

Does Economic Policy Uncertainty Move the Market? An Econometric Analysis of Stock Market Volatility and Uncertainty Indices

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This paper examines the relationship between stock market volatility and economic policy uncertainties in financial, economic and political realms. We select eight policy related uncertainty indices developed by Baker, Bloom and Davis (2016) and subject them to causality tests to determine their utility in forecasting stock market volatility, as measured by volatility index (VIX). Of the eight indices, five are found to possess predictive causality. We then develop a distributed lag (DL) model to assess the explanatory powers of each of the indices. Based on the DL model, we run impulse response analyses for each variable to observe the stock market's reaction over time to policy uncertainty shocks. The econometric analyses of this paper reveal how market volatility is an increasing function of the product of economic uncertainty. In a less technical way, our findings show that the stock market is an informative gauge to understand the cost of policy uncertainty.

Keywords: Stock Market Volatility, Economic Policy Uncertainty, Policy Indices, VIX

JEL classifications: G12; E6

1. Introduction

In the last decade of the financial market literature, the scholarship on the relationships between equity market volatility and uncertainties in economic, financial and political realms has blossomed. As early as 1981, Robert Shiller demonstrated that future dividends discounted at a constant rate cannot be used to rationalize stock market volatility. Shiller's findings led to the development of two distinct fields of research: one examined the effects of rational agents in determining stock prices while the other studied the role of non-rational atypical factors.

In the understanding of the latter type of factors, the works of Baker, Bloom and Davis (2016, 2019) on policy related uncertainties have become influential. Developed by Baker, Bloom and Davis in their 2016 work, the economic uncertainty index tracks the uncertainty around economic policy based on the frequency of news coverage of the subject. At the time of writing this paper, the authors have expanded the indices to cover a wide array of uncertainties, ranging from those related to monetary policy to taxation. By focusing on these wide range of uncertainties, the authors have highlighted the role of public perception of policies in determining the volatility in the financial markets. Broadly speaking, the success of Shiller's 2019 *Narrative Economics* shows that the relation between the stock market and uncertainties created by public perception of different policies has become a part of the mainstream economic discourse.

Our understanding of stock market volatility itself has improved immensely in the past few decades. One of the key early works on this field was Robert Engle's 1982 seminal work on volatility clustering. Then Engle et al. (2013) applied the volatility models to study market volatility and macroeconomic fundamentals. In addition, recent developments in options pricing literature have combined continuous time models, such as Stochastic Volatility (SV) models, and discrete time models like the autoregressive conditional heteroscedasticity (ARCH) models. These developments have improved our ability to forecast volatility over relatively short periods, ranging from a day to several weeks.

There has been an interest in literature to understand the different aspects of policy uncertainty and its relationship with the financial markets. Baker et al. (2016) constructs the policy uncertainty indices based on newspaper reports. The authors aim to reflect uncertainty about who makes economic policy decisions, what economic policy moves will be made and when, and the economic outcomes of policy actions or inactions. As Pástor and Veronesi (2012, 2013) demonstrate, EPU bears significant relations with stock market volatility, correlation and jumps. Kelly, Pástor and Veronesi (2016) also show the role of EPU in pricing of stock options. Likewise, Asgharian, Christiansen and Hou (2018) further establish that long-run US-UK stock market correlation depends positively on US economic policy uncertainty shocks.

Economic policy uncertainty can influence the stock market in various ways and dimensions. Chiang (2019) show that stock returns are negatively correlated with economic policy uncertainty innovation. The paper also demonstrates that lagged EPU can lead to a rise in stock return volatility. Liu and Zhang (2015) investigate the predictability of economic policy uncertainty (EPU) to stock market volatility and show that incorporating EPU as an additional predictive variable into the volatility prediction models improves forecasting ability. Findings by Balli et al. (2020) suggest that New Zealand equity sectors receive quite strong spillover effects from US EPU compared to the local counterpart (NZ EPU), and particularly, sectors with export/import concentration with the US are more susceptible to US EPU. Geyfman et al. (2020) examine the time-varying nature of bank beta coefficients during periods of extreme market volatility. They observe a rise in betas during the global financial crisis of 2007–2009 and the Covid-19 pandemic using banking indices and the S&P 500 index as proxies for systematic risk.

Based on these studies and past research on the subject, we expect that EPU indices will play an important role in determining and forecasting stock market volatility. This study examines a set of diverse economic indicators and attempts to uncover correlations, causal or otherwise, between these indices and the volatility in equity market. We select a set of nine indicators that capture the uncertainties and volatilities in different sectors of the market. The nine EPU indices developed by Baker, Bloom, and Davis (2016), quantify newspaper coverage of policy related economic uncertainty to derive EPU shocks.

While the above-mentioned research played a critical role in shaping the direction of this paper, this paper is mostly inspired by Baker et al., 2019 work based on news cycle. Some of the findings of the above research were also validated and evidenced by our investigations. We improve this framework by expanding beyond policy related news and including detailed policy specific indices.

We first measure the suitability of all these variables against the Chicago Board Options Exchange Volatility Index (CBOE VIX) and only include the cases of significant correlation. We then develop a distributed lag (DL) model for each time series, in which a regression is used to predict the effect of the various indices on stock market volatility. For instance, we use the current values and the past values (lags) of the indices, e.g., Monetary Policy Uncertainty, to predict stock market volatility.

We demonstrate that the stock market's response to a policy related uncertainty is quite different for each uncertainty index. To understand how stock market reacts to policy related shocks and the three other indicators, we run impulse response analysis. We build the model by making necessary adjustments to our DL model. Common to many univariate or multivariate models, we include the differences in lags to track the evolution of VIX in reaction to a shock in one of the variables. As a result, variables and information included in constructing policy-related uncertainty in the commodity market, regulatory market, monetary policy, and fiscal restrictions are consistently relevant in explaining stock market volatility. Moreover, during the times of high risk, results indicate that stock prices fluctuate more strongly, relative to their policy uncertainty indices.

The paper presents the data in Section 2 and introduces the econometric methods in Section 3. Section 4 discusses the findings and results. Section 5 presents concluding remarks including identification of areas for future research.

2. Data

As our study focuses on accounting for stock market volatility based on economic policy indicators, we have chosen to include several indices that we believe can reflect the fluctuations of the market. In the initial round, we selected eight indicators that assess and quantify volatility and uncertainties in fiscal, financial, and political spheres. For the study of stock market volatility, we selected Equity Market Volatility (EMV) developed by Baker et al (2012) and the Chicago Board Options Exchange Volatility Index (CBOE VIX) compiled from the St. Louis Federal Reserve. While EMV is a newspaper-based tracker that moves similarly with the realized volatility of returns on the S&P 500, VIX measures market expectations of near-term volatility conveyed by stock index option prices. To ensure uniformity and for ease of interpretation, all the data was arranged monthly.

Indices

All of the indices are available at the US Economic Policy Uncertainty Index database developed by Bloom et al (2012). The decision to include these uncertainty indices was motivated by the classic findings of Robert Shiller (1981, 84) about the non-rational and arbitrary perceptions of stock market returns that in turn influence the stability of the stock market. In particular, the burgeoning scholarship and interest in this field in recent years (Boyd et al 2005; Killian and Park 2009; Bloom 2011; Bekaert et al 2013; Hassan et al. 2019; Bloom et al 2019) have highlighted the importance of current events and news in our understanding of the stock market.

Composition of Uncertainty Indices:

As Bloom et al (2019) explain, the uncertainty indices are generated from newspaper reports of relevant terms for each category. For instance, the articles that contain one or more of the following terms will be classed under monetary policy uncertainty.

Monetary Policy: {monetary policy, money supply, open market operations, fed funds rate, discount window, quantitative easing, forward guidance, interest on reserves, taper tantrum, Fed chair, Greenspan, Bernanke, Volker, Yellen, Draghi, Kuroda, Jerome Powell, lender of last resort, central bank, federal reserve, the fed, European Central Bank, ECB, Bank of England, Bank of Japan, People's Bank of China, PBOC, PBC, Central Bank of China, Bank of Italy, Bundesbank}

Likewise, Tax Policy Uncertainty would be derived from analyzing articles that contain relevant words that pertain to taxation. By the same logic, Regulation Uncertainty (RU) derivation contains a lot of the same keywords that are under Financial Regulations Uncertainty (FRU).

3. Assessing the Effects of Policy Uncertainties on Stock Market Volatility

In this section, to assess the effects of policy uncertainties on stock market volatility, we first study the Granger causality tests. Then we study the relationship between policy uncertainty and market volatility. Finally, we explore how changes in policy uncertainty can lead to changes in market volatility.

3.1 Causality Analysis

In this section, we run a five lag Granger causality test for all nine indicators against both EMV and VIX to build a model that best explains the fluctuations in the equity market. Aside from identifying the variables with the highest correlation and causal link with stock market volatility, this process also helped us identify extraneous indices that do not successfully account for these fluctuations.

As seen in, the first five indices to be selected were Fiscal Policy Uncertainty (FPU), Financial Regulation Uncertainty (FRU), Monetary Policy Uncertainty (MPU), Regulations Uncertainty (RU), and Tax Policy Uncertainty (TaxPU). The results in Tables 1 and 2 also confirm that there are more indicators that can explain the fluctuations in stock market as represented by VIX than represented by EMV. We thus decided to use VIX for the rest of our analysis. Five uncertainty indices – FPU, FRU, MPU, RU and TaxPU – can Granger cause so they can explain the VIX dynamics, while all indices except for some IRU and MPU lags fail the Granger causality test.

Table 1: Summary of the results of Granger causality tests: Indices and VIX

VIX <i>Indices</i>	P values				
	<i>Lag1</i>	<i>Lag2</i>	<i>Lag3</i>	<i>Lag4</i>	<i>Lag5</i>
Election and Political Governance (EPG)	0.09	0.15	0.44	0.63	0.56
Fiscal Policy Uncertainty (FPU)	0	0	0.01	0	0.01
Financial Regulation Uncertainty (FRU)	0	0	0	0	0
Interest Rate Uncertainty (IRU)	0.83	0.07	0.4	0.41	0.54
Monetary Policy Uncertainty (MPU)	0.03	0.02	0.18	0.12	0.14
Regulations Uncertainty (RU)	0	0	0	0	0
Tax Policy Uncertainty (TaxPU)	0	0	0	0	0
Trade Policy Uncertainty (TPU)	0.49	0.44	0.81	0.8	0.9

Table 2: Summary of results for Granger causality tests: Indices and EMV.

EMV <i>Indices</i>	P values				
	<i>Lag1</i>	<i>Lag2</i>	<i>Lag3</i>	<i>Lag4</i>	<i>Lag5</i>
Election and Political Governance (EPG)	0.68	0.35	0.52	0.65	0.69
Fiscal Policy Uncertainty (FPU)	0.21	0.48	0.64	0.59	0.5
Financial Regulation Uncertainty (FRU)	0.18	0.25	0.48	0.61	0.88
Interest Rate Uncertainty (IRU)	0.02	0.04	0.12	0.1	0.24
Monetary Policy Uncertainty (MPU)	0.16	0.03	0.02	0.05	0.03
Regulations Uncertainty (RU)	0.39	0.1	0.24	0.3	0.47
Tax Policy Uncertainty (TaxPU)	0.44	0.68	0.77	0.66	0.61
Trade Policy Uncertainty (TPU)	0.96	0.66	0.85	0.93	0.94

3.2 Relationship Between Policy Uncertainty and Market Volatility

A dynamic regression model first developed by Pankratz (1991) was used in this study to predict how changes in the predictor series affect the dependent series over time. The distributed lag (DL) model that we use in the study allows us to determine whether or not the variable is predictively causal. The DL model is represented by the following equation:

$$y_t = \beta_0 + \gamma_0 x_t + \gamma_1 x_{t-1} + \dots + \gamma_k x_{t-k} + \eta_t,$$

where η_t is an ARIMA process.

We used a two-pronged process to determine the most accurate value of k. We first ran a model with 24 lags and only included in our analysis the lags that yielded statistically significant results. For instance, the DL model showed that FRU was only statistically significant for 4 lags. We then re-ran the whole model, but this time with only 4 lags.

The segment below briefly discusses the results from the DL model test for each of the indices used. The discussions feature models with the number of lags for which the results were statistically significant. For the comparison of the overall results of the dynamic regression model, see table 3.

Table 3: Comparison of overall results from DL model estimations.

<i>Indices</i>	<i>B</i>	<i>a1</i>	<i>a2</i>	<i>a3</i>	<i>a4</i>	<i>a5</i>
FPU	7.6411***	1.1377***	0.5175***			
	0.8412	0.1264	0.1264			
FRU	6.6434***	2.4232***	1.0561***	0.5255*	0.4103*	
	0.6686	0.2424	0.2727	0.2726	0.2422	
MPU	10.8711***	0.9374***	0.4145***			
	0.7978	0.1215	0.1214			
RU	3.3375***	1.6841***	0.7035***	0.4196*	0.3655*	
	0.8683	0.1714	0.1919	0.1925	0.1718	
TaxPU	6.4488***	1.4693***	0.6823***			
	0.8769	0.1579	0.1578			

i. FPU and VIX

Obtained from Bloom, Baker and Davis (2016) database, the Fiscal Policy Uncertainty quantifies the uncertainty in fiscal policy and government spending. For FPU, only two of the twenty-four lags appeared to be significant (see table 4).

The findings confirm that fears and uncertainties regarding budget, deficit, debt and government spending drive stock market volatility.

Table 4: Fiscal Policy Uncertainty and VIX.

	Estimate	Significance
(Intercept)	7.6411	***
L(dFPU.ts, c(1:nlags))1	1.1377	***
L(dFPU.ts, c(1:nlags))2	0.5175	***

Residual standard error: 5.855 on 347 degrees of freedom

Multiple R-squared: 0.396, Adjusted R-squared: 0.3925

F-statistic: 113.7 on 2 and 347 DF, p-value: < 2.2e-16

ii. FRU and VIX

This uncertainty index pertains to the uncertainties around supervision and regulations of the financial sector. In our model, the first four lags out of the twenty-four lags turned out to be statistically significant and based on the result, we re-modeled our DL model with four lags of FRU (see table 5).

Banks and financial sectors are critical players in the equity market. Any regulations, or rather the fear of regulations, and the uncertainties around them naturally influence investor behaviors, which in turn reflect these uncertainties.

Table 5: Financial Regulation Uncertainty and VIX.

	Estimate	Significance
(Intercept)	6.6434	***
L(dFRU.ts, c(1:nlags))1	2.4232	***
L(dFRU.ts, c(1:nlags))2	1.0561	***
L(dFRU.ts, c(1:nlags))3	0.5255	
L(dFRU.ts, c(1:nlags))4	0.4103	

Residual standard error: 4.949 on 343 degrees of freedom

Multiple R-squared: 0.5732, Adjusted R-squared: 0.5683

F-statistic: 115.2 on 4 and 343 DF, p-value: < 2.2e-16

iii. MPU and VIX

Monetary Policy Uncertainty (MPU) is an important index that assesses the uncertainty around money supply, federal funds rate, quantitative easing, and several other relevant monetary policy issues. In our model, we found that out of the initial 24 lags two of the lags were statistically significant (see table 6).

The decisions of the federal reserve and other monetary news have obvious repercussions in the stock market. Our research bolsters the findings of previous research in the field and validates the impact of monetary policy in the equity markets.

Table 6: Monetary Policy Uncertainty and VIX

	Estimate	Significance
(Intercept)	10.8711	***
L(dMPU.ts, c(1:nlags))1	0.9374	***
L(dMPU.ts, c(1:nlags))2	0.4145	

Residual standard error: 6.359 on 347 degrees of freedom

Multiple R-squared: 0.2873, Adjusted R-squared: 0.2832

F-statistic: 69.96 on 2 and 347 DF, p-value: <2.2e-16

iv. RU and VIX

Regulation uncertainty (RU) determines the uncertainties surrounding a whole host of regulations that pertain to the realms of finance, economics and business. In our model, we found that of the initial twenty-four lags, the first four lags were statistically significant (see table 7).

Studying the effect of RU, a broad category with sweeping range, is especially helpful in determining the relationship between regulations, in general, and their reception in the stock market. One area that we think could benefit from future research is the reception of the regulation, rather than the impacts of the regulations themselves, on stock market volatility.

Table 7: Regulations Uncertainty and VIX

	Estimate	Significance
(Intercept)	3.3375	***
L(dRU.ts, c(1:nlags))1	1.6841	***
L(dRU.ts, c(1:nlags))2	0.7035	***
L(dRU.ts, c(1:nlags))3	0.4196	*
L(dRU.ts, c(1:nlags))4	0.3655	*

Residual standard error: 5.129 on 343 degrees of freedom

Multiple R-squared: 0.5416, Adjusted R-squared: 0.5363

F-statistic: 101.3 on 4 and 343 DF, p-value: <2.2e-16

v. TaxPU and VIX

Tax Policy Uncertainty (TaxPU) captures the uncertainties around new taxes, increase or decrease in taxes. For TaxPU, our model returned two out of the twenty-four lags to be statistically significant (see table 8).

The increase or decrease of taxes directly affects the revenues and profits of companies traded in the stock exchange, and this in turn can affect stock prices. Furthermore, consumers make individual decisions (buying, selling, or holding) on their portfolio, which can manipulate the price of a stock.

Table 8: Tax Policy Uncertainty and VIX

	Estimate	Significance
(Intercept)	6.4488	***
L(dTaxPU.ts, c(1:nlags))1	1.4693	***
L(dTaxPU.ts, c(1:nlags))2	0.6823	***

Residual standard error: 5.745 on 347 degrees of freedom

Multiple R-squared: 0.4183,
Adjusted R-squared: 0.415

F-statistic: 124.8 on 2 and 347 DF, p-value: < 2.2e-16

3.3. Impulse Response Analysis

Central to our research is the question of ‘How does the stock market react when there is a shock from a policy such as policy uncertainty?’ To understand how the stock market volatility is affected by an exogenous shock, we run impulse response analyses for each of the five indices.

The model

The model is,

$$\Delta y_t = \alpha + \beta_0 \Delta x_t + \beta_1 \Delta x_{t-1} + \beta_2 \Delta x_{t-2} + \dots + \beta_n \Delta x_{t-n}$$

The equation above helps us determine the effect of a regressor x on y occurs over time rather than all at once. In other words, we can assess the long-run cumulative effect of x on y through the DL model. Moreover, if the DL model takes into account the differences in observations, we can determine how the stock market reacts to exogenous impulses, or shocks, from different sectors that affect the economy.

We developed our impulse response analysis model by making necessary adjustments to our DL model. In particular, we added the differences in our model.

In regressive and autoregressive models, impulse response analysis describes the evolution of a model’s variables in reaction to a shock in one or more variables. This also allows scholars and policymakers to assess the effects of a single shock within an otherwise noisy system of equations and, thus, makes them very useful tools in the assessment of economic policies.

i. FPU and VIX

As shown by our model, the stock market reacts most strongly to a shock from financial policy (see figure 1) in the tenth to eleventh months after the outset. The significance of the shock steeply declines after the fifteenth to sixteenth month. Statistically, the p values remained lower than $10e - 4$ until the 22nd month.

ii. FRU and VIX.

Our model shows that the impact of a fiscal regulation uncertainty related shock is felt relatively strongly until for the first few months and reaches its peak during the eighth month (see figure 2). A steep decline continues until the fourteenth month, after which the curve

flattens to a plateau, which declines steeply to relative insignificance after the twenty-fourth month. The p value remained lower than $10e - 4$ until the 23rd month.

Figure 1: Financial Policy Uncertainty Shock

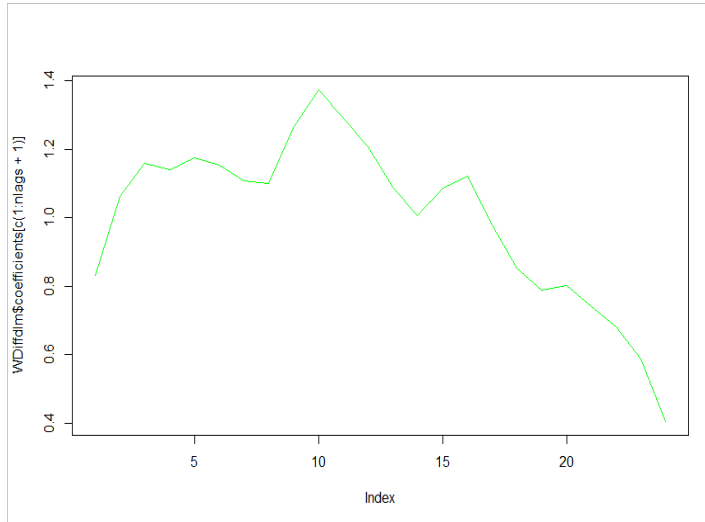
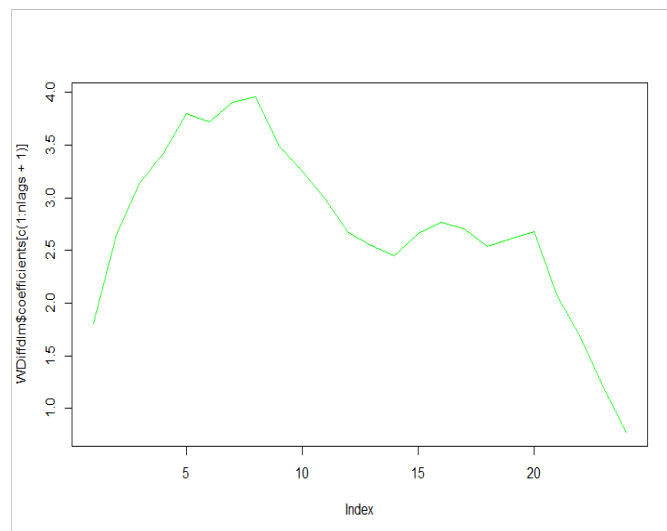


Figure 2: Fiscal Regulation Uncertainty Shock



iii. MPU and VIX

Before rising to its highest point during the sixteenth to seventeenth months, the shock of monetary policy related uncertainty in the stock market reaches periods of brief highs during the fifth and the tenth months (see figure 3). After reaching its peak, the decline is relatively steep, with the p value dropping below $10e - 4$ after the twenty-third lag.

The possibility of similarities between IRV and MPU is discussed briefly in the Findings section.

iv. RU and VIX

A shock from regulation related policy uncertainties peaks rises to its highs in the fifth month and peaks around the eighth month (see figure 4). What follows is a period of gradual decline, in which p values remain consistently significant. The p value remained lower than $10e-3$ until the 23rd month.

Figure 3: Monetary Policy Uncertainty Shock

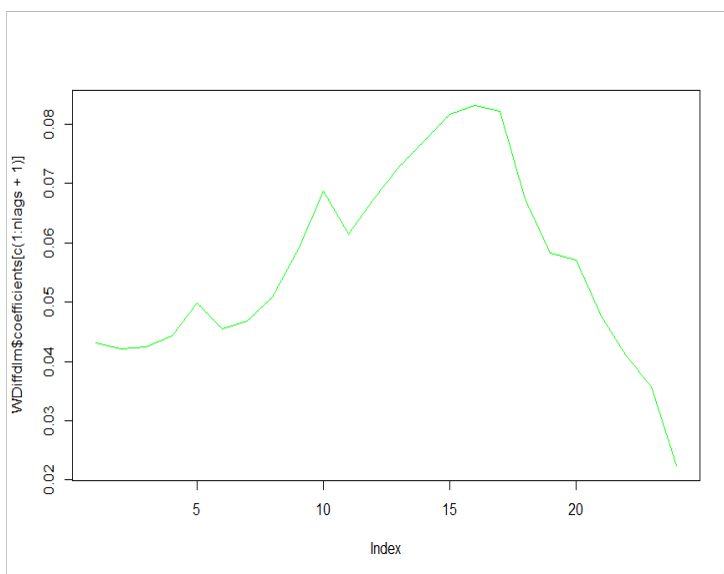
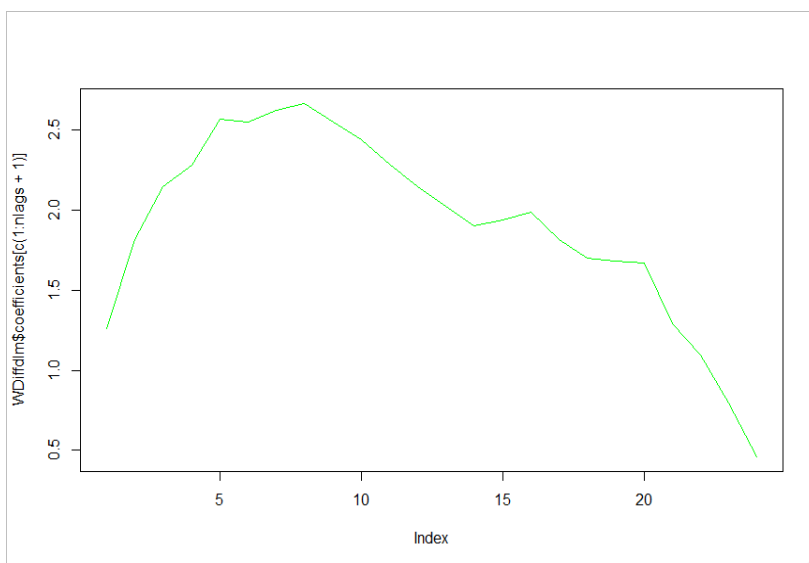


Figure 4: Regulations Uncertainty Shock



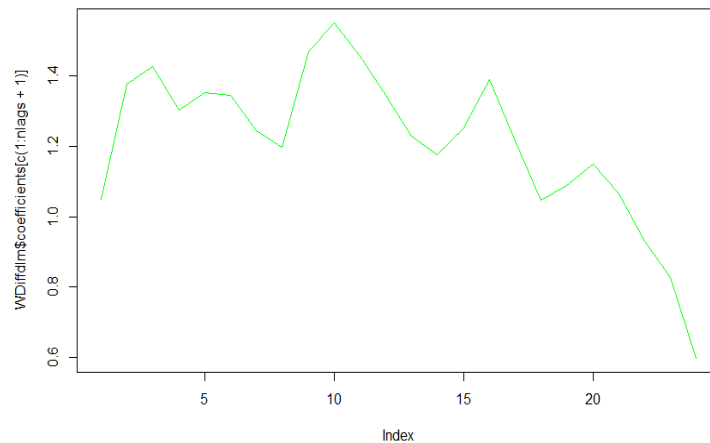
v. TaxPU and VIX

As our model shows, tax related policy shocks can have consistent effects in the stock market (see figure 5). Although it reaches its highest around the tenth month, the effect of

the shock in the equity market also rises significantly during the third and the sixteenth month. In all this, the p value remains lower $10e-3$, even during the 24th lag.

The possible ramifications of this result are briefly discussed in the upcoming section.

Figure 5: Tax Policy Uncertainty Shock



4. Discussion of the Results

In this section, we will elaborate the possible meaning and the implications of the findings from DL model and the adjusted DL model. To some extent, we have already discussed the probable causes and consequences of the results of the DL model. This section, hence, will focus more on the results from the adjusted model that we used for generating impulse response analyses.

The results from DL model suggest a number of conclusive analyses. First, it allows us to assess the predictive power of the uncertainty indices, both from Baker et al. (2019) and our calculations. For just an example, we find that looking at two lags (months) worth of interest rate volatility data could help us forecast stock market volatility. This was also particularly useful in comparing the variables amongst each other. Since it takes two lags of FPU to forecast stock market volatility while we would need four lags of FRU to do so, it can be inferred that FPU is a more powerful variable than FRU. The two-step process further refines our results since we only include the lags that were initially significant.

Likewise, the results from the adjusted DL model allows us to determine the ways and the patterns of an exogenous shock affecting stock market volatility. It also allows us to glean whether the shock will have a sustained long-term impact or have a high immediate impact. For instance, in the case of FRU reaches its peak during the eighth month, after which its impact gradually declines. Given the volume and extent to which the US economy trades goods and services, fluctuations in exchange rates have immediate effects on trade, finance, and investment, and the market quickly cashes in this volatility.

When it comes to indices that represent factors whose effects are not immediately apparent and have long term consequences (regulations, interest rates and monetary policy decisions), the impulse is felt most strongly somewhere in the middle or the latter section of

the graph. In the cases where the impulse is sustained and continuous, such as the case with TaxPU, we can infer that this may be the case as taxes, once introduced, are in place for a long-term and have long-term effects.

5. Conclusions

Our study contributes towards the wider literature on stock market volatility by providing detailed econometric analyses for determining the effects of several policy related uncertainties on stock market volatility. Furthermore, our study also provides additional empirical evidence in support of long held observations of the financial world such as the rise in stock market volatility corresponding to the rise in economic uncertainties.

We first determine the economic uncertainty indices that possess predictive causality. The econometric analyses of this paper then reveal how market volatility is an increasing function of the product of economic uncertainty. In a less technical way, our findings show that economic uncertainty can explain the volatility in the stock market.

We also think that reliance on the policy related uncertainty indices developed by Baker, Bloom and Davis (2016) alone may not encapsulate the volatility and uncertainties. It may not be always accurate to assume that every time aforementioned news can hint towards uncertainty and doubts. We thus think it is important to complement these uncertainties, many of which are based on newspaper coverage, with the use of economic indices that measure volatilities and uncertainties.

We conclude with directions that will point towards areas of future research in the field. The relationship between market volatility and policy uncertainty can be studied at the global level. Policy uncertainty indices can further be constructed with the use of internet browsers such "Google trends" and used in the market volatility analysis.

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