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Causality Effect of Returns, Continuous Volatility and Jumps: Evidence from the U.S. and European Index Futures Markets

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Abstract

This study examines the intraday causality between returns, volatility and jumps in the U.S. and European index futures markets during the financial crisis from 2007 to 2009. We examine whether during the financial crisis, the S&P 500, Dow Jones, Nasdaq, FTSE, DAX and CAC index futures markets have a significant impact on the leverage and volatility feedback effects, as well as whether these interactions also occur between returns and jumps. The intraday behavior of 1-min, 5-min and 1-hour index futures returns, volatility and jumps is examined by employing data from the period between January 2003 and May 2014. Thus, the study covers the major upward and downward trends in the market. Our empirical data indicate the main leverage and volatility feedback effects caused by intraday volatility and jump clustering significantly increased after the financial crisis. The effects with different sampling frequencies before, during and after the financial crisis show that jumps have increased the volatility feedback effect, especially when in a 5-min and 60-min sampling frequency is used. These findings have important implications for both policymakers and investors.

Keywords: High-frequency Trading; Leverage Effect; Volatility Feedback Effect; Causality; Jumps
JEL Classification: B26; C58; G15

1. Introduction

Based on a recent asset pricing model applied in option pricing or risk management, previous empirical results indicate that intraday returns and volatility show an inconsistent phenomenon, suggesting that negative intraday return volatility is expected to rise. However, positive intraday return volatility is expected to decline. The literature on the leverage and volatility feedback effects can explain inconsistencies that affect the relationship between equity price volatility and returns (Black, 1976; Christie, 1982; Pindyck 1984).

In a previous study, the relationship between intraday returns and volatility is shown to be affected by the leverage and volatility feedback effects. Barndorff-Nielsen and Shephard (2004) apply the concept of substantive continuous variation to the substantive powers of variation; if the estimates show integral variation under a stochastic volatility model (Integrated Volatility), continuous variation is more consistent than the realized variation (Realized Volatility). This means that if jump differences are included in the stochastic volatility model, the essence and substance of variation between the quadratic variations can be used to measure the jump and continuous variation. The empirical results show statistically significant jumps in high-frequency data. After the second variation method proposed to decompose continuous models with jump terms, Barndorff-Nielsen and Shephard (2005) use a given time series of price data to determine through statistical tests concept these data are a continuous path data. Therefore, this study employs a nonparametric test method to determine whether asset prices show a dependent continuous path. Barndorff-Nielsen and Shephard (2004) define the measure of continuous volatility and propose an asymptotic statistical test to assess the null hypothesis of no jumps in the proposed distribution theory, and they ignore the market microstructure. Furthermore, they adopt the Andersen *et al*. (2007) method to measure jump behavior. Further, this study measures realized volatility and jump clustering in high-frequency data to detect causality among the U.S. market and three European markets before and after the financial crisis.

This paper aims to examine the relationship among intraday returns, volatility and jumps by considering causality measures on high-frequency data to study the interaction among the U.S. and three European index futures markets. In addition, we assess the importance of distinguishing between bipower variation and implied volatility in realized volatility when studying leverage and volatility feedback effects. This evidence can help to verify the exact variable in causality. Furthermore, to compare the strength of the leverage and volatility feedback effects, we adopt vector autoregressive (VAR) models of returns and various measures of volatility using high-frequency data. This study also takes into account jumps in the causality effect during, before and after the financial crisis by employing VAR models.

2. Previous Research

The relationship between returns and volatility has been verified by empirical data. First, returns and volatility have direct causal relationship that can be explained the impact of the relationship between equity prices (Black, 1976). Further, financial leverage is used to explain the negative correlation between with price changes and volatility. In a poor financial situation, the negative shock in equity prices leads to an increase in financial leverage and the probability of bankruptcy, where higher risk leads to higher volatility. This is referred to as the leverage effect, which explains the negative correlation between returns and volatility.

Reverse causality is used to describe volatility that has been properly measured. Expected volatility reflects the required increase in intraday returns, so the need to lower prices now reflects the increase in equity returns at a future date. The leverage effect from financial leverage is also a debt-to-equity ratio as derived from Christie (Christie, 1982). When asset prices are such that a company's financial leverage increases, the probability of bankruptcy and exposure increase, resulting in an increase in expected volatility. Thus, expected intraday return volatility is negatively correlated with the leverage effect (Black, 1976; Christie, 1982).

In addition, the empirical results of Hasanhodzic and Lo (2011) show that for a company that does not have pure equity debt, the leverage effect also exists, leading to strong returns from its equity price volatility.

Another influence on the volatility feedback effect is the time variation described in the risk premium theory. Specifically, expected intraday returns and volatility have a negative impact on the volatility feedback effect; thus, volatility is expected to rise when future returns need to rise, leading to lower current asset prices (Pindyck, 1984; French, Schwert, and Stambaugh, 1987; Campbell and

Hentschel, 1992; Bekaert and Wu, 2000; Bollerslev, Litvinova and Tauchen 2006). Using a measure of the extent of the impact of intraday return on the intraday return volatility leverage effect and the volatility feedback effect, Bekaert and Wu (2000) report the empirical results showing that a significant volatility feedback effect can account for the leverage effect.

In addition, models of the dynamics of asset prices usually include a continuous Brownian motion and discontinuous jumps. Therefore, Aït-Sahalia (2004) attempt to identify the impact of these two factors in price dynamics. The study shows that Brownian motion indeed engenders isolated jump disturbances. The model in this study differs from past models that often use maximum likelihood to estimate a Poisson jump process, and thus results confirm the existence of an infinite number of small amplitude jumps in Brownian motion. In fact, verifying this phenomenon from Brownian motion is difficult; thus, Aït-Sahalia (2004) conducts subsequent tests to determine whether the model with continuous jump factors makes an important contribution.

Aït-Sahalia and Jacod (2009a) define a broad index for jump behavior in several discrete samples, and the results show that the estimates are consistent with related theories. The study shows that even if there is variation caused by Brownian motion in the sample process, these estimators can still be used, so there is an infinite number of tiny inference jumping movements in this process. The application of this method to the pricing of high-frequency data has shown the existence of an infinite number of small jumps in these processes, but they method can also be used to estimate index jumping behavior in these processes. Aït-Sahalia and Jacod (2009b) propose a new test to verify the jumping phenomenon in returns on assets or other discrete processes. If there is no jumping phenomenon, the test statistics will be approaching other known values. This test method is applicable to all semi-martingale dynamic processes, and regardless of whether it is finite or infinite, an arbitrary Blumenthal-Getoor index also applies to jumping phenomenon. Aït-Sahalia and Jacod (2012) adopt a jump factor decomposition and use high-frequency data on asset returns. The decomposition consists of a continuous, small jumps factor and a big jumps factor. They first determine the relative vibration in these factors; then they conduct further detailed analysis of the characteristics of these jump factors. They also integrate the efficiency of the market microstructure in the statistical tests, apply such methods to high-frequency data in order to analyze stocks, transactions and quotes, and compare the data to quantify the characteristics of the estimation process and analyze the results for the affected economies.

The above findings show the importance of considering the jump factor in continuous models. This study may explain the way to test time-series data, and there are an infinite number of small jumps, as high-frequency data are used; thus, the continuous factor of the model can actually be ignored. Aït-Sahalia and Jacod (2010) examine this issue in exploring there is a continuous part in a high-frequency sampling test of a half martingale process. The high-frequency equity asset prices that may engender intraday returns and volatility do not seem to be captured by this phenomenon. Aït-Sahalia, Fan and Li (2013) use an asymptotic distribution to measure the leverage effect of the estimated bias and consecutive days. The measure of the consecutive volatility of the substance of variables and discrete terms is the continuous volatility and discrete jump items of Brownian motion. The measure of each variable with the appropriate bias is the leverage effect.

Moreover, from the stock market, it can be found that the negative impact of the market will spread to the rest of the world. Jumping occurs when the possibility of the occurrence of jumps in other regions has increased. To capture this contagious effect, Aït-Sahalia, Julio and Laeven (2011) show that the negative impact of a stock market will spread to the rest of the world when the probability of the occurrence of jumps in other regions has increased.

Dufour, Garcia and Taamouti (2012) discuss the use of VAR models and show that volatility (RV), implied volatility (IV) and the volatility risk premium are related. The evidence is presented for day-level data; the data show that in the first four hours of a week, a dynamic leverage effect indicates a strong dynamic leverage effect. The authors not that the implied volatility is a measure of the volatility feedback effect and is an important factor. In detecting the dynamic leverage and volatility feedback effects, Bollerslev, Sizova and Tauchen (2012) use nonparametric methods, and the empirical findings show substantive inter-day volatility of returns with the leverage and volatility feedback effects and that they are sustainable. In addition, the time-varying volatility risk explains the expected intraday returns and short-term risk premium.

3. Methodology

In this study, we examine financial markets in the U.S. and European index futures markets, including the S&P 500, Dow Jones, Nasdaq, FTSE, DAX and CAC index futures of high-frequency trading data. Following Barndorff-Nielsen and Shephard (2004) and Aït-Sahalia (2004), we define the measure of continuous volatility, and we use the Aït-Sahalia (2009) method to measure jumping behavior. Further, we use the narrative days of S&P 500 index futures returns, the continuous fluctuation degree and the causal relationship of jumps, and we use VAR models and Granger causality to measure the direction of causality between the variables. We explore the causal relationship between the days of returns, volatility and substantive jump items to measure the impact of the leverage and volatility feedback effects, and we consider the resistance of intraday returns and volatility to realized jumps (RJ).

The logarithmic price of $p(t) := \ln(P(t))$ is the index price or risky asset at time t, and the continuously compounded return is from time t to $t+1$. This belongs to the class of continuous jump diffusion processes.

$$dp(t) = \mu(t)dt + \sigma(t)dw(t) + \kappa(t)dq(t), \quad 0 \le t \le T \tag{1}$$

Where $\mu(\mathrm{t})$ is the drift term and is a continuous and locally bounded variation process, $\sigma(\mathrm{t})$ is the stochastic volatility process, $w(\mathrm{t})$ denotes a standard Brownian motion, and $dq(\mathrm{t})$ is a counting process, in which $dq(\mathrm{t}) = 1$ represents a jump at time t and $dq(\mathrm{t}) = 0$ no jump at time t, with jump intensity $\lambda(\mathrm{t})$ and jump size $\kappa(\mathrm{t})$. The return of the stochastic process is denoted as follow

$$r(t) := \int_0^t \sigma(s)dw(s) + \sum_{0\le s\le t} \kappa(s), \tag{2}$$

Furthermore, the quadratic variation of return from time 0 to t is given by

$$[r,r]_t := \int_0^t \sigma^2(s)ds + \sum_{0\le s\le t} \kappa^2(s) \tag{3}$$

The daily realized volatility is defined as the summation of the corresponding fixed m high-frequency intraday squared returns. The length of the fixed period is defined as $m = 1/\delta$. Let the sampled return be denoted by $r_{t+j/m} = p_{t+j/m} - p_{t+(j-1)/m}$ and the daily return be the summation of the intraday return by $r_{t+1} = \sum_{j=1}^{m} r_{t+j\delta,\delta}$. The daily realized volatility is defined as the summation of the corresponding m intraday squared return, as denoted by

$$RV_{t+1} = \sum_{j=1}^{m} r_{t+j/m}^2 \tag{4}$$

The realized volatility will generally converge uniformly in probability to the quadratic variation as the fixed sampling frequency, δ, at time t. The realized volatility is defined as the summation of the corresponding intraday squared returns

$$RV_{t+1}(\delta) \to \int_t^{t+1} \sigma^2(s)ds + \sum_{t\le s\le t+1} \kappa^2(s) \tag{5}$$

,

In the measurement, the realized power variation can be represented by realized volatility, which is a consistent estimator of the sum of the integrated variance $\int_t^{t+1} \sigma^2(s)ds$ and the jump contribution. Thus, a measure of standardized bipower variation is unaffected by jumps and given by

$$BV_{t+1}(\delta) \rightarrow \int_t^{t+1} \sigma^2(s)ds \tag{6}$$

The measurement of the standardized bipower variation is given by

$$BV_{t+1} = \frac{\pi}{2}\left(\frac{m}{m-1}\right)\sum_{j=2}^{m} \left|r_{t+(j-1)/m}\right|\left|r_{t+j/m}\right| \tag{7}$$

According equation (5), we provide an estimator of the integrated variance that is unaffected by jumps (Barndorff-Nielsen and Shephard, 2006; Huang and Tauchen, 2005; Andersen *et al*. 2007b). The results from equations (5) and (6) then allow the separation of the continuous and discontinuous components of the quadratic variation, isolating the contribution of jumps,

$$J_{t+1} = \sum_{t \le s \le t+1} \kappa^2(s) := RV(\delta) - BV(\delta) \tag{8}$$

In the empirical data, there is the potential to identify very small values in the jump variation that do not represent genuine jumps. The asymptotic distribution alleviates this problem, and the use of such a distribution is consistent with recent literature. Huang and Tauchen (2005) argue that these are more robust measures of the contribution of jumps to the total price, and the relative jumps are identified according to

$$J_{t+1}/RV_{t+1} = \frac{RV_{t+1}(\delta) - BV_{t+1}(\delta)}{RV_{t+1}(\delta)} \tag{9}$$

This test and the jump detection procedure is conducted using staggered measures of realized bipower variation (Andersen *et al*., 2007; Andersen *et al*., 2008)

Andersen *et al*. (2007) provide statistically significant jumps, which are identified according to

$$Z_{1,t+1} = \frac{(RV_{t+1} - BV_{t+1})/RV_{t+1}}{\sqrt{(\upsilon_{bb} - \upsilon_{qq})\frac{1}{m}TP_{t+1}}} \tag{10}$$

where υ_{qq} is 2 and $\upsilon_{bb} = (\pi/2)^2 + \pi - 3$, with tripower quarticity defined as

$$TP_{t+1} = \mu_{4/3}^{-3}\left(\frac{m}{m-2}\right)\sum_{j=3}^{m} \left|r_{t+1,j-2}\right|^{4/3}\left|r_{t+1,j-1}\right|^{4/3}\left|r_{t+1,j}\right|^{4/3} \tag{11}$$

using $\mu_{4/3} = 2^{2/3}\Gamma\left(\frac{7}{6}\right)\Gamma\left(\frac{1}{2}\right) \approx 0.8309$. The significant jumps are identified through the realization of $Z_{1,t+1} \xrightarrow{D} N(0,1)$ in excess of the 99.9% critical value $\Phi_{1-\alpha}$

$$RJ_{t+1}(Z) \equiv I[Z_{1,t+1} > \Phi_{1-\alpha}] \cdot [RV_{t+1} - BV_{t+1}] \tag{12}$$

This study aims to define the relationship among intraday returns, realized volatility and realized jumps to measure the strength of the leverage and volatility feedback effects in high-frequency data. These effects are quantified in the context of a Vector Autoregressive (VAR) model. The asymmetric volatility phenomenon can be the result of causality from returns to volatility (leverage effect) and from volatility to returns (volatility feedback effect), and we further investigate the causality from returns to jumps and from jumps to return.

The joint process of returns and the logarithmic volatility follows an autoregressive linear model:

$$\begin{bmatrix} r_t \\ \sigma_t^2 \end{bmatrix} = \begin{bmatrix} \mu_r \\ \mu_\sigma \end{bmatrix} + \sum_{j=1}^{p} \begin{bmatrix} \Phi_{11j} & \Phi_{12j} \\ \Phi_{12j} & \Phi_{22j} \end{bmatrix} \begin{bmatrix} r_{t-j} \\ \sigma_{t-j}^2 \end{bmatrix} + \begin{bmatrix} u_t^r \\ u_t^\sigma \end{bmatrix} \tag{13}$$

with $E[u_t] = 0$ and $Var[u_t] = \sum_u$, $u_t = (u_t^r, u_t^\sigma)'$, where r_t is the mean of the intraday return and σ_t^2 is the true volatility measured by the realized volatility RV_t, or the bipower variation BV_t. We also incorporate the realized jump into the VAR model.

4. Empirical Results

This study focuses on realized volatility and jump risk as applied to measure the leverage and volatility feedback effects. For this purpose, we focus on the U.S. and European index futures markets, which include the S&P 500, Dow Jones, Nasdaq, FTSE(UK), DAX(Germany) and CAC(France) index futures of high-frequency trading data. We measure the causality in intraday returns, realized volatility, bipower variation and realized jumps among the U.S. and three European index futures markets.

In this study, we draw data on the S&P 500, Dow Jones, Nasdaq, FTSE, DAX and CAC index futures markets from the Tick Data Source database. The sample period is from January 2003 to May 2014, and a total of 2,888 trading days are examined. Further, the sample is divided into three periods: the pre-financial crisis period, January 2003 to July 2007; the financial crisis period, August 2007 to June 2009; and the post-financial crisis period, July 2009 to May 2014. The high-frequency trading data are presented as the days of the transaction price in intraday trading hours daily from 8:00 to 15:15, where the transaction prices are prone to high volatility at opening of the first transaction. Therefore, Bollerslev, Litvinova, and Tauchen (2006) suggest removing the first intraday return data to construct a substantive volatility measure. In this study, we use a sampling frequency of intraday data at 1 min, 5 min and 60 min to set a fixed distance when calculating intraday returns, yielding 495, 99 and 8 observations of intraday returns, respectively.

Descriptive statistics for the S&P 500 index futures intraday returns and observable variables are presented in Table 1. In Table 1, the intraday return is negative during 2003 to 2014. In addition, the jump is decomposed by the difference between the realized volatility(RV) and bipower variation(BV). In Andersen, Bollerslev, Diebold (2001), volatility is measured by using high-frequency data, which can be converted into approximately normally distributed variables by logarithmically transforming the variables. Dufour, Garcia, Taamouti (2012) argue that in empirically measuring the causal relationships between variables, the logarithmic transformation of the variables in the VAR model does not significantly affect the estimates. Therefore, this study adopts the variable logarithmic volatility to construct the VAR model in order to investigate the causality between the examined variables.

In this study, results for the period from January 2003 to May 2014 for the S&P500 index futures regarding realized volatility, bipower variation, jumps, jump ratio, number of significant jumps and the ratio of jump number to trading day within each year with a 5 minute sampling frequency are presented in Table 2. In Table 2, S&P500 index futures volatility is presented in real terms, and the average term and continuous fluctuation of jumping items can be seen in the high-frequency data. The realized volatility (RV) is decomposed into continuous and discontinuous jump variance items for the financial crisis period 2007-2009. The number of jumps significantly increased in 2009 as its 72-day risk ratio was 28.13%. However, the number of jumps in 2010 and 2011 was 68 and 62, respectively.

Table 1: Summary statistics for S & P 500 index futures returns

	r_t	RV_t	BV_t	J_t	$\ln(RV_t)$	$\ln(BV_t)$
Min	-0.0246	2.84E-06	2.72E-06	-0.0002	-2.2548	-2.3828
Max	0.0367	0.0055	0.0047	0.0008	2.6437	2.8550
Mean	-1.35E-06	0.0001	0.0001	7.99E-06	-0.0008	-0.0008
Std	0.0012	0.0002	0.0002	3.22E-05	0.5563	0.5640
Skew	0.3810	9.5961	9.0029	10.5146	0.1359	0.1545
Kurtosis	30.3876	144.1379	118.6436	214.3243	3.8652	3.8404

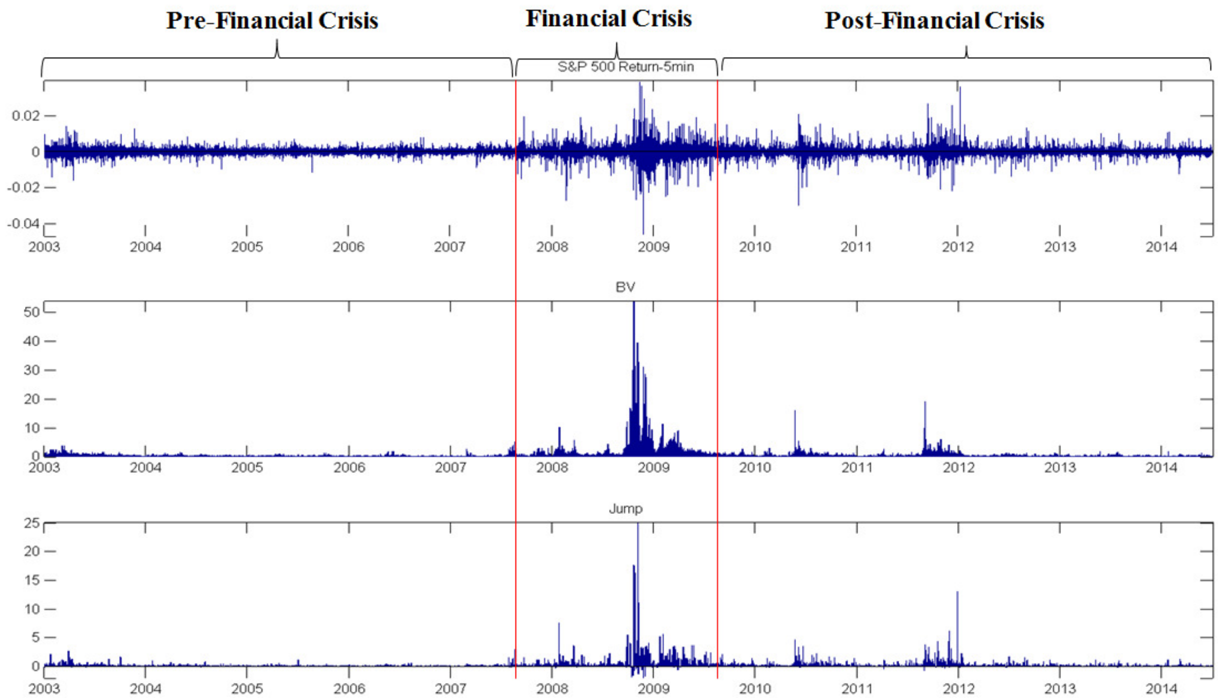
Note: r_t denotes the intraday return sampled at a 5-minute frequency, RV_t denotes the realized volatility, BV_t denotes the bipower variation, J_t denotes the difference between realized volatility and bipower variation, and $\ln(\cdot)$ denotes the log-transformed variation.

Table 2: S&P 500 index futures for realized volatility, continuous volatility and jumps

	2003	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Trading day	249	248	248	247	247	256	257	259	258	259	257	103
Realized Volatility (RV)	0.000097	0.000045	0.000037	0.000034	0.000065	0.000443	0.000188	0.000093	0.000130	0.000047	0.000034	0.000037
Continuous Volatility (BV)	0.000077	0.000036	0.000030	0.000029	0.000052	0.000373	0.000142	0.000070	0.000095	0.000033	0.000025	0.000027
Jump	0.000020	0.000009	0.000007	0.000005	0.000013	0.000070	0.000046	0.000023	0.000036	0.000014	0.000009	0.000009
Jump ratio	0.175911	0.172913	0.170839	0.147369	0.185242	0.180374	0.220485	0.216075	0.220053	0.239634	0.227768	0.215315
Jump test statistics	3.008605	2.939591	2.811022	2.479765	3.249105	3.580581	4.487865	4.141978	4.891995	4.948386	5.007486	4.786219
Number of significant jumps	29	18	10	15	47	72	50	68	62	48	46	26
Ratio of no. jumps to trading day	11.6466	7.2581	4.0323	6.0729	19.0283	28.125	19.4553	26.2548	24.031	18.5328	17.8988	25.2427

Note: A measure for the log-transformed realized volatility in a single market for trading day *t*. RV_t denotes the realized volatility, BV_t denotes the bipower variation, J_t denotes the difference between the realized volatility and bipower variation, and J_t/RV_t denotes the jump ratio as a measure of the contribution of the jump variation to the realized volatility. Jump test statistics are asymptotically standard normally distributed with a 99.75% significance level. The ratio of the number of jumps to trading day in each year is also presented.

Figure 1: Time Series of intraday returns, bipower variation, and realized jumps with a 5-minute sampling frequency



In addition, the S&P 500 index futures instantly fell in May 6, 2010, which is describe as the Flash Crash. The jump series also reflected the European debt crisis in the middle of 2011. The S&P 500 index futures results also show significant fluctuations. The results concerning the European debt crisis shows that with the volatility and jump clustering phenomenon, the sequence trends fluctuated more during the financial crisis than during the crisis in Europe.

We explore the high-frequency data with a different sequence sampling frequency in terms of the jumping trends. We use the high-frequency data to explore the jump basis. We decompose the substance of the jump and explore the difference in volatility variation between the two items. Jumps are considered significant jump at the 99.75% confidence level. During the days of the financial crisis, the results mainly reflect the volatility caused by a substantive increase in the frequency of S&P 500 index futures. The study sample will be divided into three different periods of before, during and after the financial crisis to explore the causal relationships between the variables.

4.1 The Empirical Results Regarding Causality

First, in the construction of VAR model, we include the days of the date of returns for the intraday returns for generalization, and we add five minutes every day for the total intraday returns (Bollerslev, Litvinova, and Tauchen, 2006). Further, we explore S&P 500 index returns on future days and determine the causal relationships between the variables. Causality effect is used to identify the influential relationship between the variables and the direction, and daily returns are examined for the leverage effect on the aggregate continuous volatility, while the high volatility feedback effect will produce negative returns.

We explore the intraday return and volatility variables in different stages of causality: the main measure of influence and the direction and effect between the variables. First, we construct the intraday return and realized volatility in the VAR model and set it up in linear equations, as follows:

$$\begin{bmatrix} r_t \\ RV_t^* \end{bmatrix} = \begin{bmatrix} \mu_r \\ \mu_{RV^*} \end{bmatrix} + \sum_{j=1}^{p} \begin{bmatrix} \Phi_{11t-j} & \Phi_{12t-j} \\ \Phi_{21t-j} & \Phi_{22t-j} \end{bmatrix} \begin{bmatrix} r_{t-j} \\ RV_{t-j}^* \end{bmatrix} + \begin{bmatrix} u_t^r \\ u_t^{RV^*} \end{bmatrix}$$

$$r_t = \mu_t + \sum_{j=1}^{p} \Phi_{11t-j} r_{t-j} + \sum_{j=1}^{p} \Phi_{12t-j} RV_{t-j} + u_t^r$$

$$RV_t^* = \mu_t + \sum_{j=1}^{p} \Phi_{21t-j} r_{t-j} + \sum_{j=1}^{p} \Phi_{22t-j} RV_{t-j}^* + u_t^{RV^*} \tag{14}$$

Dufour, Garcia and Taamouti (2012) adopt a VAR model to test causality and explore the normal distribution and allocation of serial correlation in each lagged variable with the related impact of the order. This study is the first to explore the causal relationship between the intraday return and realized volatility. The coefficient of the order of the lag term and causality test are compiled in Table 3. Table 3 provides estimates the intraday return and realized volatility for significant coefficients in VAR model.

Table 3: The coefficient of lagged intraday returns and realized volatility in the VAR model of S&P 500 index futures with a 5-minute sampling frequency

$$\begin{bmatrix} r_t \\ RV_t^* \end{bmatrix} = \begin{bmatrix} \mu_r \\ \mu_{RV^*} \end{bmatrix} + \sum_{j=1}^{p} \begin{bmatrix} \Phi_{11t-j} & \Phi_{12t-j} \\ \Phi_{21t-j} & \Phi_{22t-j} \end{bmatrix} \begin{bmatrix} r_{t-j} \\ RV_{t-j}^* \end{bmatrix} + \begin{bmatrix} u_t^r \\ u_t^{RV^*} \end{bmatrix}$$

		r_t		RV_t^*	
		$\Phi_{\bullet 1t-j}$	**t-statistic**	$\Phi_{\bullet 2t-j}$	**t-statistic**
r_{t-j}	lag1	-0.0579***	-3.1682	0.0549***	2.8185
	lag2	-0.0431**	-2.2195	0.0676**	3.3283
	lag3	0.0495**	2.5314	-0.0751***	-3.5970
	lag4	-0.0009	-0.0481	-0.0231	-1.1383
	lag5	-0.0306	-1.6161	0.0082	0.4258
RV_{t-j}^*	lag1	-0.3306***	-19.3515	0.3567***	19.6161
	lag2	-0.1050***	-5.7820	0.2457***	12.9540
	lag3	-0.0904***	-4.9485	-0.0554***	-2.8387
	lag4	-0.0673***	-3.6979	0.2157***	11.3630
	lag5	0.0001	0.0080	0.1096***	6.1041

Note: r_t denotes the summation of intraday returns at t. The realized variance adopts a logarithmic transformation: $RV_t^* = \ln(RV_t)$. *** and ** represent significance at the 5% and 1% level of significance, respectively.

We further explore the causality between intraday returns and realized volatility. The leverage effect is used to explain that low intraday returns will have higher volatility, and the volatility feedback effect is used to explain that high volatility will lead to negative intraday returns. The results from the causality tests on intraday returns and realized volatility with a sampling frequency of 1, 5 and 60 minutes for the S&P 500, Dow Jones, Nasdaq, FTSE, DAX and CAC index futures markets are presented in Tables 4 to 9, respectively.

Table 4: The causality measurement of intraday returns and realized volatility in the VAR model of S&P 500 index futures sampling

	Whole period	**Pre-Financial Crisis**	**Financial Crisis**	**Post-Financial Crisis**
1-minute sampling				
Leverage Effect	7.8948***	2.0841*	3.1785***	2.2022*
Volatility Feedback	30.4822***	4.7603***	10.0861***	5.8174***
5-minute sampling				
Leverage Effect	8.5271***	1.9006*	3.4156***	3.2435***
Volatility Feedback	38.5867***	6.9164***	11.9921***	8.2291***
60-minute sampling				
Leverage Effect	6.3892***	2.8649**	2.1415*	7.5991***
Volatility Feedback	82.8980***	7.7899***	20.9324***	24.1475***

Note: Leverage and volatility feedback effects, with the summation of intraday return r_t and realized volatility RV_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively..

Table 5: The causality measurement of intraday returns and realized volatility in the VAR model of Dow Jones index futures sampling

Effect	**Whole period**	**Pre-Financial Crisis**	**Financial Crisis**	**Post-Financial Crisis**
1-minute sampling				
Leverage	7.7400***	2.0765*	1.8616*	3.2470***
Volatility Feedback	30.9686***	8.2036***	6.3506***	5.6888***
5-minute sampling				
Leverage	6.8249***	3.4373***	1.7011	4.0626***
Volatility Feedback	40.4912***	10.7277***	8.8395***	7.5467***
60-minute sampling				
Leverage	7.2528***	6.9547***	2.1162*	7.9628***
Volatility Feedback	81.8913***	9.3496***	20.6390***	17.5923***

Note: Leverage and volatility feedback effects, with the summation of intraday return r_t and realized volatility RV_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 6: The causality measurement of intraday return and realized volatility in VAR model of Nasdaq index futures sampling

	Whole period	**Pre-Financial Crisis**	**Financial Crisis**	**Post-Financial Crisis**
1-minute sampling				
Leverage	1.8686*	0.4148	3.0928***	2.1921*
Volatility Feedback	8.6327***	0.9038	17.3998***	3.4278***
5-minute sampling				
Leverage Effect	2.7472**	0.3260	3.1429***	2.6394**
Volatility Feedback	12.2672***	1.0576	16.7370***	5.2212***
60-minute sampling				
Leverage Effect	5.2735***	0.6087	2.1062*	7.9084***
Volatility Feedback	53.0039***	1.5078	16.6390***	12.5964***

Note: Leverage and volatility feedback effects, with the summation of intraday return r_t and realized volatility RV_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

In this study, the causality effect is detected by intraday returns and realized volatility among three index futures in the U.S. market with different sampling frequencies, as shown by the consistency of the significant leverage and volatility feedback effects for the whole sample period. However, comparative analysis of the results for the pre-financial crisis period reveals that there are no significant causality effects in the Nasdaq index futures market. The results regarding the leverage and volatility feedback effects are also similar for the S&P 500, Dow Jones and Nasdaq index futures markets in the financial crisis and post-financial crisis periods.

The intraday returns and volatility show similar significant leverage and volatility feedback effects between the pre-financial crisis, financial crisis and post-financial crisis periods for the FTSE and DAX index futures markets. However, comparative analysis of the results only shows the volatility feedback effect for the CAC index futures market in the pre-financial crisis and financial crisis periods. In addition, the empirical results show higher magnitudes of the leverage and volatility feedback effects when a sampling frequency of 5 and 60 minutes is used. The 1-min sampling frequency shows lower volatility and intraday returns and less information, but volatility still has significant feedback effects and shows causality.

Table 7: The causality measurement of intraday returns and realized volatility in the VAR model of FTSE index futures sampling

	Whole period	**Pre-Financial Crisis**	**Financial Crisis**	**Post-Financial Crisis**
1-minute sampling				
Leverage Effect	9.2566***	3.1241***	2.3715**	11.9025***
Volatility Feedback	59.0440***	6.8093***	17.4965***	26.6035***
5-minute sampling				
Leverage Effect	5.6850***	3.6842***	2.6587**	12.5188***
Volatility Feedback	78.9044***	6.6684***	23.8639***	23.5811***
60-minute sampling				
Leverage Effect	12.3927***	5.4476***	3.7074***	11.8698***
Volatility Feedback	61.7725***	11.8185***	17.0493***	27.8430***

Note: Leverage and volatility feedback effects, with the summation of intraday return r_t and realized volatility RV_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 8: The causality measurement of intraday returns and realized volatility in the VAR model of CAC index futures sampling

	Whole period	**Pre-Financial Crisis**	**Financial Crisis**	**Post-Financial Crisis**
1-minute sampling				
Leverage Effect	2.0276*	0.9936	0.8052	2.6585**
Volatility Feedback	29.4927***	2.3805**	9.0473***	19.4176***
5-minute sampling				
Leverage Effect	2.1445*	1.1701	0.4509	4.1363***
Volatility Feedback	28.4172***	2.1828*	6.7703***	17.7128***
60-minute sampling				
Leverage Effect	2.8615**	0.9733	1.5039	3.1439***
Volatility Feedback	22.6073***	6.3676***	4.4002***	27.4438***

Note: Leverage and volatility feedback effects, with the summation of intraday return r_t and realized volatility RV_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 9: The causality measurement of intraday returns and realized volatility in the VAR model of DAX index futures sampling

	Whole period	Pre-Financial Crisis	Financial Crisis	Post-Financial Crisis
1-minute sampling				
Leverage Effect	3.5160***	3.0277**	5.5547***	2.9149**
Volatility Feedback	34.1143***	14.0525***	21.6741***	5.2928***
5-minute sampling				
Leverage Effect	4.5300***	2.1692*	3.5115***	6.3566***
Volatility Feedback	57.3189***	10.8067***	22.4057***	14.4077***
60-minute sampling				
Leverage Effect	6.7354***	2.0206*	2.7526***	7.2186***
Volatility Feedback	40.2068***	14.4173***	10.8505***	18.8382***

Note: Leverage and volatility feedback effects, with the summation of intraday return r_t and realized volatility RV_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Furthermore, volatility is decomposed into two variables, namely, bipower variation and realized jumps, to measure causality in the VAR model. The VAR model is set up as linear equations as follows:

$$\begin{bmatrix} r_t \\ BV_t \\ RJ_t \end{bmatrix} = \begin{bmatrix} \mu_r \\ \mu_{BV} \\ \mu_{RJ} \end{bmatrix} + \sum_{j=1}^{p} \begin{bmatrix} \Phi_{11t-j} & \Phi_{12t-j} & \Phi_{13t-j} \\ \Phi_{21t-j} & \Phi_{22t-j} & \Phi_{23t-j} \\ \Phi_{31t-j} & \Phi_{32t-j} & \Phi_{33t-j} \end{bmatrix} \begin{bmatrix} r_{t-j} \\ BV_{t-j} \\ RJ_{t-j} \end{bmatrix} + \begin{bmatrix} u_t^r \\ u_t^{BV} \\ u_t^{RJ} \end{bmatrix}$$

The empirical results indicate that during the financial crisis, the S&P 500, Dow Jones, Nasdaq, FTSE, DAX and CAC index futures markets have a significant impact on the leverage and volatility feedback effects. In addition, interactions are also found between returns and jumps. To investigate the intraday behavior of 1-min, 5-min and 1-hour index futures returns, volatility and jumps, we employ data for the period between January 2003 and May 2014; thus, the data cover the major upward and downward trends in the market. Our empirical data indicate that the main leverage and volatility feedback effects caused by intraday volatility and jump clustering significantly increased after the financial crisis. The results with different sampling frequencies before, during and after the financial crisis show that jumps have significantly increased the volatility feedback effect, especially when in a 5-min and 60-min sampling frequency is used.

Table 10: The causality effect of intraday returns, bipower variation and realized jumps in the VAR model of S&P 500 index futures sampling

	Whole period	Pre-Financial Crisis	Financial Crisis	Post-Financial Crisis
1-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	6.3073*** 9.5534***	2.3386** 1.1744	2.6165** 4.1064***	2.5570*** 0.9349
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	26.7472*** 7.2236***	5.0308*** 1.9691*	9.1508*** 2.8982**	3.1193*** 1.3061
5-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	5.6180*** 8.7498***	3.1213*** 1.1364	2.7608** 3.6899***	2.9287*** 0.5464
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	32.2451*** 6.8051***	8.1573*** 1.3894	10.3230*** 2.3630**	4.7475*** 2.3148**

	Whole period	Pre-Financial Crisis	Financial Crisis	Post-Financial Crisis
60-minute sampling				
$r_{t-1} \rightarrow BV_t^*$	8.2728***	2.3069**	2.6678**	11.1299***
$r_{t-1} \rightarrow RJ_t$	7.5546***	1.9087*	3.0162**	1.4461
$BV_{t-1}^* \rightarrow r_t$	48.8064***	5.5035***	10.5358***	23.9877***
$RJ_{t-1} \rightarrow r_t$	31.5818***	1.5149	9.7647***	2.3369**

Note: The coefficient of the VAR model sampled with a 5-minute frequency and the leverage and volatility feedback effects, with the summation of intraday return r_t and realized jump RJ_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 11: The causality effect of intraday returns, bipower variation and realized jumps in the VAR model of Dow Jones index futures

	Whole period	Pre-Financial Crisis	Financial Crisis	Post-Financial Crisis
1-minute sampling				
$r_{t-1} \rightarrow BV_t^*$	7.0412***	1.1751	1.5634	3.3396***
$r_{t-1} \rightarrow RJ_t$	10.1570***	1.3279	3.1740***	1.2099
$BV_{t-1}^* \rightarrow r_t$	24.2683***	10.5387***	5.4151***	2.8997**
$RJ_{t-1} \rightarrow r_t$	9.3860***	1.5691	3.0026***	1.5322
5-minute sampling				
$r_{t-1} \rightarrow BV_t^*$	5.8901***	2.2976**	1.6937	2.7397***
$r_{t-1} \rightarrow RJ_t$	12.0020***	2.5709**	3.2849***	0.7106
$BV_{t-1}^* \rightarrow r_t$	28.5641***	11.8224***	5.6545***	4.3788***
$RJ_{t-1} \rightarrow r_t$	7.7969***	2.0328*	2.1638*	2.1401*
60-minute sampling				
$r_{t-1} \rightarrow BV_t^*$	6.8298***	5.9833***	1.8789*	5.3022***
$r_{t-1} \rightarrow RJ_t$	9.0253***	2.5651**	2.6992**	3.1659***
$BV_{t-1}^* \rightarrow r_t$	41.7721***	7.4409***	9.3473***	18.1369***
$RJ_{t-1} \rightarrow r_t$	32.7241***	0.5476	9.0103***	4.5563***

Note: The coefficient of the VAR model sampled with a 5-minute frequency and the leverage and volatility feedback effects, with the summation of intraday return r_t and realized jump . F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 12: The causality effect of intraday returns, bipower variation and realized jumps in the VAR model of Nqsdaq index futures

	Whole period	Pre-Financial Crisis	Financial Crisis	Post-Financial Crisis
1-minute sampling				
$r_{t-1} \rightarrow BV_t^*$	3.3776***	1.2629	6.7212***	3.3396***
$r_{t-1} \rightarrow RJ_t$	3.0889***	0.6969	7.8856***	1.2099
$BV_{t-1}^* \rightarrow r_t$	8.8764***	1.7733	19.7972***	2.8997**
$RJ_{t-1} \rightarrow r_t$	0.4448	0.2918	0.3403	1.5322
5-minute sampling				
$r_{t-1} \rightarrow BV_t^*$	2.4891**	1.2167	3.3275***	2.7397**
$r_{t-1} \rightarrow RJ_t$	2.4774**	0.7626	4.7058***	0.7106
$BV_{t-1}^* \rightarrow r_t$	11.9380***	1.9378*	16.6371***	4.3788***
$RJ_{t-1} \rightarrow r_t$	1.2664	0.7175	2.2666**	2.1401*

60-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	8.2968*** 3.2561***	0.7176 1.3955	3.1135*** 1.7452	5.3022** 3.1659***
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	40.1589*** 11.9124***	2.4890** 1.3639	13.4260*** 6.6521***	18.1369*** 4.5563***

Note: The coefficient of the VAR model sampled with a 5-minute frequency and the leverage and volatility feedback effects, with the summation of intraday return r_t and realized jump RJ_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 13: The causality effect of intraday returns, bipower variation and realized jumps in the VAR model of FTSE index futures sampling

	Whole period	**Pre-Financial Crisis**	**Financial Crisis**	**Post-Financial Crisis**
1-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	14.1795*** 16.2197***	3.7176*** 1.4671	3.5897*** 5.4835***	3.6583*** 1.2639
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	46.9420*** 12.5090***	6.9543*** 0.4652	13.8118*** 6.9167***	4.7322*** 1.6771
5-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	4.4157*** 1.3571	5.8700*** 1.4161	2.2517** 1.2401	15.3719*** 2.8241**
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	67.7706*** 4.7886***	4.2411*** 4.4956***	21.5512*** 0.5325	22.5338*** 2.7705**
60-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	4.6872*** 13.1400***	4.0994*** 6.2620***	3.4986*** 6.9434***	12.6547*** 1.9460*
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	50.2233*** 4.7000***	7.0454*** 10.5110***	11.4009*** 1.9692*	26.4505*** 3.3506**

Note: The coefficient of the VAR model sampled with a 5-minute frequency and the leverage and volatility feedback effects, with the summation of intraday return r_t and realized jump RJ_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 14: The causality effect of intraday returns, bipower variation and realized jumps in the VAR model of CAC index future sampling

	Whole period	**Pre-Financial Crisis**	**Financial Crisis**	**Post-Financial Crisis**
1-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	2.1337* 5.0257***	0.3555 0.5777	0.4213 6.6030***	4.7646*** 0.3784
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	25.8685*** 4.2844***	3.0032** 0.5504	5.8978*** 2.3935**	14.3773*** 3.2317***
5-minute sampling				
$r_{t-1} \to BV_t^*$ $r_{t-1} \to RJ_t$	1.4282 1.8474	0.5448 2.0487*	0.5692 1.6495	2.9660** 0.8499
$BV_{t-1}^* \to r_t$ $RJ_{t-1} \to r_t$	23.9807*** 9.4128***	6.6470*** 1.1609	6.1244*** 4.9175***	16.7308*** 2.8118**

	Whole period	Pre-Financial Crisis	Financial Crisis	Post-Financial Crisis
60-minute sampling				
$r_{t-1} \to BV_t^*$	3.9543***	1.2657	2.3885**	1.3435
$r_{t-1} \to RJ_t$	3.0534***	3.1878***	2.7064**	0.3304
$BV_{t-1}^* \to r_t$	22.3665***	4.9467***	6.0414***	21.4545***
$RJ_{t-1} \to r_t$	4.3554***	7.6117***	0.9940	1.0585

Note: The coefficient of the VAR model sampled with a 5-minute frequency and the leverage and volatility feedback effects, with the summation of intraday return r_t and realized jump RJ_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

Table 15: The causality effect of intraday returns, bipower variation and realized jumps in the VAR model of DAX index future sampling

	Whole period	Pre-Financial Crisis	Financial Crisis	Post-Financial Crisis
1-minute sampling				
$r_{t-1} \to BV_t^*$	1.4459	2.4227**	2.7897**	4.6944***
$r_{t-1} \to RJ_t$	2.6578***	0.8420	4.7764**	2.4218***
$BV_{t-1}^* \to r_t$	28.8114***	14.6886***	7.2629***	7.9642***
$RJ_{t-1} \to r_t$	1.8914*	0.5797	2.1842*	4.0035***
5-minute sampling				
$r_{t-1} \to BV_t^*$	5.5933***	3.8650***	3.4730***	7.0826***
$r_{t-1} \to RJ_t$	3.2377***	0.7878	0.8520***	2.6499***
$BV_{t-1}^* \to r_t$	52.9296***	13.8301***	19.9649***	18.9939***
$RJ_{t-1} \to r_t$	3.5416***	0.9693	3.3442***	2.3197**
60-minute sampling				
$r_{t-1} \to BV_t^*$	3.6837***	3.6198***	2.5404**	2.1107*
$r_{t-1} \to RJ_t$	4.4793***	0.4532	3.5157***	1.2797
$BV_{t-1}^* \to r_t$	24.8095***	12.4533***	8.3576***	13.9544***
$RJ_{t-1} \to r_t$	7.2859***	3.8051***	4.5912***	5.6085***

Note: The coefficient of the VAR model sampled with a 5-minute frequency and the leverage and volatility feedback effects, with the summation of intraday return r_t and realized jump RJ_t^*. F-test statistics are presented for the causality measurement. *, ** and *** represents significance at the 10%, 5% and 1% level of significance, respectively.

5. Conclusion

In this study, we explore the causality among intraday returns, realized volatility, continuous volatility and jumps as constructed in a VAR model. We examine the intraday causality between returns, volatility and jumps within the U.S. and European index futures markets during the financial crisis from 2007 to 2009 to measure the leverage and the volatility feedback effects, and we further explore the existence of jumps (realized jumps, RJ) and identify the impact on intraday returns. The empirical results indicate that during the financial crisis, the S&P 500, Dow Jones, Nasdaq, FTSE, DAX and CAC index futures markets have a significant impact on the leverage and volatility feedback effects; in addition, interactions are also found between returns and jumps. To investigate the intraday behavior of 1-min, 5-min and 1-hour index futures returns, volatility and jumps, we employ data for the period between January 2003 and May 2014; thus, the data cover the major upward and downward trends in the market. Our empirical data indicate that the main leverage and volatility feedback effects caused by intraday volatility and jump clustering significantly increased after the financial crisis. The results with different sampling frequencies before, during and after the financial crisis show that jumps have significantly increased the volatility feedback effect, especially when in a 5-min and 60-min sampling frequency is used.

During the financial crisis (July 2007-July 2009), the results show the sequence clustering phenomenon, where realized volatility (RV) and jumps are more severe than during the crisis in Europe. Therefore, this study explores causality in intraday returns, realized volatility, the degree of continuous volatility and jumps between the pre-financial crisis, financial crisis and post-financial crisis periods. The empirical results show that intraday returns and realized volatility show significant leverage and volatility feedback effects with different sampling frequencies during the financial crisis and post-financial crisis periods. In addition, the intraday returns with a 1-min sampling frequency do not show a significant volatility leverage effect. During the pre-financial crisis period, the sampling frequency is too short, and less volatility as reflected in lower amount of information; however, the volatility feedback effect still has significant causality.

Moreover, during the pre-financial crisis, the continuous intraday returns and volatility show a significant volatility feedback effect with different sampling frequencies, though the leverage effect is not significant. Under different sampling frequencies for intraday returns and real causality, the empirical results show that for the sample intraday returns during the day, a substantial causal relationship exists between the leverage effect and volatility feedback effect. With a five-minute sampling frequency, the leverage effect and volatility feedback effect are found before, during and after the financial crisis. However, with a 60-minute sampling frequency, the leverage effect and volatility feedback effect occur only during the financial crisis; for the other periods only the volatility feedback effect is significant. In support of the empirical results, Bekaert and Wu (2000) report that the volatility feedback effect has a greater influence on returns than the leverage effect when using high-frequency trading data.

In this study, continuous volatility and substantial jump items are simultaneously included in the VAR model to examine intraday returns at different sampling frequencies for the S&P 500 index futures market. The causality between continuous volatility and substantial jumps is empirically examined in terms of the degree of continuous fluctuation, and substantial jump items are included in the VAR model to examine intraday returns. The sampling frequency on different days of the financial crisis has an effect on the real intraday returns only for items with a significant leverage effect. The different sampling frequencies affect the results before the financial crisis, and after the financial crisis, the leverage effect significantly impacts the real jump inconsistencies. In addition, under different sampling frequencies and during the financial crisis, the continuous fluctuation of days after the return has a significant volatility feedback effect. For different sampling frequencies before, during and after the financial crisis, the jump substantive items probably have a significant volatility feedback effect on intraday returns. However, in the first 5 minutes of the sampling frequency, the jump items do not show the volatility feedback effect on real intraday returns during the financial crisis. The reason is that during the pre-financial crisis period, the S&P 500 index shows less notable jumps. These findings have important implications for both policymakers and investors.

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