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Leverage Effect, Volatility Feedback and the Influence of Jumps *

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Abstract

We investigate the importance of the leverage and volatility feedback effects in stock market, and examine the influence of jumps on them. We do this using high-frequency data and a structural VAR model with sign restrictions to identify the inter-dependencies among market returns, realized volatility and jumps. To better capture sign and size asymmetries of price jumps we employ signed-jump variation measures, instead of traditional jump variation measures often used in practice. We provide clear cut evidence that the leverage effects are more persistent and prevalent in long-term than the volatility feedback effects. On the contrary, volatility feedback effects are found to be contemporaneous. Additionally, we show that the leverage effect can also originate from stock market jumps. Our results remain robust to the use of jump-adjusted measures of returns.

JEL: C32, C58, C80, G12.

Keywords: Leverage effect, Volatility feedback, Structural VAR, Sign restrictions, Realized variance, Bipower variation, Signed-jump variation.

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1 Introduction

The negative relationship between stock market returns and volatility is one of the most studied empirical stylized facts in finance. Two main explanations for this have been proposed in the literature. The first one is the leverage effect referring nowadays to a negative correlation between lagged returns and current volatility.[1] The second explanation is the volatility feedback effect, which is directly related to a time-varying risk premium. According to it, if volatility is priced in stock market, then an anticipated increase in volatility raises the required rate of return due to risk premium effects, implying an immediate stock price decline (see, e.g., Poterba and Summers (1986), French et al. (1987) and Campbell and Hentschel (1992)).

The evidence provided in the literature about the relative importance and persistence of these two effects is rather ambiguous, if not inconclusive. For instance, Bekaert and Wu (2000) argue that the volatility feedback effect tends to dominate the leverage one. On the other hand, Engle and Ng (1993), and Glosten et al. (1993), among others, argue that the leverage effect is stronger and more persistent than the volatility feedback. The ambiguity around the relative importance of these two effects has been attributed to several factors, such as the identification of the two effects by the data, the frequency of the data, the measurement of volatility and the specification of the parametric framework that is being used. The identification issue stems from the fact that the two effects predict a two-direction causal relationship between stock market returns and volatility which is hard to be distinguished empirically. The leverage effect predicts a negative relationship between return and future paths of volatility, whereas the volatility feedback effect predicts a negative relationship from volatility to current stock returns. At lower frequencies, it would difficult to ascertain the direction of causality since both effects appear to be contemporaneous (see Bollerslev et al. (2006)).

To distinguish the dynamic leverage effects from the feedback volatility ones, recently Dufour et al. (2012) estimated a reduced-form VAR model with two endogenous variables, namely returns and realized volatility

[1] The term was initially ascribed to financial leverage. A drop in the current asset price, which increases financial leverage by reducing market capitalization, makes the firm more riskier and therefore leads to higher volatility (see Black (1976) and Christie (1982)).

estimated from high-frequency data, and applied the short-run and long run causality measures proposed by Dufour and Taamouti (2010). These measures can quantify causality between returns and realized volatility at horizons greater than one and account for indirect causal effects based on the reduction of the forecast error variance (see, e.g., Granger (1969)). That is, causality considers the reduction in the forecast error variance of one endogenous variable when another endogenous variable is added in the information set. The method can gauge the size of the dynamic effects between two variables, but it cannot identify the dynamic pattern of them and, more importantly, cannot capture their contemporaneous relationship.

To shed light on above issues, in this paper we suggest a structural VAR (SVAR) framework based on a sign identification scheme to study the relative importance and persistence of the leverage and feedback effects. SVAR models are one of the most popular and flexible econometric tools to examine the dynamic relationship between economic variables and their interaction. They can identify contemporaneous or dynamic effects between variables by imposing a set of restrictions. For instance, traditional identification schemes impose zero restrictions often assuming one-way, recursive ordering (causation) among variables (see, e.g., the Cholesky decomposition scheme), whereas the sign-restriction identification scheme imposes weaker restrictions (see, e.g., Canova and De Nicolo (2002), Uhlig (2005), Inoue and Kilian (2013) and Arias et al. (2018)).[2] It can allow for two-directional causality between two variables by imposing sign restrictions. This enables us to distinguish the contemporaneous and/or dynamic effects between returns and volatility, by identifying their structural shocks. Then, we can study the impact of these shocks on the current and future paths of returns and volatility by calculating the impulse response functions and variance decomposition functions of forecast errors, which are the main tools of the SVAR analysis.

A second contribution of this paper consists in examining the influence of jumps on the leverage and volatility feedback effects. As recent evidence suggests (see, e.g., Eraker (2004), Todorov and Tauchen (2011), and Bandi and Reno (2016)), there is a negative relationship between jumps in returns and volatility, referred to as "jump leverage effects". The suggested SVAR framework can shed light in the direction of causation

[2]See also Kilian and Lütkepohl (2017) for a comprehensive treatment on the alternative VAR identification schemes and their comparative advantages.

between price jumps and volatility. In particular, whether current negative price jumps lead to higher subsequent volatility or positive shocks in volatility result in negative jumps in returns.

In the empirical analysis, we use data from the S&P500 index. We estimate the SVAR model at a daily frequency. Our benchmark specification is a three-variable model which includes daily log-returns, bipower variations and signed-jump variations calculated using high-frequency (i.e., intraday) index returns. The bipower variation measure is a well-established consistent estimator of the continuous part of quadratic variation introduced by Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2004). In our context, it provides an estimate of the intraday variability of index returns free of jumps. As aptly noted by Patton and Sheppard (2015), the signed-jump variation measure is preferable over more traditional jump variation estimators often used in practice (see Andersen, Bollerslev, and Diebold (2007) and Bollerslev et al. (2009)), as it can capture asymmetric effects (in terms of both sign and size) of upside and downside jumps. This helps to better identify the influence of stock market jumps on the leverage and volatility feedback effects.

Our empirical results provide a series of interesting new conclusions, which can enhance our understanding about the leverage and volatility feedback effects, as well as the role of stock market jumps on them. First, we show that the leverage effect is clearly more persistent and important in long-term than the volatility feedback effect. We find that current negative shocks in index returns have a positive sizeable cumulative effect on stock market volatility. On the contrary, current positive shocks in the intraday volatility tends to induce only an immediate and significant negative shift on the stock index price. These results point towards a highly significant prolonged leverage effect and an almost instantaneous volatility feedback effect. Second, we provide clear cut evidence that the leverage effect is not only due to an ordinary stock market return shock, but also to a shock in the signed-jump variation measure. We find that a negative signed-jump variation shock, measuring an unexpected stock price fall during the day, leads to an immediate and sizeable increase in volatility which persists for several days ahead. Interestingly, this "jump leverage" effect is of equal importance to the leverage effect generated by ordinary stock return shocks. This happens despite the fact that the signed-jump variation own shock effects are very short lived, i.e., they last for up two days ahead.

The remainder of paper is organized as follows. Section 2 presents the theoretical framework employed to obtain non-parametric measures of volatility and jumps, used in our analysis. Section 3 presents the SVAR framework with sign identification restrictions and justifies the sign restrictions assumed in our empirical analysis. This is done based on theory and empirical evidence in the literature. Section 4 carries out the empirical analysis. Section 5 presents robustness checks of our results and, finally, Section 6 concludes the paper.

2 Continuous and discontinuous measures of quadratic variation

In this section, we provide all necessary notation and briefly present the relevant theory underlying the different variation estimators (measures) used in our empirical analysis.

Let p_t denote the logarithmic stock price at time (trading day) t, where $0 \leq t \leq T$, which admits the following generic jump-diffusion process:

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dJ_t, \tag{1}$$

where $\sigma_t > 0$ is a càdlàg instantaneous volatility process, dW_t is a standard Brownian Motion, $\mu_t = \lambda\sigma_t$ is a time-varying drift component capturing risk-premium effects in stock returns, with λ being the return-risk trade-off coefficient, and dJ_t is a counting processes with possibly time-varying intensity and discrete jumps of size κ_t.

Now let $r_{t,i}$ be the i-th intraday return on a day t, i.e.:

$$r_{t,i} = p_{t,\frac{i}{N}} - p_{t,\frac{i-1}{N}}, \quad i = 1, 2, ..., N,$$

where N is the number of equally-spaced intraday observations (with $p_{t,0}$ and $p_{t,1}$ being the opening and closing daily log-prices, respectively). The realized variance over the day t can be defined as follows:

$$RV_t = \sum_{i=1}^{N} r_{t,i}^2.$$

As $N \to \infty$, RV_t converges uniformly in probability to the quadratic variation process increment $\langle p, p \rangle_{t-1,t}$, which consists of a continuous and discontinuous component (see, e.g., Andersen et al. (2001)), i.e.,

$$RV_t = \sum_{i=1}^{N} r_{t,i}^2 \xrightarrow{p} \langle p, p \rangle_{t-1,t} = \int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1<j\leq t} (\kappa_j)^2 \tag{2}$$

where $\int_{t-1}^{t} \sigma_s^2 ds$ represents the continuous part of $\langle p, p \rangle_{t-1,t}$ over day t, often referred to as integrated variance (IV_t), and $\sum_{t-1<j\leq t}(\kappa_j)^2$ captures the discontinuous part of $\langle p, p \rangle_{t-1,t}$, also known as jump variation (JV_t). To measure IV_t, Barndorff-Nielsen and Shephard (2004) suggested a $\sqrt{N}$-consistent nonparametric estimator given by the bipower variation (denoted as BV_t), i.e.,

$$BV_t = \frac{\pi}{2} \frac{N}{N-1} \sum_{i=2}^{N} |r_{t,i}||r_{t,i-1}| \xrightarrow{p} IV_t = \int_{t-1}^{t} \sigma_s^2 ds \tag{3}$$

Combining the results of eqs. (2) and (3) gives a simple $\sqrt{N}$-consistent estimator of the jump variation component, JV_t, defined as $RJV_t = RV_t - BV_t$, i.e.,

$$RJV_t = RV_t - BV_t \xrightarrow{p} JV_t = \sum_{t-1<j\leq t} (\kappa_j)^2. \tag{4}$$

The RJV_t estimator is often employed to investigate the effects of JV_t on stock market volatility and returns (see, Andersen, Bollerslev, and Dobrev (2007), Corsi and Renò (2012) and, more recently, Papantonis et al. (2023), inter alia). However, as noted recently by Patton and Sheppard (2015), these effects tend to be asymmetric in sign or magnitude. To capture these asymmetries, these authors suggest using the so-called signed-jump variation (SJV_t) estimator:

$$RSJV_t = RV_t^+ - RV_t^-, \tag{5}$$

where RV_t^+ and RV_t^- are the realized semi-variance estimators of positive and negative returns, respectively, which can be calculated as $RV_t^+ = \sum_{i=1}^N r_{t,i}^2 I(r_{t,i} > 0)$ and $RV_t^- = \sum_{i=1}^N r_{t,i}^2 I(r_{t,i} < 0)$. Barndorff-Nielsen et al. (2010) show that RV_t^+ and RV_t^- converge to $\frac{1}{2}\int_{t-1}^t \sigma_s^2 ds + \sum_{t-1<j\leq t}(\kappa_j)^2 I(\kappa_j > 0)$ and $\frac{1}{2}\int_{t-1}^t \sigma_s^2 ds + \sum_{t-1<j\leq t}(\kappa_j)^2 I(\kappa_j < 0)$, respectively, and thus, their difference $RSJV_t$ converges to the signed-jump variation (SJV_t), given as

$$SJV_t = \sum_{t-1<j\leq t}(\kappa_j)^2 I(\kappa_j > 0) \; - \sum_{t-1<j\leq t}(\kappa_j)^2 I(\kappa_j < 0). \tag{6}$$

While jump variation measures the magnitude of squared jumps, the signed-jump variation captures the asymmetric effects of upside and downside jumps occurring during day t.

3 SVAR analysis with sign identification restrictions

In this section, we present the Structural Vector Autoregressive (SVAR) framework with sign identification restrictions that we employ in our empirical analysis.

Let us start from the following SVAR model of lag-order $q = 1$, for analytic convenience:[3]

$$\Gamma y_t = C_0 + C_1 y_{t-1} + u_t, \tag{7}$$

where y_t is the vector of endogenous variables, u_t is the vector of structural shocks corresponding to the variables in y_t and Γ is an invertible matrix capturing the structural relationship among the variables in y_t.

In our analysis, we consider that y_t is a (3×1)-dimensional vector, defined as $y_t = (y_{r,t}, y_{v,t}, y_{j,t})'$, which

[3]A higher q-lag order can be also considered. This can be written in the form of a VAR(1) by stacking $y_t, y_{t-1}, ..., y_{t-q}$ in a $(q \times 1)$-vector.

consists of variables measuring the stock market index return and its associated integrated volatility, as well as signed-jump variation effects. The structural shocks corresponding to the variables of vector y, denoted as $y_{k,t}$ (for $k = \{r, v, j\}$), are denoted as $u_t = (u_{r,t}, u_{v,t}, u_{j,t})'$. These shocks have an economic interpretation, as they reflect stock market returns, volatility and signed-jump variation unexpected news which are independent of each others.

Conditionally on the σ-field $\mathcal{F}_t = \{y_{t-1}, y_{t-2}, ...\}$, u_t is a zero-mean vector assumed to have a (3×3) variance-covariance matrix $\Sigma_{uu} = I$, implying no correlation among $u_{k,t}$, for $k = \{r, v, j\}$. The reduced-form representation of SVAR, implied by (7), is given as follows:

$$y_t = \tilde{C}_0 + \tilde{C}_1 y_{t-1} + e_t, \text{ with } \tilde{C}_0 = \Gamma^{-1} C_0, \tilde{C}_1 = \Gamma^{-1} C_1 \text{ and } e_t = \Gamma^{-1} u_t, \tag{8}$$

where $e_t = (e_{r,t}, e_{v,t}, e_{j,t})'$ denotes the vector of the reduced-form (VAR) error terms (referred to as VAR innovations). The variance-covariance matrix of the vector of innovations e_t is given as

$$\Sigma = E(e_t e_t') = \Gamma^{-1} \Gamma^{-1\prime} \tag{9}$$

The reduced VAR model, defined by (8), can be employed to obtain the impulse response functions (IRFs) of y_t at h-periods ahead (denoted as y_{t+h}) to a current (t-time) structural shock $u_{k,t}$, as well as the variance decomposition functions (VDFs) of the forecast errors of y_{t+h}. These functions provide the necessary tools for the SVAR analysis to study the dynamic interactions among the variables of vector y_t. Specifically, the IRFs can reveal the dynamic effects of each of the structural shocks $u_{k,t}$ on the variables of vector y_{t+h}, i.e., $y_{k,t+h}$, for $k = \{r, v, j\}$, while the VDFs can indicate the relative importance of $u_{k,t}$ in explaining the forecast error variance of vector y_{t+h}.

To conduct structural analysis, one needs to identify matrix Γ^{-1}, also known as the impact multiplier matrix. Traditional identification schemes are based on exclusion (zero) restrictions on the relationship between the vectors of errors u_t and e_t based on economic theory, or they often use the Cholesky decomposition of the variance-covariance matrix Σ which assumes an one-way (recursive) causation scheme among the variables of vector y_t, corresponding to the order of variables $y_{k,t}$ in vector y_t. Under the Cholesky decomposition, Σ can be decomposed as follows: $\Sigma = \Lambda\Lambda'$, where Λ is a lower triangular matrix which implies that $\Gamma^{-1} = \Lambda$ (see eq.(9)).

An alternative approach to identify structural shocks is to use sign restrictions (see, e.g., Canova and De Nicolo (2002), Uhlig (2005), Inoue and Kilian (2013) and Arias et al. (2018)). One of the attractive features of the sign identification scheme is the flexibility it provides around the type of restrictions that can be imposed on the elements of matrix Γ^{-1}. We can impose sign restrictions on all, or some of the impact effects of structural shocks $u_{k,t}$ on the VAR innovations $e_{k,t}$, for $k \in \{r, v, j\}$. We can take an agnostic stance towards the impact effects that are left unrestricted, and we allow the data to diagnose their sign. Secondly, we can also impose zero (exclusion restrictions), which are also in accordance with the theory. Given that sign restrictions are set-identified, the zero impact restrictions reduces the set of models that can be identified from our data under sign restrictions. As noted by Kilian and Lütkepohl (2017), combining the zero restrictions with the sign ones is expected to better identify the structural shocks $u_{k,t}$ of the SVAR model and obtain economically meaningful IRFs and VDFs. On the other hand, assuming a relatively small number of sign restrictions may lead to implausible interpretations of the IRFs and VDFs.

To impose sign restrictions, define an orthogonal matrix Q (such that $QQ' = Q'Q = I$). This enables us to write $\Gamma^{-1} = \Lambda Q$, which satisfies $\Sigma = \Gamma^{-1}\Gamma^{-1\prime}$. Moreover, structural shocks $u_{k,t}$ remain uncorrelated to each other and have unit variance. Our goal of identifying the model via sign restrictions hinges on the ability to generate large numbers of orthogonal matrices Q. A common method for obtaining such matrices, is recently suggested by Rubio-Ramirez et al. (2010) and it is known as the Householder transformation approach.

In our analysis, we consider a sign identification scheme which can be justified on the grounds of economic theory and empirical evidence from the literature. This scheme is described by the following restrictions:

Restriction 1. The impact effect of a volatility structural shock $u_{v,t}$ on stock return innovation $e_{r,t}$ is negative.

This restriction is consistent with the volatility feedback effect hypothesis, implying a causality from $u_{v,t}$ to $e_{r,t}$ (see, e.g., Bekaert and Wu (2000) and, more recently, Carr and Wu (2017)). According to this hypothesis, an unanticipated increase in the stock market volatility raises the required return on equity by investors which, in turn, leads to an immediate stock price decline to compensate for risk premium effects.

Restriction 2. The impact effect of a stock return structural shock $u_{r,t}$ on volatility innovation term $e_{v,t}$ is zero.

This restriction is implied by the leverage hypothesis, allowing for a negative correlation only between the current return shock $u_{r,t}$ and future volatility innovations $e_{v,t+h}$, $h > 0$. According to this hypothesis (see, e.g., Black (1976) and Christie (1982)), a drop in the value of the stock price (implying a negative return) increases leverage, which then makes the stock riskier and increases its future path of volatility. Note that, in the empirical volatility literature (see, e.g., Breen et al. (1989), Yu (2005), and Martens et al. (2009)), this effect, forcefully documented by Nelson (1991), is referred to as dynamic leverage effect and is considered that it reflects the asymmetric response of the stock return volatility to lagged stock return news. As mentioned above, imposing a zero restriction on the current effect of $u_{r,t}$ on $e_{v,t}$ will help to better distinguish the leverage effect from the volatility feedback one, identified by the negative sign of the impact effect of $u_{v,t}$ on $e_{r,t}$, under Restriction 1. Otherwise, the two effects might not be well identified.

Restriction 3. The impact effect of the signed-jump variation structural shock $u_{j,t}$ on the stock market return and volatility innovation terms, $e_{r,t}$ and $e_{v,t}$, is assumed to be positive and negative, respectively.

These restrictions can be justified by the diffusion process (1), according to which the innovation terms $e_{r,t}$ and $e_{v,t}$ can be disentangled into continuous (ordinary) and discontinuous (jump) structural shocks. The discontinuous shocks are related to the signed-jump variation shocks $u_{j,t}$. A positive value of $u_{j,t}$ (implying a positive effect on SJV_t) can be attributed to "good" large-scale news in the stock market which causes a positive impact effect on stock return innovation $e_{r,t}$ and a negative on volatility innovation $e_{v,t}$. The opposite is expected to happen for a negative value of $u_{j,t}$, reflecting "bad" news in the stock market.

Let us highlight at this point, that the effect of structural shock $u_{j,t}$ on the volatility innovation term $e_{v,t}$ can be also interpreted as reflecting discontinuous (due to jump-component) leverage effects of stock returns on current and future paths of the volatility series, as discussed in the introduction. The use of a measure of the signed-jump variation (SJV_t), instead of the jump variation (JV_t), in our SVAR model is expected to better identify the above effects as they are asymmetric in sign or size. Using JV_t may not well distinguish between positive and negative effects of jumps on volatility innovations, given that these effects are smoothed out, as noted by Patton and Sheppard (2015).

Evidence of prevalent negative effects of signed-jump variation on integrated variance can be found in many recent studies using regression analysis (see, e.g., Andersen, Bollerslev, and Dobrev (2007), Patton and Sheppard (2015), Corsi and Renò (2012), and Papantonis et al. (2022), inter alia). There is also significant evidence of jump effects on stock returns and/or volatility, as highlighted in Eraker et al. (2003) and Eraker (2004). As a final note that, on the contrary to the effects of $u_{j,t}$ on $e_{r,v}$ and $e_{v,t}$, we leave the effects of the structural stock return and volatility shocks (i.e., $u_{r,t}$ and $u_{v,t}$) on the signed-jump innovations $e_{j,t}$ unrestricted. We leave our data to monitor the sign or size of these effects.

Restriction 4. The impact effects of all structural shocks, namely $u_{r,t}$, $u_{v,t}$ and $u_{j,t}$, on their corresponding VAR innovation terms (i.e., $e_{r,t}$, $e_{v,t}$ and $e_{j,t}$) are all positive.

This restriction is natural and reflects the fact that the reduced VAR innovations $e_{k,t}$ are directly related to their associated structural shocks $u_{k,t}$, $k \in \{r, v, j\}$.

We can summarize the above restrictions on the elements of matrix Γ^{-1} as follows:

$$\begin{bmatrix} e_{r,t} \\ \\ e_{v,t} \\ \\ e_{j,t} \end{bmatrix} = \begin{bmatrix} + & - & + \\ \\ 0 & + & - \\ \\ * & * & + \end{bmatrix} \begin{bmatrix} u_{r,t} \\ \\ u_{v,t} \\ \\ u_{j,t} \end{bmatrix} \tag{10}$$

where the asterisks (*) mean that no restrictions are imposed.

Finally note that the sign restrictions considered in our analysis constitute impact restrictions of $u_{k,t}$ on $e_{k,t}$, for all k, and, hence, the variables of vector y_t. The dynamic effects of these restrictions on the future path of $y_{k,t+h}$, for $h > 0$ are not a priori specified.

4 Empirical Analysis

In this section, we present the results of our empirical analysis. We start by presenting the Bayesian estimation method employed to retrieve IRFs and VDFs using zero and sign restrictions. Then, we present the descriptive statistics of the variables that we employ in our analysis. Finally, we present and discuss the results of our empirical analysis. To assess whether our results are robust to different specifications of vector y_t, we firstly consider the bivariate case of $y_t = (y_{r,t}, y_{v,t})'$, excluding the variable related to the signed-jump variation effects and, secondly, the trivariate case of y_t which constitutes its full-specification, i.e., $y_t = (y_{r,t}, y_{v,t}, y_{j,t})'$. Moreover, the comparison of the results between these two cases of y_t can highlight the relative importance of considering jump effects in analysing the leverage and/or volatility feedback relationship.

4.1 Bayesian estimation and inference

In this section, we first present in more detail our Bayesian estimation approach. Then, we describe the basic steps of the algorithm used to obtain the IRFs and VDFs based on the sign identification scheme presented in the previous section.

4.1.1 Model estimation

To present the model estimation, assume for analytic convenience that the Data Generating Process (GDP) of vector $y_t = (y_{r,t}, y_{v,t}, y_{j,t})'$ is well approximated by a VAR of lag-order $q = 1$ given by (8). Suppose that we have a sample of $T + 1$ observations for y_t, $t = 0, 1, \dots T$. The VAR system can be written compactly for all observations in the following way

$$Y = XB + E. \tag{11}$$

Let $m = Kq + 1$ denote the total number of coefficients to be estimated in each of the equations of our VAR system, where $K = 3$ denotes the number of covariates. Then, $Y = (y_1, y_2, \dots, y_T)'$ is a $T \times K$ matrix, $X = (x_1, x_2, \dots, x_T)'$ is a $T \times m$ matrix, $x_t = (1, y'_{t-1})'$ are $m \times 1$ vectors, for $t = 1, \dots T$, $B = (\widetilde{C}_0, \widetilde{C}_1)'$ is a $m \times K$ matrix, and $E = (e_1, e_2, \dots, e_T)'$ is a $T \times K$ matrix. According to Bayes's rule

$$p(B, \Sigma | Y, x_1) \propto p(Y | B, \Sigma, x_1) p(B, \Sigma), \tag{12}$$

where $p(B, \Sigma | Y, x_1)$ is the posterior distribution of the reduced form parameters conditional on the data, $p(Y | B, \Sigma, x_1)$ is the sample likelihood function, and $p(B, \Sigma)$ is the prior distribution of the reduced form parameters. Our distributional assumptions concerning the structural errors, u_t, imply that $e_t | \mathcal{F}_t \sim N_K(0, \Sigma)$. This, in turn, implies that

$$Y | B, \Sigma, x_1 \sim MN_{T \times K} (XB, I_T, \Sigma) .^4 \tag{13}$$

Hence,

$$p(Y | B, \Sigma, x_1) = \left(\frac{1}{2\pi} \right)^{\frac{TK}{2}} |\Sigma \otimes I_T|^{-\frac{1}{2}} \exp \left[-\frac{1}{2} tr \left(\Sigma^{-1} (Y - XB)' I_T^{-1} (Y - XB) \right) \right] \tag{14}$$

[4] In the following, we are using the abbreviations $MN, IW, MNIW$ when referring to the Matrix Normal, Inverse Wishart and Matrix Normal Inverse Wishart distributions, respectively.

$$\Rightarrow p(Y|B,\Sigma,x_1) \propto \left\{|\Sigma|^{-\frac{m}{2}} \exp\left[-\frac{1}{2}tr\left(\Sigma^{-1}\left(B-\widehat{B}\right)'(X'X)\left(B-\widehat{B}\right)\right)\right]\right\} \tag{15}$$

$$\left\{|\Sigma|^{-\frac{T-m}{2}} \exp\left[-\frac{1}{2}tr\left(\Sigma^{-1}\left(Y-X\widehat{B}\right)'\left(Y-X\widehat{B}\right)\right)\right]\right\}, \tag{16}$$

where $\widehat{B}$ is the ordinary least squares estimator of B. Note that, line (15) in the above expression is the kernel of a Matrix Normal distribution for B conditional on Σ

$$B|\Sigma \sim MN_{m\times K}\left(\widehat{B},(X'X)^{-1},\Sigma\right). \tag{17}$$

Moreover, line (16) is the kernel of an Inverse Wishart distribution for Σ

$$\Sigma \sim IW_K\left(\left(Y-X\widehat{B}\right)'\left(Y-X\widehat{B}\right),T-m-K-1\right). \tag{18}$$

The above two results concerning the distributions of $B|\Sigma$ and Σ in turn imply that

$$Y|B,\Sigma,x_1 \sim MNIW\left(\widehat{B},(X'X)^{-1},\left(Y-X\widehat{B}\right)'\left(Y-X\widehat{B}\right),T-m-K-1\right). \tag{19}$$

With regard to the prior distribution of B,Σ we are assuming that $(B,\Sigma)\sim MNIW(\Psi_0,\Omega_0,\Phi_0,v_0)$, where $\Psi_0,\Omega_0,\Phi_0,v_0$ denote prior hyperparameters. Note that in our context, the $MNIW$ distribution is a natural conjugate prior. Therefore, the posterior of B,Σ conditional on the data will be from the same distributional family, with parameters $\Psi_1,\Omega_1,\Phi_1,v_1$ that need to be determined, given our choice for $\Psi_0,\Omega_0,\Phi_0,v_0$. In particular

$$B,\Sigma|Y,x_1 \sim MNIW\left(\Psi_1,\Omega_1,\Phi_1,v_1\right) \tag{20}$$

with,

$$v_1 = T + v_0, \tag{21}$$

$$\Omega_1 = \left(X'X + \Omega_0^{-1}\right)^{-1}, \tag{22}$$

$$\Psi_1 = \Omega_1 \left(X'Y + \Omega_1^{-1}\Psi_0\right), \tag{23}$$

$$\Phi_1 = Y'Y + \Phi_0 + \Psi_0'\Omega_0^{-1}\Psi_0 - \Psi_1'\Omega_1^{-1}\Psi_1. \tag{24}$$

Knowledge of $p(B, \Sigma|Y, x_1)$ enables us to generate draws for the reduced-form parameters (B, Σ) in a relatively straightforward manner, without the need of employing burdensome sampling techniques.

4.1.2 Impulse response functions and variance decomposition

Knowledge of Γ^{-1} enable us to calculate the IRFs of model variables y_{t+h}, $h = 0, 1, 2, ...$, due to a unit increase in structural shock $u_{k,t}$, $k \in \{r, v, j\}$, which will be henceforth denoted as $IRF_{k,t+h}$. These functions can be obtained by the individual columns of Γ^{-1}, denoted as γ_k, $k \in \{r, v, j\}$, respectively, i.e.,

$$IRF_{k,t+h} = \tilde{C}_1^h \gamma_k, h \geq 0 \text{ and } k \in \{r, v, j\}. \tag{25}$$

The VDFs of the forecast errors of model variables at forecasting horizon $h = 1, 2, 3, ...$, can be calculated as follows. Let $R_{l,k}(h)$ denote the part of the variance of the forecast error of $y_{l,t+h}$, $l \in \{r, v, j\}$, which is attributable to structural shock u_k, $k \in \{r, v, j\}$. It can be shown that $R_{l,k}(h)$ is given by $R_{l,k}(h) = \sum_{s=0}^{h-1} \theta_{l,k,s}^2$, where $\theta_{l,k,s}$ is the (l, k)-th element of the matrix $\tilde{C}_1^s \Gamma^{-1}$. Then, the fraction of the contribution of the k-th structural shock to the forecast error variance of y_{t+h} is given as follows:

$$VDF_{k,t+h} = \left(\frac{R_{r,k}(h)}{\sum_{i \in \{r,v,j\}} R_{r,i}(h)}, \frac{R_{v,k}(h)}{\sum_{i \in \{r,v,j\}} R_{v,i}(h)}, \frac{R_{j,k}(h)}{\sum_{i \in \{r,v,j\}} R_{j,i}(h)} \right)', h \geq 1 \text{ and } k \in \{r, v, j\}. \tag{26}$$

We follow closely the algorithm developed by Arias et al. (2018), which generates draws from the posterior distribution of $IRF_{k,t+h}$ conditional on zero and sign restrictions. Without going into too much detail, the algorithm consists of the following basic steps:

1. Generate a draw for the reduced form parameters (B, Σ) from $MNIW(\Psi_1, \Omega_1, \Phi_1, v_1)$.

2. For that (B, Σ) draw, generate multiple draws of orthogonal matrices Q (designed appropriately to accommodate zero restriction) from the uniform distribution with respect to the Haar measure on the set of all orthogonal $K \times K$ matrices.

3. Keep all tuples (B, Σ, Q) that satisfy the sign restrictions.

4. Repeat steps 1, 2, 3 until the desired number of draws from the posterior of the impulse responses conditional on sign and zero restrictions has been obtained.

Once the posterior distribution of $IRF_{k,t+h}$ conditional on zero and sign restrictions has been simulated, we report the median value of the distribution, along with and the 68% symmetric credible set constructed by the 16-th and 84-th percentiles of the distribution, respectively. Regarding to $VDF_{k,t+h}$ we follow a similar approach. Note that $VDF_{k,t+h}$ are functions of the $IRF_{k,t+h}$ coefficients.

4.2 The data

We implement our SVAR framework on the S&P 500 index data. We obtain ultra high-frequency data (UHF) from the Trade and Quote (TAQ) database. This allows us to monitor all the recorded tick-level data on the S&P 500 index at millisecond-level precision. Our data-set covers the period from 1995 to 2016. Given the UHF of our data on the index, we follow the usual procedures to construct evenly-spaced observations at 5-minute intervals for the trading hours between 9:30 and 16:00 (EST), by taking the last price that was recorded within the previous 5-minute period. This ultimately leaves us 78 intraday observations per day, based on which we calculate the aforementioned realized measures, presented in Section 2. The 5-minute sampling for the intraday data strikes an ideal balance between estimation accuracy and robustness to micro structural noise. We follow standard data-cleaning procedures for our high-frequency data, as thoroughly presented in Falkenberry (2002). Note that in cases where there was no trading in a specific interval, the corresponding return is set to zero.

Table 1 presents some descriptive statistics of the variables considered for the estimation of the SVAR model, including skewness and excess kurtosis coefficients (denoted by Sk and Kurt, respectively), as well as Ljung-Box (LB) test statistics for first and fifth order autocorrelation. More specifically, Table 1 reports statistics for the following set of variables: the daily returns r_t, bipower variation (BV_t) and realized signed-jump variation ($RSJV_t$), defined in Section 2, along with statistics for their desired corresponding transformations, namely $r_t/\sqrt{RV_t}$, $\log(BV_t)$ and $RSJV_t/RV_t$. These specific transformations of the raw series are often used in the empirical literature to obtain measures of the vector of variables $y_t = (y_{r,t}, y_{v,t}, y_{j,t})'$ which are more close to the normal distribution and/or have constant variance. In particular, the standardization of the returns series r_t with the realized variance (i.e. using $r_t/\sqrt{RV_t}$), as well as working with the logarithmic transformation of BV_t (i.e. with $\log(BV_t)$), have been suggested by Andersen et al. (2001) and Bollerslev et al. (2009). Additionally, the scaling of $RSJV_t$ by RV_t (i.e., $RSJV_t/RV_t$) yields a scale-invariant measure of SJV (see also Huang and Tauchen (2005)). Note also that $RSJV_t/RV_t$ is closely related to the realized measure suggested in Feunou et al. (2016) to proxy the asymmetry (skewness) in stock returns in a non-parametric way.

The results of the Table 1 clearly indicate that the transformed series $r_t/\sqrt{RV_t}$, $\log(BV_t)$ and $RSJV_t/RV_t$ are approximately normally distributed. The series exhibit levels of skewness and excess kurtosis which are close to those of a normal distribution. To the contrary, raw series r_t, BV_t and $RSJV_t$ exhibit levels of skewness and excess kurtosis, which deviate significantly from normality. These results are in line with those reported by Andersen et al. (2001) and Bollerslev et al. (2009). Finally, another interesting conclusion that can be drawn from the table is related to the autocorrelation levels of the variables. All the series are characterized by a significant degree of serial correction, which means that the SVAR model provides the natural framework to capture the dynamic interactions among these variables. Note that this is true even for the series $RSJV_t/RV_t$, capturing signed-jump variation. The LB statistics suggest rejecting the null hypothesis of no autocorrelation, and this holds for all the above series.

4.3 The SVAR estimation results

To estimate the SVAR model (7) and obtain the $IRF_{k,t+h}$ and $VDF_{k,t+h}$, we follow the analysis of section 4.1. For vector of variables y_t, we use $y_{r,t} = r_t/\sqrt{RV_t}$, $y_{v,t} = \log(BV_t)$ and $y_{j,t} = RSJV_t/RV_t$. The lag structure of the reduced form VAR, corresponding to (7), is set up to 5 lags. This is chosen based on the Schwarz information criterion.

The results of the $IRF_{k,t+h}$ analysis are graphically illustrated in Figures 1A and 1B. Figure 1A presents $IRF_{k,t+h}$ results for the bivariate case $y_t = (y_{r,t},\ y_{v,t})'$, while 1B for the trivariate case $y_t = (y_{r,t}, y_{v,t}, y_{j,t})'$. The $VDF_{k,t+h}$ estimates that correspond to the above two $IRF_{k,t+h}$ cases are given in Tables 2A and 2B, respectively. For all IRFs and VDFs, we report values of the point-wise median estimates, as well as the 68% central credible sets (see the dark-shaded bands) constructed by the 16% and 84% quantiles of the posterior distribution of IRFs.

A number of interesting conclusions can be drawn from the inspection of the figures and tables of results. Below, we organize the discussion of our results in the following order. First, we summarize the results for the volatility feedback and leverage effects, and then we discuss influence of the signed-jump variation on both of these effects.

i) Volatility feedback vs. leverage effects

The estimates of $IRF_{k,t+h}$ and $VDF_{k,t+h}$ indicate that both the leverage and volatility feedback effects are important and can explain substantial changes in stock market volatility and index return. However, the dynamic patterns of these effects seem to differ substantially over a h-day horizon. The $IRF_{k,t+h}$ indicate that the leverage effect is more persistent and important in long-term than the volatility feedback. This result holds for both specifications of the y_t vector that we have considered; i.e. whether the signed-jump variation series $y_{j,t}$ is included in y_t or not. Augmenting the SVAR model with the signed-jump variation variable $y_{j,t}$ does not change the above results regarding both leverage and feedback effects. It only makes the 68% credible sets reported in the tables slightly wider, obviously due to the higher number of models that can be identified from the data when $y_{j,t}$ is included in y_t. This result highlights the economic plausibility and empirical robustness of our results, obtained under the SVAR sign restriction identification scheme of eq.(10).

More specifically, the results show that a structural return shock $u_{r,t}$ has a substantial effect on volatility series $y_{v,t}$, which is always negative (in line with theory predictions) and lasts for more than a month ahead. For longer horizons h, this effect has a sizable long-run effect on $y_{v,t}$, as can be seen from the graphs. The graph estimates of $IRF_{v,t+h}$ indicate that the volatility series $y_{v,t}$ is smoothly driven by both the leverage effects and its own structural shocks $u_{v,t}$, with the long-run effects of $u_{v,t}$ on $y_{v,t}$ being stronger than those of $u_{r,t}$. These results are consistent with evidence in the literature on the GARCH or stochastic volatility models emphasizing the need to include lagged return innovations and own volatility effects in modelling conditional variance functions; Andersen et al. (2009) and Bauwens et al. (2012) provide very good reviews.

On the other hand, the effect of a structural volatility shock $u_{v,t}$ on the stock return series $y_{r,t}$ (reflecting volatility feedback effects) is significant and large, but is found to concern only the current period (i.e., for $h = 0$). In particular, a positive one standard deviation shock in volatility decreases the return by 0.4%. It does not have important long-term dynamic effects on $y_{r,t+h}$, for $h > 0$. This result implies that the stock return risk premium effects driven by volatility shocks, are immediately (at once) absorbed in stock prices. It is also consistent with studies showing that risk premium models (like the GARCH-in-mean of Engle et al. (1987)) have limited predictive power on future stock returns. Summing up, our findings point towards a highly significant prolonged leverage effect and an almost instantaneous volatility feedback effect. They are in line with Bollerslev et al., 2006 using simple correlations to study the interaction between returns and volatility. They also agree with Dufour et al., 2012 providing evidence of a strong long-term leverage effect. In addition to them, we find the existence of a significant contemporaneous volatility feedback effect.

Although the dynamic and/or contemporaneous effects of structural shocks $u_{r,t}$ and $u_{v,t}$ on $y_{v,t+h}$ and $y_{r,t+h}$, respectively, are found important, the estimates of $VDF_{k,t+h}$ ($k \in \{r, v\}$) reported in Tables 2A and 2B indicate that $u_{r,t}$ and $u_{v,t}$ do not contribute largely into explaining the variance forecast errors of series $y_{v,t+h}$

and $y_{r,t+h}$. The biggest part of $VDF_{k,t+h}$ for both $y_{r,t+h}$ and $y_{v,t+h}$ (e.g., almost 90% for the bivariate case) comes from their own structural shocks (i.e., from $u_{r,t}$ and $u_{v,t}$). The contribution of either the leverage or volatility feedback effect into the $VDF_{k,t+h}$ is quite small. For $y_{r,t+h}$, it ranges between 4.9% and 7.35% across the two specifications of y_t considered (i.e., with or without $y_{j,t}$). This is true for all horizons h. A little higher than this is the contribution of the volatility feedback effect into $VDF_{r,t+h}$. This ranges between 8.98% and 13.08% across the two specifications of y_t. These results are not surprising given that the stock market volatility is mainly driven by its own shocks (as noted above), while the stock index return is close to an iid process and its relationship with volatility is contemporaneous, as shown by the feedback effects. The closeness of $y_{r,t}$ to an iid process can be seen by the estimates of the $IRF_{r,t+h}$ with respect to its own return shock $u_{r,t}$. These show that the effects of $u_{r,t}$ on $y_{r,t+h}$ are rather short-lived.

ii) The influence of jumps on the leverage and volatility feedback effects

Regarding the effects of the signed-jump variation shock $u_{j,t}$ on the leverage and feedback effects, the results of the tables and figures reveal a number of interesting new findings, which shed light not only on the sources of the leverage effects, but also on their relative importance. In particular, the estimates of $IRF_{k,t+h}$ ($k \in \{r, v\}$), graphically presented in Figure 1B, demonstrate that a positive shock $u_{j,t}$ has only contemporaneous effects of stock return series $y_{r,t}$. That is, this holds only for the day that the shock occurs; the dynamic effects of $u_{j,t}$ on $y_{r,t+h}$ are insignificant. On the other hand, a positive value of $u_{j,t}$ has negative effects on the current and future paths of volatility series $y_{v,t+h}$, as shown by $IRF_{v,t+h}$. These effects are persistent and sizable in the long-term. The negative sign of $u_{j,t}$ on $y_{v,t+h}$ means that leverage effects are also driven by the discontinuous (jump) innovations in stock returns. These reflect large-scale "bad", or "good", stock return news on $y_{v,t+h}$, as discussed in Section 3.1. As can be seen from Figure 1B, the dynamic patterns of these effects on the current and future path of volatility series $y_{v,t+h}$ is similar to those of the ordinary returns shocks $u_{r,t}$ on $y_{v,t+h}$. However, it is important to emphasize that the calculated long-run effects of $u_{j,t}$ on $y_{v,t+h}$ are bigger than $u_{r,t}$, as it can be clearly seen from the estimates of $IRF_{v,t+h}$.

The important influence of jumps on the current and future path of $y_{v,t+h}$ can be also justified by the high explanatory power of structural shock $u_{j,t}$ on the variance of the forecast errors of $y_{v,t+h}$. As can be seen from the results of Table 2B reporting the estimates of $VDF_{v,t+h}$, the shock $u_{j,t}$ contributes substantially to $VDF_{v,t+h}$, for all h. In fact, its contribution amounts to a percentage bigger than 50% and it can explain a very big part of the contribution of the own volatility shock $u_{v,t}$, which falls considerably compared to the bivariate case $y_t = (y_{r,t}, y_{v,t})'$ reported in Table 2A.

Another interesting conclusion that can be drawn from the results of Figure 1B is that, in contrast to the effect of $u_{j,t}$ on $y_{v,t+h}$, the effect of a structural volatility shock $u_{v,t}$ on the current or future path of the signed-jump variation series $y_{j,t+h}$ is unimportant, for all h. These results imply an one-way causation from $u_{j,t}$ to $y_{v,t}$, which shows that the "jump leverage effect" documented in the literature can be attributed to current price jumps leading subsequent volatility, and not inversely. Consistent with this interpretation is also the very small (almost insignificant) contribution of $u_{v,t}$ into the forecast error variance of $y_{j,t+h}$, for all h (see Table 2B). On the other hand, the results of Figure 1B indicate that there is a two-way causation between variables $y_{j,t}$ and $y_{r,t}$. At $h = 0$, there is significant and positive interaction between the two variables as expected; $u_{r,t}$ has a positive impact on $y_{j,t}$ and $u_{j,t}$ has a positive impact on $y_{r,t}$. Note that, in terms of the VDFs, the most important of these two impacts is that of $u_{r,t}$ on $y_{j,t+h}$. It accounts for the 53% of forecast error variance of $y_{j,t+h}$, for $h = 0$. Let us also highlight that the effect of $u_{r,t}$ on $y_{j,t+h}$ is not just contemporaneous, but lasts for 3 days ahead.

Finally, regarding the own effects of $u_{j,t}$ on the signed-jump variation series $y_{j,t+h}$, the estimates of $IRF_{j,t+h}$ indicate that these effects are large but die out very quickly (within a couple of days), implying that, on daily basis, self-exciting jump clustering effects (see, e.g., Carr and Wu (2017) and Ait-Sahalia et al. (2015)) are very short-lived. The estimates of $VDF_{j,t+h}$ also indicate that $u_{j,t}$ can explain only a small part of the variability of $y_{j,t+h}$ (about 14%). The biggest part of the variability of $y_{j,t+h}$ comes from the return shocks $u_{r,t}$, which is consistent with our finding that $u_{r,t}$ has significant effects on $y_{j,t+h}$.

Overall, the results of this section emphasize the existence of persistent leverage effects compared to the volatility feedback ones, which are found to be contemporaneous. They also highlight the importance of the stock market jumps in explaining the above effects, compared to the ordinary stock market shocks.

5 Robustness checks

In this Section, we conduct two exercises to examine the robustness of our results to alternative measures of the integrated variance and the use of jump-adjusted stock market index return. In particular, the first exercise uses a measure of integrated variance (IV_t) which is robust to large jumps, while the second considers stock index return values net of jumps. These values are obtained by relying on an inference procedure for jump detection based on the intraday stock index returns. The sizes of the identified jumps are also used to construct alternative measures of the signed-jump variation.

5.1 Using IV measures robust to jumps in finite samples

One possible drawback of the BV_t estimator used in the previous section, is that the jumps only vanish at rate $\sqrt{N}$, which means that the estimates of BV_t may be biased in the presence of large jumps, especially when using small intraday samples. To overcome this problem, Barndorff-Nielsen et al. (2006) suggested Multipower Variation estimators (measures) of IV_t (denoted as MPV) while Andersen et al. (2012) suggested more efficient and robust in finite samples nonparametric estimators of IV than the MPV, called the nearest neighbor truncation estimators (NNT). One of these estimators is $MinRV_t$. The defiinition of this estimator is given below:

$$MinRV_t = \frac{\pi}{\pi - 2} \frac{N}{N-1} \sum_{i=2}^{N} \min(|r_{t,i}|, |r_{t,i-1}|)^2, \tag{27}$$

where min(.) is the minimum operator. This estimator can eliminate stock returns with large jumps. It converges to IV_t, as $N \to \infty$.

In this section, we investigate whether the results of our SVAR model analysis, presented in Section 4.2, are robust to alternative nonparametric estimators of IV_t, given by $MinRV_t$. This will be examined by employing $MinRV_t$, instead of BV_t, in the estimation of the model. As before, note that in the estimation we use the logarithmic transformation of $MinRV_t$, i.e., $y_{v,t} = \log(MinRV_t)$, which yields values of $y_{v,t}$ which are closer to the normal distribution, compared to $MinRV_t$. For reasons of space, we present results only for the trivariate case $y_t = (y_{r,t}, y_{v,t}, y_{j,t})'$. Table 3 presents the median of the estimates of the $VDF_{k,t+h}$, for all series of vector $y_{k,t}$, for $k = \{r, v, j\}$, together with their 68% symmetric credible sets in shadow areas, while Figure 2 presents the median of the $IRF_{k,t+h}$ together with their 68% symmetric credible sets.

The results of Figure 2 and Table 3 are consistent with those of our previous analysis of Section 4.2, employing series BV_t as a measure of IV_t. The median values of the reported estimates of $IRF_{k,t+h}$ and $VDF_{k,t+h}$ (for $k \in \{r, v, j\}$), together with the reported credible sets are very close to those reported in Table 2B and Figure 1B, respectively.[5] The close relationship of the results between the cases that $MinRV_t$ and BV_t are used as measures of IV_t can be obviously attributed to the high correlation between the two series. In our sample, this is found to be higher than 95% which also means that BV_t constitutes a quite robust measure to large jumps.

5.2 Using jump-adjusted returns and signed-jump variation metrics identified by intraday stock returns

In this section, we carry out the SVAR analysis by replacing the return series r_t with a jump-adjusted stock index return series, henceforth denoted as r_t^*. This may help to better distinguish the effects of the structural return shock u_r from the jump shock u_j on $y_{k,t}$, $k \in \{r, v, j\}$, as r_t^* is driven by ordinary stock returns shocks and, thus, is net of jumps. To identify from the data the size of jumps and calculate the adjusted return series r_t^*, we follow recent literature which relies on a jump detection testing procedure using intraday data (see, e.g., Andersen, Bollerslev, and Dobrev (2007), Lee and Mykland (2008), Andersen et al. (2010) and more recently Audrino and Hu (2016)). Next, we describe this procedure, briefly, and we introduce all the necessary notation.

Let i_s $(s = 1, 2, ..., N_t)$ be the exact time interval of the intraday return associated with the i-th jump, where N_t denotes the total number of jumps, during day t. Note that now we assume that N_t changes over t. At

[5] Note that we also find similar results to those of Table 2B and Figure 1B if we use the following estimator of IV_t : $MedRV_t = \frac{\pi}{6-4\sqrt{3}+1} \frac{n}{n-2} \sum_{i=3}^{n} med(|r_{t,i}|, |r_{t,i-1}|, |r_{t,i-2}|)^2$ where $med(.)$ is the median operator, suggested also by Andersen et al. (2012).

any intraday time interval, the size of the i-th jump is calculated as follows:

$$\kappa_{t,i} = r_{t,i_s}\mathcal{I}\left(\frac{|Z_{t,i_s}| - c}{d} > \xi\right), \; s = 1, 2, ..., S_t \text{ and } t = 1, 2, ..., T \tag{28}$$

where $\mathcal{I}(\cdot)$ is an index function taking values one and zero, and $Z_{t,i}$ is a test statistic calculated by intraday returns and spot volatility, where c and d are scale parameters, defined in Andersen, Bollerslev, and Dobrev (2007) and Lee and Mykland (2008). In (28), ξ constitutes a critical (threshold) value above which the statistic $\frac{|Z_{t,i}|-c}{d}$ rejects the null hypothesis of no jump and accepts its alternative of the presence of a jump, at i_s. The significance level of ξ is often set at 5%. Based on (28), we can identify the jump size per day as $\sum_{i=1}^{N_t} \kappa_{t,i}$ and define the t-day jump adjusted stock index return as follows:

$$r_t^* = r_t - \sum_{i=1}^{N_t} \kappa_{t,i}, \quad \text{for } t = 1, 2, ..., T. \tag{29}$$

Having obtained the jump size $\kappa_{t,i}$, next we can directly estimate the jump variation (JV) as:

$$JV_t^* = \sum_{i=1}^{N_t} JV_{t,i}^*, \tag{30}$$

and the continuous component of quadratic variation, the integrated variance (IV), as:

$$IV_t^* = RV_t - JV_t^*, \tag{31}$$

where $JV_{t,i}^* = \mathcal{I}\left(k_{t,i} \neq 0\right)\left(\kappa_{t,i}^2 - \frac{1}{M-N_t} \sum\limits_{w \in \{1,...,M\} \backslash i_1 ... i_{N_t}} r_{t,w}^2\right)$ is a measure which gives the contribution of the i-th jump into the total JV_t on day t. This is calculated as the difference between the square of $k_{t,i}$, detected by the above inference procedure, and the average of the $M - N_t$ squared returns that are not associated with jump(s).

Relying on the estimates of $k_{t,i}$, we can also calculate a measure of the signed-jump variation (denoted as

$RSJV_t^*$) as follows:

$$RSJV_t^* = RSJV_t^{*,+} - RSJV_t^{*,-} \tag{32}$$

where $RSJV_t^{*,+} = \sum_{i=1}^{N_t} RSJV_{t,i}^{*,+}$, with $SJV_{t,i}^{*,+} = \mathcal{I}\left(\kappa_{t,i} > 0\right)\left(\kappa_{t,i}^2 - \frac{1}{M-N_t}\sum_{w\in\{1,\ldots,M\}\setminus i_1\ldots i_{N_t}} r_{t,w}^2\right)$, and $RSJV_t^{*,-} = \sum_{i=1}^{N_t} RSJV_{t,i}^{*,-}$, with $RSJV_{t,i}^{*,-} = \mathcal{I}\left(\kappa_{t,i} < 0\right)\left(\kappa_{t,i}^2 - \frac{1}{M-N_t}\sum_{w\in\{1,\ldots,M\}\setminus i_1\ldots i_{N_t}} r_{t,w}^2\right)$.

The above jump-adjusted variables, namely r_t^*, IV_t^* and $RSJV_t^*$, can be employed to check the robustness of our SVAR analysis, presented in Section 4.

It is worth noting at this point that, although the use of these variables is expected to improve the performance of the identification procedure, as noted before, this might not be without cost. Since the values of series r_t^*, IV_t^* and $RSJV_t^*$ depend on the inference procedure detecting jump sizes $\kappa_{t,i}$, the estimation results of the SVAR model may critically depend on the performance of this procedure and, in particular, on its type I and II errors. This is the main motivation of employing non-parametric measures of IV_t and SJV_t (like BV_t and $RSJV_t$) in studies using realized measures of volatilities and jump variation (see also Bollerslev et al. (2009)). To see if the above errors can seriously affect our results, we will report descriptive statistics of the differences between series BV_t and IV_t^*, and between $RSJV_t$ and $RSJV_t^*$ which can judge the magnitude and distribution features of these errors (these differences are presented in Figure 3).

Table 4 (see Panel A) presents descriptive statistics of the jump-adjusted variables r_t^*, IV_t^* and $RSJV_t^*$ and their transformations used in our SVAR analysis, now defined as $y_{r,t} = r_t^*/\sqrt{IV_t^*}$, $y_{v,t} = \log(IV_t^*)$ and $y_{j,t} = RSJV_t^*/RV_t$. The descriptive statistics of the differences between BV_t and IV_t^*, and between $RSJV_t$ and $RSJV_t^*$ are given in Panel B of the table. Yet, in Panel B of the table we also present descriptive statistics of the difference between the unadjusted and jump-adjusted stock return series, i.e., $r_t - r_t^*$. Recall that this difference gives the jump size per day $\sum_{i=1}^{N_t} \kappa_{t,i}$. A plot of $r_t - r_t^*$ is presented in Figure 3.

A general conclusion that can be drawn from the inspection of the graphs of Figure 3 and the results of Table 4 is that IV_t^* and $RSJV_t^*$ are closely related to their non-parametric measures BV_t and $RSJV_t$, respectively. The differences between BV_t and IV_t^*, and between $RSJV_t$ and $RSJV_t^*$ are very small and have a standard deviation which is very close to zero. The positive values of skewness and excess kurtosis reported in the table (see Panel B) for $BV_t - IV_t^*$ and $RSJV_t - RSJV_t^*$ can be attributed to the fact that, during our sample, there is a non negligible mass of values of the jump size per day, i.e., $\sum_{i=1}^{N_t} k_{t,i}$, which take zero-values as a result of the inference jump detection procedure adopted. This mass tends to underestimate IV_t^* and $RSJV_t^*$, compared to BV_t and $RSJV_t$, respectively. The close relationship of IV_t^* and $RSJV_t^*$ to their unadjusted measures BV_t and $RSJV_t$ can be also justified by the high values of the correlation coefficients between them, which are found to be 98% and 76%, respectively. Taking together these results indicate that possible inference errors in detecting jumps may not influence importantly the analysis based on the jump-adjusted variables.

Another interesting conclusion that can be drawn from the figure and table concerns the difference between the jump-adjusted and unadjusted return series, i.e., $r_t - r_t^*$. First note that correlation coefficient between these two series is 90%, which means that the presence of jumps does not dominate stock market return variation. The descriptive statistics reported in the table (see Panel B) indicate that, over our sample, both the mean and median of $r_t - r_t^*$ are very close to zero, which implies a zero total size of the jumps in our sample. However, the negative values of the skewness coefficient of $r_t - r_t^*$, combined with the high value of the excess kurtosis coefficient imply that there is a considerable probability mass of jumps with negative signs in the sample. This can be obviously contributed to the financial crises occurred during our sample (e.g., the Mexican and Argentinian Crises of years 1994-1995, the East Asian and Russian crises of years 1997-1998, the dot-com crisis of 1998-2000 and the recent global financial crises of 2008-2009). We have found that our sample estimates of $\sum_{i=1}^{N_t} \kappa_{t,i}$ are closely related to the dates of the above crises. Yet, another interesting feature about series $r_t - r_t^*$ is that it is serially correlated. This is supported by our findings concerning the Ljung-Box (LB) test statistic, reported in the table, which rejects the null hypothesis of no serial correlation. In fact, we have found that $r_t - r_t^*$ can be best fit with the MA(1) process: $r_t - r_t^* = \varepsilon_t - 0.045\varepsilon_{t-1}$ with GARCH(1,1) effects.

Finally, as in Table 1, the results of Table 4 (see Panel A) demonstrate that the scale transformations of the jump-adjusted variables (i.e., $y_{r,t} = r_t^*/\sqrt{IV_t^*}$, $y_{v,t} = \log(IV_t^*)$ and $y_{j,t} = RSJV_t^*/RV_t$) are closer to the normal distribution (in terms of skewness and excess kurtosis coefficients), compared to the unadjusted variables, and thus we use these variables in the estimation of the SVAR model. Note that, with the exception of $y_{j,t}$ which is fat-tailed, the other two series $y_{r,t} = r_t^*/\sqrt{IV_t^*}$, $y_{v,t} = \log(IV_t^*)$ have both level of skewness and excess kurtosiswhich correspond to those of the unadjusted series used in the analysis of Section 4, i.e., $y_{r,t} = r_t/\sqrt{RV_t}$ and $y_{v,t} = \log(BV_t)$.

The results of our SVAR empirical analysis based on the jump-adjusted series $y_{r,t} = r_t^*/\sqrt{IV_t^*}$, $y_{v,t} = \log(IV_t^*)$ and $y_{j,t} = RSJV_t^*/RV_t$ are presented in Table 5 and Figure 4. Table 5 presents the median of $VDF_{k,t+h}$ estimates, while Figure 4 presents the median of $IRF_{k,t+h}$ estimates. As before, both the table and figure present the 68% symmetric credible sets of $IRF_{k,t+h}$ and $VDF_{k,t+h}$ estimates in brackets and shaded areas, respectively. The results of the table and figure are consistent with those of Section 4.2, based on the jump-unadjusted series. They clearly demonstrate that the leverage effects are more persistent and important in long-term than the volatility feedback ones. They also emphasize that there exist significant and persistent leverage effects on volatility series $y_{v,t+h}$ which are driven by jump effects, captured by signed-jump variation shocks $u_{j,t}$. These effects are equally important to those caused by ordinary stock return shocks $u_{r,t}$ on $y_{v,t+h}$.

Our results show that there are only some very small quantitative differences between the results based on the jump-adjusted return series and those of Section 4.2, based on their unadjusted counterparts. These mainly concern the magnitude of the effects of a structural stock return shock $u_{r,t}$ on the path of the signed-jump variation series $y_{j,t+h}$ and, inversely, of $u_{j,t}$ on $y_{r,t+h}$. As shown by the $IRF_{k,t+h}$ estimates, both of these effects now seem to be smaller and not so important as before (see Section 4.2). Furthermore, the distribution of these effects are more asymmetric and kurtotic than before.[6]

[6]The asymmetry and excess kurtosis of the posterior distribution of the estimates of $IRF_{j,t+h}$ with respect to $u_{r,t}$ may be associated with the distribution properties of series $y_{j,t} = RSJV_t^*/RV_t$, especially, its excess kurtosis implying substantially deviations from the normal distribution, compared to the jump-unadjusted series $RSJV_t/RV_t$. These properties of $y_{j,t} = RSJV_t^*/RV_t$ may also explain the smaller contribution of structural shock $u_{r,t}$ in interpreting $VDF_{j,t+h}$ and the bigger contribution of $u_{j,t}$ in interpreting $VDF_{j,t+h}$, as well as the wider density credible sets of $VDF_{j,t+h}$ found under the jump-adjusted stock returns, compared to the unadjusted ones.

6 Conclusions

In this paper, we investigate the relative importance of the leverage and volatility feedback effects in asset pricing, as well as the influence of jumps on them. This is done using a Structural Vector Autoregressive (SVAR) framework with sign restrictions. To measure realized volatility and jumps, we use model-free (non-parametric) estimators based on high-frequency (intraday) data of the S&P500 stock market index. We rely on a signed-jump variation estimator, instead of the traditional jump variation measure to capture jump effects. This estimator can help to better evaluate the influence of stock market jumps on the leverage and volatility feedback effects, as it captures asymmetries in sign and size.

The sign identification scheme allows us to impose weaker conditions on the structural inter-dependencies among stock returns, volatility and price jumps, as well as their associated structural shocks compared to traditional identification schemes, like the Cholesky decomposition. This scheme can allow for two-directional causation among the above variables which can help to distinguish the volatility feedback effects from the leverage ones, and to identify the impact of jumps on them.

We provide a number of new results which enhance our knowledge about the effects of leverage and volatility feedback on asset prices. Firstly, we show that the leverage effects are more persistent and prevalent in long-term than the volatility feedback effects. The leverage effects tend to last for many days ahead and have a substantial long-run effect on stock market volatility. In contrast, shocks in volatility have only immediate effects on stock returns, which mainly concern the current day. These effects are found to adjust at once stock prices, by a significant amount which reflects risk premium effects driven by volatility. Secondly, we provide clear cut evidence that responsible for the financial leverage effects is not only ordinary shocks (news) of the stock market index return, but also signed-jump variation shocks related to jumps in the stock market return. We have found that these shocks can cause substantial and persistent effects on the current and future path of stock market volatility of equal importance to ordinary stock market return shocks. Finally, we show that the signed-jump variation shocks are very short lived (i.e., for a couple of days). The above results are robust to nearest neighbor truncation estimators of integrated variance and to using jump-adjusted measures of the stock index return to carry out the SVAR analysis.

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Table 1: Descriptive Statistics.

Series	Mean	Std Dev	Median	Sk	Kurt	$AR(1)$	$LB(1)$	$LB(5)$
r	0.0003	0.0119	0.0006	-0.2499	8.1360	-0.06	22.59	46.57
$r/\sqrt{RV}$	0.1287	1.1670	0.0975	0.0624	-0.3750	-0.02	3.36	14.94
BP	0.0001	0.0002	0	10.99	189.6710	0.71	2833.19	11429.24
$\log(BP)$	-10.0536	1.0522	-10.1114	0.4442	0.4869	0.81	3710.75	15513.50
$RSJV$	0	0.0001	0	-2.7789	128.3060	-0.11	66.81	144.06
$RSJV/RV$	0.0322	0.3502	0.0114	0.2029	-0.3980	-0.04	8.89	30.86

Notes: The table presents descriptive statistics of the variables employed in our empirical analysis. It reports the mean, standard deviation (Std Dev), median, skewness (Sk) and excess kurtosis (Kurt) coefficients. $AR(1)$ is the first order sample autocorrelation coefficient. $LB(1)$ and $LB(5)$ give the values of the Ljung-Box test statistic at lags 1 and 5. The Ljung-Box test critical values for one lag, at 5% and 10% significance level are 3.84 and 2.70, respectively. The Ljung-Box test critical values for 5 lags, at 5% and 10% significance level are 11.07 and 9.23, respectively.

Table 2A: Variance Decomposition Functions ($VDF_{k,t+h}$): $y_{r,t} = r_t/\sqrt{RV_t}, y_{v,t} = \log(BV_t)$.

(h)	1	25	50	100	200
Contribution of $u_{r,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v\}$					
$y_{r,t+h}$	0.8702	0.8694	0.8692	0.8692	0.8692
	[0.8617, 0.8781]	[0.8608, 0.8773]	[0.8606, 0.8772]	[0.8606, 0.8771]	[0.8606, 0.8771]
$y_{v,t+h}$	0.0000	0.0731	0.0734	0.0735	0.0735
	[0.0000, 0.0000]	[0.0618, 0.0850]	[0.0618, 0.0858]	[0.0618, 0.0859]	[0.0618, 0.0859]
Contribution of $u_{v,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v\}$					
$y_{r,t+h}$	0.1298	0.1306	0.1308	0.1308	0.1308
	[0.1219, 0.1383]	[0.1227, 0.1392]	[0.1228, 0.1394]	[0.1229, 0.1394]	[0.1229, 0.1394]
$y_{v,t+h}$	1.0000	0.9269	0.9266	0.9265	0.9265
	[1.0000, 1.0000]	[0.9150, 0.9382]	[0.9142, 0.9382]	[0.9141, 0.9382]	[0.9141, 0.9382]

Notes: The table presents the median values of the variance decomposition function $VDF_{k,t+h}$, $k = \{r, v\}$, of the forecast errors of variables $y_{r,t+h}$ and $y_{v,t+h}$, h -periods ahead, with respect to structural shocks $u_{r,t}$ and $u_{v,t}$. The variables of vector y_t are given as follows: $y_{r,t} = r_t/\sqrt{RV_t}, y_{v,t} = \log(BV_t)$. The 68% central credible sets of $VDF_{k,t+h}$ are given in brackets.

Table 2B: Variance Decomposition Functions ($VDF_{k,t+h}$): $y_{r,t} = r_t/\sqrt{RV_t}, y_{v,t} = \log(BV_t), y_{j,t} = RSJV_t/RV_t$.

(h)	1	25	50	100	200
Contribution of $u_{r,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
$y_{r,t+h}$	0.6094	0.6083	0.6082	0.6082	0.6082
	[0.1081, 0.8519]	[0.1102, 0.8492]	[0.1102, 0.8490]	[0.1102, 0.8490]	[0.1102, 0.8490]
$y_{v,t+h}$	0.0000	0.0490	0.0493	0.0493	0.0493
	[0.0000, 0.0000]	[0.0093, 0.0712]	[0.0093, 0.0720]	[0.0092, 0.0721]	[0.0092, 0.0721]
$y_{j,t+h}$	0.5333	0.5335	0.5335	0.5335	0.5335
	[0.0910, 0.8320]	[0.0988, 0.8235]	[0.0988, 0.8235]	[0.0988, 0.8235]	[0.0988, 0.8235]
Contribution of $u_{v,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
$y_{r,t+h}$	0.0898	0.0907	0.0908	0.0908	0.0908
	[0.0103, 0.5912]	[0.0120, 0.5898]	[0.0121, 0.5898]	[0.0121, 0.5898]	[0.0121, 0.5898]
$y_{v,t+h}$	0.4147	0.3693	0.3688	0.3687	0.3687
	[0.0286, 0.9599]	[0.0942, 0.8372]	[0.0951, 0.8353]	[0.0952, 0.8350]	[0.0952, 0.8350]
$y_{j,t+h}$	0.0820	0.0838	0.0838	0.0838	0.0838
	[0.0089, 0.5890]	[0.0132, 0.5869]	[0.0133, 0.5869]	[0.0133, 0.5869]	[0.0133, 0.5869]
Contribution of $u_{j,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
$y_{r,t+h}$	0.1111	0.1117	0.1118	0.1118	0.1118
	[0.0237, 0.6172]	[0.0251, 0.6154]	[0.0252, 0.6154]	[0.0252, 0.6154]	[0.0252, 0.6154]
$y_{v,t+h}$	0.5853	0.5648	0.5659	0.5657	0.5657
	[0.0401, 0.9714]	[0.1287, 0.8653]	[0.1303, 0.8642]	[0.1305, 0.8640]	[0.1305, 0.8640]
$y_{j,t+h}$	0.1441	0.1453	0.1453	0.1453	0.1453
	[0.0221, 0.6971]	[0.0257, 0.6903]	[0.0257, 0.6903]	[0.0257, 0.6903]	[0.0257, 0.6903]

Notes: The table presents the median values of the variance decomposition function $VDF_{k,t+h}$ of the forecast errors of variables $y_{k,t+h}$, $k = \{r, v, j\}$, h -periods ahead, with respect to structural shocks $u_{r,t}, u_{v,t}$ and $u_{j,t}$. The variables of vector y_t are given as follows: $y_{r,t} = r_t/\sqrt{RV_t}, y_{v,t} = \log(BV_t), y_{j,t} = RSJV_t/RV_t$. The 68% central credible sets of $VDF_{k,t+h}$ are given in brackets. The identification scheme assumed is given by eq.(10).

Table 3: Variance Decomposition Functions ($VDF_{k,t+h}$): $y_{r,t} = r_t/\sqrt{RV_t}, y_{v,t} = \log(MinRV_t), y_{j,t} = RSJV_t/RV_t$

(h)	1	25	50	100	200
Contribution of $u_{r,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
$y_{r,t+h}$	0.6147	0.6137	0.6137	0.6136	0.6136
	[0.1105, 0.8547]	[0.1123, 0.8522]	[0.1123, 0.8520]	[0.1123, 0.8520]	[0.1123, 0.8520]
$y_{v,t+h}$	0.0000	0.0438	0.0441	0.0441	0.0441
	[0.0000, 0.0000]	[0.0084, 0.0639]	[0.0084, 0.0646]	[0.0084, 0.0647]	[0.0084, 0.0647]
$y_{j,t+h}$	0.5321	0.5334	0.5334	0.5334	0.5334
	[0.0898, 0.8274]	[0.0978, 0.8193]	[0.0978, 0.8193]	[0.0978, 0.8193]	[0.0978, 0.8193]
Contribution of $u_{v,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
$y_{r,t+h}$	0.0876	0.0886	0.0887	0.0887	0.0887
	[0.0103, 0.5764]	[0.0119, 0.5748]	[0.0119, 0.5747]	[0.0119, 0.5747]	[0.0119, 0.5747]
$y_{v,t+h}$	0.4078	0.3714	0.3709	0.3710	0.3710
	[0.0271, 0.9617]	[0.0882, 0.8503]	[0.0891, 0.8485]	[0.0892, 0.8483]	[0.0892, 0.8483]
$y_{j,t+h}$	0.0832	0.0848	0.0848	0.0848	0.0848
	[0.0089, 0.5870]	[0.0133, 0.5828]	[0.0133, 0.5828]	[0.0133, 0.5828]	[0.0133, 0.5828]
Contribution of $u_{j,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
$y_{r,t+h}$	0.1102	0.1108	0.1108	0.1109	0.1109
	[0.0232, 0.6164]	[0.0245, 0.6152]	[0.0246, 0.6151]	[0.0246, 0.6151]	[0.0246, 0.6151]
$y_{v,t+h}$	0.5922	0.5693	0.5690	0.5690	0.5690
	[0.0383, 0.9729]	[0.1211, 0.8757]	[0.1225, 0.8744]	[0.1227, 0.8743]	[0.1227, 0.8743]
$y_{j,t+h}$	0.1486	0.1493	0.1493	0.1493	0.1493
	[0.0239,0.7027]	[0.0273, 0.6962]	[0.0273, 0.6962]	[0.0273, 0.6962]	[0.0273, 0.6962]

Notes: The table presents the median values of the variance decomposition function $VDF_{k,t+h}$ of the forecast errors of variables $y_{k,t+h}$, $k = \{r, v, j\}$, h -periods ahead, with respect to structural shocks $u_{r,t}, u_{v,t}$ and $u_{j,t}$. The variables of vector y_t are given as follows: $y_{r,t} = r_t/\sqrt{RV_t}, y_{v,t} = \log(MinRV_t), y_{j,t} = RSJV_t/RV_t$. The 68% central credible sets of $VDF_{k,t+h}$ are given in brackets. The identification scheme assumed is given by eq. (10).

Table 4: Descriptive Statistics for the jump-adjusted series

Panel A: Descriptive statistics for r_t^*, IV_t^* and $RSJV_t^*$ and their transformations								
Series	Mean	Std Dev	Median	Sk	Kurt	$AR(1)$	$LB(1)$	$LB(5)$
r^*	0.0002	0.0101	0.0006	-0.1835	9.0767	-0.06	23.01	51.61
$r^*/\sqrt{IV^*}$	0.1117	1.0871	0.1055	0.0378	-0.3148	-0.02	2.53	14.32
IV^*	0.0001	0.0002	0	10.0286	149.1882	0.80	3570.34	14378.90
$\log(IV^*)$	-9.9790	1.0279	-10.0288	0.4406	0.5019	0.85	4057.36	17249.73
$RSJV^*$	0	0.0001	0	-9.468	339.448	-0.008	0.42	8.22
$RSJV^*/RV$	0.0082	0.2138	0	0.4929	4.8592	-0.02	2.27	15.91
Panel B: Descriptive statistics for $r_t - r_t^*$, $BV_t - IV_t^*$ and $RSJV_t - RSJV_t^*$								
Series	Mean	Std Dev	Median	Sk	Kurt	$AR(1)$	$LB(1)$	$LB(5)$
$r_t - r_t^*$	0	0.005	0.0001	-0.7947	13.6890	-0.04	10.20	19.99
$BV_t - IV_t^*$	0	0.00001	0	3.0567	164.1410	0.10	59.28	160.73
$RSJV_t - RSJV_t^*$	0	0.0001	0	3.4281	157.2029	-0.19	209.48	285.88

Notes: The table presents descriptive statistics of the jump adjusted series r_t^*, IV_t^* and $RSJV_t^*$ and their transformations $r_t^*/\sqrt{IV_t^*}$, $\log(IV_t^*)$ and $RSJV_t^*/RV_t$ used in our SVAR analysis, as well as the following differences between the adjusted and unadjusted series: $r_t - r_t^*$, $BP_t - IV_t^*$ and $RSJV_t - RSJV_t^*$. The table reports the mean, standard deviation (Std Dev), median, skewness (Sk) and excess kurtosis (Kurt) coefficients. $AR(1)$ is the first order sample autocorrelation coefficient. $LB(1)$ and $LB(5)$ give the values of the Ljung-Box test statistic at lags 1 and 5. The Ljung-Box test critical values for one lag, at 5% and 10% significance level are 3.84 and 2.70, respectively. The Ljung-Box test critical values for 5 lags, at 5% and 10% significance level are 11.07 and 9.23, respectively.

Table 5: Variance Decomposition Functions ($VDF_{k,t+h}$): $y_{r,t} = r_t^*/\sqrt{IV_t^*}, y_{v,t} = \log(IV_t^*)$, $y_{j,t} = RSJV_t^*/RV_t$

Contribution of $u_{r,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
(h)	1	25	50	100	200
$y_{r,t+h}$	0.6684	0.6669	0.6669	0.6669	0.6669
	[0.1148, 0.8869]	[0.1159, 0.8848]	[0.1158, 0.8848]	[0.1158, 0.8848]	[0.1158, 0.8848]
$y_{v,t+h}$	0.0000	0.0364	0.0367	0.0367	0.0367
	[0.0000, 0.0000]	[0.0046, 0.0572]	[0.0047, 0.0579]	[0.0047, 0.0579]	[0.0047, 0.0579]
$y_{j,t+h}$	0.2424	0.2429	0.2429	0.2429	0.2429
	[0.0133, 0.8209]	[0.0151, 0.8186]	[0.0151, 0.8186]	[0.0151, 0.8186]	[0.0151, 0.8186]
Contribution of $u_{v,t}$ to the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
(h)	1	25	50	100	200
$y_{r,t+h}$	0.0923	0.0933	0.0933	0.0933	0.0933
	[0.0141, 0.7195]	[0.0153, 0.7179]	[0.0154, 0.7179]	[0.0154, 0.7179]	[0.0154, 0.7179]
$y_{v,t+h}$	0.2024	0.2308	0.2322	0.2324	0.2324
	[0.0135, 0.9491]	[0.0609, 0.8282]	[0.0614, 0.8265]	[0.0614, 0.8263]	[0.0614, 0.8263]
$y_{j.t+h}$	0.1746	0.1750	0.1750	0.1750	0.1750
	[0.0140, 0.6415]	[0.0152, 0.6396]	[0.0152, 0.6396]	[0.0152, 0.6396]	[0.0152, 0.6396]
Contribution of $u_{j,t}$ to the the forecast error variance of $y_{k,t+h}$, $k = \{r, v, j\}$					
(h)	1	25	50	100	200
$y_{r,t+h}$	0.0682	0.0692	0.0693	0.0693	0.0693
	[0.0108, 0.3648]	[0.0126, 0.3633]	[0.0126, 0.3633]	[0.0126, 0.3633]	[0.0126, 0.3633]
$y_{v,t+h}$	0.7976	0.7367	0.7354	0.7353	0.7353
	[0.0509, 0.9865]	[0.1500, 0.9060]	[0.1515, 0.9052]	[0.1517, 0.9051]	[0.1517, 0.9051]
$y_{j,t+h}$	0.2204	0.2213	0.2213	0.2213	0.2213
	[0.0344, 0.8055]	[0.0357, 0.8043]	[0.0357, 0.8043]	[0.0357, 0.8043]	[0.0357, 0.8043]

Notes: The table presents the median values of the variance decomposition function $VDF_{k,t+h}$ of the forecast errors of variables $y_{k,t+h}$, $k = \{r, v, j\}$, h-periods ahead, with respect to structural shocks $u_{r,t}, u_{v,t}$ and $u_{j,t}$. The variables of vector y_t are based on the jump-adjusted stock returns series, i.e., $y_{r,t} = r_t^*/\sqrt{IV_t^*}$, $y_{v,t} = \log(IV_t^*)$ and $y_{j,t} = RSJV_t^*/RV_t$. The 68% central credible sets of $VDF_{k,t+h}$, $k = \{r, v, j\}$, are given in brackets. The identification scheme assumed is given by (10).

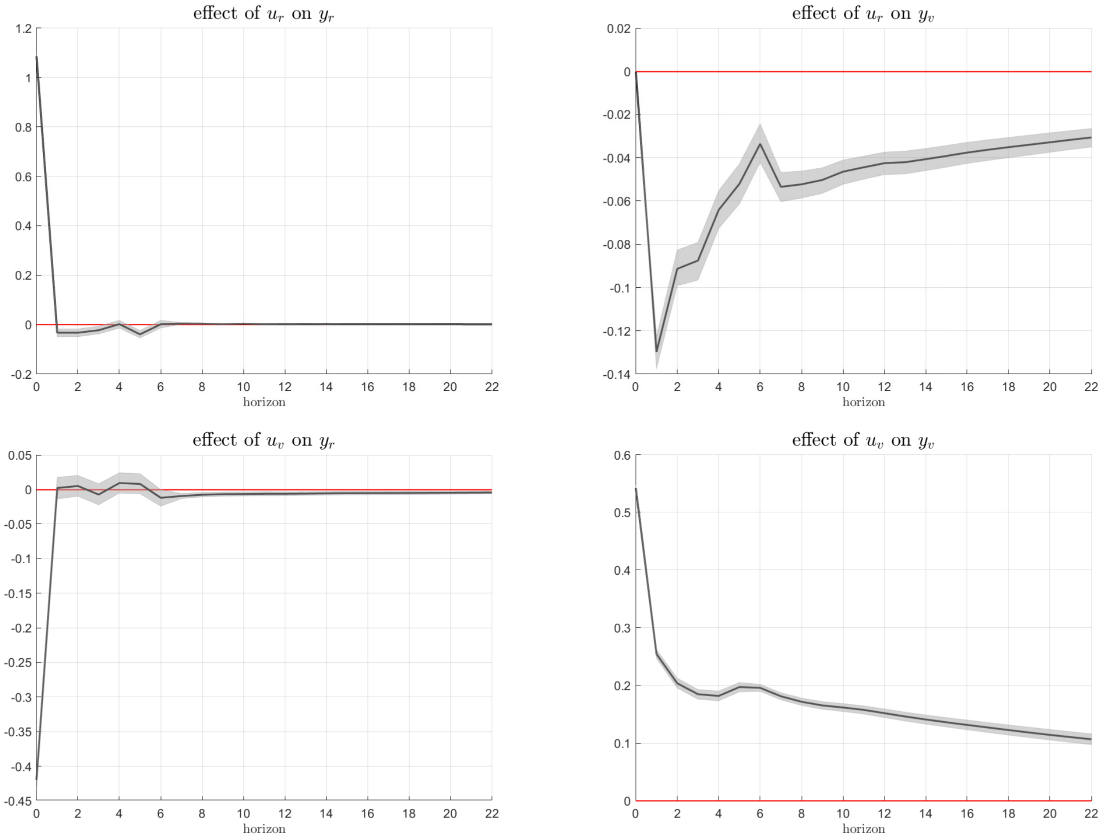

Figure 1A: Impulse Response Functions ($IRF_{k,t+h}$, $k \in \{r, v\}$) corresponding to the bivariate case $y_t = (y_{r,t}, y_{v,t})' = \big(r_t/\sqrt{RV_t}, \log(BV_t)\big)'$ and $u_t = (u_{r,t}, u_{v,t})'$. The innovations in the structural errors are of magnitude equal to one standard deviation. The solid lines depict the point-wise posterior median responses and the shaded area represents the 68 per cent (point-wise) equal-tailed credible sets.

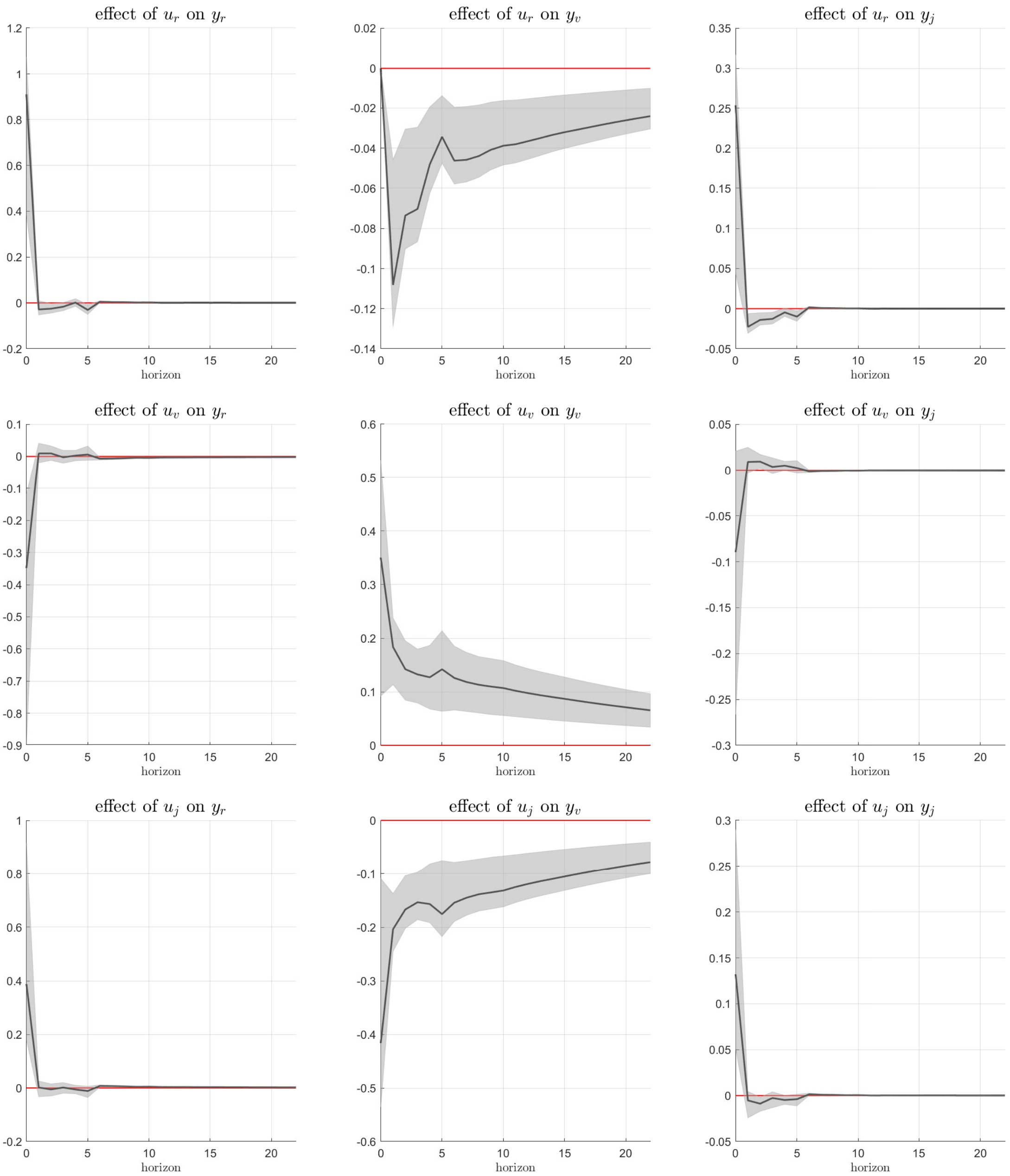

Figure 1B: Impulse Response Functions ($IRF_{k,t+h}$, $k \in \{r, v, j\}$) corresponding to the trivariate case $y_t = (y_{r,t}, y_{v,t}, y_{j,t})' = \left(r_t/\sqrt{RV_t}, \log(BV_t), RSJV_t/RV_t\right)'$ and $u_t = (u_{r,t}, u_{v,t}, u_{j,t})'$. The innovations in the structural errors are of magnitude equal to one standard deviation. The solid lines depict the point-wise posterior median responses and the shaded area represents the 68 per cent (point-wise) equal-tailed credible sets.

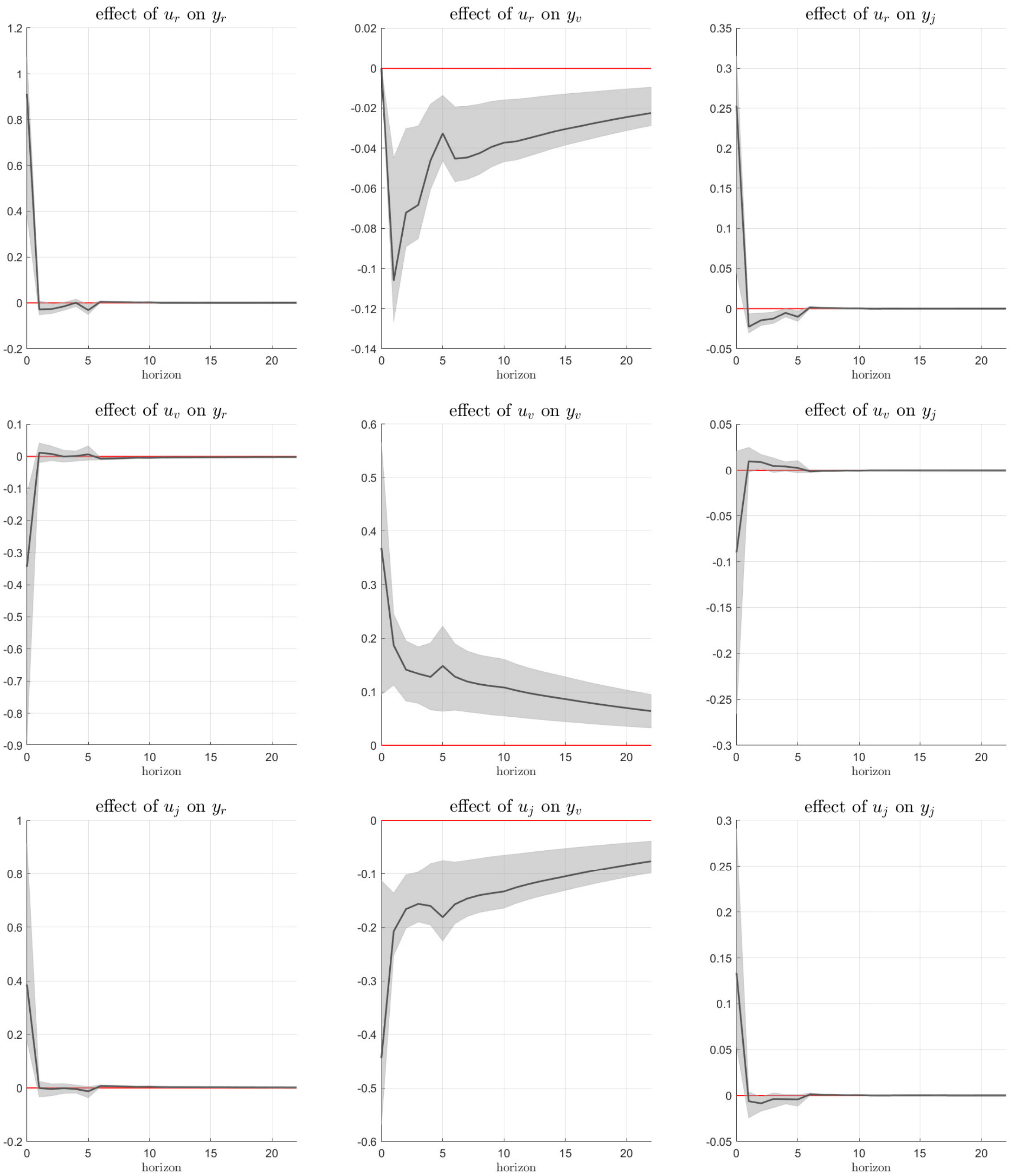

Figure 2: Impulse Response Functions ($IRF_{k,t+h}$, $k \in \{r, v, j\}$) corresponding to the trivariate case $y_t = (y_{rt}, y_{vt}, y_{jt})' = \left(r_t/\sqrt{RV_t}, \log(MinRV_t), RSJV_t/RV_t\right)'$ and $u_t = (u_{r,t}, u_{v,t}, u_{j,t})'$. The innovations in the structural errors are of magnitude equal to one standard deviation. The solid lines depict the point-wise posterior median responses and the shaded area represents the 68 per cent (point-wise) equal-tailed credible sets.

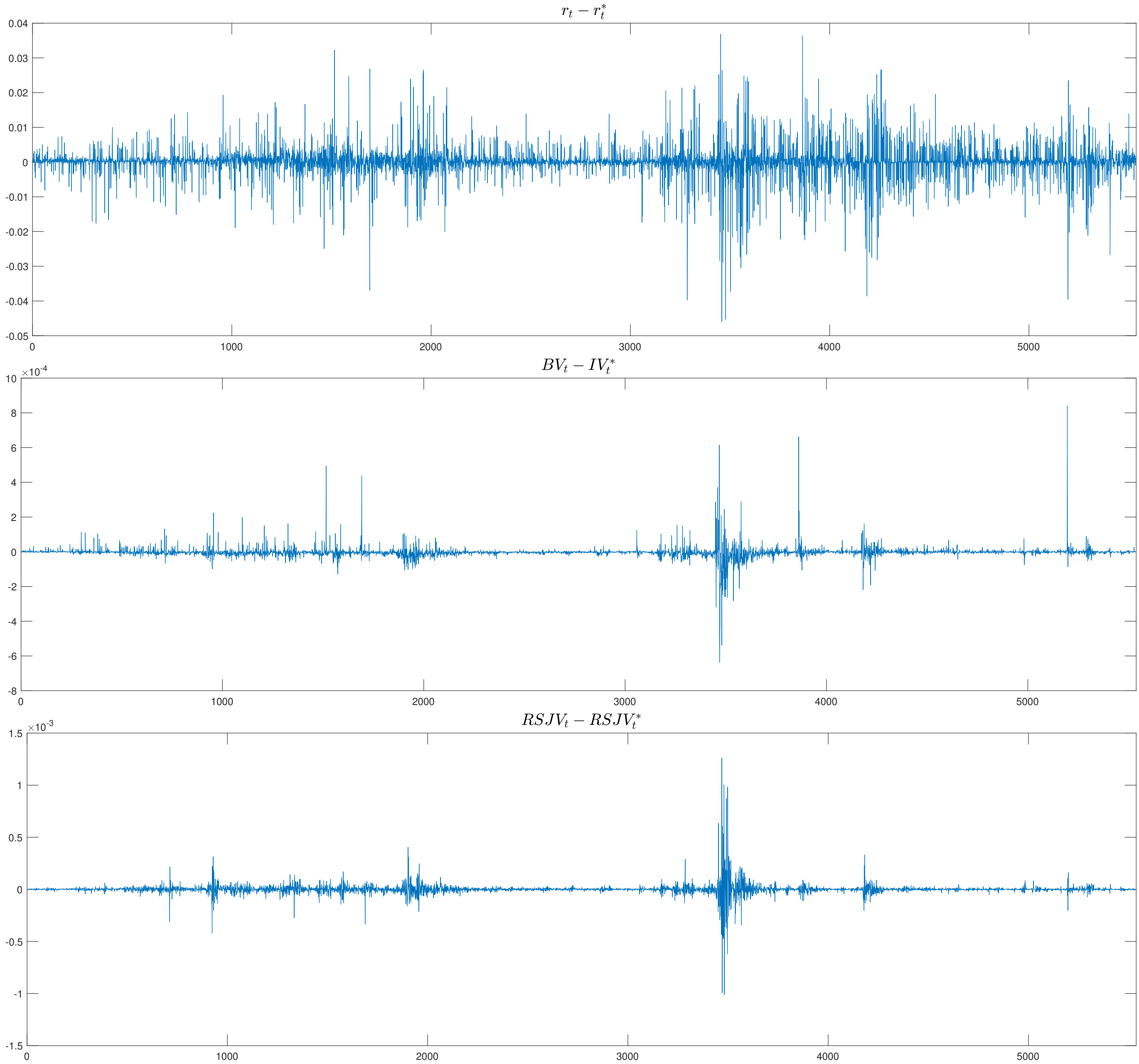

Figure 3: The figure presents plots of the difference between our original variables, i.e., daily returns r_t, bipower variation BV_t and realized signed jump variation $RSJV_t$ and their jump-adjusted counterparts, i.e., r_t^*, IV_t^* and $RSJV_t^*$

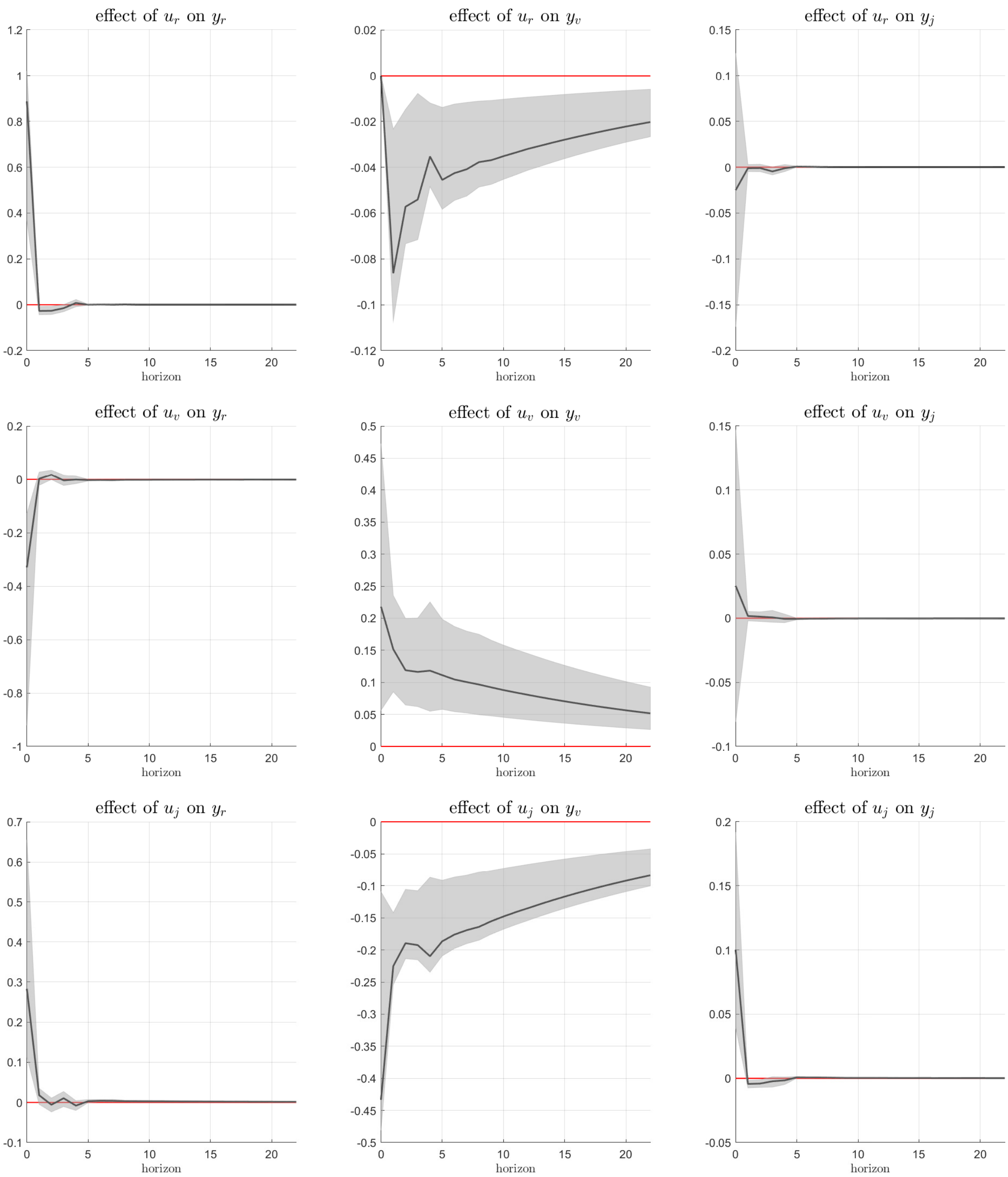

Figure 4: Impulse Response Functions ($IRF_{k,t+h}$, $k \in \{r, v, j\}$) corresponding to the trivariate case $y_t = (y_{rt}, y_{vt}, y_{jt})' = \left(r_t^*/\sqrt{IV_t^*}, \log(IV_t^*), RSJV_t^*/RV_t\right)'$ and $u_t = (u_{r,t}, u_{v,t}, u_{j,t})'$. The innovations in the structural errors are of magnitude equal to one standard deviation. The solid lines depict the point-wise posterior median responses and the shaded area represents the 68 per cent (point-wise) equal-tailed credible sets.

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