ERASMUS UNIVERSITEIT ROTTERDAM

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Spillovers in Volatility Risk Premiums across US Equity Indices

Masters' Thesis - Quantitative Finance

Author:
Vishal Nagwani

Student number:
611501

Supervisor: Daan Opschoor
Second assessor: Dr. Rutger-Jan Lange

Abstract

This thesis describes an exploratory analysis of the spillovers in volatility risk premium (VRP) components (upside and downside) emanating from European call and put options traded for the period Jan 2012 - Dec 2021. SP500, NASDAQ100, DJIA and RUSSELL2000 equity indices are considered for this analysis. The spillovers are estimated using the Diebold-Yilmaz connectedness framework based on VAR models using their forecast error variance decomposition. In addition, the evaluation of upside and downside VRP is based on a non-parametric approach to calculate implied volatility. We find that the DVRP is positive while the UVRP is mixed. There are significant spillovers during 2018 and 2020 due to shrinking of Fed's balance sheet and covid-19 respectively.

Keywords— MFIV, spillovers, VRP, OTM Calls, OTM Puts, forecast error variance decomposition, regularized VAR

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1 Introduction

In recent decades, globalization, improvement in technology and increasing inter-connectedness between entities (organizations, equity markets within a country and across countries) has led to a surge in cross-entity impact,i.e. spillovers. At a macro level, it means the Russia-Ukraine war will not only have an impact on the economies and markets of these two nations but other European, Asian and US markets as well. While at the micro level, it could be defined as the increase in stock price of a tea manufacturer due to higher demand leading to an increase in the stock price of a milk distributing firm (tea complements milk). At the same time, it is still quite difficult to consider such 'externalities' given that accounting for own variation is itself a challenging task.

Given the tendency of linkages across the globe to grow over time and recent crisis (covid-19 pandemic) being of such nature as well, this research provides insights into how investors price the risk of uncertainty in one index while the corresponding risk premium in another index changes. For investors and traders, it is important that they consider all kinds of scenarios while making market bets. One kind of uncertainty is the variation in returns, which is the volatility. For derivatives such as options, the volatility of the underlying is also a factor determining the option price. An option trader has to take into account the uncertainty associated with volatility as well.

First, we describe the topic of our analysis. After quantifying volatility risk premium (VRP) for SP500, NASDAQ100, Dow Jones and RUSSELL2000 indices, we assess the spillovers due to upside and downside VRP. It is well known that investors view upside and downside variance differently across the business cycle. We assess if the premiums charged in option markets are also different. By considering VRP components, we assess the asymmetric effect of expected uncertainty in option markets. Furthermore, the spillovers amongst the components could help us understand the changing nature of financial markets and trading therein across US, i.e., how inter-connections evolve over time. Spillovers between upside and downside VRP of one index due to another index are interesting to assess if the tendency of variance in one market inducing variance in another market also translates to how investors price this uncertainty in the option markets, which are again asymmetric due to which the spillovers amongst the different components across indices are bound to be different.

In this paragraph, we provide a preliminary understanding of VRP. VRP is defined as the compensation expected by a market participant for bearing volatility risk. The idea that there is a cost and benefit associated with uncertainty in returns is inherent here. A behavioral explanation for VRP is that investors give more weight to events that they can recall, e.g. 2007-09 crisis. This reasoning provides the inference that investors are willing to hedge large losses, thus inducing the VRP. Buyers of options expect that the underlying will move in a particular direction, thus leading to profits. By definition, there are more possibilities of price movements captured in options as compared to the actual deviations eventually observed, which determine realized volatility of the underlying. Thus, there exists a difference in the option-implied volatility and the realized volatility, which is the VRP. A popular idea in research is that this difference is most prominent in index option markets. While jump risk may contaminate the results for individual stock options, indices have relatively low probability of a jump.

As an example, out-of-the-money (OTM) put options are instruments available to hedge negative moves in the underlying. In both theory and practice, the impact of volatility risk for option returns is considered important. Popular references in this regard are Bakshi and Kapadia (2003), Chen, Shu, and Zhang (2016), Carr and Wu (2009) among others. It is also possible that an investor prefers a lower return with higher certainty as compared to a higher return with lower certainty. Given the asymmetric return profiles of options, an investor would be inclined to choose the side (long/short) that has potential for large gains. Given this gap in supply and demand of options, volatility sellers have the option to charge a premium while trading.

In the next couple of paragraphs, we describe why this research is relevant. From an empirical perspective, this research would be relevant for organizations involved in day-to-day market operations such as market makers and High Frequency speculators as well as long-term investors looking to approach their derivative investments quantitatively. As a practice, market makers are known to trade options. While trading these options, a frequent approach is to hedge their exposure to the underlying by going short/long in delta amount of the underlying, which leaves them exposed to variance risk. By acting as option sellers in crunch times, market makers can profit from these scenarios if they have a clear understanding of the VRP for their particular market(s).

In addition, for market makers, one part of the puzzle is forecasting variance, while another part is estimating variance risk for their delta-hedged portfolio. By gaining an understanding of variance risk premium and quantifying the spillovers, trading strategies which facilitate liquidity in the market could be developed for both business-as-usual and crisis periods. For example, 'early warning' indicators of possible trading opportunities could be developed. Another related aspect is that by assessing VRP spillovers across the country, measures of financial health can be developed to monitor these spillovers across economic cycles, which would be interesting for both theory and practice. In particular, it is relevant for risk managers and policy makers.

Next, we describe how the current research fits into the overall landscape. In the existing literature, VRP spillovers and upside/downside VRP components have been considered separately, but they have not been combined. We believe that a change in the price of uncertainty captured via particular type of options (call/put) for a particular index will cause a change in the price of uncertainty captured via call/put options for another index. Furthermore, the definitions of the components allow us to segregate the impact of OTM calls and OTM puts. From an academic perspective, it would be interesting to see how the Model-Free Implied Volatility (MFIV) Method works when considering VRP components' spillovers across indices. Whether this method is able to capture some of the more nuanced causalities in financial markets (effect of Central Banks, within-country spillovers) is of particular interest, given that the standard practice in the industry is to use At-the-Money (ATM) options with Black-Scholes Equation to obtain the Implied Volatility. Now while spillovers in returns and volatility have been actively analyzed with the advent of ARMA-GARCH framework and extensions, the research on spillovers in VRP is still at a nascent stage. Feunou, Jahan-Parvar, and Okou (2018) and Londono and Xu (2019) consider downside and upside components of VRP and we borrow that approach from them in addition to considering spillovers based on these components, which we could not find in existing literature. A natural impact of such a study would be to conclude if increase in VRP in one index market leads to an increase in VRP in another index market of the same country during crisis and otherwise.

Given the limitations of the Black-Scholes (BS) equation, we compute implied volatility using the concept of model-free implied volatility (MFIV), thereby circumventing the need to assume a particular parametric model for the data generating process. Since 2003, the VIX index published by Chicago Board of Options Exchange (CBOE) is also based on a model-free methodology and several other exchanges across the globe have followed them. Another advantage of using MFIV over BSIV is that BSIV only takes into account ATM options while MFIV also inculcates the impact of out-of-the-money options, which are vital when evaluating volatility risk premium, as these represent the contrarian market views given the current scenario.

The next two paragraphs depict the preprocessing steps taken and the results obtained. The data sanity checks applied such as removing data with absurd quotes or not following no-arbitrage bounds and removing options whose time-to-maturity exceeds 90 days leave little room for gaps in data preprocessing. We consider interpolation-extrapolation schemes to deal with gaps in trading information. We find that calls and puts indeed capture different expectations about volatility. While purchasing of call options represents the expectations of upside movement in the underlying, the purchasing of put options represents the downside expectations. The time series of MFIV are positively skewed and leptokurtic while the mean of volatility owing to puts is much higher than that owing to calls. In general, the relation exists that with an increase in the underlying's volatility, the price of an option increases as now there is a higher chance that the option will provide a positive payoff, be it a call or a put.

A higher mean volatility for puts implies that investors expect more downside movement in the underlying. On the other hand, leptokurtic MFIV time series mean that there are relatively extreme values of volatility, which in turn means that there are days when investors expect relatively large changes in the underlying. The Realized Volatility components are less extreme while still skewed and leptokurtic. The VRP components turn out to be stationary, which is critical for assessing spillovers. The forecast error variance decomposition of monthly VAR models fitted on the VRP components yields interesting results, with several instances of spillovers coinciding with key events such as FOMC meetings and Big-tech stocks leading the market (large intra-day variation in stock market). The quarterly spillovers generated using the regularized VAR model generate smooth spillovers prior to covid-19 crisis as well implying that the model has been able to capture significant spillovers during earlier phase changes of quantitative easing.

The remainder of the paper is organized as follows. Section 2 provides an overview of the literature around this topic. Section 3 lists down the data sources and preliminary data processing steps. Section 4 describes the MFIV and spillovers methodology. Section 5 provides the results and their analysis. Section 6 concludes.

2 Literature Review

The first two paragraphs provide an overview of recent research on sign and quantification of VRP and its components alongside market inputs that can be utilized to extend a comparative study. Bakshi and Kapadia (2003) test the hypothesis of a nonzero volatility risk premium by considering delta-hedged returns for European option contracts on SP500. In particular, they perform several cross-sectional and time-series tests that support this hypothesis. The review done as part of this thesis indicates that Carr and Wu (2009) are the first to quantify the VRP using variance swaps. Feunou, Jahan-Parvar, and Okou (2018) capture the idea to decompose VRP into upside and downside components corresponding to asymmetric returns and establish a link between these VRP components and equity premium. Specifically, they find a positive and statistically significant link between downside VRP and equity premium and a negative but statistically insignificant link betwee upside VRP and equity premium. Apart from considering similar components of VRP, Londono and Xu (2019) establish their cyclical behaviour (counter/pro-cyclical) as compared to the time variation in VRP and observe patterns during market turmoil. Carr and Wu (2016) develop a new option pricing framework related to the approach taken by institutional investors. They have also defined the concepts of option-specific realized and expected volatilities, which differ across strikes and maturities. The idea that realized volatility can also be determined particular to a given strike and maturity can help align the corresponding information from implied volatility and thus define VRP for the given strike and maturity, at least potentially.

Furthermore, Chen, Shu, and Zhang (2016) demonstrate that the volatility risk premium is positive during the time of financial crisis such as 2008 by defining it as the difference between realized volatility and VIX index, which is a measure of implied volatility in SP500 options for the next 30 days. Since 2003, VIX is calculated independent of any parametric option-pricing model using market observables by CBOE. In addition to VIX, the CBOE also publishes implied volatility indices for Dow Jones, NASDAQ100 and RUSSELL2000, which can be used for comparative study. Other than the US market, European market data provides implied volatility estimates for FTSE 100 and EURO STOXX 50 index options. In Asia, Taiwan, Korea and India publish model-free implied volatility indices. Fassas and Papadamou (2018) contain the full details.

Diebold and Yilmaz (2009) propose to utilize the forecast error variance decomposition by fitting a VAR model to quantify return and volatility spillovers. They develop their approach for a two-variable system and then extend it further. They find that return and volatility spillovers exhibit different behaviour over time. In their subsequent paper, Diebold and Yilmaz (2012) extend the spillover index by providing measure of directional spillovers in volatility across US stock, bond, FX and commodity markets. A related approach is that of Time Varying Parameter(TVP)-VAR, which allows the coefficients to change over time and is potentially appealing for macroeconomic studies. Korobilis and Yilmaz (2018) implement a TVP-VAR model of volatilities where they highlight that it does not suffer from built in persistence which occurs in case of Rolling Window (RW) - VAR during the period 2004-2016. They also find that TVP-VAR outperforms RW-VAR in predicting future systemic events and Coulombe (2020) shows that the state-space framework of

TVP models is equivalent to ridge regressions, which greatly improves the computational feasibility of this approach. To handle time varying parameters, we utilize the daily observations to obtain monthly and quarterly subsets of the data, which are completely disjoint, and eventually evaluate spillovers based on a regularized VAR model.

The research in this thesis is connected to the work done till date on VRP spillovers. The first ones in this regard are Finta and Aboura (2020), focusing on how a shock in risk premia of one market can cause a shock in risk premia of another market and another moment (variance and skewness). In an extreme sense, it is expected that a crisis in one part of the world would cause investors to become more risk averse in other parts of the world as well. This is extreme as a few decades ago this would be unexpected but with the advent of internet, it is pretty much expected now. In addition to risk premia associated with variance and skewness, they also consider their relation with kurtosis risk premium. Another work is Hattori, Shim, and Sugihara (2021), capturing the VRP spillovers amongst developed as well as emerging market economies and decomposing VRP into jump and diffusive components. They find that developed economies have significant spillovers onto the emerging markets and not the other way around. As stated in the Introduction, the research on VRP spillovers is at a nascent stage, also attributing to the fact that data governance across the globe has improved only recently. Our contribution to the literature is decomposing VRP into its upside and downside components and assessing spillovers using those components between indices within a country.

Bollerslev and Todorov (2011) emphasize the fact that a major part of the compensation achieved by risk premia is present due to the fear of extreme losses occurring in a short span of time, better referred to as jump tail risk. In addition, they also provide an approach to estimate the amount of fear in investors. Another aspect to learn is that this risk and the associated risk premium embedded in option prices varies across strikes and maturity. Todorov (2010) assesses if the VRP varies over time. He identifies that in addition to volatility being stochastic, another factor contributing to the evolution of VRP is the incidence of jumps. The idea is that once a jump occurs, the market takes time to return to its long term mean for the VRP. In the meantime, there is a perception of increased variance risk.

Wu (2011) considers the variance risk premium in SP500 by considering the VIX index as the risk-neutral counterpart and several quadratic variation estimators as the physical counterpart constructed from High-Frequency data in VRP's calculation. Using the results, he establishes that the magnitude of VRP is related to the variance level at the time. Han and Zhou (2012) find that VRP is a significant factor in the determination of cross-section of stock returns. They highlight the fact that information related to options can help in predicting stock returns. Apart from enhancing our understanding of the evolution of VIX index, these papers provide us with the standard approach taken by practitioners to calculate VRP, which we then extend based on the research in the next paragraph.

Jackwerth and Rubinstein (1996) describe a non-parametric approach to extract risk-neutral probabilities from market prices. By using the October 1987 crash as an example, they highlight the fact that a perceived outlier can have massive impact on volatility estimation. Bollerslev, Tauchen, and Zhou (2009) provide the approach to obtain model-free implied volatility (MFIV) estimates alongside an overview of why high-frequency returns and MFIV provide better VRP estimates. Given that the MFIV approach circumvents the lognormal assumption, it is naturally a more robust approach to such outliers. Andersen and Bondarenko (2007) describe the construction of MFIV measures using the concept of corridor implied volatility (CIV), which is an improvement over MFIV in the sense that the MFIV approach inherently truncates the tails of the risk-neutral distribution for strikes where options are not traded. The 'corridor' in CIV refers to the interval of strikes prices acting as the corridor and utilized to estimate CIV.

Jiang and Tian (2005) extend the model-free approach to estimating implied volatility for diffusion models by taking jumps into account. They find that MFIV contains richer information than ATM BS implied volatilities or historical volatilities and that the MFIV is also a more efficient forecast of future realized volatility. In their subsequent paper, Jiang and Tian (2007) show that CBOE's approach for Model-Free VIX, while an improvement on its predecessor, is still flawed due to the presence of truncation and discretization errors. To deal with these errors, they propose an interpolation-extrapolation scheme. We adopt this scheme while estimating MFIV components.

This paragraph lists the comparative studies performed for forecasting purposes using various volatility measures. Hseu, Chen, and Chung (2007) compare the forecasting performance of Historical Volatility, BSIV, MFIV and GARCH (1,1) estimators to predict Realized Volatility for Taiwan Index Options market. They find that while BSIV outperforms HV and GARCH (1,1) methods, MFIV improves over BSIV as well given its superior information content. Apart from comparing the forecasting performance of various measures of MFIV, Yao and Izzeldin (2018) formulate that calls and puts contribute to separate components of MFIV.

3 Data

3.1 Realized Volatility

The first step to calculate VRP for a given underlying is to obtain estimates of realized volatility (RV). In order to do that, We utilize the 'realized oxford' database[1] to obtain the 5 - minute RV estimates at a daily frequency of different indices for the time-frame 1st January 2012 to 31st December 2021. We also obtain the realized semi-variance measure from the same database for the same time duration.

As such, we intend to analyze the spillovers between VRP embedded in SP500, NASDAQ100, DJIA and RUSSELL2000. These indices are the key market indices for the US stock market and are considered as a gauge to assess the health of different representatives of US economy. Dow Jones has 30 large-cap stocks and is the oldest of the lot. It includes the key firms leading various sectors (blue-chip stocks - Amex, Apple, Boeing, etc.) except for utility and transportation. The SP500 is also a large-cap index but it is value-weighted while the dow is price-weighted. NASDAQ100, on the other hand, comprises of the top 102 value weighted stocks traded on the NASDAQ stock exchange.

[1] https://realized.oxford-man.ox.ac.uk/

Thus, by definition, it includes only technology stocks. RUSSELL2000 is another value-weighted index capturing 2000 small-cap stocks. A common feature of these 4 indices is that options are traded on these indices which are relatively liquid, thus providing hedging opportunities for the investors. In terms of composition, SP500 is composed of 500 stocks, DJIA is composed of 30, NASDAQ100 is composed of 102[2] while RUSSELL2000 comprises of 2000 securities.

3.2 Implied Volatility

For the indices listed above, we have obtained the price data of European options for the same time-frame from Wharton Research Data Services (WRDS)[3]. Next, we describe the 2 intermediate steps we have to take to preprocess the options data and calculate MFIV. Bond prices are being used as part of the methodology to calculate IV only. Therefore, the data generating steps for bond prices are described as a subsection within IV:

3.2.1 Bond Prices

Bond prices are required to normalize the option prices and underlying's price currently being traded. Section 4.1 provides the full description. We are using the 'LIBOR3M' yield curve to obtain the corresponding Zero-coupon bond prices using the following equation after obtaining these yields from Bloomberg.

$$P_t(\tau) = \exp(-r_t(\tau)\tau), \tag{1}$$

where $r_t(\tau)$ is the yield as of time t and τ, the time to maturity, which is 3 months.

3.2.2 Data Sanity Checks

Following Finta and Aboura (2020), for the European option prices, we discard the information that falls into the following categories - bid-ask option contracts pairs with missing quotes or zero bids, contracts with zero trading volume and finally, contracts with option prices that violate arbitrage restrictions. The first two checks are based on liquidity while the final check ensures that options which can be traded to benefit from arbitrage and will eventually converge to the no-arbitrage price, are excluded from the estimation of the risk neutral distribution. This is done so that inefficient information can be removed from the analysis. In addition to that, as we are considering the ex-ante risk-neutral expectation of volatility, we need to define the forward looking time-frame. Our choice is also motivated by the fact that we are using LIBOR 3 month yield curve in our analysis. We choose a period of 90 days and therefore, remove the data for dates where time-to-maturity exceeds 90 days.

[2] https://en.wikipedia.org/wiki/Nasdaq-100
[3] https://wrds-www.wharton.upenn.edu/

4 Methods

Volatility Risk Premium is defined as the difference between the ex-ante risk neutral expectation and the ex-post physical expectation of volatility/variance. The ex-ante risk neutral expectation can be captured by Implied Volatility (IV) which can be obtained using the data on European Options.

4.1 Implied Volatility

Option prices can be arranged in a grid with 2 dimensions: moneyness and time to maturity. Let's define:

$$\kappa = f(S_t, K), \tag{2}$$

and

$$\tau = f(t, T), \tag{3}$$

where κ is moneyness, τ is time to maturity, K is the strike price, T is the maturity date, t is the current date and S_t is the underlying's price. Given K and T, option prices can be represented as a function of current stock price and current date. On the other hand, given S_t and t, option prices can be represented as a function of strike price and maturity date. We will use these representations alternatively.

In order to obtain the IV using option prices, a standard approach is to invert the BS Equation. Rachev, Menn, and Fabozzi (2008) provide a nice overview of the BS equation. It is primarily based on 5 assumptions: (1) the underlying stock returns follow a lognormal distribution, (2) there are no transaction costs, (3) markets are random, (4) there are no dividends from the underlying till the option expires and (5) risk-free rate and underlying's volatility are constant over time.

$$C(\kappa, \tau) = S_t N(d_1) - K \exp(-r(T-t)) N(d_2), \tag{4}$$

$$P(\kappa, \tau) = K \exp(-r(T-t)) N(-d_2) - S_t N(-d_1), \tag{5}$$

where $N(.)$ is the cumulative distribution function of the normal distribution, $C(\kappa, \tau)$ is the price of a European call option, $P(\kappa, \tau)$ is the price of a European put option and

$$d_1 = \frac{1}{\sigma\sqrt{T-t}}[\ln \frac{S_t}{K} + (r + \frac{\sigma^2}{2})(T-t)], \tag{6}$$

$$d_2 = d_1 - \sigma\sqrt{T-t}. \tag{7}$$

In the above equations, r is the rate of interest and σ is the volatility of the underlying.

However, it is well documented that the BS approach has its limitations. For example, it only utilizes the ATM options to calculate IV. This is done because ATM options are liquid and represent reliable prices. To add to that, the assumptions of constant volatility and lognormal distribution of the underlying's returns are impractical assumptions generally. The assumption of lognormality is plausible only for ATM options. To combat that, we construct the model-free implied volatility (MFIV). This is a non-parametric approach which does not make any prior assumptions about the distribution of the returns of the underlying. This approach is based on the descriptions available in Hseu, Chen, and Chung (2007) and Yao and Izzeldin (2018). While they utilize the market convention of using BS equation to complete the grid of option prices, the actual evaluation of Implied volatility is devoid of any parametric model. It would be inconvenient to apply any kind of interpolation-extrapolation schemes on the option prices directly as these prices are not smooth all throughout due to the inherent non-linearity in the payoff structure. On the other hand, IV is relatively smooth.

Before we describe the approach to get MFIV, let's discuss what IV is. IV is the forward-looking volatility of the underlying given the options' price and other market and contract variables. IV represents the expectations of option buyers and sellers corresponding to their subjective hypothesis about where the market is going to go (upward/downward to a certain value) in the next $T-t$ days. IV calculation should be based on a measure of these expectations irrespective of the sampling or true distribution of returns. This is where the concept of MFIV comes into the picture. Britten-Jones and Neuberger (2000) provide the fundamentals of this approach, further developed by Jiang and Tian (2005).

Following Biktimirov and Wang (2017), the squared change of the underlying can be given by

$$E_0\left[\int_0^{T-t}\left(\frac{dS_t}{S_t}\right)^2\right] = 2\int_0^{\infty}\frac{C(\kappa,\tau)-\max(S_t-K,0)}{K^2}dK, \tag{8}$$

where E_0 is the risk-neutral expectation operator, $C(\kappa,\tau)$ is the observed price of a European call option with strike price K and maturity date T and S_t is the price of the underlying at time t. The LHS of the above equation represents the risk-neutral expectation of the variation in stock returns $(\frac{dS_t}{S_t})$ while the RHS represents the forward-looking variation in the underlying as captured by the market prices of options representing investor preferences.

By considering the difference between the current option price and possible payoff at maturity based on the intrinsic value, this approach is able to capture the expectations around uncertainty in the return of the underlying. The descriptions available in Hseu, Chen, and Chung (2007) and Yao and Izzeldin (2018) guide us in the step-by-step implementation of Equation (8). In addition, we consider components emanating from OTM calls and OTM puts as they represent different asymmetric information. For example, a call option is used to hedge positive moves in the underlying, so it provides protection from upside variance. Hence, we refer to the corresponding IV as upside MFIV and the one obtained using OTM puts as downside MFIV.

Hseu, Chen, and Chung (2007) and Yao and Izzeldin (2018) make use of numerical integration to arrive at these estimates which leads to two kinds of approximation errors. The first kind is truncation error, which occurs because we only have a limited number of strikes (K_{min} to K_{max}) and the second kind is discretization error, which is there because we have a discrete set of strikes rather than a continuous range. We make use of the same approach as Hseu, Chen, and Chung (2007) to tackle these errors.

First, given the grid of option prices across maturity and moneyness, we remove option prices that do not follow criteria as listed in Section 3. Next, we back out IV for the remaining options using the BS model. This step is taken as instead of applying any approximation techniques on call and put option prices, it is more appropriate to apply the approximations on BSIV obtained from those prices and then use the BS equation to obtain the grid of option prices. The name "Model-Free Implied Volatility" can be confusing given the use of the BS model, but please consider that the BS model is only being used for interpolation-extrapolation scheme to complete the grid of option prices. Once this grid has been obtained, the actual calculation of IV does not include any parametric model. Given that this approach improves on the limitations of BSIV evaluation, such as the assumption of lognormality, it is easily justified in existing research such as Jiang and Tian (2007), Andersen and Bondarenko (2007), and Biktimirov and Wang (2017)

For missing values within the grid, we perform polynomial interpolation of IV and for missing values outside the grid, we perform flat extrapolation for 5 grid points on either side of the strike grid. The extrapolation accounts for the truncation error by extending the grid while the interpolation reduces the discretization error by increasing the number of grid points and smoothening the grid. The IV within the original range of strikes, where interpolation is applied, is expected to follow a smooth curve, making polynomial interpolation appropriate. By definition, outside the original range of strikes, options are not traded frequently and thus, IV is kept flat. The choice of 5 grid points at either end stems from the fact that the different pairs of dates (current date, option maturity date) has somewhere between 15 and 25 contracts with different strikes. Thus extending the grid with 5 more strikes on either side is a plausible approximation given that there is a trade-off with computation time and OTM options are relatively less liquid. From the equations of MFIV below, it will be clear that extending the grid from 0 to ∞ is not the right approach due to no real contracts existing for extreme strikes and that these measures are not option specific and are additive over options trading on a given day. Thus, the choice of 5 grid points for flat extrapolation is appropriate.

Next, we convert the IV grid again into option prices using the BS model. This is done so that the MFIV calculation can be performed using the option prices. In order to do that we also needed to fill the grid for yield and index price, which we have done using linear interpolation and flat extrapolation. Finally, we use Equations (9) and (10) to obtain the MFIV components. Given K_{min} as the minimum strike price available for a particular index and K_{max} as the maximum strike price available for that index,

$$DMFIV_t = \sum_{i=1}^{m} [g(\kappa_i, \tau) + g(\kappa_{i-1}, \tau)]\Delta K, \tag{9}$$

and

$$UMFIV_t = \sum_{i=1}^{m}[h(\kappa_i, \tau) + h(\kappa_{i-1}, \tau)]\Delta K, \tag{10}$$

where

$$\Delta K = \frac{(K_{max} - K_{min})}{m}, \tag{11}$$

$$K_i = K_{min} + i\Delta K; i = 0, 1, ..., m, \tag{12}$$

$$g(\kappa_i, \tau) = \frac{P^*(\kappa_i, \tau) - max(0, K_i - S_t^*)}{K_i^2}, \tag{13}$$

$$h(\kappa_i, \tau) = \frac{C^*(\kappa_i, \tau) - max(0, S_t^* - K_i)}{K_i^2}, \tag{14}$$

$$P^*(\kappa_i, \tau) = \frac{P(\kappa_i, \tau)}{B(t, T)}, \tag{15}$$

$$C^*(\kappa_i, \tau) = \frac{C(\kappa_i, \tau)}{B(t, T)}, \tag{16}$$

$$S_t^* = \frac{S_t}{B(t, T)}. \tag{17}$$

$B(t, T)$ is the time t price of a zero coupon bond (ZCB) that pays 1 unit of currency at time T. $C(\kappa_i, \tau)$ is the observed price of a call option with strike K_i and time to maturity $T - t$ and $P(\kappa_i, \tau)$ is the observed price of a put option with strike K_i and time to maturity $T - t$.

To obtain the appropriate value of $B(t, T)$ using the yields, we will consider τ in Equation (1) to be the minimum of 3 months and the time to maturity of the option $T - t$. As we are removing all entries where the time to maturity exceeds 90 days, τ is simply $T - t$.

4.2 DVRP and UVRP

In order to capture the asymmetric effect of positive and negative returns in the indices on option returns, we consider realized semi-variance leading to the definition of downside volatility risk premium (DVRP) and upside volatility risk premium (UVRP) similar to the analysis considered in Feunou, Jahan-Parvar, and Okou (2018) and Londono and Xu (2019).

By using the estimates for realized semi-variance and the estimates for implied volatility using options data, we can obtain the downside - VRP:

$$DVRP_t = DMFIV_t - \sqrt{RSV_t}, \tag{18}$$

where RSV_t is the realized semi-variance and $DMFIV_t$ is the implied volatility as defined in the previous subsection. Realized semi-variance is the observed variation in the underlying's returns in the downward direction. $DVRP_t$ represents the difference between expected downward variation and observed downward variation. A positive value of $DVRP_t$ implies that investors are speculating on higher downward moves in the underlying than what is eventually observed.

The upside VRP can be defined as follows:

$$UVRP_t = UMFIV_t - \sqrt{(RV_t - RSV_t)}. \tag{19}$$

$UVRP_t$ represents the difference between expected upward variation and observed upward variation. A positive value of $UVRP_t$ implies that investors are speculating on higher upward moves in the underlying than what is eventually observed.

4.3 Spillovers

Once we obtain the VRP components' time series for all the 4 indices, we would fit a Vector Autoregressive (VAR) model to be able to quantify the spillovers from one VRP component time series to another (across indices).

$$X_t = \Phi X_{t-1} + \epsilon_t, \tag{20}$$

where X_t is a 8 x 1 vector of VRP components' time series, ϵ_t is a 8 x 1 vector of residuals and Φ is a 8 x 8 matrix of constant coefficients. Note that the components of these residuals will be correlated.

Following Diebold and Yilmaz (2009), we adopt the forecast error variance decomposition approach: Since X_t is covariance stationary, the Moving Average (MA) representation of Equation (20) exists.

$$X_t = \Theta(L)\epsilon_t, \tag{21}$$

where

$$\Theta(L) = (1 - \Phi L)^{-1}, \tag{22}$$

and L is the lag operator.

Given that the components of ϵ_t are correlated, we would like to transform them so as to make them orthogonal so that the whole effect of correlations can be captured in the coefficients of the orthogonal components. Thus, we can also write Equation (21) as

$$X_t = A(L)u_t, \tag{23}$$

where

$$A(L) = \Theta(L)Q_t^{-1}, \tag{24}$$

$$u_t = Q_t\epsilon_t, \tag{25}$$

and

$$Cov(\epsilon_t) = Q_t^{-1}(Q_t^{-1})^{'}. \tag{26}$$

From Diebold and Yilmaz (2009), we know that the 1-step ahead forecast error can be expressed in terms of u_{t+1}:

$$e_{t+1,t} = A_0 u_{t+1}, \tag{27}$$

where A_0 is a 8 x 8 matrix of coefficients.

Before we proceed further, we explain how to perform the estimation of A_0. Please note that the exact approach for this step is not available in the literature. Due to this reason, we add our own approach to go through this step:
ϵ_{t+1} is known once we have fitted Equation (20) (the best approximation of ϵ_{t+1} is ϵ_t). In addition, we can obtain the inverse of the lower-triangular factor of Cholesky decomposition of the covariance matrix of ϵ_{t+1}, Q_{t+1}. Using Equation (25), we can obtain u_{t+1}:

$$u_{t+1} = Q_{t+1}\epsilon_{t+1}, \tag{28}$$

The 1-step ahead forecast error is also known, $e_{t+1,t}$ and using Equation (27), we can write:

$$e_{t+1,t} = A_0 u_{t+1}, \tag{29}$$

Post-multiplying both sides by $u_{t+1}^{'}$, we get

$$e_{t+1,t}u_{t+1}^{'} = A_0 u_{t+1}u_{t+1}^{'}, \tag{30}$$

Let's denote $u_{t+1}u_{t+1}^{'}$ (which is a matrix) as U_{t+1}. We can post-multiply both sides with U_{t+1}^{-1} to obtain:

$$A_0 = e_{t+1,t}u_{t+1}^{'}U_{t+1}^{-1}, \tag{31}$$

This completes the estimation procedure of A_0.

Now, Diebold and Yilmaz (2009) consider the covariance of forecast error and since $Cov(u_t) = I$,

$$Cov(e_{t+1,t}) = A_0 A_0^{'}. \tag{32}$$

In their paper, they provide a description of their methodology by considering:

$$X_t = \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix}, \tag{33}$$

Here, we explain the concept of spillovers using the same formulation corresponding to Equation (33). Therefore,

$$A_0 = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix}, \tag{34}$$

and

$$Cov(e_{t+1,t}) = \begin{bmatrix} a_{0,11}^2 + a_{0,12}^2 & a_{0,11}a_{0,21} + a_{0,12}a_{0,22} \\ a_{0,21}a_{0,12} + a_{0,22}a_{0,12} & a_{0,21}^2 + a_{0,22}^2 \end{bmatrix}. \tag{35}$$

The forecast error variance for x_{1t} is $a_{0,11}^2 + a_{0,12}^2$ while that for x_{2t} is $a_{0,21}^2 + a_{0,22}^2$. What Diebold and Yilmaz (2009) postulate is that this variance can be divided into components, arising from own shocks (variance of x_1 due to x_1) and others' shocks (variance of x_1 due to x_2). In other words, the spillover in variance of x_1 due to x_2 is $a_{0,12}^2$ and the spillover in variance of x_2 due to x_1 is $a_{0,21}^2$.

The diagonal terms represent the variance and by this approach, they capture the shock component arising in one index due to the other by taking into account the off-diagonal terms of A_0, which is quite appropriate as we would like to know what part of the variance of forecast error of a particular index is being generated due to its own shocks and due to others' shocks.

Now that we have established this, let's break down the estimation of spillovers for our problem. We have

$$Cov(e_{t+1,t}) = B = A_0 A_0^{'}. \tag{36}$$

where $b_{i,i} = \sum_{k=1}^{8} a_{i,k}^2$ and $b_{i,j} = \sum_{k=1}^{8} a_{i,k}a_{j,k}$ for $i \neq j$. $b_{i,j}$ is the element in the $i-th$ row and $j-th$ column of the matrix B. For any given value of i, $a_{i,i}^2$ is the component of variance due to a shock in x_i itself and $a_{i,j}^2$ is the component of variance due to a shock in x_j. If we refer to the spillover in x_i due to x_j as $d_{i,j}$, then

$$d_{i,j} = a_{i,j}^2, \tag{37}$$

Let's denote the spillover in x_i due to all other variables as $d_{i,.}$ and the spillover by x_i to all other variables as $d_{.,i}$. Then,

$$d_{i,.} = \sum_{j=1, j\neq i}^{8} a_{i,j}^2, \tag{38}$$

and

$$d_{.,i} = \sum_{j=1, j\neq i}^{8} a_{j,i}^2. \tag{39}$$

Table 1 captures the above definitions concisely. The top-left 8 x 8 sub-block captures the individual spillovers. The rightmost column captures the spillovers from the other variables into a given variable. The bottom row captures the spillovers to the other variables from a given variable. The bottom-right element captures total spillovers, which is basically the sum of all off-diagonal elements in the 8 x 8 sub-block of individual spillovers.

Table 1: This table provides a visual representation to Spillovers.

	x_1	x_2	...	x_8	From Others
x_1	$d_{1,1}$	$d_{1,2}$	...	$d_{1,8}$	$\sum_{j=1,j\neq 1}^{8} d_{1,j}$
x_2	$d_{2,1}$	$d_{2,2}$	...	$d_{2,8}$	$\sum_{j=1,j\neq 2}^{8} d_{2,j}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
x_8	$d_{8,1}$	$d_{8,2}$	...	$d_{8,8}$	$\sum_{j=1,j\neq 8}^{8} d_{8,j}$
To Others	$\sum_{j=1,j\neq 1}^{8} d_{j,1}$	$\sum_{j=1,j\neq 2}^{8} d_{j,2}$	...	$\sum_{j=1,j\neq 8}^{8} d_{j,8}$	$\sum_{i,j=1,i\neq j}^{8} d_{i,j}$

In addition, we perform regularization while fitting the VAR(1) model over monthly and quarterly disjoint windows to avoid overfitting as well as built-in persistence usually caused due to rolling windows.

Without regularization, we obtain the parameters that minimize residual sum of squares. With Ridge regularization, the loss function becomes:

$$\sum_{j=1}^{n}(X_t - \Phi_1 X_{t-1})^2 + \lambda\|\Phi_1\|^2, \tag{40}$$

where

$$\|\Phi\|^2 = \sum_{i=1}^{A}\sum_{j=1}^{B}\phi_{ij}^2, \tag{41}$$

and ϕ_{ij} is the (i, j) entry in the A X B matrix Φ. The impact of this formulation is that less relevant parameters are shrunk towards 0.

5 Results

In this section, we present the results from each step. We begin with MFIV, followed by BSIV, RV and VRP. Thereafter, we present the monthly spillovers based on the standard VAR(1) model, the monthly spillovers based on the regularized VAR(1) model and the quarterly spillovers based on the regularized VAR(1) model. Before we begin, we would like to state that the analysis involves element of speculation. This occurs due to the reason that the risk-neutral distribution represents the expected beliefs about risk aversion, which is captured via the data itself. In addition, we provide references via the web, in the form of footnotes, that, rather than being viewed as reasons, should be viewed as further proof of the validity of the results. The footnotes pertain to specific market events whose dates coincide with spikes in the data. By marking these dates with market events, we avoid the possibility of the results being generated due to some bias in the data inherently or due to the processing steps applied to the data to obtain spillovers.

5.1 DMFIV and UMFIV

We have 4 indices at our disposal, leading to 8 different MFIV components. Below we provide a table of summary statistics obtained from the time series of MFIV components. It can be observed from Table 2 that all MFIV time series are leptokurtic and positively skewed. The first column in the table represents the number of observations available. On certain days if there are no options being traded in the permissible range for a given index, that day is not taken into account, thus leading to differences in the number of observations.

Comparing the time series of Upside MFIV - SP500 and Downside MFIV - SP500, the mean is higher for DMFIV while the UMFIV covers a broader range of values and is also relatively more skewed and more leptokurtic, highlighting the fact that calls and puts represent different information. This implies that on average, option traders expect a larger amount of downward variation in SP500 as compared to upward variation. At the same time, some of the larger variations are expected in the upward direction as implied by the option market. In addition, the standard deviation of UMFIV - SP500 is higher than that of DMFIV - SP500, signifying that there is more variability in the expectation of price movements implied by call options as compared to that of put options. Similarly, the mean of DMFIV - Nasdaq is higher than the mean of UMFIV - Nasdaq and unlike SP500, the relative ordering remains the same for standard deviation, skewness and kurtosis in case of NASDAQ100. The reason for this could be that traders expect higher large moves on the downside for technology stocks during this 10-year period. Compared to UMFIV - SP500, UMFIV - Nasdaq is relatively less leptokurtic, implying that there are speculations being made with respect to SP500 as compared to NASDAQ100 for larger upside movements.

Table 2: This table reports the summary statistics for the MFIV components (upside and downside MFIV) corresponding to 4 different equity indices, i.e., SP500, NASDAQ100, Dow Jones Industrial Average and RUSSELL2000. N represents the length of the time series.

	N	Mean	Min	Max	Stdev	Skewness	Kurtosis
UMFIV - SP500	2467	0.016	0.000	7.072	0.271	23.807	580.910
DMFIV - SP500	2474	0.142	0.011	2.360	0.188	5.548	46.961
UMFIV - Nasdaq	2474	0.005	0.000	0.099	0.010	3.282	16.544
DMFIV - Nasdaq	2474	0.055	0.001	0.962	0.069	5.273	43.896
UMFIV - DJIA	2474	0.002	0.000	1.618	0.042	30.512	1058.506
DMFIV - DJIA	2474	0.015	0.000	1.456	0.074	10.703	146.185
UMFIV - Russell	2464	0.009	0.000	0.331	0.017	4.582	56.612
DMFIV - Russell	2474	0.411	0.036	7.389	0.483	5.711	54.965

The upside MFIV for Dow Jones is highly skewed and leptokurtic while it's mean is very low, signifying that there are outliers. On the other hand, downside MFIV for Dow Jones has a relatively higher mean but lower skewness and kurtosis and a higher standard deviation. On the other hand, in case of RUSSELL2000, downside MFIV is more skewed and less leptokurtic as compared to upside MFIV. We can observe that the mean of downside MFIV is much higher than that of upside MFIV for each index.

From 2012 to 2021, trading activity in options has risen gradually[4]. The data available as part of this thesis supports this inference. More people are now informed about the benefits of option trading with plenty of resources available to learn the basics of option trading on the web. To add to that, the corona crisis has led to increased volatility of market expectations about the variation in an underlying's price. There were more options traded in just the first 2 months of 2021 than the entire year of 2012 in case of SP500. Similar trends can be observed in trading of options for the other indices considered part of this study.

We would like to make a note that the relatively high kurtosis values are not unexpected. First of all, please bear in mind that these statistics are measured over a ten year interval which would possibly include multiple regime changes related to the economy. To add to that, the criticism regarding the BS equation is not that it produces extreme values, but that it estimates a very low probability of such extreme observations as compared to how probable they are in practice as soon as there are worries of a slowdown. The fact that the MFIV approach is able to produce such extreme values is further demonstration of its ability to capture the empirical risk-neutral distribution.

The standard deviation of the MFIV time series for SP500 is much higher than that of NASDAQ or Dow Jones, owing to the fact that during the period of 2020-2021 (covid-19 crisis), there were quite a few outliers in the MFIV for SP500, which is evident from the charts below as well as from the maximum values for the MFIV series. In addition, given that SP500 is the most well-understood equity index in US economy, it has been traded much more heavily compared to the rest, leading to increased estimates of MFIV as compared to NASDAQ100 or Dow Jones and this effect is also evident in the mean values. This would imply that increased trading opportunities lead to more instances of large speculations being made on the underlying via the option market. It could also be that hedging of similar nature is being executed based on the particular preferences of a portfolio manager. Next we provide a time series plot of each component for the entire sample period, 2012-2021:

[4]https://focus.world-exchanges.org/articles/stock-index-options-and-futures

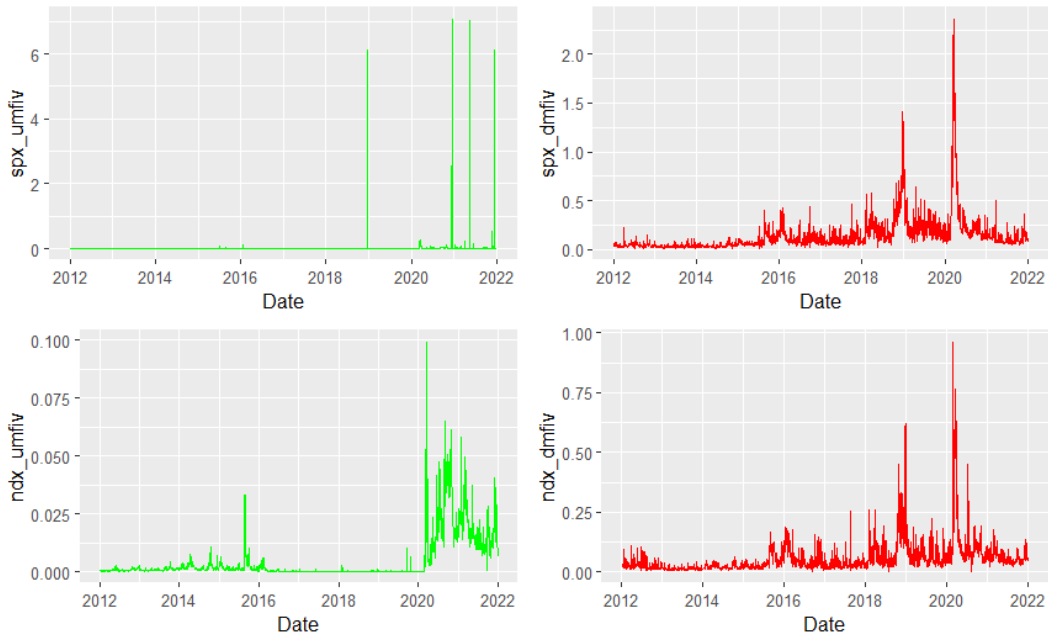

Figure 1: MFIV for SP500 and NASDAQ100 obtained using European call and put option prices with time to maturity less than 90 days for the time period 2012-2021

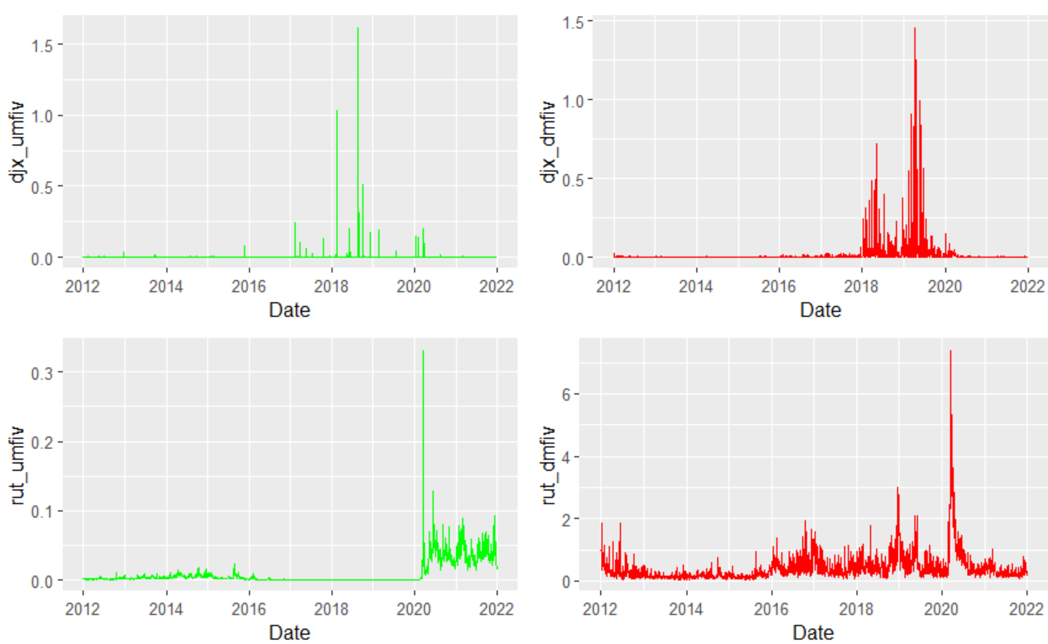

Figure 2: MFIV for Dow Jones Industrial Average and RUSSELL2000 obtained using European call and put option prices with time to maturity less than 90 days for the time period 2012-2021

The scales of UMFIV and DMFIV for SP500 are quite different, if we take into account the maximum values in different periods. However, one aspect common in the two figures is that after 2018, there were multiple instances/periods of high implied volatility for both calls and puts. This would be due to the change in stance of federal reserve with respect to quantitative easing.

From Yang, Zhou, and Cheng (2020), we learn that the Fed started shrinking its balance sheet at the maximum pace of USD 50 billion every month since Q4 2018. Particularly, on 19th December 2018, when the UMFIV for SP500 spiked for the first time, the Fed raised interest rates in combination of a forward guidance that the pace of rate hikes won't be slowed down[5]. Moreover, the clash of stance between the then President, Donald Trump and the Fed was also having its impact on how investors view the market conditions[6]. Anand et al. (2021) explain in their paper using Natural Language Processing how 'positive' speeches by the Fed Officials lead to positive returns while 'negative' or cautionary speeches lead to negative returns. They also showed that the US stock market responds relatively strongly to forward guidance of any kind. Due to this, on 18th December 2020, there was another spike after Fed Chairman Jerome Powell concluded the Federal Open Market Committee (FOMC) meeting on 17th December and the US congress' planning to submit a corona aid package[7]. The ultra-accomodative stance by the Fed along with passing of the package led to speculation of large increases in SP500 resulting in this steep rise in implied volatility. The reasoning here is that with any kind of relatively extreme stance by the Central Bank, there is a rise in volatility, upward or downward, as now more bets are being placed on large moves in the underlying. On 12th May 2021, the UMFIV-SP500 saw another spike due to inflation fears which also led to the VIX index seeing a large jump[8]. As stated in Reifschneider and Wilcox (2022), the Fed failed to anticipate the rise in inflation during 2021. On 9th December 2021, the most recent spike was caused due to the data on initial jobless claims being released by the US labor department. The claims fell to the lowest level since 1969[9] coupled with uncertainty due to the Omicron variant[10]. In general, the last 2 years have been a period of high uncertainty with lockdowns happening across the globe, which is also evident from the MFIV charts.

By comparing the UMFIV of NASDAQ100 with SP500, we can observe similar behaviour around the period 2015-2016, with different scales. This would be due to reasons such as the Greek debt default in June 2015, end of quantitative easing having its lagged effect and Brexit in June 2016[11]. Yang, Zhou, and Cheng (2020) also provides the information that the Fed started raising interest rates in December 2015 after exiting QE in 2014, hence coinciding with IV rise in UMFIV-NASDAQ100. If we compare the DMFIV of NASDAQ100 with that of SP500, we can observe that the volatility spikes around the same time periods, while the scaling is different. The volume of options traded with SP500 as the underlying is much higher than with NASDAQ100. Along with that, such a consistent increase would also imply that the premiums being charged on put options are higher for SP500. One reason for that could be that SP500 has 500 individual constituents as opposed to 102 in NASDAQ100, thus there are considerably more input variables determining

[5] https://www.cnbc.com/2018/12/19/stock-markets-dow-futures-edge-higher-federal-reserve-rate-decision.html

[6] https://finance.yahoo.com/news/stock-market-news-dec-19-143002899.html

[7] https://finance.yahoo.com/news/stock-market-news-dec-18-150503342.html

[8] https://finance.yahoo.com/news/stock-market-news-may-12-133901758.html

[9] https://finance.yahoo.com/news/stock-market-news-live-updates-december-9-2021-001847397.html

[10] https://www.bloomberg.com/news/articles/2021-12-09/asian-stocks-set-to-slip-after-wall-street-retreat-markets-wrap

[11] https://en.wikipedia.org/wiki/2015-2016_stock_market_selloff

the returns in SP500, leading to higher speculation. In both charts, the covid-19 crisis has led to significant increase in expectations of uncertainty.

The period of 2018-2019 has been particularly tumultuous for both call and put options of Dow Jones. While in 2018, the Fed raised rates 4 times with a December hike that was not expected, in 2019, rates were lowered 3 times. And both these kind of events led to increase in speculations[12]. Eksi and Tas (2017) demonstrate that during the phase of quantitative easing, the response of stocks to monetary policy actions amplified seven times. This is more evident for Dow Jones as it has only 30 constituents, leading to less diversified weights as compared to other US indices. Similar behaviour can be observed in downside MFIV of SP500 and NASDAQ100 for 2018-2020.

Similar to SP500 and NASDAQ100, the UMFIV for RUSSELL2000 has a lot of movement during the corona crisis, highlighting that a lot of speculation was being done as to where the economy is headed in parts and as a whole. The plot for downside MFIV for RUSSELL2000 is similar to the downside MFIV of SP500 and NASDAQ100, although the scale is considerably different, owing to the fact that RUSSELL2000 is a more volatile index as compared to the rest.

5.2 BSIV

It can be observed from Table 3 that all time series are positively skewed and leptokurtic, although with substantially less magnitude as compared to the MFIV series. That being said, the relative orderings based on kurtosis are pretty much the same as MFIV. We would like to provide the exact estimation process of BSIV here. After inverting the BS equation, we apply the same interpolation-extrapolation scheme as MFIV, then calculate moneyness. We choose the entries with minimum absolute moneyness and if there are more than one, we average them out. This is to ensure that we only inculcate information from 'near' ATM options. Due to this approach, some of the extremes are not as evident as they should be.

The mean and standard deviation of SP500-UBSIV are much higher than the rest along with a high maximum value, implying similar behaviour as demonstrated for SP500-UMFIV. The skewness and kurtosis of DJIA-BSIV components is also higher than the rest, similar to the results for MFIV.

[12] https://www.cnbc.com/2019/12/31/the-stock-market-boomed-in-2019-heres-how-it-happened.html

Table 3: This table reports the summary statistics for the BSIV components (upside and downside BSIV) corresponding to 4 different equity indices, i.e., SP500, NASDAQ100, Dow Jones Industrial Average and RUSSELL2000. N represents the length of the time series.

	N	Mean	Min	Max	Stdev	Skewness	Kurtosis
UBSIV - SP500	2467	1.675	0.001	9.999	3.147	1.927	5.259
DBSIV - SP500	2474	0.543	0.142	2.312	0.349	1.018	3.952
UBSIV - Nasdaq	2474	0.795	0.001	9.999	2.409	3.485	13.386
DBSIV - Nasdaq	2474	0.509	0.153	2.153	0.386	1.704	5.370
UBSIV - DJIA	2474	0.218	0.000	9.999	1.292	7.430	56.282
DBSIV - DJIA	2474	0.352	0.012	9.999	1.290	7.153	53.476
UBSIV - Russell	2464	0.656	0.001	9.999	2.118	3.939	17.161
DBSIV - Russell	2474	0.602	0.197	1.978	0.352	1.203	3.940

Below we present the charts for BSIV components. Despite the averaging feature in the methodology, the time series exhibit a lot of variability, similar to the MFIV time series. This would be due to the reason that there are lots of days when 'near' ATM option implies absolute moneyness is less than the value of 5, leading to an IV close to zero. On other days, the absolute moneyness is larger and consequently IV is also much larger.

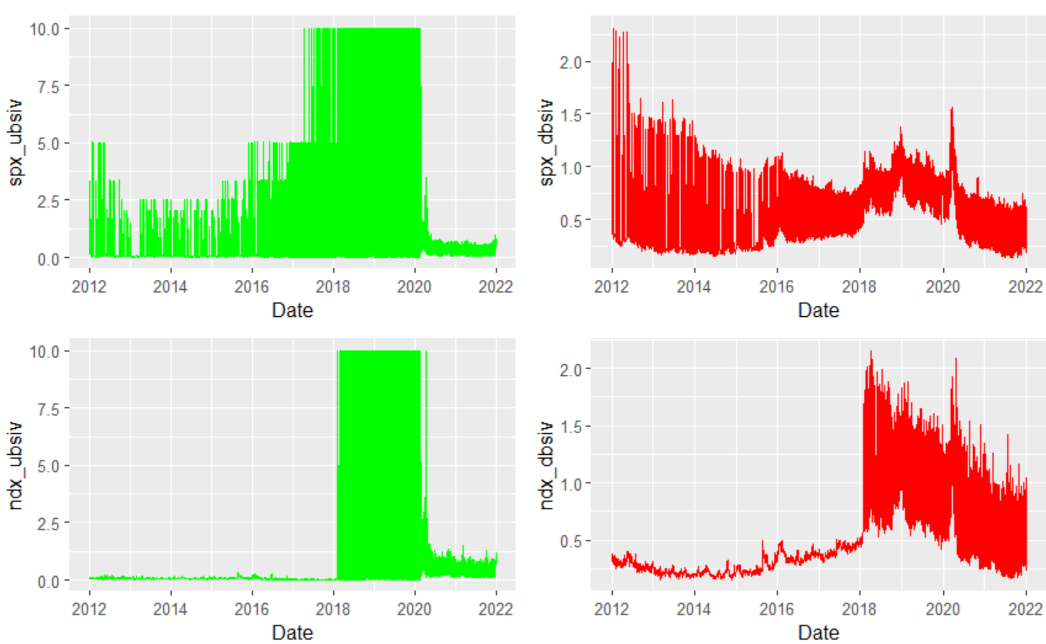

Figure 3: BSIV for SP500 and NASDAQ100 obtained using European call and put ATM option prices for the time period 2012-2021

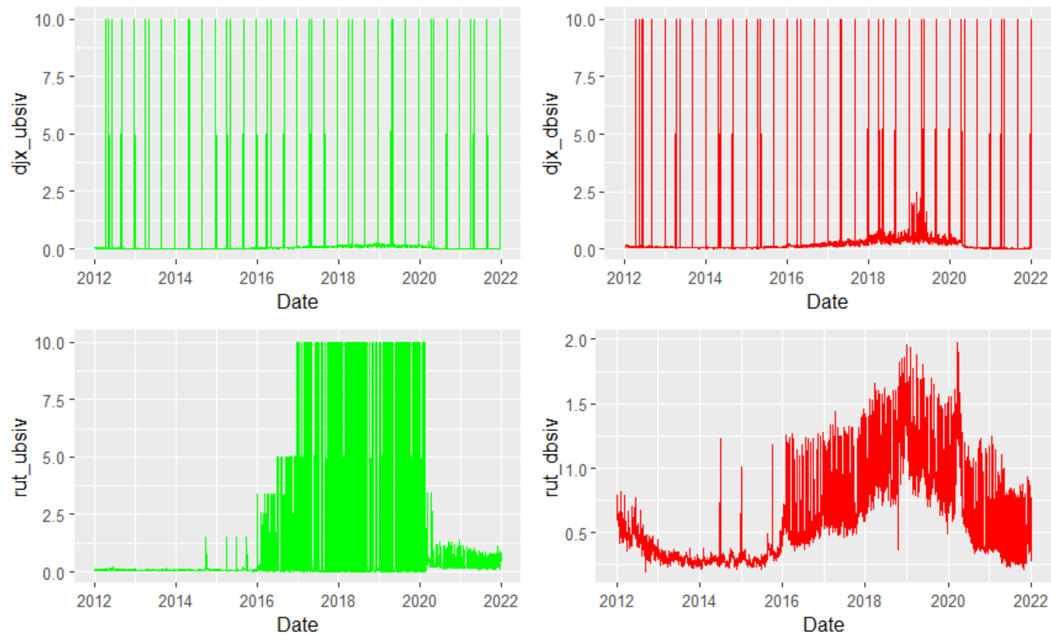

Figure 4: BSIV for Dow Jones Industrial Average and RUSSELL2000 obtained using European call and put ATM option prices for the time period 2012-2021

5.3 Realized Volatility

In Table 4, we present the summary statistics for upside and downside RV and it can be observed that these are also positively skewed and leptokurtic, similar to MFIV components, although there are no extremes in case of RV. RV is the measure of ex-post observed variation in returns, which is devoid of speculations of movements in future, unlike implied volatility. While the large movements have been captured by healthy values of skewness and kurtosis, by definition, RV lacks any speculative component, thereby avoiding very fat tails. For the same reason, the summary statistics are much more stable, which accounting for deviations in the right tail.

Comparing URV-SP500 with DRV-SP500, the means are same while DRV-SP500 is more skewed and more leptokurtic with slightly higher standard deviation, which is in contrast with the observations made for MFIV. It is expected that downside variance leads to more extreme deviations. Similarly, in case of NASDAQ100, DRV has same mean and higher skewness and kurtosis than URV, same as the case of MFIV. URV-NASDAQ100 is similar to URV-SP500 and DRV-NASDAQ100 is similar to DRV-SP500. Same observations can be made when comparing URV and DRV of Dow Jones. DRV-DJIA is more leptokurtic than DRV-SP500 and less leptokurtic than DRV-NASDAQ100. This finding can be attributed to the fact that in a price-weighted index (Dow Jones), naturally, the returns of constituents will be low, leading to lower extremes. While the returns in a value-weighted index would be higher leading to larger extremes, 500 assets diversify the effect while 102 does not, apparently. On the other hand, URV-RUSSELL2000 is more skewed and more leptokurtic than DRV-RUSSELL2000, despite having a higher maximum value. As RUSSELL2000 is a relatively younger and less mature index, such deviations from the norm can be possible.

Table 4: This table reports the summary statistics for the RV components (upside and downside RV) corresponding to 4 different equity indices, i.e., SP500, NASDAQ100, DJIA and RUSSELL2000. N represents the length of the time series.

	N	Mean	Min	Max	Stdev	Skewness	Kurtosis
URV - SP500	2506	0.005	0.001	0.042	0.003	4.522	36.301
DRV - SP500	2506	0.005	0.000	0.053	0.004	4.939	45.779
URV - Nasdaq	2509	0.005	0.001	0.039	0.003	4.563	37.237
DRV - Nasdaq	2509	0.005	0.001	0.068	0.003	4.995	60.494
URV - DJIA	2504	0.005	0.001	0.046	0.004	4.671	38.773
DRV - DJIA	2504	0.005	0.001	0.069	0.004	5.334	55.292
URV - Russell	2506	0.005	0.001	0.040	0.003	4.268	34.201
DRV - Russell	2506	0.005	0.001	0.047	0.003	3.915	31.682

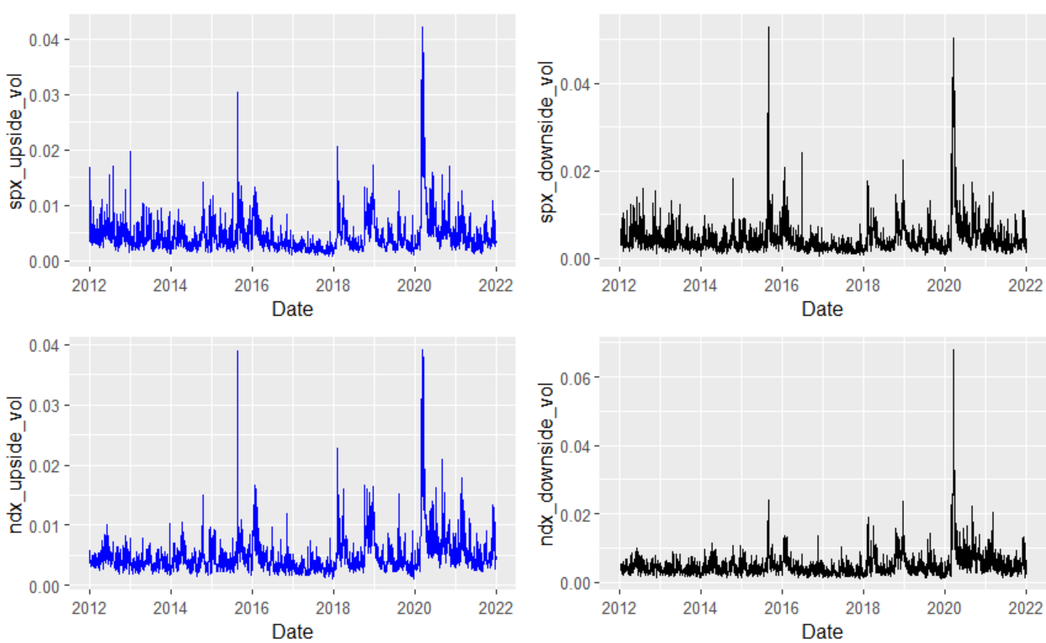

Figure 5: URV and DRV for SP500 and NASDAQ100 for the time period 2012-2021

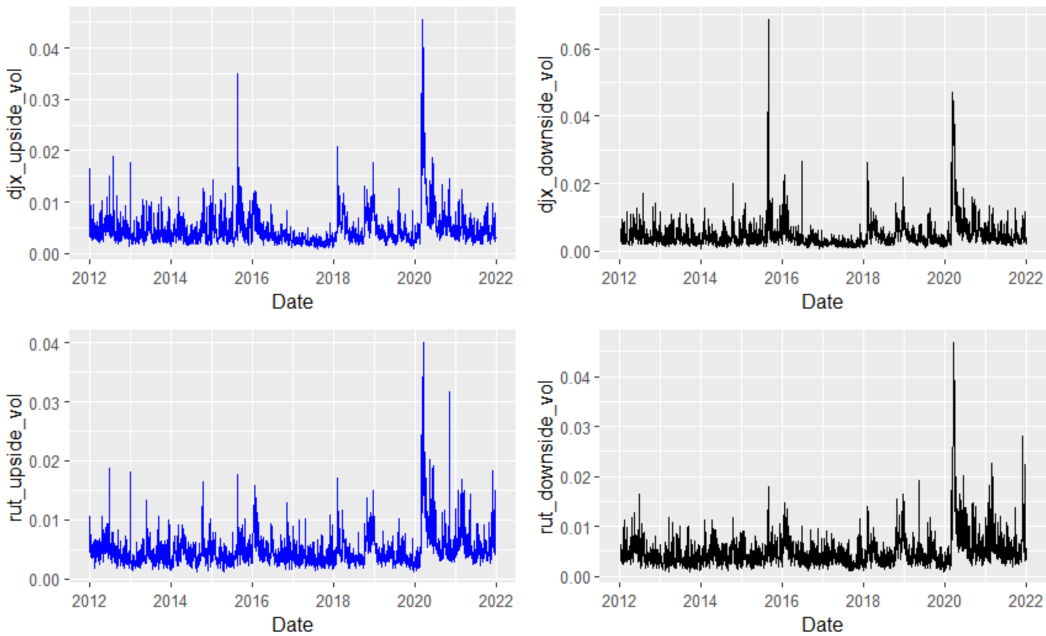

Figure 6: URV and DRV for DJIA and RUSSELL2000 for the time period 2012-2021

It can be observed that the plots for RV components are much more well-behaved and comparable within indices as compared to the plots for MFIV components. This can be attributed to the fact that due to their speculative nature, options markets consider more possibilities (of price movements) than what is eventually observed, which constitutes RV, leading to relatively more extreme values in the MFIV component time series.

Both upside and downside RV have risen in 2015-2016 and again in the first quarter of 2020. The behaviour in 2015-16 would be due to Greek debt default, effect of end of quantitative easing and Brexit while the behaviour in 2020 would be due to the covid-19 crisis. It can also be observed that post March 2020, volatility has been higher on average compared to periods before 2020. Volatility also spiked in 2018. At the end of January 2018, Fed Chairman Jerome Powell provided his outlook that implied a rise in interest rates, leading to an increase in volatility a week later[13]. Kaminska and Roberts-Sklar (2018) show that volatility in interest rates leads to a rise in stock return volatility. As mentioned in Section 5.1, on 19th December 2018, the Fed raised interest rates and provided forward guidance that the pace of rate hikes won't be slowed down[14], considering the analysis by Anand et al. (2021) that Fed speeches with a negative connotation increase equity volatility, led to the plausible implication of an increase in volatility towards the end of 2018 as well. Similar behaviour can be observed for URV-NASDAQ100 around the same dates in 2015-16, 2018 and 2020.

On the other hand, downside RV for NASDAQ100 has spiked significantly higher in the first quarter of 2020 while similar behaviour to previous charts can be observed on the other dates. Subramaniam and Chakraborty (2021) explain how anxiety around covid-19 led to decrease in

[13]https://www.cnbc.com/2018/02/05/why-the-stock-market-plunged-today.html

[14]https://www.cnbc.com/2018/12/19/stock-markets-dow-futures-edge-higher-federal-reserve-rate-decision.html

stock returns in NASDAQ100 ETF. Specifically, on 16th March 2020, the VIX rose to record highs[15] justifying this observation. While all the indices dropped by 12 percent, it was the biggest drop for the stocks listed on Nasdaq exchange[16].

In case of Dow Jones as well, upside RV shows behaviour similar to URV-SP500 and URV-NASDAQ100, with spikes in 2015-16, 2018 and 2020. The downside RV for Dow Jones shows a sharp increase on 24th August 2015, better known as "August 24 flash crash"[17]. From Shirvani et al. (2020), we find that the bear market began on August 21 with a drop of 3.1 percent in DJIA. As also cited in this article, on this day, Asian and European stock markets, which preceded trading compared to US markets, were highly volatile. On the morning of 24th August, sell orders overwhelmed the exchanges. The other spikes in 2018 and 2020 are comparable to the spikes observed in previous RV charts.

In case of RUSSELL2000, the spikes in 2015-16 and 2018 are not as prominent as SP500, NASDAQ100 or Dow Jones. Although the period of 2020-2021 has higher volatility on average as compared to the previous years. The value of the spike is comparable in March 2020 with that of SP500. In Abushosheh et al. (2022), they consider a separate phase corresponding to phase 3 trials of covid-19 vaccine and show that during this phase there were positive returns in US stock markets. Specifically, On 9th November 2020, covid-19 vaccines by BioNTech and Pfizer went through a positive trial[18], leading to improvement in market sentiment and an increase in upside RV for RUSSELL2000. This index is known to lead and lag variations in other indices due to being comprised of small-cap and mid-cap stocks[19]. The paper, Shu, Song, and Zhu (2021), describes that small-cap stocks faced larger losses than large-cap stocks during the 2020 market crash. The downside RV for RUSSELL2000 rose significantly on 26th November 2021 due to fears of a new coronavirus mutant. The RUSSELL2000 index saw it's biggest 1-day percentage drop since 25th Feb 2021.

5.4 Volatility Risk Premium

We begin by testing for a unit root in the VRP components' time series by applying an augmented Dickey-Fuller (ADF) test. Assuming a significance level of 5 percent, all the time series are stationary. Hence, our MA representation is not inappropriate.

[15] https://edition.cnn.com/business/live-news/stock-market-news-today-031620/index.html

[16] https://www.cnbc.com/2021/03/16/one-year-ago-stocks-dropped-12percent-in-a-single-day-what-investors-have-learned-since-then.html

[17] https://vantagepointtrading.com/news/2015-flash-crash-august-24-made-trading-history/

[18] https://www.cnbc.com/2020/11/09/stock-market-live-updates-today.html

[19] https://fortune.com/2020/11/24/small-cap-stocks-best-month-ever-november-2020/

Table 5: This table reports the summary statistics for the VRP components (upside and downside VRP) corresponding to 4 different equity indices, i.e., SP500, NASDAQ100, DJIA and RUSSELL2000. N represents the length of the time series. The last column reports the ADF test statistic along with the p-value in parentheses (a value of 0.01 implies p-value less than or equal to 0.01).

	N	Mean	Min	Max	Stdev	Skewness	Kurtosis	ADF-statistic
UVRP - SP500	2457	0.012	-0.028	7.067	0.271	23.775	579.155	-35.1 (0.01)
DVRP - SP500	2457	0.137	0.006	2.326	0.186	5.528	46.574	-7.6 (0.01)
UVRP - Nasdaq	2466	-0.001	-0.026	0.063	0.009	2.699	12.251	-7.8 (0.01)
DVRP - Nasdaq	2466	0.050	-0.005	0.939	0.065	5.279	44.646	-11.25 (0.01)
UVRP - DJIA	2462	-0.003	-0.045	1.614	0.037	36.842	1568.797	-34.9 (0.01)
DVRP - DJIA	2462	0.010	-0.063	1.452	0.074	10.697	146.079	-26.8 (0.01)
UVRP - Russell	2464	0.004	-0.023	0.295	0.016	4.306	50.799	-12.73 (0.01)
DVRP - Russell	2464	0.406	0.035	7.342	0.481	5.690	54.571	-10.23 (0.01)

Table 5 provides the summary statistics for the VRP components' time series. As compared to the previous time series presented, of MFIV and RV, the differences between components of VRP are quite varied. While UVRP for SP500 and Dow Jones is more skewed and more leptokurtic than the corresponding DVRP, the reverse is true in case of NASDAQ100 and RUSSELL2000. If we compare each VRP component to the corresponding MFIV component, the VRPs are relatively less skewed and less leptokurtic, except for UVRP for Dow Jones, which has become more skewed and more leptokurtic compared to UMFIV-DJIA. Please note that the mean and the maximum values have reduced as compared to UMFIV-DJIA with a lower standard deviation, so this is not intuitive, in the sense that other summary statistics should also demonstrate presence of extremes in UVRP-DJIA.

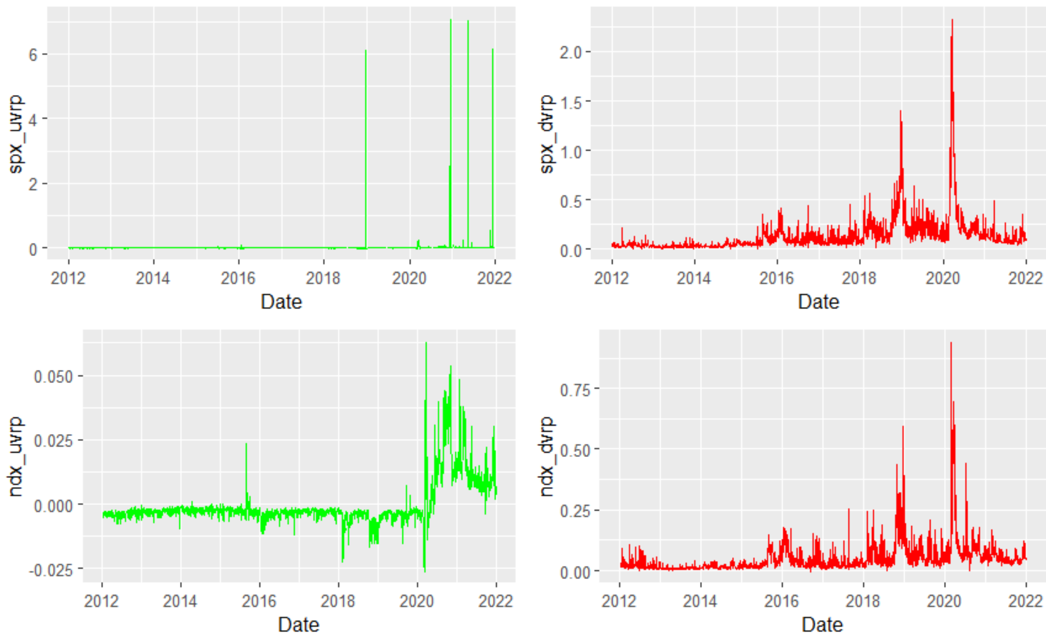

Figure 7: VRP for SP500 and NASDAQ100 for the time period 2012-2021

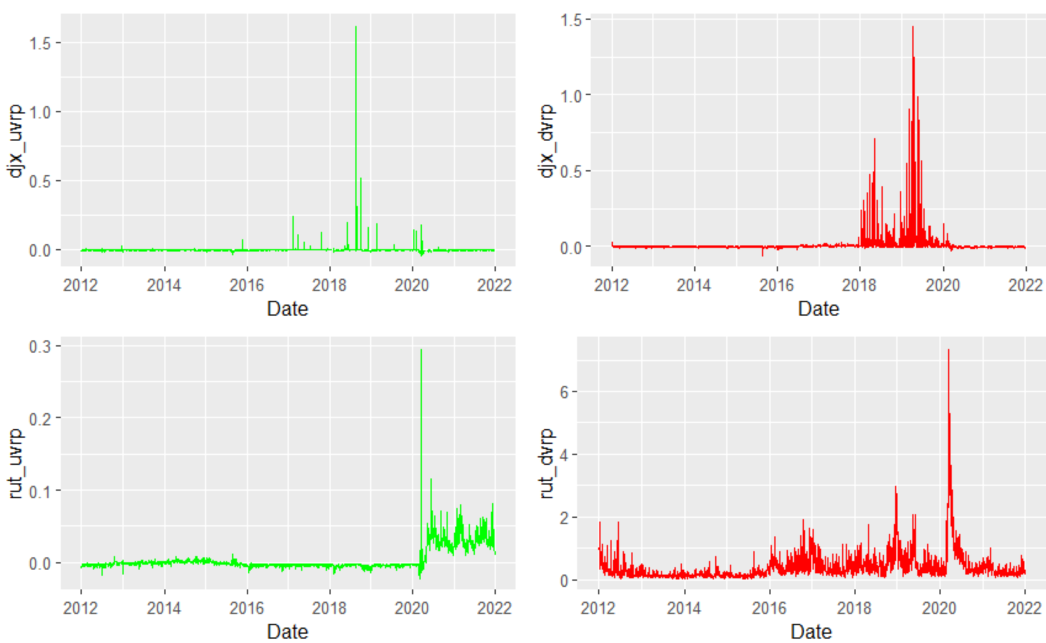

Figure 8: VRP for Dow Jones Industrial Average and RUSSELL2000 for the time period 2012-2021

Similar to the corresponding UMFIV-SP500 series, there are clear spikes in 2018 and during corona crisis, for the same reasons as cited earlier in Section 5.1. There was a gradual rise in DVRP for SP500 in the week of Christmas in December 2018, due to tensions between Donald Trump and

Jerome Powell[20]. The tweet by the President stating that the Fed is the "only problem" in the US economy was quite contradictory to what the central bank was trying to achieve. The spike of 18th March 2020 coincides with the covid-19 crash[21].

The upside VRP for NASDAQ100 was consistently negative before 2020, signifying that the UMFIV was lower than URV, implying that investors were willing to pay a premium to be exposed to the upside volatility of NASDAQ100. Only after 2020, it turned positive, implying that in this period, any kind of volatility was less preferred to certainty in the returns of NASDAQ100 stocks. During the last 10 days of August 2015 and first 10 days of September 2015, UVRP-NASDAQ100 was very volatile with alternating signs every few days. The most significant positive value occurs 1 day after the "August 24 flash crash" described for DRV-DJIA in section 5.3, signifying that after the crash on August 24, investors were charging a premium to be exposed to upside volatility in NASDAQ100. On the other hand, there is a sharp increase in downside VRP for NASDAQ100 on 24th October 2018, which coincided with a downturn in the stock market[22], as explained in Yang, Zhou, and Cheng (2020) in Section 5.1, due to the Fed reducing the balance sheet by amounts of USD 50 billion starting October 2018. The premium remained relatively high till the end of 2018, with a spike being observed on 21st December coinciding with worries of the Fed pursuing Quantitative tightening[23], as stated in Brown (2018) where he assesses the President's public attack on the Fed. Using a TVP-VAR model, He, Lucey, and Wang (2021) show that trade policy uncertainty has a statistically significant impact on stock returns. The policies by the trump administration around trade tariffs were also a cause of concern towards the end of 2018[24]. In Q3 2018, US imposed tariffs on imported Chinese goods, in response to which China imposed tariffs on imported US goods, as discussed in-depth in Selmi, Errami, and Wohar (2020). DVRP-NASDAQ100 saw a sharp increase in the week leading to 28th February 2020, coinciding with a sky-high rise in the VIX index[25]. By developing a covid-19 fear index based on search terms on google, Subramaniam and Chakraborty (2021) show that queries related to covid-19 have a statistically significant and negative relationship with returns on NASDAQ100 ETF.

If we look at the price chart for Dow Jones, there is evident choppiness during 2018. UVRP for Dow Jones is mostly negative before 2017. On 10th February 2017, President Donald Trump announced his preparations for a tax plan which made investors expect a low tax environment[26], leading to a jump in UVRP. Wagner, Zeckhauser, and Ziegler (2018) explain that the expectation of lower taxes meant that firms with high deferred-tax liabilities, possibly due to overseas profits which are yet to be brought back to the US, would benefit more than others. Naturally, the big tech firms such as Apple and Microsoft benefited the most. Thereafter, the UVRP is mostly negative, but then again shifts sign starting 2018, at the same time when the tax plan was eventually implemented.

[20]https://www.cnbc.com/2018/12/24/us-stock-futures-fall-slightly-as-the-dow-attempts-to-rebound-from-its-worst-week-in-a-decade.html

[21]https://www.cnbc.com/2020/03/18/stock-market-today-live.html

[22]https://www.marketwatch.com/story/dow-futures-drop-220-points-as-stock-market-extends-rout-2018-10-24

[23]https://finance.yahoo.com/news/stock-market-news-dec-21-143002849.html

[24]https://www.pbs.org/newshour/economy/making-sense/6-factors-that-fueled-the-stock-market-dive-in-2018

[25]https://finance.yahoo.com/news/stock-market-news-feb-28-143502111.html

[26]https://finance.yahoo.com/news/stock-market-news-february-10-151003262.html

DVRP-DJIA is slightly negative starting in 2012, then starts taking some positive values scattered through 2016, 2017 and 2018, with the density of positive values gradually increasing. In the first week of May 2018, amid expectations that the Fed will raise interest rates[27], DVRP went significantly higher in the positive direction. This can be understood by the reasoning that a rise in interest rates would lead to a fall in the stock market, thus increasing the demand for put options. Thereafter, the volatility in DVRP continued in 2019. Then on 11th April 2019, the value jumped to a little less than 1.5, due to the release of FOMC minutes from the meeting held on 19-20 March, which contemplated a patient vs aggressive approach to rate hikes[28]. Gospodinov and Jamali (2012) explain that surprises with respect to the Federal funds rate lead to increase in Implied Volatility, in this case also leading to a positive DVRP. Then, again on 23rd May 2019, as the trade conflict between US and China worsened, the value once again jumped close to 1[29] (reasoning provided in previous paragraph). On the other hand, there is little difference in implied and realized volatility during the covid period, owing to the fact that DJIA is a price-weighted index and has only 30 constituents. Being price-weighted with relatively low number of assets implies that unexpected volatility will be low.

UVRP-RUSSELL2000 starts as slightly negative and then takes some positive values in late 2013. It turns positive for most days in 2014 and then the density of positive values gradually declines through 2015, again becoming negative starting 2016. The spike of 17th March 2020 coincides with the covid-19 crash, after which it remains consistently positive, signifying that investors were pricing in uncertainty due to covid-19. DVRP-RUSSELL2000 is positive and takes very high values as compared to the other time series. The value rose further during the end of 2016 and start of 2017. For example, on 13th October 2016, the value jumped to 1.92 due to release of FOMC minutes showing that a rate hike should be expected soon. The value remains highly volatile thereafter. Then on 21st December 2018, a large spike occurred, coinciding with timing of the Fed pursuing Quantitative tightening (Yang, Zhou, and Cheng (2020)). The spikes in March 2020 coincided with the covid-19 crash.

5.5 Spillovers

Now, we present the results of spillover estimation starting with the full period. Please note that we believe fitting a single VAR model for 10 years is not appropriate as market conditions change. We first present the connectedness table for the full period using MFIV. Next, we present the same table for the full period using BSIV. However, our main results are an application of regularized VAR(1) model using MFIV where the penalty term corresponds to ridge regression. We estimate the regularized VAR(1) model for each month starting January 2012 and ending December 2021 and obtain monthly estimates of spillovers. In addition, we bias the diagonals of our U_{t+1} matrix to make it non-singular, as otherwise it is possible that U_{t+1} is not invertible, creating roadblocks in the estimation procedure. This works in a manner that the singular matrix has an eigenvalue

[27]https://www.nasdaq.com/articles/stock-market-news-for-may-2-2018-2018-05-02
[28]https://seekingalpha.com/article/4254282-s-and-p-500-weekly-update-april-2019-deja-vu-all-over-again
[29]https://finance.yahoo.com/news/stock-market-news-may-23-134401883.html

equal to 0 and adding a small bias makes it non-zero, also making the matrix non-singular. The results are agnostic to the scale of the bias.

5.5.1 Full Period Spillovers using MFIV

In Table 6, we present the Connectedness matrix from spillovers obtained by fitting a VAR(1) model on VRP components calculated using MFIV for the full duration of 10 years. It can be read in the following manner: SP500-UVRP's own spillovers are 0.00002, SP500-DVRP's spillovers to SP500-UVRP are 0.00005, NASDAQ100-UVRP's spillovers to SP500-UVRP are negligible and so on. Similarly, the spillovers from SP500-UVRP to SP500-DVRP are negligible. The last column can be interpreted in the following manner: Spillovers to SP500-UVRP from all others except itself are 0.00118, which is $\approx$ 98 percent of the variation in SP500-UVRP. The last row can be interpreted in the following manner: Spillovers from SP500-UVRP to all others except itself are 0.00036 out of total spillovers from SP500-UVRP of 0.00038. The bottom-right cell represents the sum of all off-diagonal elements in the upper 8x8 matrix, which is 0.01109 out of 0.02286, or $\approx$ 48 percent. So, out of the total variation in these 8 VRP components, 48 percent variation is caused in a given component by another component. To interpret these spillovers, please note that they should be assessed relative to the overall sum of spillovers (all elements of the upper 8x8 matrix).

Table 6: Connectedness Matrix for the full period from VAR(1) model using MFIV

	SPX UVRP	SPX DVRP	NDX UVRP	NDX DVRP	DJX UVRP	DJX DVRP	RUT UVRP	RUT DVRP	From Others
SPX-UVRP	.00002	.00005	.00000	.00009	.00000	.00001	.00037	.00067	.00118
SPX-DVRP	.00000	.00001	.00000	.00002	.00000	.00000	.00007	.00012	.00021
NDX-UVRP	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000
NDX-DVRP	.00000	.00001	.00000	.00001	.00000	.00000	.00004	.00008	.00013
DJX-UVRP	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000
DJX-DVRP	.00000	.00000	.00000	.00000	.00000	.00000	.00001	.00002	.00003
RUT-UVRP	.00000	.00000	.00000	.00000	.00000	.00000	.00001	.00001	.00001
RUT-DVRP	.00035	.00094	.00000	.00162	.00001	.00010	.00648	.01172	.00951
To Others	.00036	.00100	.00000	.00173	.00002	.00011	.00697	.00089	.01109

5.5.2 Full Period Spillovers using BSIV

In Table 7, we present the Connectedness matrix from spillovers obtained by fitting a VAR(1) model on VRP components calculated using BSIV for the full duration of 10 years. In this case, spillovers to SP500-UVRP from all others except itself are 0.01298 out of 0.01301, which is 99.76 percent of the variation in SP500-UVRP. Spillovers from SP500-UVRP to all others except itself are 94.82 percent out of total spillovers from SP500-UVRP. Out of the total variation in these 8 VRP components, 85 percent variation is caused in a given component by another component. To interpret these spillovers, please note that they should be assessed relative to the overall sum of spillovers.

Table 7: Connectedness Matrix for the full period from VAR(1) model using BSIV

	SPX UVRP	SPX DVRP	NDX UVRP	NDX DVRP	DJX UVRP	DJX DVRP	RUT UVRP	RUT DVRP	From Others
SPX-UVRP	.00003	.00257	.00027	.00614	.00012	.00002	.00000	.00386	.01298
SPX-DVRP	.00004	.00386	.00040	.00920	.00018	.00002	.00000	.00579	.01564
NDX-UVRP	.00023	.01937	.00203	.04619	.00089	.00012	.00001	.02908	.09589
NDX-DVRP	.00010	.00837	.00088	.01995	.00038	.00005	.00000	.01256	.02234
DJX-UVRP	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000
DJX-DVRP	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00001
RUT-UVRP	.00010	.00821	.00086	.01958	.00038	.00005	.00000	.01233	.04151
RUT-DVRP	.00009	.00732	.00077	.01745	.00033	.00005	.00000	.01098	.02600
To Others	.00055	.04585	.00318	.09857	.00227	.00031	.00002	.06362	.21437

5.5.3 Monthly Spillovers

First, we present the monthly spillovers using MFIV with the standard VAR(1) model, i.e., without regularization.

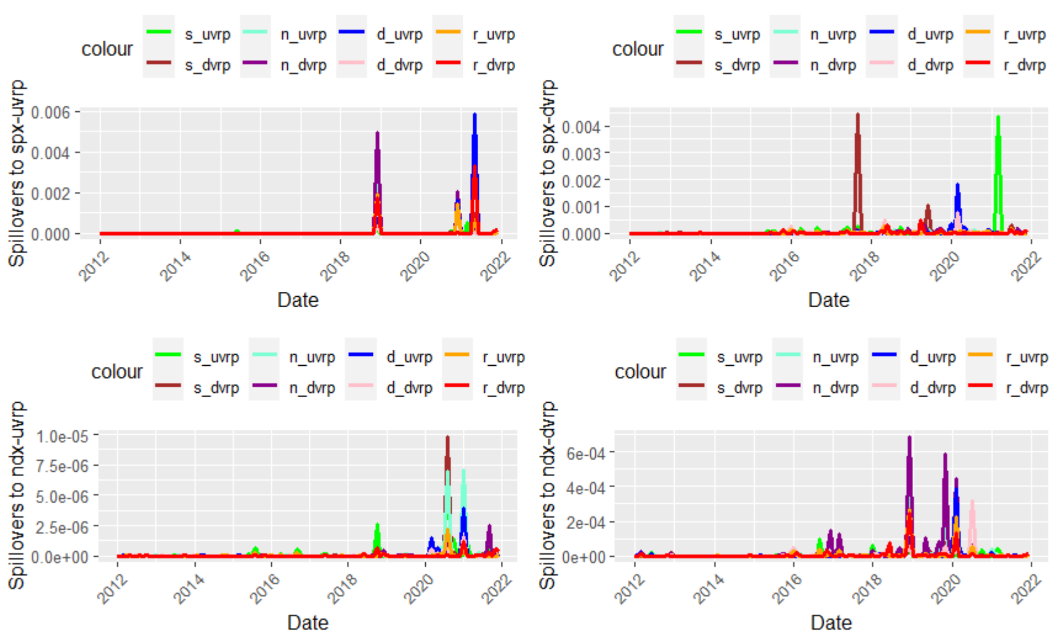

Figure 9: Spillovers to VRP components of SP500 and NASDAQ100 from the 8 VRP components based on VAR(1) model

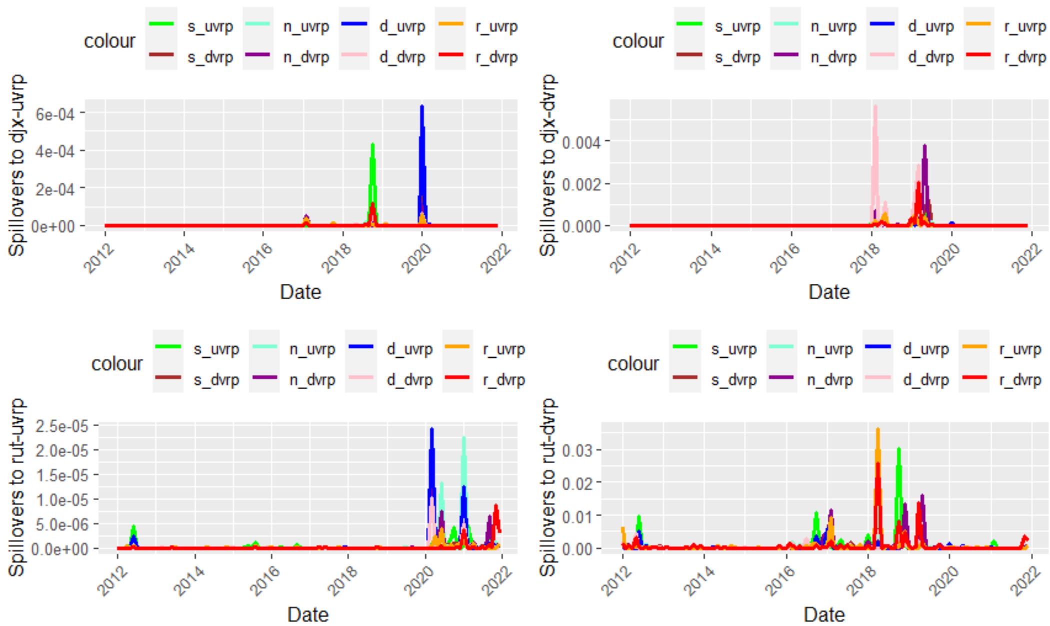

Figure 10: Spillovers to VRP components of Dow Jones and RUSSELL2000 from the 8 VRP components based on VAR(1) model

From Figure 9, we see that in December 2018, the spillovers to UVRP for SP500 showed a spike with NASDAQ100-UVRP leading followed by RUSSELL2000-UVRP, RUSSELL2000-DVRP, DJIA-UVRP, DJIA-DVRP and itself. Then again in December 2020, the spillovers showed a spike, although of less intensity led by NASDAQ100-UVRP followed by DJIA-UVRP and RUSSELL2000-UVRP. Finally in May 2021, there was the largest spike in 10 years with DJIA-UVRP leading and followed by RUSSELL2000-DVRP, SP500-DVRP and RUSSELL2000-UVRP.

December 2018 was the end of a year which was the worst in a decade[30]. From Section 5.1 we know that during 2018, the Fed went about increasing bond tapering provisions. Uncertainty in interest rates and tensions between Fed and Donald Trump together with trade war with China, all contributed to volatility in SP500 from 1st to 31st December 2018[31] as explained in Section 5.4. From the observations, it is clear which segments of the market contributed to the overall variance in error projected from a standard VAR(1) model fitted to the VRP components. In other words, the variation in price of upside uncertainty in SP500 was driven by variation in price of upward uncertainty in NASDAQ100, upward and downward uncertainty in RUSSELL2000 as well as Dow Jones and upward uncertainty in SP500. Technology stocks were leading the sell-off while impacting the rest of the market with RUSSELL2000 index also joining the fray[32]. Garcia (2018) states that tech stocks were indeed going through a sell-off. Trade tensions, regulations and hints of slowdown due to the Central Banks changing their stance on Quantitative Easing across the globe in the months to come paired up to cause this sell-off in tech firms. This article by NY times

[30]https://www.washingtonpost.com/graphics/2018/business/stock-market-crash-comparison/

[31]https://www.cnbc.com/2018/12/31/stock-market-wall-street-stocks-eye-us-china-trade-talks.html

[32]https://www.nytimes.com/2018/12/21/business/nasdaq-stocks-bear-market.html?auth=link-dismiss-google1tap

from November 2018[33] can be quoted as saying, "Monday's slide in the United States had already spilled over into Europe and Asia before trading on Wall Street opened on Tuesday. By the end of the trading day, the Euro Stoxx 50, an index of eurozone blue-chips, had dropped more than 1.4 percent.", highlighting that this sell-off was building up. And then, several national and global issues piled up during the end of December[34] leading to large spillovers.

May 2021 was another month with significantly higher spillovers, when expectations of rising inflation engulfed markets and the Dow Jones in particular, which is composed of value stocks, and value stocks tend to perform relatively well during high inflation, thus leading to increased demand in upward uncertainty of DJIA. In this case, the variation in price of downward uncertainty in RUSSELL2000 (primarily growth stocks) as well as SP500 also contributed to variation in price of upward uncertainty in SP500.

For SP500-DVRP, the first major spike occurs in September 2017 due to itself. Then again in June 2019, there are significant own spillovers. In March 2020, for the first time there are significant other spillovers led by DJIA-UVRP, NASDAQ100-UVRP and DJIA-DVRP. Then again in March 2021, the significant spillovers are by SP500-UVRP. Apart from these, there are small spillovers by SP500-UVRP and RUSSELL2000-DVRP throughout the 10 year period.

In September 2017, hurricanes in US coupled with inflation concerns and the Fed providing forward guidance on its unwinding of balance sheet[35], led to increase in variation in the premium being paid to be exposed to downward uncertainty in SP500. In their paper, Yang and Zhou (2017) demonstrate that quantitative easing explains more than 40 percent variation in US volatility spillovers. In June 2019, amid an expected rate cut, the Fed clarified that it is not necessary[36], leading to the variation in price of downward variance in SP500 rising again. Gospodinov and Jamali (2012) explain that any kind of surprise component in FOMC announcements causes a rise in SP500 volatility. March 2020 is well-known now to be a part of the covid-19 crash when the dow lost roughly 26 percent of its value, as stated in Mazur, Dang, and Vega (2021). The paper also explains that conventional sectors such as entertainment and hospitality suffered. Dow Jones contains 30 well-established firms, thus leading to the large spillovers. As explained in Zefirov and Shadrina (2022), finally, in March 2021, after President Joe Biden's signing of coronavirus relief package and announcement of his USD 2 trillion infrastructure proposal[37], the variation in price of upward uncertainty in SP500 also led to variation in price of downward uncertainty in it.

The first significant spike for NASDAQ100-UVRP occurs in August 2020 led by SP500-DVRP, NASDAQ100-UVRP and SP500-UVRP. Then again in January 2021, there is another spike due to NASDAQ100-UVRP. After the 23rd March 2020 low, the market had been slowly building up towards a bull market. With the Fed slashing rates, launching an asset-purchasing program and inflation policy designed to keeps rates low[38], August 2020 turned out to be a month with significant

[33]https://www.nytimes.com/2018/11/20/business/stock-markets.html
[34]https://finance.yahoo.com/news/stock-market-news-dec-21-143002849.html
[35]https://finance.yahoo.com/news/fed-fomc-monetary-policy-decision-september-2017-133948830.html
[36]https://www.cnbc.com/2019/06/25/stock-market-wall-street-in-focus-as-investors-await-more-fed-talk.html
[37]https://www.cnbc.com/2021/03/31/stock-market-futures-open-to-close-news.html
[38]https://www.cnbc.com/2020/08/30/stock-market-futures-open-to-close-news.html

upward volatility for technology stocks, taking both NASDAQ100 and SP500 higher[39]. Kilci and Yilanci (2022) show that increase in money supply and total assets of the Fed has a positive effect on consumer expenditure, and thus the stock market. Sunder (2021) explains in his paper that during Q2 2020, the Fed expanded it's balance sheet by 66 percent, leading to a stock market recovery in August 2020. January 2021 was a volatile month[40] for tech stocks, leading to increase in variation in NASDAQ100-UVRP. By this time, it was very evident that technology stocks will be the ones benefiting from the covid-19 crisis.

The significant spillovers for NASDAQ100-DVRP are led by itself in December 2018 and followed by NASDAQ100-UVRP. Then again in November 2019, there is another spike led by itself and NASDAQ100-UVRP. In February 2020, there is the last significant spike led by itself and DJIA-UVRP.

As explained while analyzing the results for SP500-UVRP using Yang, Zhou, and Cheng (2020), December 2018 involved sell-off in technology stocks[41]. November 2019 was a positive month, while uncertainty around the awaited US-China trade negotiations[42], as explained in He, Lucey, and Wang (2021), caused increase in VRP spillovers. The covid-19 market crash had began in February itself[43] leading to investors willing to pay a premium to be exposed to upward volatility of NASDAQ100 or Dow Jones.

From Figure 9, we can also say that within the VRP components of an index, there are significant spillovers from SP500-UVRP to SP500-DVRP but not the reverse or in case of either component of NASDAQ100. On the other hand, if we consider spillovers from any of the downside components in case of SP500-UVRP, there are spillovers from NASDAQ100-DVRP and RUSSELL2000-DVRP. Similarly, in case of NASDAQ100-DVRP, there are spillovers from DJIA-UVRP. In Figure 10, we observe that within the same index, only in case of RUSSELL2000-DVRP there are spillovers from RUSSELL2000-UVRP. If we consider spillovers from the other component given any index, there is no significant change in the findings.

By considering SP500 as a proxy for large-cap stocks and RUSSELL2000 as a proxy for small-cap stocks, we find that there are spillovers from small-cap-DVRP to large-cap-UVRP (from Figure 9) and vice-versa (from Figure 10).

For Dow Jones' upside VRP, the first spike occurs in October 2018, when SP500-UVRP and RUSSELL2000-DVRP provide significant spillovers. Thereafter in January 2020, a bigger spike occurs due to spillovers provided by itself, SP500-DVRP and NASDAQ100-DVRP. October volatility, coupled with Fed Chair stating that the economy does not need very low interest rates led to volatility in SP500[44] during October 2018. As explained in the results for DJIA in Section 5.1, the response of stock markets to Fed announcements got amplified by 7 times amidst unconventional

[39] https://www.nytimes.com/2020/08/19/technology/big-tech-business-domination.html

[40] https://www.marketwatch.com/story/what-januarys-market-decline-means-for-stock-returns-in-2021-11611960535

[41] https://www.nytimes.com/2018/12/21/business/nasdaq-stocks-bear-market.html?auth=link-dismiss-google1tap

[42] https://www.cnbc.com/2019/11/29/dow-futures-black-friday-thanksgiving-holiday.html

[43] https://en.wikipedia.org/wiki/2020_stock_market_crash

[44] https://www.cnbc.com/2018/10/31/the-stock-market-lost-more-than-2-trillion-in-october.html

monetary policy actions. Trade tensions with China were responsible for downward pressure on small-cap stocks, leading to increase in spillovers due to RUSSELL2000-DVRP[45] due to lower margins and less pricing power. As stated in Boer, Menkhoff, and Rieth (2021), the trade tariffs on Chinese goods increased to 21 percent by end of 2019, leading to retaliation from China. In January 2020, China's National Health Commission confirmed the covid-19 cases[46]. Airlines started cancelling flights between US and China, for example. Several of the blue-chip stocks in Dow ended in red, given their conventional business policies.

In February 2018, the first major spike in spillovers to DJIA-DVRP occurs, due to itself. Then again in May 2018, there are multiple spillovers led by itself, SP500-UVRP and RUSSELL2000-UVRP. Thereafter in 2019 first half, there are spillovers due to itself in February, itself and RUSSELL2000-DVRP in March, NASDAQ100-DVRP in May and finally, SP500-DVRP in June. Inflation worries, coupled with Fed stance on interest rates and post-election surge in valuations led to significant volatility in Dow Jones[47] in February 2018. Yang, Zhou, and Cheng (2020) also state that there was a massive sell-off in February 2018 coinciding with a jump in VIX. The fears of a rate hike were intensified due to a better than expected report for jobs[48]. When unemployment reduces, it implies that people have more disposable income on average, allowing central banks to raise interest rates. In May, Italy's political crisis led to global uncertainty in markets with both Dow and SP500 seeing consistent negative days[49]. As explained in He, Wang, and Yin (2020), uncertainty around international policies leads to volatility in US stock markets. In 2019, the US-China trade war, FOMC meetings, Brexit[50] and fears of a global recession led to uncertainty[51] as explained in the results for DJIA-DVRP in Section 5.4 (Gospodinov and Jamali (2012)).

Please note that the scale of spillovers to RUSSELL2000-UVRP is much smaller as compared to the previous charts. In 2020-2021, there were significant spillovers due to others when aggregated, and we attempt to break it down here. The largest spillovers occur due to DJIA-UVRP, followed by SP500-DVRP and NASDAQ100-DVRP in March 2020. Then, in June, there are spillovers due to NASDAQ100-UVRP. In January 2021, there are spillovers led by NASDAQ100-UVRP and DJIA-UVRP. March 2020 is the beginning of the covid-19 crash when Dow lost 26 percent as stated in the results for spillovers to SP500-DVRP (Mazur, Dang, and Vega (2021)). The spillovers due to NASDAQ100-UVRP in 2020-21 are explained in the results for spillovers to NASDAQ100-UVRP (Kilci and Yilanci (2022)). To add to that, in January 2021, Joe Biden taking up the administration led to expectations of healthier relief packages for corona, eventually leading to spillovers due to variation in price of upward uncertainty in NASDAQ100 and Dow Jones[52], as also shown later in

[45] https://www.barrons.com/articles/small-cap-stocks-decline-1540490469

[46] https://www.cnbc.com/2020/01/31/what-happened-to-the-stock-market-on-friday-coronavirus-sparks-sell-off-to-end-january.html

[47] https://money.cnn.com/2018/02/28/investing/stock-market-february-dow-jones/index.html

[48] https://www.theguardian.com/business/2018/feb/02/us-bond-market-rout-fears-trigger-wall-street-sell-off

[49] https://www.cnbc.com/2018/05/29/us-stock-futures-dow-data-earnings-geopolitics-and-international-markets-on-the-agenda.html

[50] https://en.wikipedia.org/wiki/Timeline_of_Brexit

[51] https://www.cnbc.com/2019/03/22/stock-market-wall-street-in-focus-as-growth-concerns-persist.html

[52] https://www.nasdaq.com/articles/3-blue-chip-tech-stocks-to-buy-now-after-strong-earnings-2021-01-29

Zefirov and Shadrina (2022).

The scale of spillovers for RUSSELL2000-DVRP is again different from the corresponding previous charts, towards the other side this time, and rightly so (the total VRP is the sum of the two components). The first significant spillovers occur in 2012 itself, led by RUSSELL2000-UVRP in January, itself in May, SP500-UVRP in June and followed by DJIA-UVRP and RUSSELL2000-UVRP. Then, there is a cluster of spillovers in late 2016 and early 2017, starting with SP500-UVRP in October 2016. Then in Q1 2017, there are significant spillovers led by NASDAQ100-DVRP, with the peak being achieved in February, when there are other significant spillovers by RUSSELL2000-UVRP, NASDAQ100-UVRP, SP500-UVRP and DJIA-DVRP. Note that there are very minor spillovers relative to others by RUSSELL2000-DVRP itself till now. Thereafter, in April 2018, the largest spillovers occur led by RUSSELL2000-UVRP and itself, followed by NASDAQ100-UVRP and SP500-DVRP. In Q4 2018 again, there are significant spillovers led by SP500-UVRP in October, NASDAQ100-DVRP and NASDAQ100-UVRP in December with considerable spillovers due to itself in both the months. In Q2 2019, there are spillovers due to itself and NASDAQ100-DVRP. Finally, in Nov-Dec 2021, there are small spillovers due to itself.

Global slowdown fears led to the spillovers in 2012[53]. While large-cap stocks were relatively safe, small-cap stocks exhibited the concerns. Then in 2016, the US presidential elections started showing their effect on the markets[54]. In Wolfers and Zitzewitz (2016), they estimate that a Trump victory led to significant increase in market volatility with considerable expected changes from a policy perspective. The period after Trump's appointment saw the market reacting to expected policies[55]. As described in the results for spillovers to DJIA-UVRP, during 2018, trade conflict with China was leading to pressure on small-cap stocks[56]. Amid trade tensions with China in 2019, there were spillovers from demand of put options on RUSSELL2000 as well as put options on NASDAQ100.

Next, we present the monthly spillovers using MFIV with the regularized VAR(1) model. Comparing the results with the standard VAR(1) model, we find that while the spillovers via the 2 models are synchronized with less relevant spillovers reduced to 0, the severity varies.

[53]https://www.theguardian.com/business/2012/jun/01/world-markets-global-crisis-deepens

[54]https://www.cnbc.com/2016/10/31/us-markets.html

[55]https://www.nasdaq.com/articles/stock-market-news-for-february-28-2017-2017-02-28

[56]https://www.barrons.com/articles/small-cap-stocks-decline-1540490469

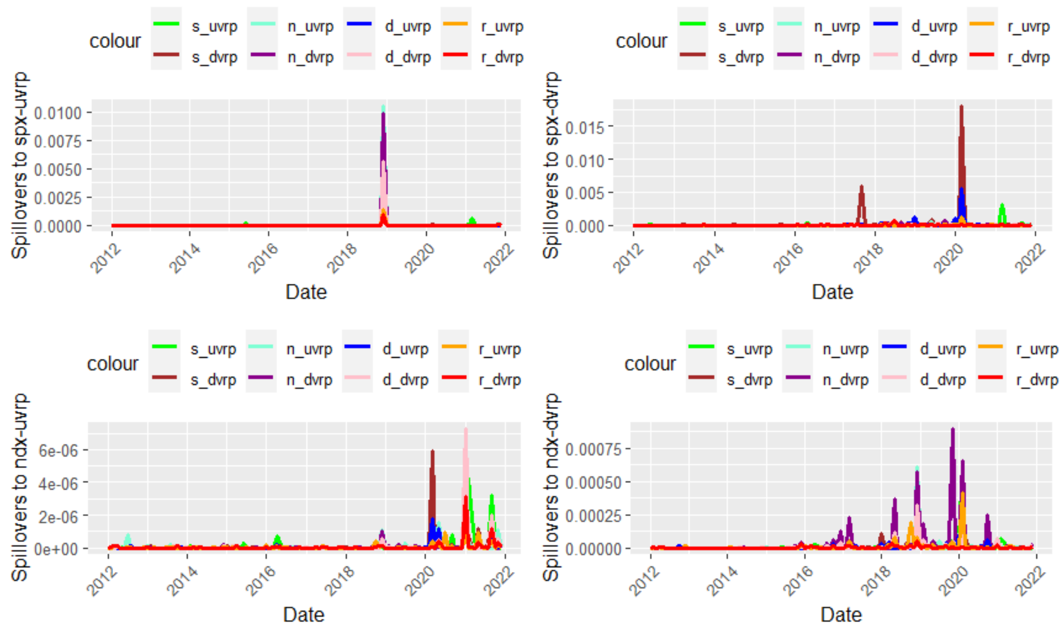

Figure 11: Spillovers to VRP components of SP500 and NASDAQ100 from the 8 VRP components based on regularized VAR(1) model

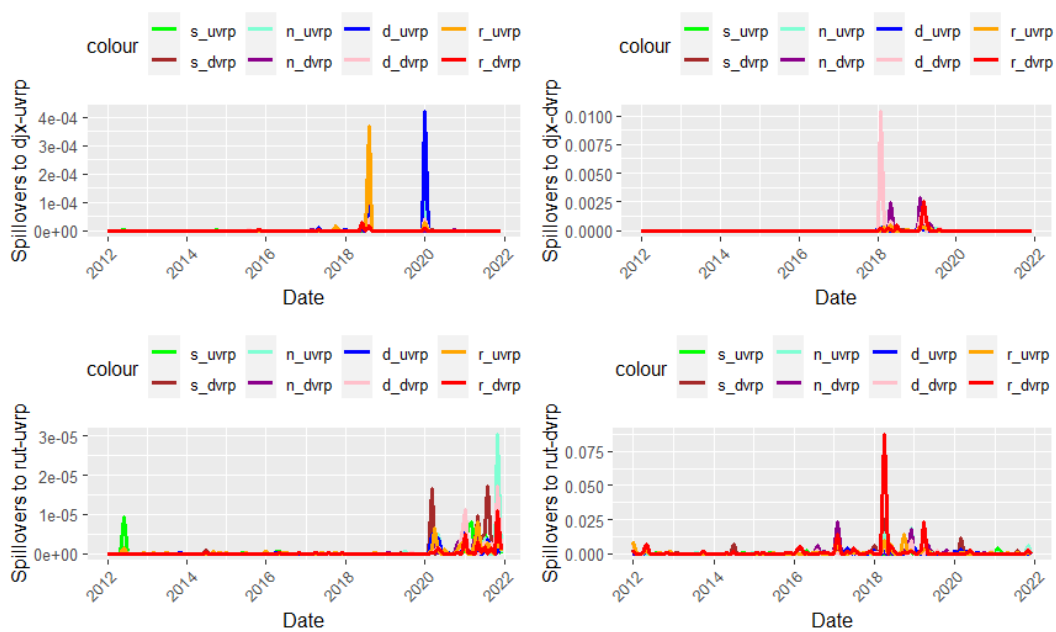

Figure 12: Spillovers to VRP components of Dow Jones and RUSSELL2000 from the 8 VRP components based on regularized VAR(1) model

Compared to the standard VAR(1) case, there are no spillovers to SP500-UVRP in 2020. In December 2018, there are significant spillovers due to NASDAQ100-UVRP, NASDAQ100-DVRP, DJIA-DVRP and DJIA-UVRP. As explained in the results for the standard VAR(1) model, December 2018 followed multinational concerns around trade conflict with China as well as rate hike leading to these spillovers. The first significant spillovers to SP500-DVRP are due to itself in September 2017. Then again in March 2020, the significant spillovers are led by itself and followed by DJIA-UVRP and NASDAQ100-DVRP. Finally, in March 2021, there are spillovers due to SP500-UVRP. The rationale behind these spillovers is explained in the results for the standard VAR(1) model.

There is a cluster of spillovers to NASDAQ100-UVRP during 2020-2021, with the most significant spillovers happening in March 2020 due to SP500-DVRP and DJIA-UVRP. Then in January 2021, there are spillovers relatively significant to other dates due to all VRP components, led by DJIA-DVRP and DJIA-UVRP. In February, there are spillovers due to SP500-UVRP. In September, there are spillovers due to SP500-UVRP again, followed by DJIA-DVRP and SP500-DVRP. These spillovers since March 2020 to January 2021 have been explained in the results for the standard VAR(1) model. In February, the"VIX dropped to its lowest level since the pandemic hit the US"[57]. In September, spike in corona cases due to the Delta variant, coupled with inflation, led to variation in SP500-VRP components[58]. Yan (2022) highlights that the Delta variant brought global uncertainty.

For NASDAQ100-DVRP, there is a cluster of significant spillovers in Q4 2018, starting with RUSSELL2000-UVRP in October and NASDAQ100-UVRP, itself and DJIA-DVRP in December. Then again in late 2019 and early 2020, there is a cluster of spillovers due to itself, SP500-UVRP, NASDAQ100-UVRP and RUSSELL2000-UVRP. By and large, these spillovers have been explained in the results for spillovers to NASDAQ100-DVRP based on the standard VAR(1) model (Yang, Zhou, and Cheng (2020), He, Lucey, and Wang (2021)). To add to that, in 2019, technology stocks were having their best year in a decade[59] and led the movements in all the other sectors.

In case of the regularized model, there are no spillovers from the other component of the same index based on Figure 11 while in Figure 12, we observe that there are spillovers from RUSSELL2000-DVRP towards RUSSELL2000-UVRP. If we expand our consideration towards other components of any index (all downside components w.r.t. upside VRP and vice-versa), we find that in case of SP500-UVRP, there are spillovers from NASDAQ100-DVRP and DJIA-DVRP. Towards SP500-DVRP, there are spillovers from DJIA-UVRP. In case of NASDAQ100-UVRP, there are spillovers from SP500-DVRP and DJIA-DVRP as well as RUSSELL2000-DVRP while there are spillovers from RUSSELL2000-UVRP towards NASDAQ100-DVRP and in case of RUSSELL2000-UVRP, there are spillovers from SP500-DVRP. There are no significant spillovers from small-cap VRP components to large-cap VRP components or the reverse, given the representations defined in the results for the standard VAR(1) model.

In August 2018, there are significant spillovers to DJIA-UVRP due to RUSSELL2000-UVRP, SP500-DVRP, SP500-UVRP, NASDAQ100-DVRP and NASDAQ100-UVRP. Then, in January 2020, there are significant spillovers led by itself and followed by SP500-DVRP, SP500-UVRP

[57]https://www.fool.com/investing/2021/02/28/5-biggest-market-stories-you-missed-in-february/

[58]https://www.adviceperiod.com/blog/september-2021-market-commentary/

[59]https://www.nasdaq.com/articles/november-2019-review-and-outlook-2019-12-02

and NASDAQ100-UVRP. As we discussed in the results for the standard VAR(1) model, the spillovers in 2018 were due to multiple reasons. Among them, trade tensions with China affected small-cap stocks more leading to large spillovers from RUSSELL2000-UVRP. And in January 2020, corona concerns led to spillovers from itself. The first significant spillovers to DJIA-DVRP occur in February 2018 due to itself, then in May 2018 due to NASDAQ100-DVRP and finally in Q1 2019 due to NASDAQ100-DVRP, RUSSELL2000-DVRP, DJIA-DVRP and NASDAQ100-UVRP. These spillovers have been explained in the results for spillovers to DJIA-DVRP based on standard VAR(1) model.

There is a cluster of spillovers to RUSSELL2000-UVRP in 2020-2021, starting with SP500-DVRP in March 2020, DJIA-DVRP and DJIA-UVRP in January 2021, SP500-DVRP and itself in May 2021, SP500-DVRP in August 2021 and NASDAQ100-UVRP, DJIA-DVRP and RUSSELL2000-DVRP in November 2021. The spillovers in March 2020 and January 2021 have been explained in the results for spillovers to RUSSELL2000-UVRP based on the standard VAR(1) model. The last few spillovers in 2021 are relatively small in scale.

The significant spillovers to RUSSELL2000-DVRP begin in January 2012, due to RUSSELL2000-UVRP and DJIA-DVRP, then in May 2012 due to itself. Thereafter, in February 2017, there are spillovers due to NASDAQ100-DVRP and itself. The largest spillovers occur due to itself in Q2 2018, followed by SP500-DVRP, NASDAQ100-UVRP and RUSSELL2000-UVRP. There is a cluster of spillovers a few months later, from October 2018 to April 2019, due to NASDAQ100-DVRP, NASDAQ100-UVRP, DJIA-DVRP and itself. In March 2020, there are spillovers due to SP500-DVRP. Majority of these spillovers have been explained in the results for spillovers to RUSSELL2000-DVRP based on the standard VAR(1) model. Noteworthy are the largest spillovers which occur due to trade conflict with China. Finally, there were spillovers because of the covid-19 crash.

5.5.4 Quarterly Spillovers

In this section, we present the quarterly spillovers using MFIV via the regularized VAR(1) model. Comparing the results with monthly spillovers via the regularized VAR(1) model, we find that the quarterly spillovers are not restricted to the corona crisis and are smoother.

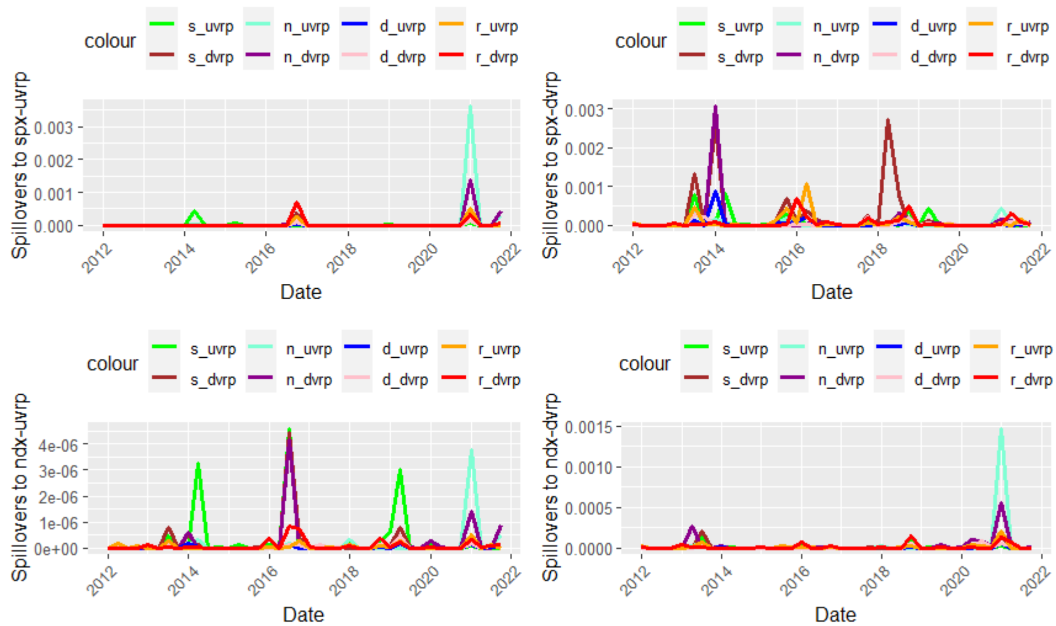

Figure 13: Quarterly Spillovers to VRP components of SP500 and NASDAQ100 from the 8 VRP components based on regularized VAR(1) model

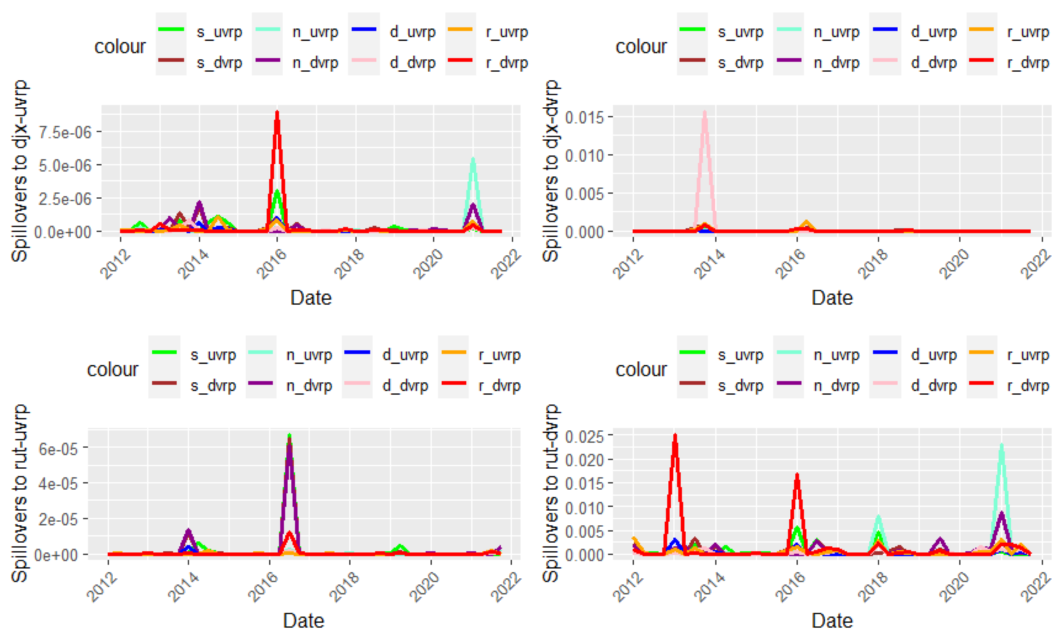

Figure 14: Quarterly Spillovers to VRP components of Dow Jones and RUSSELL2000 from the 8 VRP components based on regularized VAR(1) model

The quarterly spillovers to SP500-UVRP occur in Q4 2016 due to RUSSELL2000-DVRP and then in Q1 2021 due to NASDAQ100-UVRP and NASDAQ100-DVRP. Q4 2016 included the effects of Presidential elections (Wolfers and Zitzewitz (2016)) and rate hike by the Fed[60], leading to these spillovers while the spillovers in Q1 2021 have been explained in the results of spillovers to RUSSELL2000-DVRP based on the standard VAR(1) model. The significant spillovers to SP500-DVRP are in multiple clusters, starting with itself, SP500-UVRP and RUSSELL2000-UVRP in Q3 2013. Then, in Q1 2014, there are spillovers due to NASDAQ100-DVRP, itself and DJIA-UVRP. The next cluster is from Q4 2016 to Q2 2017, due to itself, RUSSELL2000-DVRP and RUSSELL2000-UVRP. The third cluster occurs in Q2-Q4 2018, due to itself, NASDAQ100-DVRP, RUSSELL2000-DVRP and SP500-UVRP. Finally, in the first half of 2021, there are spillovers due to NASDAQ100-UVRP and RUSSELL2000-DVRP.

2013-14 was the period when central banks (Fed, ECB) started rolling out plans for tapering back their quantitative easing programmes started in response to the 2007-09 crisis. The Fed Chairman had guided the markets by indicating that it would be a data-driven approach[61]. This led to significant transfer of flows from emerging markets to US, most of which was owned by US investors itself, which affected the dollar as well. These factors acting together would be expected to generate uncertainty leading to spillovers within the US equity markets as well. 2016-17 was the period after the presidential elections and Brexit, both of which brought unexpected results. The spillovers in 2018 were due to Trump imposing tariffs on commodities[62], concerns around hikes in interest rates by Fed and scrutiny on the largest tech firms by regulators, as also explained in the results for spillovers to DJIA-DVRP, DJIA-UVRP and SP500-UVRP for the standard VAR(1) model. Q1 2021 spillovers have been explained in the previous result. One observation is that NASDAQ100 stocks rose around 3 percent on an aggregate level and RUSSELL2000 stocks rose around 12 percent. Hedging by calls in case of NASDAQ and hedging by puts in case of RUSSELL are reasonable given the uncertainty (a small upward move implies chances of further upward movement while a large upward move implies chances of correction), thus leading to spillovers due to the respective VRPs.

While any of the individual spillovers do not seem to be significant for NASDAQ100-UVRP, the chart shows that there are clusters of spillovers, which can be significant together. First in 2013-14, there are spillovers led by SP500-DVRP and SP500-UVRP. Again, in 2016, there are spillovers due to the SP500-VRP components and others as well. Then, in early 2019 and the cusp of 2021, there are spillovers led by SP500-UVRP and NASDAQ100-UVRP respectively. The spillovers in 2013-14 and 2016 have been explained in the previous paragraph. The uncertainty in 2019 has been explained in the results for DJIA-DVRP in Section 5.4. Q1 2021 was a volatile month for US stocks, as explained in the results for spillovers to NASDAQ100-UVRP based on the standard VAR(1) model. In case of NASDAQ100-DVRP, there are clusters of significant spillovers. First, in 2013, there are spillovers led by itself and SP500-DVRP. Then in Q1 2021, there are spillovers led by NASDAQ100-UVRP and itself. The reasoning for 2013 spillovers has been provided in the results of SP500-DVRP for this model and for 2021 spillovers has been provided in the results of

[60]https://www.schroders.com/en/us/insights/economic-views/quarterly-markets-review—q4-2016/

[61]https://www.reuters.com/article/us-usa-fed-2013-timeline-idUSKCN1P52A8

[62]https://www.pbs.org/newshour/economy/making-sense/6-factors-that-fueled-the-stock-market-dive-in-2018

NASDAQ100-UVRP for the standard VAR(1) model.

To answer if there are spillovers from the other component of the same index, from Figure 13, we find that there are spillovers from SP500-UVRP to SP500-DVRP, from NASDAQ100-DVRP to NASDAQ100-UVRP and from NASDAQ100-UVRP to NASDAQ100-DVRP. From Figure 14, we find that there are no spillovers from the other component within the same index. On the other hand, if we consider spillovers from the other component of any other index, we observe that there are spillovers from NASDAQ100-DVRP and RUSSELL2000-DVRP to SP500-UVRP, from DJIA-UVRP and RUSSELL2000-UVRP to SP500-DVRP, from RUSSELL2000-DVRP to DJIA-UVRP, from NASDAQ100-DVRP to RUSSELL2000-UVRP and from NASDAQ100-UVRP to RUSSELL2000-DVRP. To add to that, there are spillovers from small-cap DVRP to large-cap UVRP as well as from small-cap UVRP and DVRP to large-cap DVRP. In the reverse case, there are spillovers from large-cap UVRP to small-cap DVRP only.

Given the scale, the only significant spillovers to DJIA-UVRP occur due to RUSSELL2000-DVRP and NASDAQ100-UVRP in Q1 2016 and Q1 2021 respectively. The momentum built in RUSSELL2000[63] led to the spillovers in Q1 2016 and Q1 2021 was a volatile month for tech stocks as explained in the results for spillovers to NASDAQ100-UVRP based on the standard VAR(1) model. For DJIA-DVRP, the only instances of significant spillovers occur in 2013 and 2016. In Q4 2013, there are spillovers due to itself as well as RUSSELL2000-VRP components and SP500-DVRP. In the first half of 2016, there are spillovers led by RUSSELL2000-UVRP and RUSSELL2000-DVRP. In Q4 2013, reports on consumer confidence and housing led to gains in Dow Jones[64]. The spillovers due to RUSSELL2000 in 2016 have been explained in the results for spillovers to SP500-DVRP based on this specification.

There is a cluster of spillovers to RUSSELL2000-UVRP in 2013-14, although the individual contributions are not significant. Then, in 2016, there are spillovers due to SP500-UVRP, SP500-DVRP, NASDAQ100-DVRP and RUSSELL2000-DVRP. The 2013-14 spillovers have been explained in the results for spillovers to SP500-DVRP based on this model. In the first half of 2016, US markets had been soaring with SP500 leading[65]. One of the reasons was Shinzo Abe's re-election in Japan. Auslin (2016) states that due to strategic motivations based on power struggles in the Asia-Pacific region, Abe had been strengthening the US-Japan alliance.

There are multiple clusters of significant spillovers to RUSSELL2000-DVRP during the 10-year period. In Q1 2012, there are spillovers due to itself. In 2013, there are spillovers led by itself, DJIA-DVRP and SP500-DVRP. In 2016, there are spillovers led by itself, SP500-UVRP, SP500-DVRP and NASDAQ100-DVRP. In 2018, there are spillovers due to NASDAQ100-UVRP and SP500-UVRP. Finally, in 2021, there are spillovers led by NASDAQ100-UVRP, NASDAQ100-DVRP, RUSSELL2000-UVRP, itself and SP500-DVRP. 2012 spillovers have been explained in the results for spillovers to RUSSELL2000-DVRP based on the standard VAR(1) model while 2013 spillovers have been explained in the results for spillovers to SP500-DVRP based on this specifica-

[63] https://content.ftserussell.com/sites/default/files/research/smallcapperspectives0816q2finalp0.pdf

[64] https://www.cnbc.com/2013/12/31/us-stocks.html

[65] https://www.cnbc.com/2016/07/11/us-markets.html

tion. 2016's spillovers have been explained in the results for spillovers to SP500-DVRP based on this specification. The results for spillovers to SP500-UVRP for this model explain the spillovers in 2018. Q1 2021 spillovers have been explained in the results of NASDAQ100-UVRP for the standard VAR(1) model.

6 Conclusion

We show that the different market segments of the US equity market are interconnected. We decompose Volatility Risk Premium (VRP) into its upside and downside components by segregating the data on European calls and puts. Upside VRP (difference between IV due to calls and upside RV) is negative in half cases and positive in the other half while Downside VRP (difference between IV due to puts and downside RV) is usually positive. In constructing these components, we utilize a non-parametric approach to calculate Implied Volatility. The behaviour of the IV components and VRP components over time can be explained by a combination of academic references and market events. In addition, we model the inter-connections by utilizing the forecast error variance decomposition of a VAR(1) Model - standard and regularized. We do this because with monthly or quarterly window, we do not have a lot of observations given the number of parameters to be estimated. The regularized model enables us to shrink the coefficients representing less relevant relationships towards 0.

For the full period of 2012-2021, 48 percent of the variation can be explained by cross-component spillovers. Comparing the monthly standard VAR with monthly regularized VAR, we find that the timing of spillovers in most cases matches, while the intensity of individual spillovers may vary. Majority of the spillovers from the regularized model are a subset of the spillovers from the standard model. Comparing the quarterly regularized VAR with the monthly regularized VAR, the quarterly spillovers are smoother, and not condensed to the corona crisis like the monthly spillovers. As such, the results are sensitive to these choices in methodology. However, the changes in spillovers can be explained by market events such as Fed's minutes and the US presidential elections.

Spillovers in financial markets have multiplied given globalization in the last 2 decades. This research intends to shed light on how price of asymmetric uncertainty percolates within different market segments. Policy managers can utilize the results to understand the driving behaviours of the US equity market and design measures which monitor the cross-component spillovers. This methodology captures the asymmetric information represented by calls and puts (and thus, market expectations about upside and downside variance) in an efficient manner given that we avoid any unnecessary assumptions. Volatility is being increasingly seen as an alternative asset class uncorrelated to the market and fund managers can potentially devise investment strategies based on the relationships established.

The main limitation of this study is using Cholesky decomposition to calculate spillovers, which is sensitive to the relative positioning of the variables. Another key limitation is the inability to explain the magnitude of spillovers in certain scenarios. Another limitation is the consideration of a limited number of estimation windows (monthly, quarterly) as the results appear to be sensitive to this choice. The final limitation is the usage of BS equation for the interpolation-extrapolation scheme to calculate IV. We reiterate that the actual IV calculation does not make any parametric assumptions and this usage is based on current market practices.

For future research, a key area would be to employ a grid search method for estimation window and considering a larger period for the study. Researchers can conduct the same analysis while using the directional spillovers' framework by Diebold and Yilmaz (2012). The study can also be extended to include other developed and emerging markets. Another possible research question is to figure out what particular movements in indices cause these spillovers and use the answer to see how short-term and long-term investment strategies can be built for the volatility asset class. Finally, by analyzing the change in magnitudes of RV and IV, one can potentially assess jump tail risk using this methodology for individual stock options.

References

Abushosheh, Manar, Shabbir Bohara, Davide Contu, Elgilani Elshareif, and Ikhlaas Gurrib (2022). "How did the US and UK markets react to the COVID-19 vaccines' announcements? A preliminary assessment". In: *F1000Research* 11.485, p. 485.

Anand, Abhinav, Sankarshan Basu, Jalaj Pathak, and Ashok Thampy (2021). ""Who Moved The Market"? Analyzing The Role of Federal Reserve Speeches". In: *Analyzing The Role of Federal Reserve Speeches (August 12, 2021). IIM Bangalore Research Paper* 622.

Andersen, Torben G and Oleg Bondarenko (2007). "Construction and interpretation of model-free implied volatility". In: *National Bureau of Economic Research, Working Paper 13449 - http://www.nber.org/papers/w13449.*

Auslin, Michael (2016). "Japan's new realism: Abe gets tough". In: *Foreign Affairs* 95.2, pp. 125–134.

Bakshi, Gurdip and Nikunj Kapadia (2003). "Delta-hedged gains and the negative market volatility risk premium". In: *The Review of Financial Studies* 16.2, pp. 527–566.

Biktimirov, Ernest N and Wang (2017). "Model-based versus model-free implied volatility: Evidence from North American, European, and Asian index option markets". In: *The Journal of Derivatives* 24.3, pp. 42–68.

Boer, Lukas, Lukas Menkhoff, and Malte Rieth (2021). "The multifaceted impact of US trade policy on financial markets". In: *DIW Berlin Discussion Paper 1956, 76S.*

Bollerslev, Tim, George Tauchen, and Zhou (2009). "Expected stock returns and variance risk premia". In: *The Review of Financial Studies* 22.11, pp. 4463–4492.

Bollerslev, Tim and Viktor Todorov (2011). "Tails, fears, and risk premia". In: *The Journal of Finance* 66.6, pp. 2165–2211.

Britten-Jones, Mark and Anthony Neuberger (2000). "Option prices, implied price processes, and stochastic volatility". In: *The Journal of Finance* 55.2, pp. 839–866.

Brown, Ellen (2018). "Trump's war on the Fed". In: *AMASS* 23.2, pp. 26–29.

Carr, Peter and Liuren Wu (2009). "Variance risk premiums". In: *The Review of Financial Studies* 22.3, pp. 1311–1341.

— (2016). "Analyzing volatility risk and risk premium in option contracts: A new theory". In: *Journal of Financial Economics* 120.1, pp. 1–20.

Chen, Shu, and Jin E Zhang (2016). "Investor sentiment, variance risk premium and delta-hedged gains". In: *Applied Economics* 48.31, pp. 2952–2964.

Coulombe, Philippe (2020). "Time-varying parameters as ridge regressions". In: *arXiv e-prints*, arXiv–2009.00401.

Diebold, Francis X and Kamil Yilmaz (2009). "Measuring financial asset return and volatility spillovers, with application to global equity markets". In: *The Economic Journal* 119.534, pp. 158–171.

— (2012). "Better to give than to receive: Predictive directional measurement of volatility spillovers". In: *International Journal of Forecasting* 28.1, pp. 57–66.

Eksi, Ozan and Bedri Kamil Onur Tas (2017). "Unconventional monetary policy and the stock market's reaction to Federal Reserve policy actions". In: *The North American Journal of Economics and Finance* 40, pp. 136–147.

Fassas, Athanasios P and Stephanos Papadamou (2018). "Variance risk premium and equity returns". In: *Research in International Business and Finance* 46, pp. 462–470.

Feunou, Bruno, Mohammad R Jahan-Parvar, and Cédric Okou (2018). "Downside variance risk premium". In: *Journal of Financial Econometrics* 16.3, pp. 341–383.

Finta, Marinela Adriana and Sofiane Aboura (2020). "Risk premium spillovers among stock markets: Evidence from higher-order moments". In: *Journal of Financial Markets* 49, p. 100533.

Garcia, Jean (2018). "Asian stocks slide after Wall Street losses, Nissan arrest". In: *UWIRE Text, https://link.gale.com/apps/doc/A563073698/AONE?u=anon 35f5582&sid=googleScholar &xid=0798dbc1.*

Gospodinov, Nikolay and Ibrahim Jamali (2012). "The effects of Federal funds rate surprises on S&P 500 volatility and volatility risk premium". In: *Journal of Empirical Finance* 19.4, pp. 497–510.

Han, Bing and Zhou (2012). "Variance risk premium and cross-section of stock returns". In: *Citeseer (Unpublished paper) https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.475.8051& rep=rep1&type=pdf.*

Hattori, Masazumi, Ilhyock Shim, and Yoshihiko Sugihara (2021). "Cross-stock market spillovers through variance risk premiums and equity flows". In: *Journal of International Money and Finance* 119, p. 102480.

He, Feng, Brian Lucey, and Wang (2021). "Trade policy uncertainty and its impact on the stock market-evidence from China-US trade conflict". In: *Finance Research Letters* 40, p. 101753.

He, Feng, Wang, and Libo Yin (2020). "Asymmetric volatility spillovers between international economic policy uncertainty and the US stock market". In: *The North American Journal of Economics and Finance* 51, p. 101084.

Hseu, Chen, and Chung (2007). “The Forecasting Performance of Model Free Implied Volatility: Evidence from an Emerging Market”. In: *http://pbfea2005.rutgers.edu/2007/Papers/095-the%20forecasting%20performance.pdf.*

Jackwerth, Jens Carsten and Mark Rubinstein (1996). “Recovering probability distributions from option prices”. In: *The Journal of Finance* 51.5, pp. 1611–1631.

Jiang, George J and Yisong S Tian (2005). “The model-free implied volatility and its information content”. In: *The Review of Financial Studies* 18.4, pp. 1305–1342.

— (2007). “Extracting model-free volatility from option prices: An examination of the VIX index”. In: *The Journal of Derivatives* 14.3, pp. 35–60.

Kaminska, Iryna and Matt Roberts-Sklar (2018). “Volatility in equity markets and monetary policy rate uncertainty”. In: *Journal of Empirical Finance* 45, pp. 68–83.

Kilci, Esra N and Veli Yilanci (2022). “Impact of Monetary Aggregates on Consumer Behavior: A Study on the Policy Response of the Federal Reserve against COVID-19”. In: *Applied Economics* 29.1, pp. 100–122.

Korobilis, Dimitris and Kamil Yilmaz (2018). “Measuring dynamic connectedness with large Bayesian VAR models”. In: *Available at SSRN 3099725.*

Londono, Juan M and Nancy R Xu (2019). “Variance risk premium components and international stock return predictability”. In: *https://www.federalreserve.gov/econres/ifdp/files/ifdp1247.pdf.*

Mazur, Mieszko, Man Dang, and Miguel Vega (2021). “COVID-19 and the march 2020 stock market crash. Evidence from S&P1500”. In: *Finance Research Letters* 38, p. 101690.

Rachev, Svetlozar T, Christian Menn, and Frank J Fabozzi (2008). “Black-Scholes Option Pricing Model”. In: *Handbook of Finance* 3, Ch. 43, pp. 459–466.

Reifschneider, David and David Wilcox (2022). *The case for a cautiously optimistic outlook for US inflation.* Tech. rep.

Selmi, Refk, Youssef Errami, and Mark E Wohar (2020). “What Trump’s China tariffs have cost US Companies?” In: *Journal of Economic Integration* 35.2, pp. 282–295.

Shirvani, Abootaleb et al. (2020). “Stock returns and roughness extreme variations: A new model for monitoring 2008 market crash and 2015 flash crash”. In: *Applied Economics and Finance* 7.3, pp. 78–95.

Shu, Ruiqiang Song, and Wei Zhu (2021). “The 2020 US Stock Market Crash”. In: *2021 JSM Proceedings, Alexandria, VA: American Statistical Association*, pp. 713–720.

Subramaniam, Sowmya and Madhumita Chakraborty (2021). “COVID-19 fear index: Does it matter for stock market returns?” In: *Review of Behavioral Finance.*

Sunder, Shyam (2021). *How did the US stock market recover from the Covid-19 contagion?*

Todorov, Viktor (2010). “Variance risk-premium dynamics: The role of jumps”. In: *The Review of Financial Studies* 23.1, pp. 345–383.

Wagner, Alexander F, Richard J Zeckhauser, and Alexandre Ziegler (2018). “Company stock price reactions to the 2016 election shock: Trump, taxes, and trade”. In: *Journal of Financial Economics* 130.2, pp. 428–451.

Wolfers, Justin and Eric Zitzewitz (2016). “What do financial markets think of the 2016 election”. In: *University of Michigan and Dartmouth College Unpublished Working Paper, https://www.brookings.edu/wp-content/uploads/2016/10/what-do-financial-markets-think-of-the-2016-election_102016_wolferszitzewitz.pdf.*

Wu, Liuren (2011). “Variance dynamics: Joint evidence from options and high-frequency returns”. In: *Journal of Econometrics* 160.1, pp. 280–287.

Yan, Mengfei (2022). “The Impacts of Different Phrases of COVID-19 on the US Stock Market and How Investors Reacted”. In: *2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022).* Atlantis Press, pp. 2799–2804.

Yang, Zihui and Zhou (2017). “Quantitative easing and volatility spillovers across countries and asset classes”. In: *Management Science* 63.2, pp. 333–354.

Yang, Zihui, Zhou, and Xin Cheng (2020). “Systemic risk in global volatility spillover networks: Evidence from option-implied volatility indices”. In: *Journal of Futures Markets* 40.3, pp. 392–409.

Yao, Xingzhi and Marwan Izzeldin (2018). “Forecasting using alternative measures of model-free option-implied volatility”. In: *Journal of Futures Markets* 38.2, pp. 199–218.

Zefirov, Vladimir and Valeriya Shadrina (2022). “The policies and regulations of transportation economic effects on the prospects of the growth of the US stock market”. In: *Transportation Research Procedia* 63, pp. 2015–2020.