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A Supply-Demand Analysis of the Index Option Market*

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Abstract

This paper uses an identification approach based on sign restrictions to infer the supply and demand components of the index option market. This analysis allows us to evaluate the relative impact of (i) changes in investors' risk aversion (demand), and (ii) changes in intermediaries' funding constraints (supply) in driving the option price and quantity. Using daily data between 1996 and 2019, we find that both sides of the market are equally important in explaining the variation in option price and quantity. However, supply shocks represent the dominant factor around FOMC announcement days.

JEL Codes: C12, E52, E58, G32

Keywords: Option Price, Option Quantity, Structural Shocks, FOMC Announcements

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1 Introduction

The variance risk premium (VRP) measures the compensation associated with changes in the variance of the stock market. While this premium is embedded in the prices of various assets, it can be easily inferred from the price of index options. In other words, the VRP captures the expensiveness of option prices - it is equal to the difference between the squared Volatility Index (VIX) obtained from option prices and the conditional expectation of the realized variance (RV) of the stock market (see Carr and Wu (2009)).

Whereas the time-variation in the VRP is widely followed by investors, academics, and policy makers, its interpretation remains debated. A common interpretation is that the VRP is the most readily available gauge of investors' risk aversion or sentiment (e.g., Ben-Rephael, Kandel, and Wohl (2012), Bollerslev, Gibson, and Zhou (2011), Drechsler and Yaron (2010)). Alternatively, the VRP is regularly interpreted as a proxy for the funding constraints faced by financial intermediaries, or market makers, in capital markets (e.g., Adrian and Shin (2010), Barras and Malkhozov (2016), Bates (2003, 2008)).

These two interpretations resonate with recent analyses of the index option market. Garleanu, Pedersen, and Poteshman (2009) construct a model where investors' option trading induces price pressure because market makers take risk when they serve as counterparties. Consistent with this view, they find that the price of SP500 options is positively related to several proxies of investors' demand. In contrast, Chen, Joslin, and Ni (2018) examine a model where options are more expensive when financial intermediaries face funding constraints. Empirically, they confirm that times when these constraints likely bind are associated with a lower trading activity and higher option prices.

In this paper, we apply a supply-demand decomposition of the option market. This decomposition determines the relative importance of supply and demand factors in determining the option quantity and price. The option market is ideal for such a decomposition because of its particular two-sided structure (see Chen, Joslin, and Ni (2018) and Garleanu, Pedersen, and Poteshman (2009)). On one side, investors take long net positions in index options (particularly in out-of-the-money put options). On the other side, financial intermediaries take short positions to clear the market. This structure provides a natural interpretation of (i) supply shocks as changes in the funding conditions faced by intermediaries, and (ii) demand shocks as changes in the investors' risk aversion or sentiment.

Our approach has several advantages. First, we infer the supply and demand factors directly from the equilibrium quantity and price observed in the option market. We therefore sidestep the challenge of finding appropriate proxies for the willingness of intermediaries and investors to trade options. Second, the identification of the supply and demand shocks rest on mild and standard sign restrictions. With less structure, our estimation approach is less prone to misspecification. Third, we extract the supply and demand factors using daily data. This high-frequency decomposition allows for a granular analysis of the VRP during particular times and events (e.g., financial crises, FOMC announcements).

In considering demand and supply forces jointly, our work speaks to the different nature of financial market dislocations observed, for instance, during the global financial crisis and at the onset of COVID-19 pandemic. According to the common narrative, during the global financial crisis, the balance sheet of financial intermediaries deteriorated significantly, prompting their withdrawal from multiple markets. In contrast, intermediaries remained resilient after the onset of COVID-19, but their intermediation capacity was outstripped by the demand imbalances, notably in the Treasuries market (see Duffie (2020) and Vissing-Jorgensen (2021)). Identifying the demand and supply shifts in the option market can shed further light on these episodes of market stress.

The intuition behind the estimation approach is straightforward. We only use as inputs the time series of quantity and price in the option market. We then identify the supply and demand shocks by imposing sign restrictions such that (i) positive demand shocks increase both quantity and price, whereas (ii) positive supply shocks increase quantity, but decrease price. This set identification based on sign restrictions builds on the large literature on structural vector autoregression and only requires the specification of the conditional mean of the variables.[1]

We conduct our analysis at the daily frequency using the VRP and traded volume as measures of the option price and quantity. We compute the daily VRP as the difference between the squared VIX and the conditional expectation of the market RV over the next month obtained with the model of Bekaert and Horoeva (2014). To compute the daily volume, we use the CBOE Open-Close dataset and take the sum of open net positions for the two categories of investors (public customers and proprietary traders).

Our decomposition over the period 1996-2019 reveals that the supply and demand components are equally important in explaining the dynamics of the index option market. First, supply and demand shocks have the same impact on the option price and quantity across different horizons. For instance, their instantaneous effect on impact both represent around 30% and 60% of the daily standard deviation of the VRP and volume, respectively. Second, the variance decomposition reveals that the demand and supply factors contribute equally to the fluctuations of the VRP and volume. Third, both factors exhibit

1. See, among others, Faust (1998), Uhlig (2017), Kilian and Lutkepohl (2017).

a similar ability in predicting the future daily return of the SP500.

These results suggest that changes in investors' risk aversion and intermediaries' funding constraints are both essential in understanding the dynamics of the option market - a prediction that resonates with the theoretical analyses of both Chen, Joslin, and Ni (2018) and Garleanu, Pedersen, and Poteshman (2009). They also differ from the evidence documented by Goldberg and Nozawa (2021) in the corporate bond market. Whereas they find that demand shocks merely capture temporary investors' liquidity needs, we find that demand shocks play a key role in setting the option price and quantity.

Next, we conduct a supply-demand decomposition around the FOMC announcement days. We find that the VRP drops on the announcement date, after increasing over the previous five days. This price pattern is primarily driven by the supply - for one, the supply shock explains 73% of the decrease in the VRP (versus 27% only for the demand shock). Consistent with this supply-based interpretation, we observe a gradual decrease in the traded volume, followed by a sharp increase on the FOMC day.

The predominance of the supply side resonates with the uncertainty risk premium documented by Hu, Pan, Wang, and Zhu (2021). Our results suggest that this premium is mostly the outcome of a contraction of the supply curve, which possibly arise because intermediaries face tighter funding or risk management constraints around FOMC announcements.

The remainder of the paper is as follows. Section 2 provides an review of the existing literature. Section 3 presents the data on option price and quantity. Section 4 describes our identification approach based on sign restrictions. Section 5 contains the empirical analysis, and Section 6 concludes.

2 Literature Review

Our work is related to several strands of the literature. The supply side of our analysis is motivated by the large literature that highlights the important role played by financial intermediaries across capital markets (see, among others, He and Krishnamurthy (2013) and Adrian, Etula, and Muir (2014)). In particular, the empirical results in He, Kelly, and Manela (2017) and Haddad and Muir (forthcoming) suggest that financial intermediaries are marginal investors in the option market and are therefore key in capturing the dynamics of option price and quantity.

The demand side of our analysis is related to previous papers that examine the time-variation in the compensation required by investors for bearing risk. This variation can arise from shifts in the investors' risk aversion as in habit models (e.g., Campbell and Cochrane (1999), Campbell, Pflueger, and Viceira (2020)). Alternatively, it can also be driven by behavioral biases, or sentiment (e.g., Lettau and Wachter (2007, 2011)). In particular, Ben-Rephael, Kandel, and Wohl (2012) find that changes in the VIX are negatively correlated with the risk appetite of investors for the equity market.

Our paper builds on several papers on the pricing of index options. The role of intermediaries in setting option prices is discussed by Adrian and Shin (2010)) and Bates (2003, 2008). Garleanu, Pedersen, and Poteshman (2009) show that excess demand from investors induces price pressure because market makers take risk when supplying additional options. Chen, Joslin, and Ni (2018) argue that the ability of intermediaries to supply index options to investors depends on the tightness of their funding constraints. When these constraints bind, the amount of risk sharing in the economy decreases, which yields to higher option prices and higher future stock market returns. Finally, Constantinides, Czerwonko, Jackwerth, and Perrakis (2011) provide evidence of mispricing among SP500 index options, which are possibly driven by local supply and demand factors in the option market (e.g., Barras and Malkhozov (2016)).

Our paper is also related to recent studies that apply sign restrictions in finance. Cieslak and Pang (2021) use such restrictions to measure how US equity and government bond prices are impacted by monetary, growth, and risk premium shocks. In a closely related paper to ours, Goldberg and Nozawa (2021) measure how supply and demand shocks drive the liquidity and volume in the corporate bond market. They find that supply shocks, which capture the tightness of intermediaries' funding constraints, are persistent and thus have a strong impact on bond liquidity.

Finally, our paper resonates with the growing literature on the price impact of FOMC announcements. Lucca and Moench (2015) document positive abnormal equity returns on the FOMC announcement days, which Cieslak and Pang (2021) trace back to a reduction in risk premium. Kurov, Wolfe, and Gilbert (2020) further show that the abnormal equity returns weaken after 2015 which coincide with a decrease in uncertainty (measured with the VIX). Formalizing this idea, Hu, Pan, Wang, and Zhu (2021) present a model that ties together abnormal equity return and the VIX. On FOMC announcement days, the uncertainty risk premium is resolved which leads to a sharp increase in equity prices and a drop in the VIX.

3 Data Description

3.1 Option Price

To conduct our supply-demand analysis, we use as inputs the time series of the daily price and quantity of traded index options. We summarize the price information contained in the cross-section of options using one particular portfolio. Specifically, we focus on the portfolio of options that replicates the sum of squared daily log returns on the SP500 over the next month (the next 22 trading days). The forward price of this portfolio is simply equal to the Squared Volatility Index (VIX).[2]

The VIX does not only reflect demand and supply shocks from investors and intermediaries. It also captures the expected daily realized variance (RV) over the next month (the cash flow component). To remove this component, we model the conditional expected RV $E_t[RV_{t,t+22}]$ using the preferred specification of Bekaert and Horoeva (2014). As a result, our daily option price measure is defined as:

$$VRP_t = (VIX_t)^2 - E_t[RV_{t,t+22}], \tag{1}$$

which corresponds to the variance risk premium (VRP), i.e., the compensation for bearing variance risk.

2. The construction of the VIX from option data is summarized by the VIX white paper available at https://www.optionseducation.org/referencelibrary/white-papers/page-assets/vixwhite.aspx. The methodology of CBOE leads the VIX to feature deterministic movements such as seasonality, which we neglect here consistently with the existing literature. Martin (2017) discusses more extensively the use of VIX as representative of the yield of a variance swap.

3.2 Option Quantity

We use the CBOE Open-Close dataset to measure the quantity of options traded in the market. The data consist of daily records of trading volume activity for all CBOE listed option on the SP500. Each option in the dataset is identified as a put or call, and by its strike price, and time to expiration.

The Open-Close dataset contains the buying and selling positions taken by two types of investors, namely public customers and proprietary traders. It also contains volume data on market makers which is inferred from market clearing. Using this information, we compute the total daily as the sum of the positive open net positions (buying or selling orders) of the two investor types (public customers and proprietary traders). This variable, which only takes positive values, is denoted by VOL_t.

3.3 Summary Statistics

Figure 1 plots the daily time series of the VRP (Panel a) and the log volume (Panel b) over our sample period from January 1996 to October 2019. On Panel (a), we recognize the typical properties of the VRP - it is persistent with periods of sudden peaks and agitation, and decreases at exponential speed to its long-run mean. Compared to standard volatility series, the VRP is mostly positive but can also take negative values. These events happens only a dozen times during our sample, most blatantly at the onset of the great financial crisis.

On Panel (b), the volume series shows a different behavior. It is much more volatile, showing both high- and low-frequency fluctuations. We also notice a trend which does not, however, point towards non-stationarity. By putting both series in a VAR model (as discussed in Section 4), we can foresee that the model will try to reproduce and control for these features. One linear combination of the past variables will be long-lasting, while the other one will show high-frequency fluctuations.

Please insert Figure 1 and Table 1 here.

These observations are confirmed by the standard summary statistics presented in Table 1. The VRP has a large first order autocorrelation of 0.88 against only 0.2 for the volume series. However, the former shows a decreasing pattern to a value of 0.66 at the monthly frequency compared to a fairly flat autocorrelation structure for the volume data, reaching only 0.18 at the monthly level. Table 1 also provides evidence of high skew and kurtosis of both data. Since our identification method does not rely on normality or time independence of residuals, these features are unlikely to pose a serious challenge.

Please insert Tables 2 and 3 here.

4 Methodology

4.1 Identification with sign restrictions

We use sign restrictions to infer the supply and demand shocks from the observed option price and quantity. To see the intuition, consider a simple supply-demand framework (without any temporal dynamics):

$$\begin{cases} VOL_{d,t} &= \beta_d VRP_t + \xi_{d,t}, \\ VOL_{s,t} &= -\beta_s VRP_t + \xi_{s,t}, \end{cases} \tag{2}$$

where $VOL_{d,t}$, $VOL_{s,t}$ denote the (demeaned) quantities that are demanded and supplied at a given price VRP_t, and $\xi_{d,t}$, $\xi_{s,t}$ denote the two orthogonal demand and supply shocks that we want to identify.

At equilibrium, we have $VOL_{d,t} = VOL_{s,t} = VOL_t$ which implies that the price and quantity both depend on the demand and supply shocks. To see this point, we can work with the standardized versions of the shocks defined as $\varepsilon_{d,t} = \xi_{d,t}/\sigma_d$ and $\varepsilon_{s,t} = \xi_{s,t}/\sigma_s$ to obtain:

$$\begin{pmatrix} VRP_t \\ VOL_t \end{pmatrix} = \begin{pmatrix} \frac{\sigma_d}{\beta_d+\beta_s} & -\frac{\sigma_s}{\beta_d+\beta_s} \\ \frac{\sigma_d\beta_s}{\beta_d+\beta_s} & \frac{\sigma_s\beta_d}{\beta_d+\beta_s} \end{pmatrix} \begin{pmatrix} \varepsilon_{d,t} \\ \varepsilon_{s,t} \end{pmatrix} = B \begin{pmatrix} \varepsilon_{d,t} \\ \varepsilon_{s,t} \end{pmatrix}. \tag{3}$$

As shown by the structural VAR literature, the matrix B has one degree of freedom and cannot be identified without further assumptions (see, e.g., Kilian and Lutkepohl (2017)). To address this issue, we follow Uhlig (2005) and use an identification scheme based on sign restrictions.[3] This allows us to estimate the matrix B and identify the demand and supply shocks from the observed variables VRP_t and VOL_t. Formally, we impose that

$$\text{sign}(B) = \text{sign}\begin{pmatrix} \frac{\sigma_d}{\beta_d+\beta_s} & -\frac{\sigma_s}{\beta_d+\beta_s} \\ \frac{\sigma_d\beta_s}{\beta_d+\beta_s} & \frac{\sigma_s\beta_d}{\beta_d+\beta_s} \end{pmatrix} = \begin{pmatrix} + & - \\ + & + \end{pmatrix}. \tag{4}$$

Equation (4) imposes the standard economic restrictions that (i) a positive demand shock ($\varepsilon_{d,t} > 0$) increases both the price and quantity, and (ii) a positive supply shock ($\varepsilon_{s,t} > 0$) increases the quantity, but decreases the price.

3. Other identification strategies have been suggested following the Cholesky factorization approach of Sims (1980). Lanne, Meitz, and Saikkonen (2017) and Gouriéroux, Monfort, and Renne (2020) show that structural shocks are identified when they are non-Gaussian and have independent elements. Kilian and Lutkepohl (2017) provide an overview of identification methods based on heteroskedasticity.

4.2 Estimation Procedure

Our estimation procedure extends the simple example in Equation (2) to capture the dynamic evolution of the option price and quantity over time. To this end, we gather the standardized VRP and volume data at time t in a vector $X_t = (VRP_t, VOL_t)'$ and assume that it follows a VAR(p):

$$\Phi(L)X_t = u_t \tag{5}$$

where L is the lag polynomial $\Phi(L) = I - \Phi_1 L - \ldots - \Phi_p L^p$, and u_t is the vector of VRP and volume shocks (i.e., the reduced-form shocks). Similar to Equation (3), we can write this vector as a function of the demand and supply shocks, i.e.,

$$u_t = B\varepsilon_t. \tag{6}$$

In our baseline specification, we estimate Equation (5) using daily data and a number of 22 lags, which corresponds to the number of trading days in a month. We estimate the VAR model using the Matlab VAR-Toolbox of Cesa-Bianchi. We first estimate the autoregressive matrices via standard OLS. We then use a simulation approach to infer B and ε_t from the estimated outputs of the VAR model.

To elaborate, we compute the time series of the innovation vector as $\widehat{u_t} = \widehat{\Phi}(L)X_t$ and its variance-covariance matrix as $\widehat{\Sigma} = \frac{1}{T-1}\sum_{t=1}^{T} \widehat{u_t}\widehat{u_t}'$. We then simulate uniformly rotation matrices to obtain the parameters of the B matrix, that we denote by $B^{(s)}$, enforcing that for all $s \in \{1, \ldots, S\}$, $B^{(s)}B^{(s)'} = \widehat{\Sigma}$. This defines a set of matrices with one degree of freedom. We reduce this set of solutions by dropping any $B^{(s)}$ that is inconsistent with the sign restrictions of Equation (4). Each potential solution that survives this test is equally probable, indistinguishable without further identifying assumptions, and produce their own series of structural supply and demand shocks, i.e., we have

$$\widehat{\varepsilon_t^{(s)}} = B^{(s)^{-1}} \widehat{u}_t, \quad \text{where} \quad B^{(s)} B^{(s)\prime} = \widehat{\Sigma}\,. \tag{7}$$

Equation (7) implies that the supply and demand shocks are only set-identified under the sign-restriction approach. For the analysis of the structural VAR model, a standard practice is to focus on (i) the median variance decomposition, and (ii) the median impulse-response function (IRF) for different horizons. However, this approach is problematic for at least two reasons. First, the median IRF and the median variance decomposition are potentially inconsistent with each other as they may be obtained with a different structural matrix $B^{(s)}$. Second, the median responses across horizons may not be generated with the same structural coefficients either.

We circumvent this issue by following Cieslak and Pang (2021) and choosing the matrix $B^{(s)}$ that minimizes the average distance of all parameters of the B matrix to their medians across the set of solutions. More formally, we write:

$$\widehat{B} = \underset{B_{1,1}, B_{1,2}, B_{2,1}, B_{2,2}}{\operatorname{argmin}} \quad \left\| \frac{\operatorname{Vec}(B) - \operatorname{Vec}\left(\operatorname{median}\left(B^{(s)}\right)\right)}{\sqrt{\operatorname{Vec}\widehat{\mathbb{V}}\left(B^{(s)}\right)}} \right\|^2, \tag{8}$$

where the median operator is taken element-by-element across simulations, as well as the standard deviation in the denominator. This procedure allows us to select a unique estimate for the structural matrix $\widehat{B}$ as well as a unique set of structural shocks $\widehat{\varepsilon}_t$.

5 Empirical Results

5.1 Supply-Demand Decomposition

5.1.1 Impact of Demand and Supply Shocks

We begin our empirical analysis by measuring the impact of the demand and supply shocks on the option market. To this end, we use the estimated structural matrix $\widehat{B}$ as input to compute the impulse-response function (IRF) and variance decomposition. Both quantities allows us to see how shocks are incorporated into the option price and quantity. The results are presented on Figures 2 and 3 for different horizons ranging from 0 to 66 days (three months).

Looking first at Figure 2, we see that the supply and demand shocks have roughly the same (absolute) effect on both the price and quantity. For the VRP (panel a), the impact of the supply and demand shocks represents 30% of the daily standard deviation of the VRP. In addition, both shocks persist for several months. Whereas the effect drops to 5% after a week, it remains largely unchanged after three months.

For the volume (panel b), the impact of the supply and demand shocks is higher - it represents around 60% of the daily standard deviation of volume. However, its degree of persistence is significantly weaker. The effect decreases sharply after one day and remains close to zero afterwards.

The analysis of the variance decomposition of the option price and quantity yield similar insights. Figure 3 reveals that for both the VRP (panel a) and the volume (panel b), the share of variance explained by the supply and demand shocks is about 50% across the different horizons. These results are robust to using different lag structures for the VAR model.

The similarity between the effects of the supply and demand shocks are in line with the estimated coefficients of the structural matrix $\widehat{B}$:

$$\widehat{B} = \begin{pmatrix} 0.3073 & -0.2941 \\ 0.6553 & 0.6185 \end{pmatrix} \tag{9}$$

where the magnitude of the two columns are nearly identical. Using Equation (3), we can also infer the price sensitivities β_s and β_d by taking the ratio of the second row over the first. We find that these sensitivities are roughly equal as $\widehat{\beta}_s = 2.13$ and $\widehat{\beta}_d = 2.10$.

Overall, the supply and demand shocks are equally important in explaining the behavior of the option price and quantity. This result suggests that changes in investors' risk aversion and intermediaries' funding constraints have a significant impact on the option market. It also reconcile the demand- and supply-based analyses of Garleanu, Pedersen, and Poteshman (2009) and Chen, Joslin, and Ni (2018).

The evidence documented here differs from the analysis of Goldberg and Nozawa (2021) in the corporate bond market. They find that demand shocks simply capture the temporary liquidity needs of investors (or noise traders). As a result, the corporate bond market is mainly driven by the financial standing of intermediaries. In contrast, the two-sided structure of the option market implies that investors play a key role in setting the price and quantity.

Please insert Figures 2 and 3 here.

5.1.2 Historical Decomposition

Using the Wold representation, we decompose the vector of price and quantity shocks into uncorrelated vectors that capture the impact of the supply and demand shocks. Formally, we have:

$$u_t = u_{d,t} + u_{s,t} = \varepsilon_{d,t} \times Be_1 + \varepsilon_{s,t} \times Be_2, \tag{10}$$

where e_1 and e_2 are the first and second columns of the identity matrix. We thus obtain a twofold decomposition of both the VRP and volume that allows us to observe the historical evolution of each variable linked to supply and demand shocks, respectively. The results of this analysis are presented on Figure 4 and 5, respectively.

We begin our analysis with the historical decomposition of the VRP. Both supply and demand components share a high persistence. However, the cyclical u-shaped behavior of the VRP between peaks is mostly reproduced by the demand component alone (panel b). In contrast, the supply component (panel a) is slightly trending down during the sample, but does not exhibit any cyclical pattern. As a result, positive supply shocks contribute to gradually lower the VRP during the entire sample period - especially after the great financial crisis.

We also find that the supply and demand components are skewed in opposite directions. The high-frequency supply-induced movements are generally negatively skewed, which induces a downward pressure on the price. On the contrary, the high-frequency movements are positively skewed for the demand, which leads to a high VRP.

Finally, the large peak that is observed in the midst of the financial crisis (2008-2009) is equally linked to supply and demand. It provides evidence of a high investors' demand for insurance and a limited ability of intermediaries to intermediate risk.

We now turn to the analysis of the historical decomposition of the volume. An important difference with the VRP decomposition is that the supply and demand components are less persistent. Both are positively skewed which implies that large volume shocks typically have positive sign.

Over the sample period, we observe a slight trend upwards in the volume series which is mostly due to an increased willingness of intermediaries to supply options. We also observe a change of behavior around the financial crisis when the supply and demand components become more volatile than in the first half of the sample.

Similar to our previous analysis, we find that the supply and demand sides are both important in capturing the time-variation of the price and quantity. In particular, the supply side is instrumental in gradually reducing the size of the VRP, while the demand side generates the cyclical patterns in the VRP.

Please insert Figures 4 and 5 here.

5.1.3 Stock Return Predictability

We now examine the information content of the option demand and supply by measuring their ability to forecast the future stock market return. To this end, we use the disaggregated series presented on Figures 4 and 5 as predictors of the future daily return of the SP500. The results are presented on Table 4.

Consistent with the previous literature (e.g., Bollerslev, Tauchen, and Zhou (2009)), we find that the VRP significantly predicts the market return. The slope coefficient is positive and implies that a high VRP predicts a high future market returns.

Our second specification performs the same regression after splitting the demand and supply components of the VRP (shown in Figure 4). We obtain two significant coefficients of similar magnitude (0.075 for the demand and

0.053 for the supply).[4] Consistent with our previous analysis, this result implies that the two components contain relevant information about the future market return.

Next, we repeat the analysis using as regressors the volume and its supply and demand components (shown in Figure 5). Both the supply and demand components are significant but with opposite signs (0.103 for the demand and -0.067 for the supply). These signs are consistent with the ones associated with the VRP regression since a higher demand brings VRP upwards, whereas a higher supply brings VRP downwards.

Decomposing the volume is essential to uncover its ability to predict the market return. Whereas the demand and supply components contain relevant information, they cancel out when combined together. As a result, the coefficient associated with volume is close to zero (0.012) and not statistically significant.

Finally, we consider a specification with all four components together. We find that the disaggregated volume dominates the VRP in predicting the SP500 returns. As previously explained, the volume exhibits a higher frequency component which better captures daily fluctuations of the market return. This information is partly diluted in the VRP whose time horizon covers the next month.

In short, we find that both the supply and demand components play a significant and equal role in predicting the future market return. It is therefore consistent with our previous analysis which highlights the importance of both components in explaining the dynamics of the option market.

4. Naturally, the two estimated coefficients sum to the one obtained in the first specification.

Please insert Table 4 here.

5.2 News Content on FOMC Days

5.2.1 Full Period Analysis

We now turn to the analysis of the FOMC announcement days. Our objective is to examine the news content of the Fed announcement for the supply and demand of index options. To conduct this analysis, we focus on the 189 scheduled announcements made by the FOMC over our sample period between 1996 and 2019.[5]

Our methodology can be summarized as follows. To begin, we examine how the price and quantity variables change using a ten-day window around the FOMC announcement day (i.e., $d-5, ..., d-1, d, d+1, ..., d+5$). Formally, we run the following time-series regression:

$$u_{i,t}^{(x)} = \alpha_i^{(x)} + \sum_{d=-5}^{5} \beta_{i,d}^{(x)} \mathbb{1}_{FOMC,t+d} + \eta_{i,t}^{(x)}\,, \tag{11}$$

where $x \in \{VRP,\, Vol\}$ and $i \in \{d,\, s\}$, such that $u_{i,t}^{(x)}$ is the supply- or demand-related innovation of price or quantity, obtained from the VAR model in Equation (5). We also perform this analysis for the VRP (volume) residual, where the left-hand side variable is replaced by $u_t^{(x)} = u_{d,t}^{(x)} + u_{s,t}^{(x)}$. Hence the estimated coefficients from the supply and demand regressions sum to the coefficient associated with the VRP (volume) residual. The coefficients of the regression coefficients are reported in Table 5, where the coefficients for $d = -5$ to $d = -2$

5. We exclude the unscheduled announcements from the sample. Adding them back does not have a material impact on the empirical results

and $d = 2$ to $d = 5$ are combined together for brevity.

We begin our empirical analysis with the option price (first column). We observe a strong and significant reduction of the VRP on the FOMC day. On average, it represents 15.8% of the daily standard deviation of the VRP. This reduction continues on the following day, but its magnitude is smaller and insignificant. On the contrary, we find that the price increases prior to the announcement day (the daily coefficients are equal to 0.065 on day $d - 1$, and 0.02 between days $d - 5$ and $d - 2$). This price pattern resonates with the empirical analysis of Hu, Pan, Wang, and Zhu (2021) who suggest that FOMC announcements lead to a higher level of uncertainty. As a result, the VRP initially increases and then drops on the FOMC day as the uncertainty risk premium is realized.

We next turn to the analysis of the option quantity (fourth column). On the FOMC day, the volume of traded options is high on average - the quantity shock represents 15% of the daily standard deviation of the volume. Similarly, the volume is also unusually high on the next day (the coefficient equals 0.053). These results depart from the strong and significant reduction in traded volume on the day prior to the announcement (with a magnitude equal to -0.135).

Applying our methodology, we can now investigate whether these changes originate from the supply or the demand side of the option market. The results of this analysis are shown in the second-third columns for the price (VRP) and in the fifth-sixth columns for the quantity (volume).

We find that the supply side dominates the demand side. On the FOMC day, the supply shock explains 73% of the decrease in the VRP (-0.116/-0.158) versus 27% only for the demand shock (-0.043/-0.158). The supply is also the main reason why quantity increases on the FOMC day - the supply shock is strong and positive (0.243), which more than compensates for a weak option demand (-0.09). Supply shocks also capture the changes in price and quantity around the FOMC announcement. In particular, they fully explain why the price increases and the quantity decreases one day prior to the FOMC announcement (i.e., the coefficients equal to the aggregated ones).

Overall, our results suggest that financial intermediaries are instrumental in driving the option market around the FOMC days. Prior to the announcement, intermediaries are reluctant to supply options to investors. As a result, the VRP increases and the volume drops. However, this reluctance vanishes on the FOMC day, which leads to a decrease in price along with an increase in quantity. These results provide a sharper interpretation of the uncertainty risk premium documented by Hu, Pan, Wang, and Zhu (2021). This premium is mostly the outcome of a contraction of the supply curve - possibly due to tighter funding or risk management constraints faced by intermediaries around FOMC days.

Please insert Table 5 here.

5.2.2 Subperiod Analysis

Recent studies show that the impact of the FOMC announcement on stock returns becomes weaker over time (Boguth, Gregoire, and Martineau (2019), Kurov, Wolfe, and Gilbert (2020)). To elaborate, Lucca and Moench (2015) find that the average market return is equal to 50 bps on the FOMC announcement day between 1994 and 2011. However, Kurov, Wolfe, and Gilbert (2020) find that the average return is a mere 5 bps between 2011 and 2019 – a number very close to the average return over non-announcement days.

Motivated by these results, we examine whether the news content of the

FOMC announcement for the option market changes over time. To this end, we divide the entire sample into three subperiods ranging between (i) 1996 and 2011, (ii) 2012 and 2015, and (iii) 2016 and 2019. The results of this analysis are reported in Tables 6 to 8.

Consistent with the analysis of Kurov, Wolfe, and Gilbert (2020), we find that the price reaction on the FOMC day becomes weaker over time. Between 1996 and 2011, the drop in the VRP represents, on average, 20% of its daily standard deviation. Hovewer, the VRP drop is more than halved during the last subperiod 2016-2019 (i.e., the coefficient drops from 0.20 to 0.035).

This change is not caused by the supply side of the market - the willingness of intermediaries to supply options around FOMC announcements remains qualitatively unchanged. On the FOMC day, the supply expands which leads to a drop in price and a rise in quantity. On the day prior to the announcement, the supply contracts as intermediaries are reluctant to serve as counterparties. It is particularly, the case during the second subperiod 2012-2015.

In contrast, we find that the demand side behaves differently across the three subperiods. Between 1996 and 2011, the demand is particularly weak on the FOMC day. Combined with a positive supply shock, it produces a strong decrease in the VRP. However, the demand grows stronger over time and becomes positive during the third subperiod 2016-2019 (the coefficient increases from -0.088 to 0.138).

The surge in option demand partly offsets the downward price pressure caused by excess supply and leads to a lower option price reaction on the FOMC day. This stronger demand also produces a sharp increase in traded volume. Between 2016 and 2019, the average quantity shock on the FOMC day represents 66% of the daily standard deviation of the volume (versus 4.5% and statistically insignificant for the first subperiod). In other words, the strong increase in quantity is the outcome of the joint influence of both the supply (0.36/0.66=54%) and demand (0.30/0.66=46%).

The overall evidence suggests that the observed price changes around the FOMC announcement are driven by the demand side. One possible explanation for this result is that investors progressively adjust their trading behavior to take advantage of the ample supply of options on announcement days. As they exploit this opportunity to buy cheap insurance against market downturns, they exert an upward pressure on the VRP.

6 Conclusion

This paper provides a supply and demand decomposition of the index option market. This decomposition captures the two-sided nature of the option market with investors on the side (demand) and financial intermediaries (supply) on the other. Therefore, demand shocks capture changes in investors' risk aversion (sentiment), while supply shocks capture changes in intermediaries' funding constraints. We identify each component by estimating a structural VAR model with sign restrictions on the option price and quantity measured with the VRP and traded volume. Our identification structure has the merit of relying on few assumptions beside the linearity of the dynamics.

We show that both supply and demand shocks are equally important in explaining the time series dynamics of the daily option price and quantity. While demand shocks are the main drivers of cyclical fluctuations in the VRP, supply shocks contribute to a gradual downward trend in the VRP over the sample. Focusing on the dates surrounding FOMC announcements, we find that most of the policy uncertainty build-up and resolution are linked to the supply side. Specifically, the supply dries up in the pre-FOMC period and expands substantially after the announcement. This result suggests that the pricing of options around these announcements may be linked to changes in intermediaries' funding constraints.

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A Appendix

A.1 Tables

Table 1: Descriptive statistics

	Mean	Volatility	Skewness	Kurtosis	AC(1)	AC(5)	AC(22)
VRP	16.79	18.76	3.39	21.75	0.88	0.75	0.66
Volume	22428.70	25251.20	5.02	47.28	0.20	0.22	0.18

Table 2: VRP min and max weeks

Week min	Value min	Week max	Value max
2008-09-19	-19.80	2008-12-12	122.37
2015-08-21	-17.75	2008-10-24	131.98
2008-01-25	-12.46	2008-11-14	138.03
2011-08-12	-0.04	2008-12-05	141.95
2005-07-22	0.26	2008-11-21	170.98

Notes: Dates are presented as end-of-week

Table 3: Volume min and max weeks (in thousands)

Week min	Value min	Week max	Value max
2001-05-11	2.5450	2015-01-02	89.7415
2001-03-30	2.6688	2015-03-20	92.4500
2004-07-02	3.0758	2007-08-24	92.9476
2001-06-29	3.1410	2010-10-22	100.9004
1999-09-10	3.6820	2011-11-18	110.7098

Notes: Dates are presented as end-of-week

Table 4: SPX daily predictive regressions

	SPX daily return (in percent)				
	SPX				
	(1)	(2)	(3)	(4)	(5)
VRP(-1)	0.065***				
	(0.015)				
VRP/d(-1)		0.075***			0.030
		(0.021)			(0.025)
VRP/s(-1)		0.053**			−0.021
		(0.023)			(0.037)
Volume (-1)			0.012		
			(0.015)		
Volume/d(-1)				0.103***	0.085***
				(0.022)	(0.027)
Volume/s(-1)				−0.067***	−0.083**
				(0.021)	(0.034)
Cst	0.025	0.025	0.026*	0.025*	0.025
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	5,953	5,953	5,953	5,953	5,953
R^2	0.003	0.003	0.0001	0.005	0.006
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 5: Systematic FOMC movements: Full sample (1996 - 2019)

	Dependent variable:					
	VRP total	VRP demand	VRP supply	Volume total	Volume demand	Volume supply
FOMC(-5:2)	0.018	0.015	0.002	0.027	0.032	-0.005
	(0.017)	(0.012)	(0.012)	(0.036)	(0.026)	(0.024)
FOMC(-1)	0.065^{**}	0.001	0.065^{***}	-0.135^{**}	0.001	-0.136^{***}
	(0.031)	(0.023)	(0.022)	(0.067)	(0.049)	(0.046)
FOMC	-0.158^{***}	-0.043^{*}	-0.116^{***}	0.152^{**}	-0.091^{*}	0.243^{***}
	(0.031)	(0.023)	(0.022)	(0.067)	(0.049)	(0.046)
FOMC(+1)	-0.035	-0.005	-0.030	0.053	-0.010	0.063
	(0.031)	(0.023)	(0.022)	(0.067)	(0.049)	(0.046)
FOMC(+2:5)	-0.0004	-0.015	0.015	-0.063^{*}	-0.032	-0.031
	(0.017)	(0.012)	(0.012)	(0.036)	(0.026)	(0.024)
Cst	0.002	0.002	0.00004	0.005	0.005	-0.0001
	(0.007)	(0.005)	(0.005)	(0.014)	(0.010)	(0.010)
Observations	5,954	5,954	5,954	5,954	5,954	5,954
R^2	0.006	0.001	0.007	0.002	0.001	0.007
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 6: Systematic FOMC movements: Subsample (1996 - 2011)

	Dependent variable:					
	VRP total	VRP demand	VRP supply	Volume total	Volume demand	Volume supply
FOMC(-5:2)	0.016	0.016	0.0003	0.033	0.034	−0.001
	(0.024)	(0.016)	(0.015)	(0.040)	(0.033)	(0.031)
FOMC(-1)	0.083*	0.021	0.062**	−0.085	0.045	−0.130**
	(0.045)	(0.029)	(0.028)	(0.075)	(0.062)	(0.058)
FOMC	−0.200***	−0.088***	−0.111***	0.045	−0.189***	0.234***
	(0.045)	(0.029)	(0.028)	(0.075)	(0.062)	(0.058)
FOMC(+1)	−0.065	−0.009	−0.056**	0.098	−0.019	0.117**
	(0.044)	(0.029)	(0.028)	(0.074)	(0.062)	(0.058)
FOMC(+2:5)	−0.001	−0.018	0.017	−0.074*	−0.039	−0.035
	(0.024)	(0.016)	(0.015)	(0.040)	(0.033)	(0.031)
Cst	0.014	0.003	0.011*	−0.015	0.007	−0.022*
	(0.010)	(0.006)	(0.006)	(0.016)	(0.013)	(0.013)
Observations	4,004	4,004	4,004	4,004	4,004	4,004
R^2	0.007	0.003	0.007	0.002	0.003	0.007

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Systematic FOMC movements: Subsample (2012 - 2015)

	Dependent variable:					
	VRP total	VRP demand	VRP supply	Volume total	Volume demand	Volume supply
FOMC(-5:2)	0.027	0.0002	0.027	−0.056	0.0003	−0.056
	(0.022)	(0.029)	(0.028)	(0.110)	(0.061)	(0.058)
FOMC(-1)	0.016	−0.090*	0.106**	−0.416**	−0.193*	−0.223**
	(0.041)	(0.053)	(0.052)	(0.205)	(0.114)	(0.109)
FOMC	−0.110***	−0.030	−0.080	0.103	−0.065	0.167
	(0.041)	(0.053)	(0.052)	(0.205)	(0.114)	(0.109)
FOMC(+1)	0.017	−0.023	0.040	−0.134	−0.050	−0.084
	(0.041)	(0.053)	(0.052)	(0.205)	(0.114)	(0.109)
FOMC(+2:5)	−0.031	−0.041	0.010	−0.110	−0.088	−0.022
	(0.022)	(0.029)	(0.028)	(0.110)	(0.061)	(0.058)
Cst	−0.017*	0.010	−0.028**	0.080*	0.022	0.058**
	(0.009)	(0.012)	(0.011)	(0.044)	(0.025)	(0.024)
Observations	1,006	1,006	1,006	1,006	1,006	1,006
R^2	0.011	0.005	0.008	0.006	0.005	0.008
Note:				*p<0.1; **p<0.05; ***p<0.01		

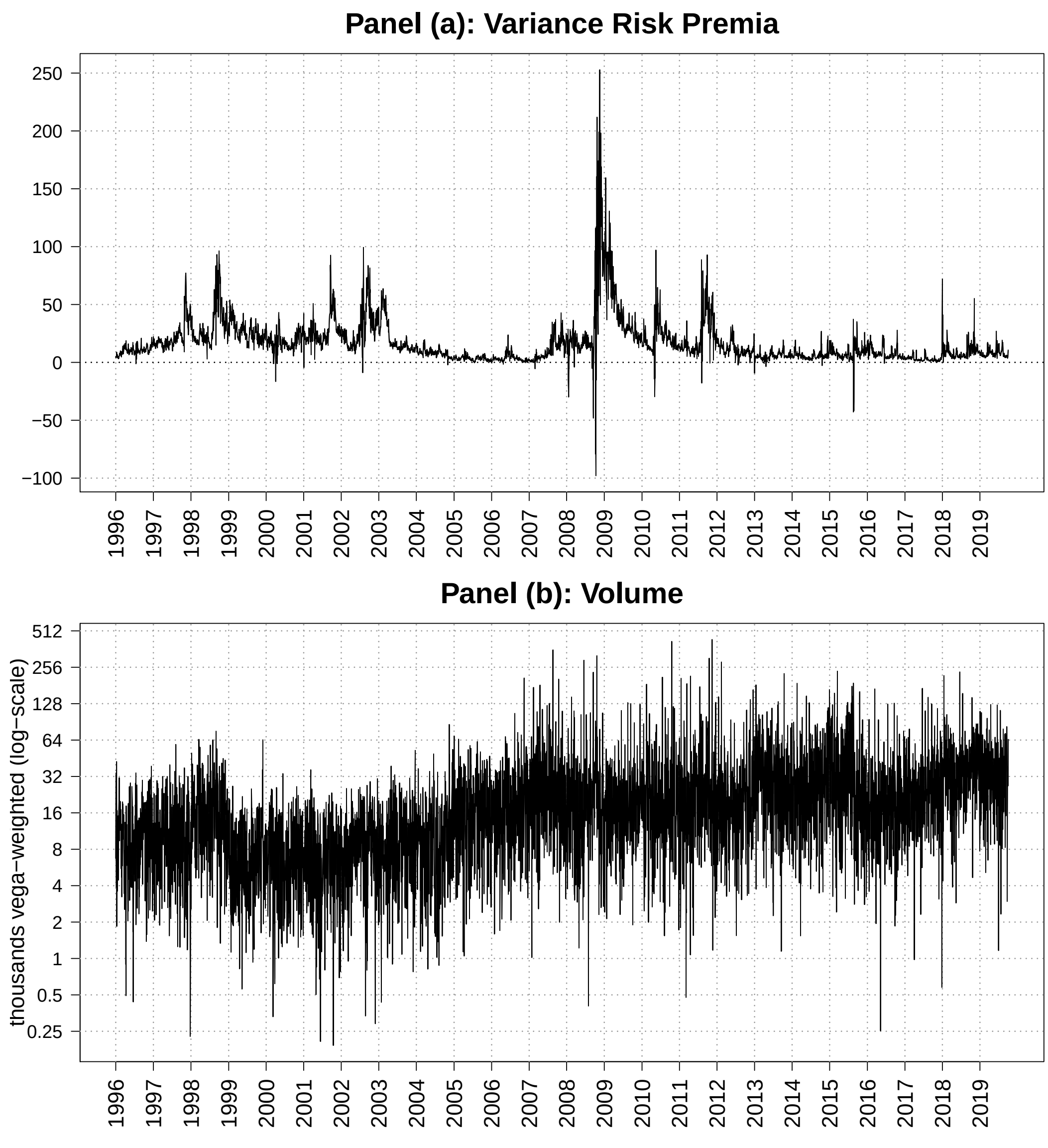
Table 8: Systematic FOMC movements: Subsample (2016 - 2019)

	Dependent variable:					
	VRP total	VRP demand	VRP supply	Volume total	Volume demand	Volume supply
FOMC(-5:2)	0.014	0.028	−0.014	0.090	0.060	0.030
	(0.022)	(0.024)	(0.024)	(0.091)	(0.052)	(0.050)
FOMC(-1)	0.043	0.010	0.033	−0.047	0.022	−0.069
	(0.041)	(0.046)	(0.044)	(0.170)	(0.098)	(0.093)
FOMC	−0.035	0.138***	−0.173***	0.658***	0.294***	0.364***
	(0.041)	(0.046)	(0.044)	(0.170)	(0.098)	(0.093)
FOMC(+1)	0.039	0.034	0.004	0.063	0.073	−0.009
	(0.041)	(0.046)	(0.044)	(0.170)	(0.098)	(0.093)
FOMC(+2:5)	0.036	0.026	0.010	0.034	0.055	−0.021
	(0.022)	(0.024)	(0.024)	(0.091)	(0.052)	(0.050)
Cst	−0.027***	−0.011	−0.016	0.009	−0.024	0.033
	(0.009)	(0.010)	(0.010)	(0.037)	(0.021)	(0.020)
Observations	944	944	944	944	944	944
R^2	0.006	0.011	0.018	0.016	0.011	0.018

Note: *p<0.1; **p<0.05; ***p<0.01

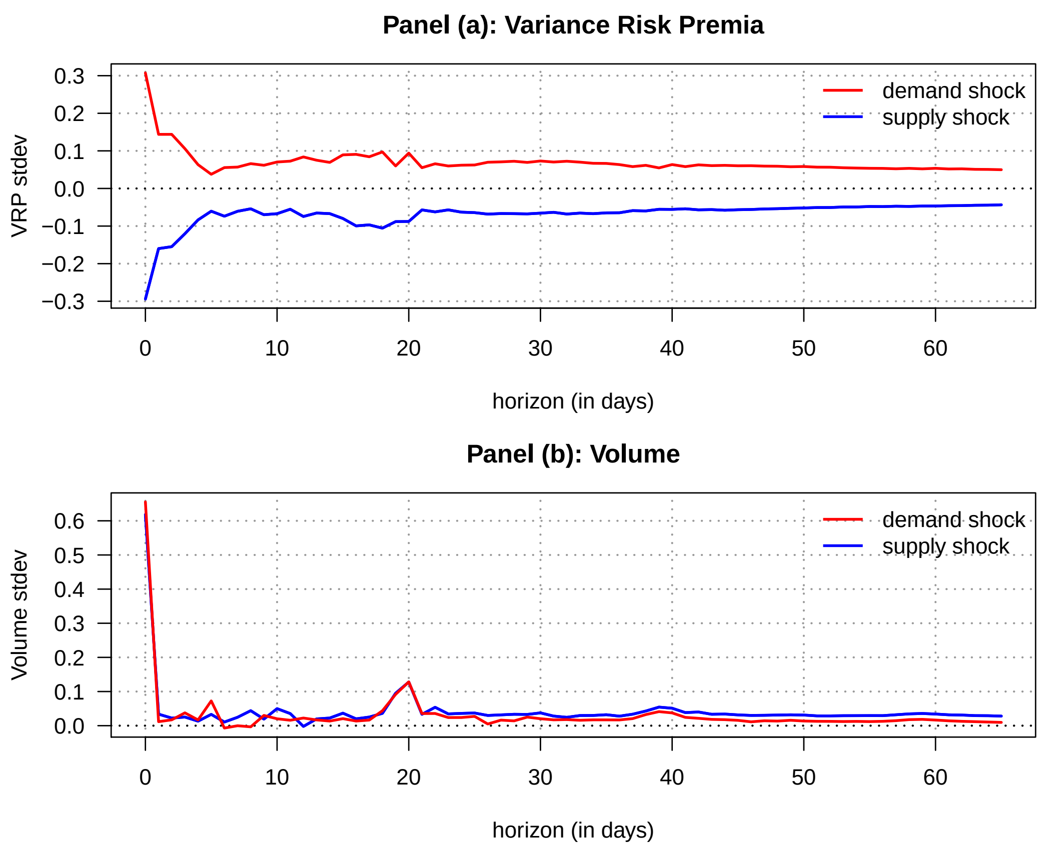
A.2 Figures

Figure 1: Variance risk premia and Volume time series



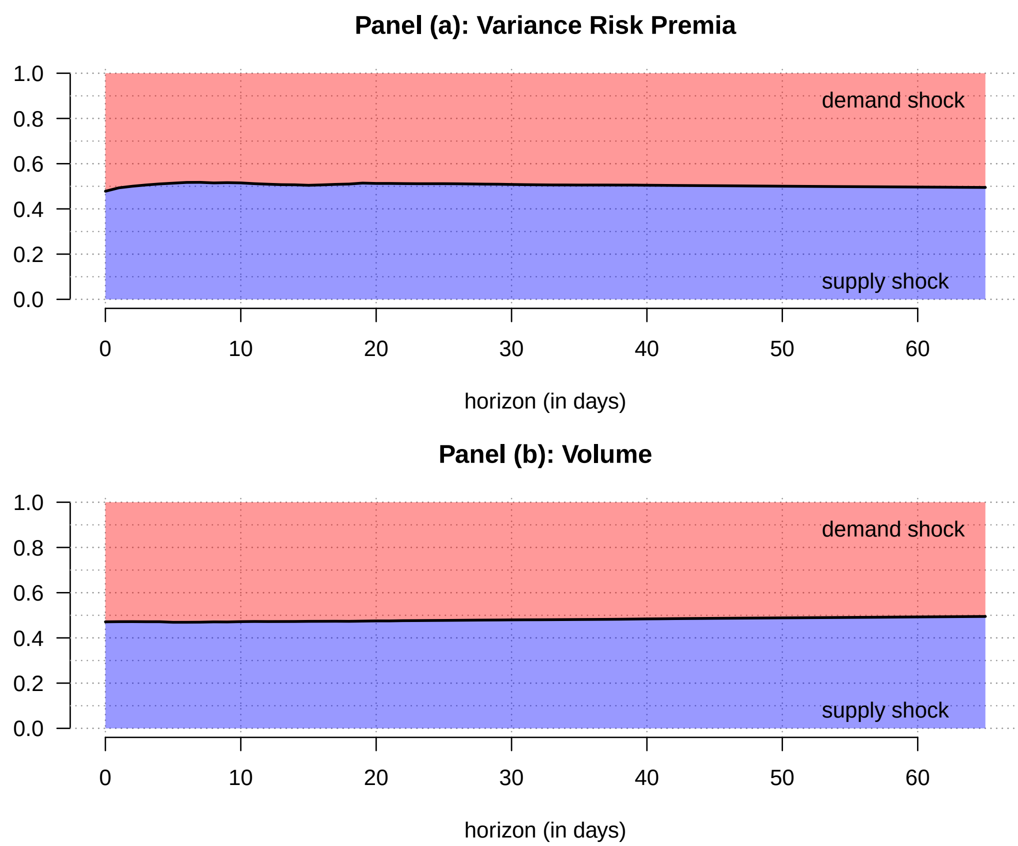
Notes: This figure presents the time series of the variance risk premia and volume that is used in the SVAR. Both series are observed at the daily frequency from January 1996 to October 2019. The variance risk premia is taken from Bekaert and Horoeva (2014) and is the difference between the squared VIX and the result of a 22-day linear model for RV prediction. The volume series is obtained from CBOE Open-Close data set.

Figure 2: Impulse Response Functions



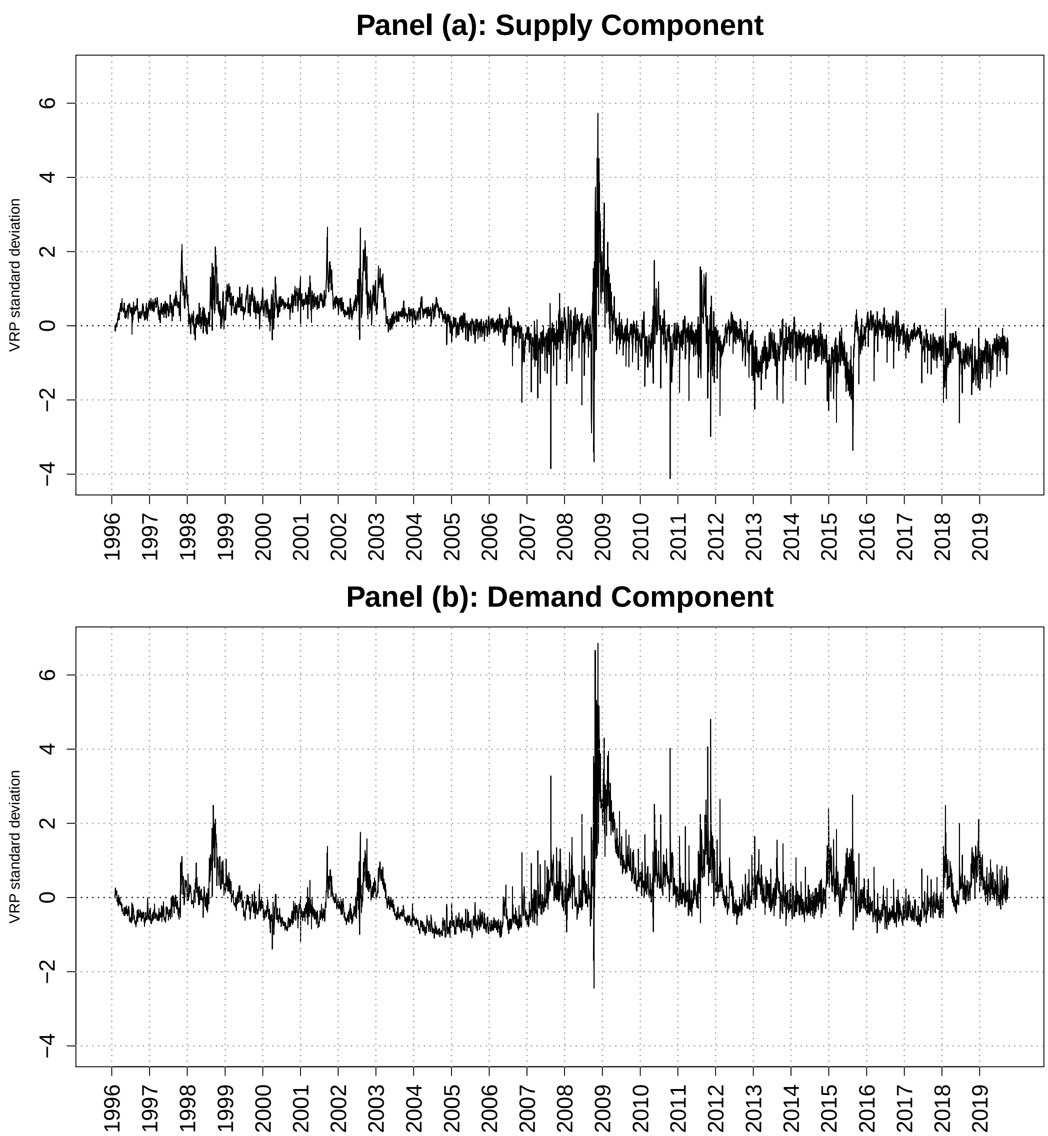
Notes: This figure presents the impulse-response functions of the variance risk premia and volume series with respect to a supply (blue) and demand (red) shocks, as estimated by the SVAR of Equations (5) and (4). Equation (9) presents the final estimate of the structural shock matrix that is used for the computation of the IRFs. The model is estimated from daily series observed from January 1996 to October 2019. Both input series have been normalized by their standard deviations, hence the y-axis unit is in fraction of the series standard deviation.

Figure 3: Variance Decomposition



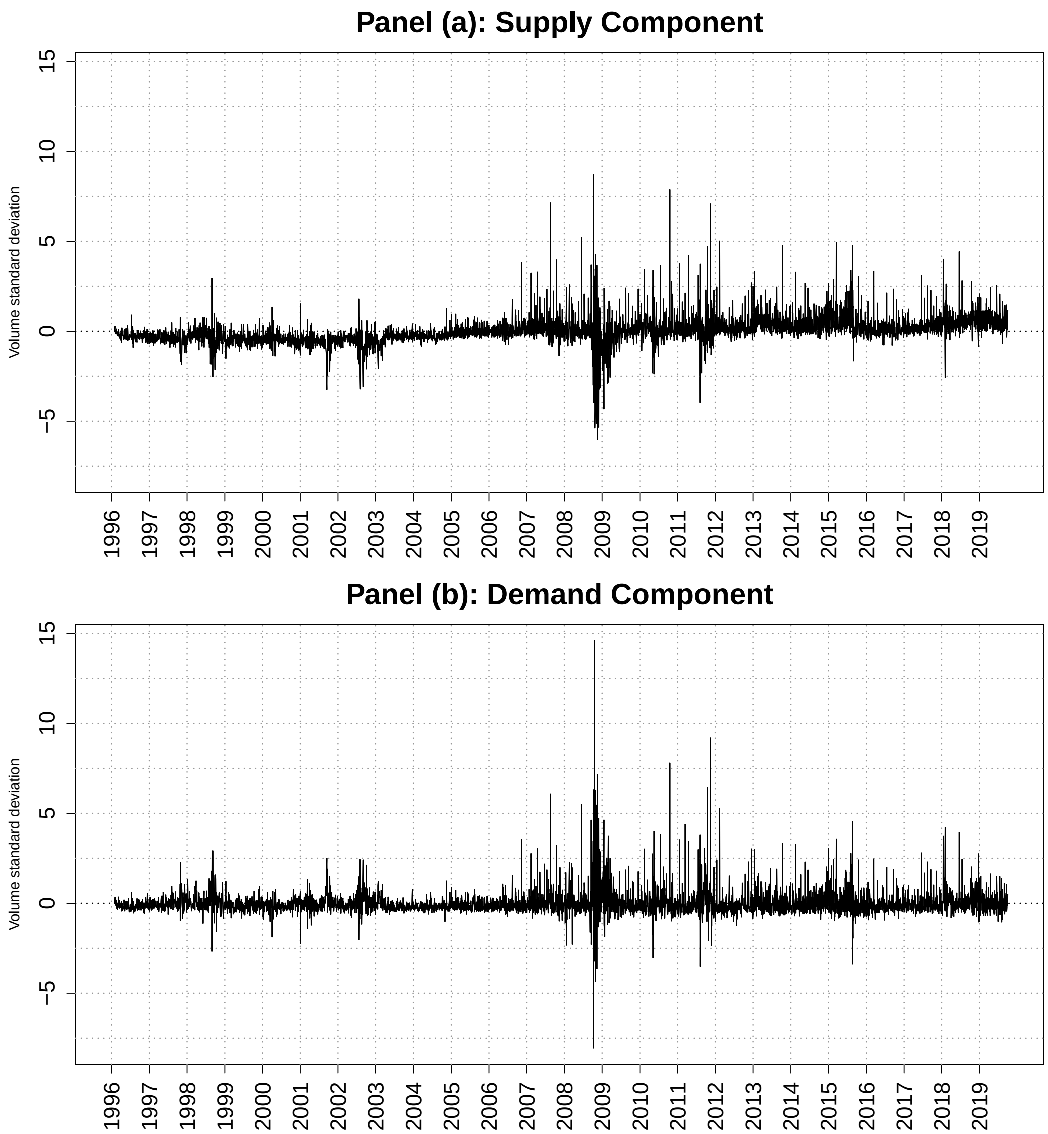
Notes: This figure presents the variance decomposition of the variance risk premia and volume series with respect to a supply (blue) and demand (red) shocks, as estimated by the SVAR of Equations (5) and (4). Equation (9) presents the final estimate of the structural shock matrix that is used for the computation of the variance decomposition. The model is estimated from daily series observed from January 1996 to October 2019.

Figure 4: Variance risk premia supply/demand decomposition



Notes: This figure presents the time series of the variance risk premia decomposed into supply component (panel a) and demand component (panel b), obtained from the sign-restricted SVAR of Equations (5) and (4). The model is estimated from daily series observed from January 1996 to October 2019. Both input series have been normalized by their standard deviations, hence the y-axis unit is in fraction of the series standard deviation.

Figure 5: Volume supply/demand decomposition



Notes: This figure presents the time series of the volume decomposed into supply component (panel a) and demand component (panel b), obtained from the sign-restricted SVAR of Equations (5) and (4). The model is estimated from daily series observed from January 1996 to October 2019. Both input series have been normalized by their standard deviations, hence the y-axis unit is in fraction of the series standard deviation.