic polynomials. All the eigenvalues of the models are inside the unit circle, supporting that they are stationary.

VAR model. If some of the variables Granger Causes the others, it implies that variables in a model are not arbitrarily chosen, thereby validating the internal validity of a model. Moreover, given that the result of a VAR model can vary in the length and order of variables, this test is beneficial for finding a good order of variables in a VAR model.

We establish four different vector autoregressions between the EPU index and each of the time-varying volatility of the indexes and perform four VAR Granger Causality/Block Exogeneity Wald Tests.

Table 3. VAR Granger Causality/ Block Exogeneity Wald Tests between the EPU index and each of the time-varying volatility of the indexes

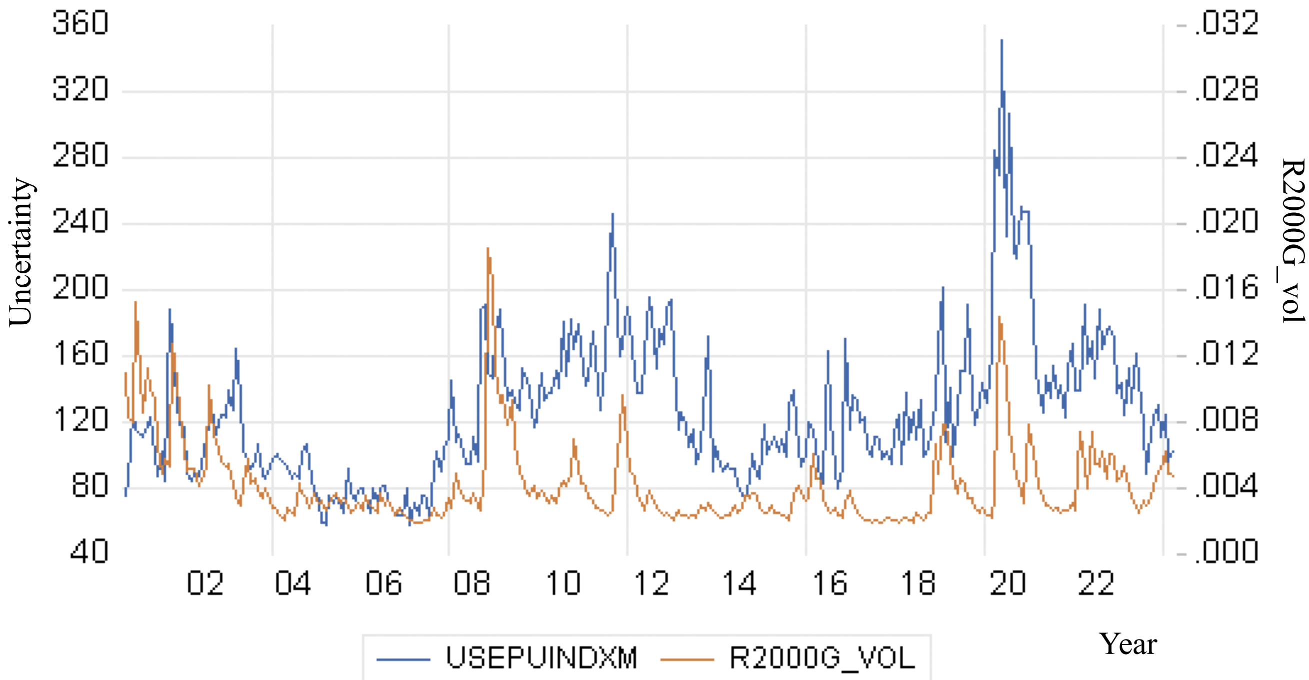
Excluded	Dependent variable	Chi-sq	df	prob
EPU	R1000G_vol	27.65869	4	0.0000 ***
	R1000V_vol	45.77817	4	0.0000 ***
	R2000G_vol	55.04549	4	0.0000 ***
	R2000V_vol	51.14364	4	0.0000 ***

*** denotes significance at 1%.

Table 3 displays the results of the Granger causality tests between the EPU index and each of the time-varying volatility of the indexes. Dependent variables are the time-varying volatility of each index. The null hypothesis of the Granger causality is that an independent series does not Granger Cause a dependent series. Because we reject every null hypothesis at the 1% level, the EPU index Granger Causes each of the time-varying volatility of the indexes. It suggests that the EPU index is prior to the volatility of the indexes. This result is aligned with the graph presented in Figure 2. Figure 2 depicts the graphs that overlap with the EPU index and the conditional volatility of small-cap growth stocks (arbitrarily chosen among the four dependent variables).

The blue line represents the EPU index, and the orange one expresses the conditional volatility of small-cap, growth stocks. The blue line tends to rise before the orange line spikes.

<Figure 2> The graph with the EPU and the conditional volatility of small-cap growth stocks



3.2.Methods[16]

Our empirical framework is based on Vector Autoregressive (VAR) models. We analyze their impulse response functions to investigate the impact of the economic policy uncertainty index on the volatility of growth and value stocks.

In order to analyze the volatility of a stock with an exogenous variable (here the EPU index), it is possible to use an EGARCH (Exponential Generalized Autoregressive Conditional

[16] This section largely depends on Professor Jeffrey Russell's Time series lectures.

Heteroskedastic) model: $h_t = \sigma^2(1-\alpha-\beta) + \alpha{\varepsilon_{t-1}}^2 + \beta h_{t-1} + \gamma x_{t-1}$, where x is an exogenous variable (Nelson, 1991). This model helps forecast the volatility of a stock with an exogenous variable. However, the purpose of this study is not to forecast the volatility of a stock with an exogenous variable but to analyze the impact of the EPU index on the volatility of stocks. This aim can be achieved with the vector autoregressive (VAR) process—a joint model between the EPU index and the volatility series of each stock index. This is why we use the VAR model for this study.

3.2.1. Vector AutoRegression (VAR)

A vector autoregressive (VAR) process is an extended version of an autoregressive (AR) process.[17] Yet, it is not a mere combination of multiple variables. Rather, it deals with the dynamics between variables (Sims, 1980; Hamilton, 1994). Let a multivariate stationary series $\boldsymbol{y}_t$ be a vector autoregressive model, with lag p, VAR(p):

$$\boldsymbol{y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta}_1\boldsymbol{y_{t-1}} + \cdots + \boldsymbol{\beta}_p\boldsymbol{y_{t-p}} + \boldsymbol{v_t}$$

$$= \boldsymbol{\beta_0} + \sum_{j=1}^{p}\boldsymbol{\beta}_j\boldsymbol{y_{t-j}} + \boldsymbol{v_t}, t = 1, 2, \cdots, T$$

where $\boldsymbol{y_t}$ is an $(n \times 1)$ vector of variables $\begin{bmatrix} x_{1,t} \\ x_{2,t} \\ \vdots \\ x_{N,t} \end{bmatrix}$, $\boldsymbol{\beta_0}$ is an $(n \times 1)$ vector of constants $\begin{bmatrix} \beta_{1,0} \\ \beta_{2,0} \\ \vdots \\ \beta_{N,0} \end{bmatrix}$,

$\boldsymbol{\beta}_j$ is an $(n \times n)$ matrix of autoregressive coefficients for $j = 1, 2, \ldots, p$ $\begin{bmatrix} \beta_{1,1} & \cdots & \beta_{1,N} \\ \vdots & \ddots & \vdots \\ \beta_{N,1} & \cdots & \beta_{N,N} \end{bmatrix}^j$, $\boldsymbol{v_t}$

[17] A univariate AR(p) is a model that allows us to predict future outcomes from the past outcomes—that is, y_t depends on its past $y_{t-1}, y_{t-2}, \cdots$, if there is dependence in returns: $y_t = \beta_0 + \sum_{j=1}^{p}\beta_j y_{t-j} + \epsilon_t, t = 1, 2, \cdots, T$, where ϵ_t is white noise ($\perp y_{t-1}, y_{t-2}, \cdots$).

is an $(n \times 1)$ vector of white noise $\begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{N,t} \end{bmatrix}$ and $E(\boldsymbol{v_t}) = 0$. The dependence of each variable on the past is summarized by the matrix $\boldsymbol{\beta}_j$. The elements of $\boldsymbol{v_t}$ are *i.i.d* normal with the variance covariance matrix of the error terms:

$$E\left(\boldsymbol{v_t v'_{t-j}}\right) = \begin{cases} \Omega \text{ (j} = 0) \\ 0 \ (j \neq 0) \end{cases}$$

For this study, we establish four bivariate VAR(4) models:

$$\boldsymbol{y_t} = \boldsymbol{\beta_0} + \sum_{j=1}^{4} \boldsymbol{\beta}_j \boldsymbol{y_{t-j}} + \boldsymbol{v_t}$$

where $\boldsymbol{y_t} = \begin{bmatrix} EPU_t \\ vol_t \end{bmatrix}$, $\boldsymbol{\beta_0} = \begin{bmatrix} {\beta_0}^{EPU} \\ {\beta_0}^{vol} \end{bmatrix}$, $\boldsymbol{\beta}_j = \begin{bmatrix} {\beta_1}^{EPU} & {\beta_2}^{EPU} \\ {\beta_1}^{vol} & {\beta_2}^{vol} \end{bmatrix}^j$, $\boldsymbol{v_t} = \begin{bmatrix} \varepsilon_{EPU,t} \\ \varepsilon_{vol,t} \end{bmatrix}$, $E(\boldsymbol{v_t v'_t}) = \Omega =$ $\begin{bmatrix} {\sigma_{\epsilon_{EPU}}}^2 & \sigma_{\epsilon_{EPU}\epsilon_{vol}} \\ \sigma_{\epsilon_{vol}\epsilon_{EPU}} & {\sigma_{\epsilon_{Vol}}}^2 \end{bmatrix}$. ${\sigma_{\epsilon_{EPU}}}^2$ is the variance of EPU, ${\sigma_{\epsilon_{Vol}}}^2$ is the variance of vol (the conditional volatility of each stock index), and $\sigma_{\epsilon_{EPU}\epsilon_{vol}}$ is the contemporaneous covariance.

3.2.2. Impulse Response Function

The impulse response function is the primary method to understand the implied dynamics of a VAR model. It shows the responses of current and future values of a variable to a one-unit increase in another variable in the VAR model (Stock and Watson, 2001). That is, the impulse response function of variable i to a change in variable j. When we substitute the VAR (1) recursively, it is expressed in:

$$\boldsymbol{y_t} = \boldsymbol{\beta_0}^* + \boldsymbol{\beta_1}^{\boldsymbol{k}} \boldsymbol{y_{t-k}} + \sum_{\boldsymbol{j=0}}^{\boldsymbol{k-1}} \boldsymbol{\beta_1}^{\boldsymbol{j}} \boldsymbol{v_{t-j}}$$

Where $\boldsymbol{\beta_0}^* = \sum_{\boldsymbol{j=0}}^{\boldsymbol{k-1}} \boldsymbol{\beta_1}^{\boldsymbol{j}}\, \boldsymbol{\beta_0}$. When we take the derivative of $\boldsymbol{y_t}$ with respect to $\boldsymbol{y_{t-k}}$, we have $[\beta_1{}^k]_{i,j}$, which, as a function of k, shows how future values of variable i are impacted by a one unit change in variable j, *k* periods in the past. The power of the matrix β_1 determines how a change in one variable today influences the future values.

Considering the definition of the impulse response function, we will investigate how the volatility of each stock index is impacted by a one-unit change in the EPU index and compare their impulse response functions: Among the volatility of the four stock indexes, which one is more impacted (strong and persistent) by a one unit change in the EPU than the others?

When we write the VAR in its infinite MA representation, it is expressed in:

$$\boldsymbol{y_t} = \boldsymbol{\beta_0}^* + + \sum_{\boldsymbol{j=0}}^{\infty} \boldsymbol{\beta_1}^{\boldsymbol{j}}\, \boldsymbol{v_{t-j}}$$

Where $\boldsymbol{\beta_0}^* = \boldsymbol{\mu} = (\mathbf{1} - \boldsymbol{\beta_1})^{-\mathbf{1}}\boldsymbol{\beta_0}$**.** In this equation, if we take the derivative of $\boldsymbol{y_t}$ with respect to $\boldsymbol{v_{t-k}}$**,** $\frac{d\boldsymbol{y}_{t,i}}{d\boldsymbol{y}_{t-k,j}} = \frac{d\boldsymbol{y}_{t,i}}{d\boldsymbol{v}_{t-k,j}} = [\beta_1{}^k]_{i,j}$. If we change $\boldsymbol{y_t}$ by one unit, with all past values of **y** fixed, it is equivalent to changing $\boldsymbol{v_t}$ one unit larger.

However, unlike an autoregressive AR(p) process, the VAR model handles the dynamics between variables. The dynamics between them may cause an issue that errors can be contemporaneously correlated. Unless the variance covariance matrix Ω is not diagonal, the errors are contemporaneously correlated ($\sigma_{\epsilon_{EPU}\epsilon_{vol}}$ or $\sigma_{\epsilon_{vol}\epsilon_{EPU}}$). This is problematic because movements in one innovation tend to be associated with movements in the other. We may not be able to observe how future values of variable i are purely impacted by a one-unit change in variable j.

To recover orthogonal shocks and impose the one-directional causality, we use a Cholesky decomposition and choose an order in which shocks propagate. We create a vector of orthonormal innovations and then pre-multiply by a lower triangular matrix $v_t = Pu_t$ where $E(u_t u_t') = I$ and P is a lower triangular matrix. Since P is a lower triangular matrix, a movement in the first element of u_t changes all elements of v_t while movements in the second element of u_t only affect the second element of v_t. With a Cholesky decomposition, we decompose the variance covariance matrix Ω into PP' where P is a unique lower triangular matrix:

$$P^{-1}\Omega P^{-1} = I_n$$

Next, we can get the vector u_t by pre-multiplying the error vectors by P^{-1}

$$u_t = P^{-1}v_t$$

The vector u_t is now a vector of shocks with uncorrelated elements with unit variance.

$$v_t = \begin{bmatrix} \epsilon_t{}^{EPU} \\ \epsilon_t{}^{vol} \end{bmatrix} = \begin{bmatrix} P_{11} & 0 \\ P_{21} & P_{22} \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} = \begin{bmatrix} P_{11}u_{1t} \\ P_{21}u_{1t} + P_{22}u_{2t} \end{bmatrix}$$

Now, u_1 and u_2 are uncorrelated. If we move u_1 by one unit, $\epsilon_t{}^{EPU}$ changes by P_{11}, and $\epsilon_t{}^{vol}$ changes by P_{21}. If we move u_2 by one unit, $\epsilon_t{}^{EPU}$ does not change at all, and $\epsilon_t{}^{vol}$ changes by P_{22}, which means a top-down causality.[18] In this study, to investigate the effect of the EPU index on the volatility of stocks, we place the EPU variable at the top and the volatility of stocks at the bottom of the VAR model.

In the graph of an impulse response function, the horizontal axis represents the time periods after a shock. Its vertical axis expresses the expected level (or magnitude) of the response of a variable to the shock. Its solid line represents the estimated response of the variable to the

[18] P determines how moving one variable in period t affects other variables.

shock, and the dashed lines represent the confidence interval around that estimate. If the solid line climbs after the shock, the variable's response to the shock is positive initially. In contrast, if the solid line goes below zero, it indicates a negative response to the shock. If the solid line goes back to zero over time, it implies that the effect of the shock is temporary. However, if the line stays above or below zero, the effect is persistent.

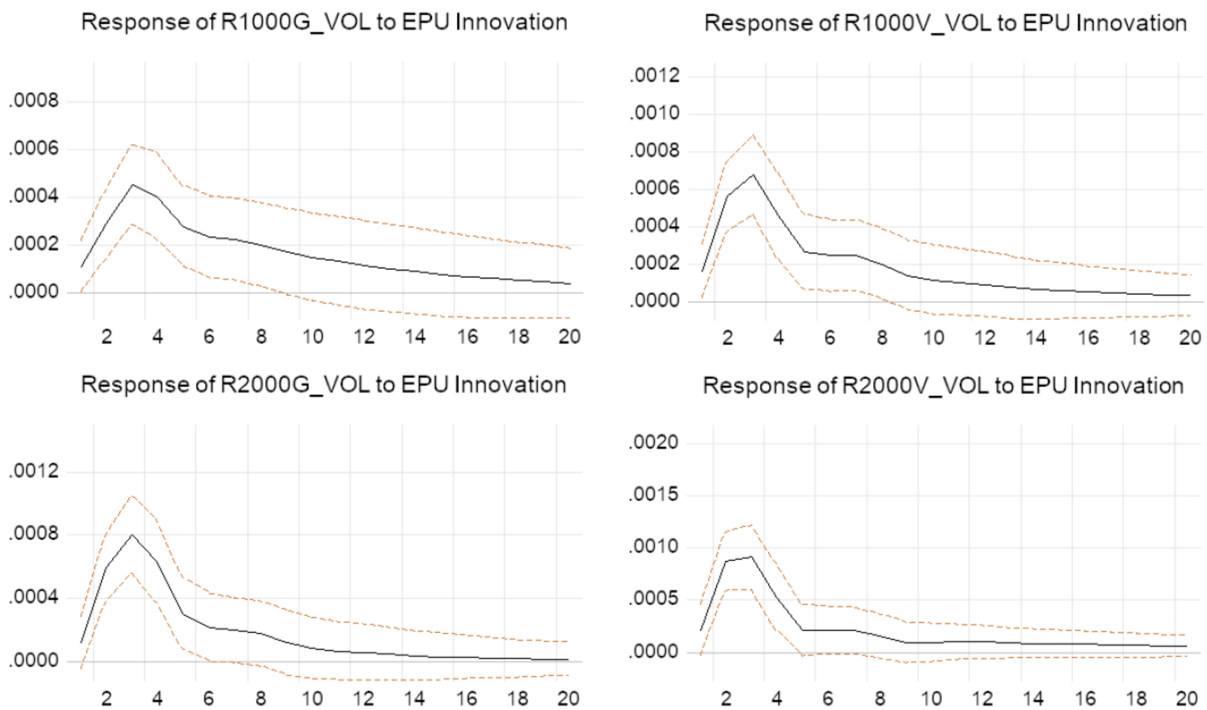
4. Empirical Results

Before performing the vector autoregression analysis, the choice of the lag length of the vector autoregressive (VAR) process is based on the Akaike information criterion (AIC), Schwarz Bayesian criterion (BIC), and correlograms (Shibata, 1976). Four lags are recommended by the tests.

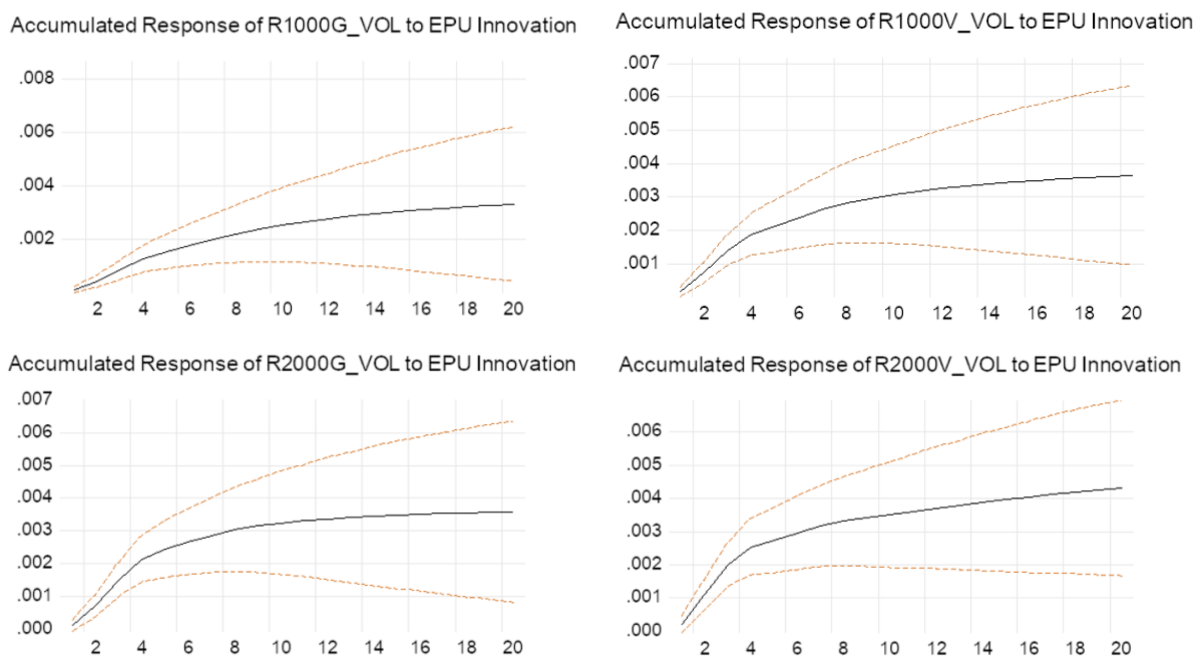
Figure 3 presents the impulse response functions of the conditional volatilities of large-cap growth, large-cap value, small-cap growth, and small-cap value stock index to the EPU index. All the solid lines of the four impulse response functions exhibit an immediate and upward trajectory after the shock. This pattern signifies a positive response of each stock index's volatility to the EPU shock, a key insight into the relationship between the economic policy uncertainty index and stock market volatility. The peaks of the responses occur around Step 3, and the post-peak, the lines gradually return to approximately zero over time, suggesting a temporary yet persistent effect of the EPU shock.

However, the expected levels of the responses of the volatilities to the EPU index differ. If we look at the vertical axis of the response of R1000G_vol (large-cap growth stocks) to the EPU shock, the peak of the expected level is around .0004. In contrast, if we look at the vertical axis of the response of R1000V_vol (large-cap value stocks) to the EPU shock, the peak of the expected level is around .0006. Moreover, in comparing the periods between Step 1 and Step 2, the response of large-cap value stocks to the EPU shock is steeper than the response of large-cap growth stocks to the EPU shock. Considering that impulse response functions give information about how much future values of variable i are impacted by a one-unit change in variable j in the k-periods past, the volatility of large-cap value stocks is more impacted by one-unit change in the EPU index than that of large-cap growth stocks.

<Figure 3> The impulse response functions of the time-varying volatility of stock indexes to the EPU shock



<Figure 4> The accumulated impulse response functions of the time-varying volatility of stock indexes to the EPU shock



Moreover, in Figure 3, if we look at the vertical axis of the response of R2000G_vol (small-cap growth stocks) to the EPU shock, the peak of the expected level is around .0008. In contrast, if we look at the vertical axis of the response of R1000V_vol (small-cap value stocks) to the EPU shock, the peak of the expected level is around .0009. These results suggest that the volatility of small-cap stocks is more affected by the EPU shock than that of large-cap stocks. In addition, small-cap value stocks are more impacted by one unit change in the EPU index than small-cap growth stocks. Furthermore, the volatility of small-cap value stocks is most affected by the EPU shock.

Table 4. The results of the impulse response functions

Step	R1000G_vol	R1000V_vol	R2000G_vol	R2000V_vol
1	.00011	.00016	.00012	.00022
2	.00029	.00056	.00059	.00087
3	.00045	.00068	.00080	.00091
4	.00040	.00046	.00063	.00053
5	.00028	.00026	.00030	.00021
6	.00023	.00025	.00022	.00021
7	.00023	.00025	.00020	.00021
8	.00020	.00020	.00018	.00015
9	.00017	.00014	.00012	.00010
10	.00015	.00011	.00008	.00009
11	.00013	.00010	.00007	.00010
12	.00012	.00009	.00006	.00010
13	.00010	.00007	.00005	.00009
14	.00009	.00006	.00004	.00008
15	.00008	.00005	.00003	.00008
16	.00007	.00005	.00003	.00008
17	.00006	.00004	.00002	.00007
18	.00005	.00004	.00002	.00007
19	.00005	.00003	.00002	.00006
20	.00004	.00003	.00002	.00006

Response to Cholesky one standard (degrees of freedom adjusted) innovations $\pm$ 2 analytic asymptotic standard errors. Each column represents its response to the EPU index innovation.

Table 5. The results of the accumulated impulse response functions

	R1000G_vol	R1000V_vol	R2000G_vol	R2000V_vol
Lag 1	.0001	.0002	.0001	.0002
Lag 2	.0004	.0007	.0007	.0011
Lag 3	.0009	.0014	.0015	.0020
Lag 4	.0013	.0019	.0021	.0025
Lag 5	.0015	.0021	.0025	.0027
Lag 6	.0018	.0024	.0027	.0030
Lag 7	.0020	.0026	.0029	.0032
Lag 8	.0022	.0028	.0030	.0033
Lag 9	.0024	.0030	.0032	.0034
Lag 10	.0025	.0031	.0032	.0035
Lag 11	.0026	.0032	.0033	.0036
Lag 12	.0028	.0033	.0034	.0037
Lag 13	.0029	.0033	.0034	.0038
Lag 14	.0030	.0034	.0035	.0039
Lag 15	.0030	.0034	.0035	.0040
Lag 16	.0031	.0035	.0035	.0040
Lag 17	.0032	.0035	.0035	.0041
Lag 18	.0032	.0036	.0036	.0042
Lag 19	.0033	.0036	.0036	.0042
Lag 20	.0033	.0036	.0036	.0043

Accumulated response to Cholesky one standard (degrees of freedom adjusted) innovations $\pm$ 2 analytic asymptotic standard errors. Each column represents its accumulated response to the EPU index innovation.

Table 4 gives us more detailed information about the results in the previous paragraphs. We can see the peaks of the impulse response functions in Step 3, where the expected responses of a one-unit increase in EPU shock to the volatility are as follows:

$$R1000G\_vol\ (.00045) < R1000V\_vol\ (.00068) < R2000G\_vol\ (.00080) < R2000V\_vol\ (.00091)$$

The analysis reveals that the volatility of small-cap value stocks is most affected by the EPU shock. Furthermore, the comparison of Step 20 of R2000G_vol (small-cap growth stocks) and R2000V_vol (small-cap value stocks)in Table 4 supports our findings, with R2000G_vol being closer to zero, indicating that R2000V_vol (small-cap value) is more persistent.

Figure 4 and Table 5 show the accumulated impulse response function results. All the solid lines in the graphs in Figure 4 almost converge to a specific value. If we focus on Step 20 in Table 5, the accumulated response of R2000V_vol is most enormous among the variables. In addition, the accumulated response of R1000V_vol is greater than that of R1000G_vol, and the accumulated response of R2000V_vol is greater than that of R2000G_vol. These results suggest that the EPU shock most impacts the volatility of small-cap value stocks.

5. Conclusion and Discussion

This study investigates the asymmetric impacts of the economic policy uncertainty index on the different types of stocks' volatility. We use the standard VAR models between the EPU index and the GARCH volatility of each stock index (large-cap growth, large-cap value, small-cap growth, and small-cap value stocks). We compare and analyze their impulse response functions, especially the responses and accumulated responses of the GARCH volatility of each stock index to the EPU index innovation. The empirical results show that the EPU index influences the volatility of value stocks more than that of growth stocks for both large-cap and small-cap stocks. In addition, small-cap value stocks are affected by the EPU index the most. This conclusion is aligned with Aboura and Arisoy (2016). This research is meaningful in that it investigates the impact of the EPU index on the volatility of growth/value stocks. In contrast, previous research focuses on growth/value stock returns. This study can be helpful for financial risk management and portfolio allocation.

Nevertheless, the limitation of this study is that it does not consider the heterogeneous market characteristics. As Kundu and Paul (2022) have shown, the influences of the EPU index on the returns and volatility can be significant in a bear market but not in a bull market. Generally, growth stocks tend to outperform when the economy expands, and interest rates are low, while value stocks tend to outperform during periods of economic recovery (Chan and Lakonishok, 2004). These phenomena imply that the volatilities of growth and value stocks can depend on market conditions. Hence, the consideration of the heterogeneous market condition with the characteristics of growth/value stocks may change the impacts of the economic policy uncertainty on the volatility of growth/value stocks. However, a standard vector autoregression does not deal with a non-linear market condition. Thus, statistical models, such as a Markov-Switching Vector AutoRegression (MS-VAR) model or a quantile regression, would help handle this study’s limitation.

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