Price Jumps in Developed Stock Markets: The Role of Monetary Policy Committee Meetings

Abstract

In this paper, we analyze the jump intensity in the Euro area, Japan, the UK and the US and measure their reactions to the US Federal Reserve meetings together with the country's own monetary policy meetings. Evidence suggests that the jump intensity in all the markets is highly persistent. Further, the US monetary policy positively impacts the jump intensity in almost all the cases, including in the sub-sample periods found by the structural break test. Moreover, in assessing the joint effects on jump intensities, we find that the US policy dominates the monetary policy of the country itself.

JEL Codes: C22; C32; G15.
Keywords: Jump intensity; Developed stock markets; Monetary policy committee meeting dates

1. Introduction

The role of monetary policy in affecting the stock market volatility across the globe is of significant interests for macroeconomist, market participants, and policymakers. The recent crisis particularly highlighted the nexus between the monetary policy and global stock market volatility. In this paper, we measure the impact of monetary policy events on the jump intensity in the stock markets of the Euro area, Japan, UK, and the US.

Compared to continuous price changes, occasional large price changes, i.e., jumps, generate extreme fluctuations in the stock markets hold the potential to dampen economic growth (Li et al., 2015). In fact, sharp fluctuations in the stock markets were at the epicenter of the recent financial crisis of 2007–2008 (French et al. 2012). Analyzing jump intensity in financial markets is greatly important because they contribute to the non-diversifiable risks in the portfolios (Bollerslev et al. 2008), improve value-at-risk predictions (Liao 2013), and enables policymakers to evaluate their actions during the financial and economic turmoil. While the impact of monetary policy on the stock market across the globe is extensively investigated,[1] the impact of such policy actions on jump intensity in the international stock markets remains unexplored. Furthermore, the US Federal Reserve plays a central role in the financial markets of the advanced economies. This further motivates us to study the US monetary policy in driving the price (more specifically, returns) jump in the Euro area, Japan, the UK and US stock markets.

In this paper, we study first the jump intensity of various international stock markets and then measure the impact of monetary policy committee meeting dates on these jump intensity of the stock markets. We use the autoregressive conditional jump intensity (ARJI) model coupled with a generalized autoregressive conditional heteroskedasticity (GARCH) specification to extract the jump intensity in the stock markets of the Euro area, Japan, the UK and the US. The reactions of these jump intensities to the monetary policy meeting dates are then analyzed based on both the fixed-coefficient model and the multiple structural breaks model of Bai and Perron (2003). To study the incremental role of the US in the Euro area, Japan, and the UK, we include countries own monetary policy committee meeting dates as well as US Federal Open Market Committee (FOMC) meeting dates. In this regard, we follow Apergis (2015) in some sense, who uses a dummy to capture the FOMC minutes dates while analyzing the impact on returns and volatility of many assets using a GARCH-based

[1] See, for example, Bernanke (2005), Andersen et. al. (2007), Kishor and Marfatia (2013), Marfatia (2014), Apergis (2015), among others.

approach applied to intraday data over the period of 2005 to 2011. Apergis (2015) detects significant role of the dummy on returns and volatility of these assets. Our paper can be considered, in some sense, as an extension of the work of Apergis (2015), with us analyzing the impact on jump intensity for the US stock market along with three other developed markets, based on long spans of historical data. We cover the daily periods of 18/03/1936-30/12/2016; 05/01/1984-30/12/2016; 02/01/1984-30/12/2016; 01/01/1987-30/12/2016 for US, Japan, UK and the Euro Area respectively.

Evidence suggests that all the stock markets considered in the study exhibit high degrees of persistence in the conditional jump intensity. Moreover, a unit shock (increase) in the previous trading session results in a dampened effect of 0.4261, 0.1968, 0.4501 and 0.4310 on the next period's jump intensity for the UK, Japan, Euro Area and the US respectively. Results also show that the monetary policy meetings positively and significantly affect the jump intensity in all the stock markets. In fact, except Japan, the US monetary policy proves to be more important in driving the jump intensity than the countries own policy announcements. This highlights that the central role of Federal Reserve's policy announcements, perhaps even more by then the countries own monetary policy announcements. The results of structural breaks test suggest that there is evidence of multiple breaks in all the cases. However, in almost all the sub-samples monetary policy meetings of the US are found to positively impact the jump intensity of stock market in the Euro area, the UK and the US, with the exception of the jump intensity of S&P 500 during the 1936-1948 period.

2. Data

Our data consists of two variables of interest: the stock prices (from which we derive the jump intensity) and the monetary policy committee meeting dates. We consider four developed stock markets, i.e., Euro Area (EuroStoxx50), Japan (Nikkei225), UK (FTSE100) and the US (SP500), given the readily available data on the meeting dates. We compute log returns in percentages (i.e., first-differences of the stock prices in natural logarithms times 100) of these four stock prices, with the data being obtained from Global Financial Database. The stock returns data covers the daily period of 18/03/1936-30/12/2016; 05/01/1984-30/12/2016; 02/01/1984-30/12/2016; 01/01/1987-30/12/2016 for the US, Japan, the UK and the Euro Area respectively. The total number of observations are: 8124 for Japan, 8610 for the UK, 7666 for Euro Area, and 21003 for US. The monetary policy committee meeting dates for the US are obtained from Datastream of Thomson Reuters, while for the other countries, they are derived from their respective central banks. Federal Open Market Committee (FOMC) meeting dates start from 18/03/1936 for the US, while monetary policy committee meeting dates for the Euro Area, Japan and the UK starts from 04/03/1999, 16/01/1998, and 06/06/1997 respectively. During these periods, there were 950 FOMC meetings, 235, 241, and 293 monetary policy committee meetings for the UK, Euro Area and Japan respectively. During these days, we use a dummy variable which takes a value of one to capture the monetary policy committee meetings that took place. The summary statistics of the four stock returns have been reported in Table A1, with their corresponding plots in Figure A1.

[Insert Table A1 and Figure A1 about here]

3. Methodology

We adopt two steps procedure in our paper, the first step is to extract the jump intensity of various international stock markets, and then as a second step, we use this measure as a dependent variable in the regression with monetary policy committee meeting dates (both its own and that of the US for the remaining three countries). We use the Poisson distribution to govern the number of events that result in stock price movements, and the average number of events within a time interval is called the intensity. Following Chan and Maheu (2012), we use autoregressive conditional jump intensity (ARJI) to measure the conditional jump intensity, which in turn, follows an approximate autoregressive moving average (ARMA) process. In this procedure, we first retrieve the time variation in jump intensity on stock market returns using the ARJI model coupled with a GARCH specification, based on daily stock returns of four countries, namely US, Euro Area, Japan, and the UK. Following the literature, we use GARCH models to proxy the conditional variance, and to proxy the jump dynamics, we use the Poisson distribution. Let the data generating process of stock returns have the following jump specification, and we define the information set at time *t* to be the history of returns $\Phi_t = \{R_t, \ldots, R_1\}$.

$$R_t = \mu + \sum_{i=1}^{I} \phi_i R_{t-1} + \sqrt{h_t z_t} + \sum_{k=1}^{n_t} Y_{t,k}$$

$$z_t \sim NID(0,1), \quad Y_{t,k} \sim n(\theta_t, \delta_t^2) \qquad (1)$$

The conditional jump size $Y_{t,k}$, given Φ_{t-1} , is assumed to be independent and normally distributed (IID) with mean θ_t and variance δ_t^2. Following Bollersleve (1986) the conditional volatility for returns is denoted as h_t , and it follows a GARCH (p,q) specification such that:

$$h_t = \varpi + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{2}$$

where $\epsilon_t = R_t - \mu - \sum_{i=1}^{l} \phi_i R_{t-1}$. The specification of ϵ_t captures the expected jump component and thus allows it to propagate and affect future volatility through the GARCH variance factor. Let n_t denote the discrete counting process governing the number of jumps that arrive between time interval *t-1* and *t*, which is presumed to be distributed as a Poisson random variable with the parameter $\lambda_t > 0$, so that we have the density:

$$P(n_t = j|\Phi_{t-1}) = \frac{\exp(-\lambda_t)\lambda_t^j}{j!}, \qquad j = 0,1,2,... \tag{3}$$

The mean and variance for the Poisson random variable are λ_t, and it is called the jump intensity. Following Chan and Maheu (2012) we endogenously model the jump intensity according to a parsimonious ARMA structure. Let us consider the following ARJI model, denoted as *ARJI(r,s)*. Let the conditional expectation of the counting process in Eq. (3) be denoted as:

$$\lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \Upsilon_i \xi_{t-i} \tag{4}$$

where ξ_{t-i} is the innovation to λ_{t-i} and the jump intensity residual of λ_t is calculated as:

$$\begin{aligned} \xi_{t-i} &\equiv E[n_{t-i}|\Phi_{t-1}] - \lambda_{t-i} \\ &= \sum_{j=0}^{\infty} j\, P(n_t = j|\Phi_{t-1}) - \lambda_{t-i} \end{aligned} \tag{5}$$

The first term of Eq. (5) is the expected average number of jumps at time *t-i* based on time *t-i* information set. The second term represents the expected number of jumps containing information at time *t-i-1*. For the Poisson distribution to be well defined, λ_t must be positive[2].

4. Results

We now discuss the results in this section, by first devoting our attention to the estimate of the jump intensity model, and then relating it to the monetary policy committee dummies using a regression analysis. Table 1 reports the ARJI model estimates for the four stock

[2] For more details about inference and modelling please refer to Chan and Maheu (2012).

markets. We only consider the model with time-varying conditional jump intensity, since it better fitted the data when compared to models without jumps and constant jump intensity.[3] For all markets λ_t is positive and it indicates the existence of jumps. The ρ parameter in the ARJI model is estimated to be 0.8626, 0.9912, 0.9164 and 0.8866 for the FTSE100, Nikkei225, EuroStoxx50, and S&P500, with them being significant at the one percent level. The results indicate that the conditional jump intensity is significantly persistent, i.e., a high probability of many (few) jumps today tends to be followed by a high probability of many (few) jumps tomorrow. γ measures the sensitivity of λ_t to the past shock, ξ_{t-1}. A unit increase in ξ_{t-1} results in a dampened effect of 0.4261, 0.1968, 0.4501 and 0.4310 on the next period's jump intensity for UK, Japan, Euro Area and the US respectively. Among all stock markets the Nikkei225 exhibits the highest probability of many (few) jumps today to be followed by a high probability of many (few) jumps tomorrow, while EuroStoxx50 shows the highest sensitivity λ_t to the past shock, ξ_{t-1}. Figure 1 plots the jump intensity for the four stock markets.

[Insert Table 1 and Figure 1 about here]

We next turn our attention to the role played by the monetary policy committee meeting days on the jump intensity (*JI*). For our purposes, we estimate the following two models using ordinary least squares with Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors:

$$JI_{i,t}=\alpha_0+\alpha_1\, JI_{i,t-1}+\alpha_2\, FOMC_t+\varepsilon_{it},\ i=\text{EuroStoxx50, FTSE100, S\&P500}; \quad (6a)$$

$$JI_{i,t}=\alpha_0+\alpha_1\, JI_{i,t-1}+\alpha_2\, FOMC_{t-1}+\varepsilon_{it},\ i=\text{Nikkei225}; \quad (6b)$$

$$JI_{j,t}=\alpha_0+\alpha_1\, JI_{j,t-1}+\alpha_2\, FOMC_t+\alpha_3\, MPC_{j,t}+\varepsilon_{jt},\ i=\text{EuroStoxx50, FTSE100}; \quad (7a)$$

$$JI_{j,t}=\alpha_0+\alpha_1\, JI_{j,t-1}+\alpha_2\, FOMC_{t-1}+\alpha_3\, MPC_{j,t}+\varepsilon_{jt},\ i=\text{Nikkei225}; \quad (7b)$$

We allow one lag of the *JI* to capture persistence, while the errors (ε_i and ε_j) are assumed to be normally distributed with zero mean and constant variances. MPC is the monetary policy

[3] For AR(2)-GARCH (1,1) model the log-likelihoods for FTSE100, Nikkei225, EuroStoxx50, and S&P500 are: -11550.184, -13483.983, -11679.587, and -25610.653 respectively. For constant jump intensity model the log-likelihoods for FTSE100, Nikkei225, EuroStoxx50, and S&P500 are -11391.962, -13206.336, -11403.618, and -25030.434 respectively. For time-varying jump intensity model (i.e. ARJI) the log-likelihoods for FTSE100, Nikkei225, EuroStoxx50, and S&P500 are -11378.396, -13206.336, -11403.618, and -24967.038 respectively (reported in Table 1). Clearly, the time-varying jump intensity model better fits the data in terms of higher log-likelihoods, and hence, is the preferred model for jump intensity for these four stock markets. Detailed estimated results are not reported here for the model without jumps and the constant jump intensity model, but are available upon request from the authors.

committee dummy variable for the Euro Area, Japan, and UK. In Eq.(6a) and Eq.(6b), we analyze the impact of US FOMC meeting dates on the jump intensity for all the four countries, while in Eq.(7a) and Eq.(7b), we analyse the impact of individual monetary policy committee meetings dates besides the FOMC dates considered simultaneously for the Euro Area, Japan, and UK.[4] Note that for the case of Japan, the FOMC dummy enters with a lag to account for differences in time-zones.[5]

Table 2 reports the coefficients α_2 and α_3 for the full sample and also sub-samples obtained based on the Bai and Perron (2003) sequential test of multiple structural breaks (obtained based on a maximum number of five breaks at five percent significance level, and by allowing for the error distribution to differ across the breaks, if any). When, we look at the full-sample results, barring Japan, the FOMC dummy positively and significantly affects the jump intensity. When we look at the sub-samples based on break dates, the impact of lagged US FOMC on Japan continues to be insignificant, with its effect being positive for four sub-samples and negative for the last sub-sample. For the UK, the effect is always positive and significant for the three detected sub-samples, with significance holding at the ten percent level for the last of the three sub-samples. For the Euro Area, four breaks are detected leading to five sub-samples, with the effect being positive, barring the second sub-sample. However, for this period, the effect is insignificant, with significance hold corresponding to the positive impact of the US FOMC for sub-samples one and four. When we look at the US, we find that the effects are significant for the first and second sub-samples, given two breaks. However, FOMC meetings are found to reduce the jump intensity for the early sub-sample, but increase jump intensity for the second and third sub-samples; with the overall significant effect of the full-sample being driven by the second sub-sample results. In general, barring Japan, the role of FOMC meetings in explaining the jump intensity cannot be denied, though in some cases it is found to negatively affect it. Also, when we look at the sub-samples, it seems that the role of the FOMC dummy for recent periods have declined in the sense of the effects being insignificant.[6]

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[4] We also estimated a model for the Euro Area, Japan, and UK, based on just their own respective monetary policy committee meeting dummies, i.e., without the FOMC dummy. However, results were quantitatively and qualitatively similar to those obtained under Eq.(7a) and Eq.(7b). Hence, these results have not been reported to save space, but are available upon request from the authors.

[5] Results were, however, both qualitatively and quantitatively similar with the contemporaneous FOMC dummy for Japan. Complete details of these results are available upon request from the authors.

[6] We also analysed the role of US jump intensity on the jump intensities of FTSE100, EuroStoxx50 and Nikkei225. Again for Japan, lagged US jump intensity was used. In all cases the effects were positive, with the coefficients being 0.1414 (FTSE100), 0.3296 (EuroStoxx50) and 0.1096 (Nikkei225), and statistically

Next, we turn our attention to the joint effects of both the FOMC dummy and the MPC dummy on the jump intensity of Euro Area, Japan, and UK. For the Euro Area, no breaks were detected, and hence, based on the full-sample results, we find that, while the effect of US FOMC continues to be positive and significant, the Euro Area MPC has a negative but insignificant effect. For the UK as well, there are no structural breaks detected when estimating Eq.(7a), with results showing positive impact of both US FOMC and UK MPC dummies, but the effect of the latter being only significant at the ten percent level, and also smaller in magnitude than the impact of the US FOMC dummy. Finally, when we look at Japan, the impact of the Japanese MPC dummy is negative and insignificant, while that of the FOMC dummy is positive, but also insignificant. Structural break tests identified three breaks in Eq.(7b); hence, when we look at the four sub-samples, we find that the impact of US FOMC is positive barring the last sub-sample, but the effects are insignificant. While for the Japanese MPC dummy, significant (at the ten percent level) and positive impact is only detected for the second sub-sample, with effects being positive for the first sub-sample and negative for the last two sub-samples, but these effects are statistically insignificant. In sum, even after controlling for own MPC effects, the role of the FOMC dummy in positively affecting the jump intensities of the Euro Area and UK continues to hold. In addition, own country MPC effects on jump intensities for the Euro Area, Japan, and the UK, are at best statistically weak, though positive for the UK and Japan (in a specific sub-sample only).

[Insert Table 2 about here]

5. Conclusion

This paper studies the behaviour of jump intensity in the stock markets of the Euro area, Japan, UK and the US. We also analyse the role of monetary policy, captured by dummies corresponding to monetary policy committee meeting dates, in affecting the jump intensity in these markets. Results show that there is a high degree of persistence in jump intensity in all the cases with a statistically significant response of jump intensity to shocks in the previous trading session. The evidence clearly shows that the US Federal Reserve plays a large and significant role in driving the global stock market jump intensities; with it being even greater than the role of monetary policy of the country itself.

significant at the one percent level of significance. Complete details of these results are available upon request from the authors.

As part of a future research, it would be interesting to extend our analysis to volatility jumps (as in Harvey and Chakravarty (2008), and Harvey (2013)), and also look at other assets, including commodities, and other countries, like emerging stock markets.

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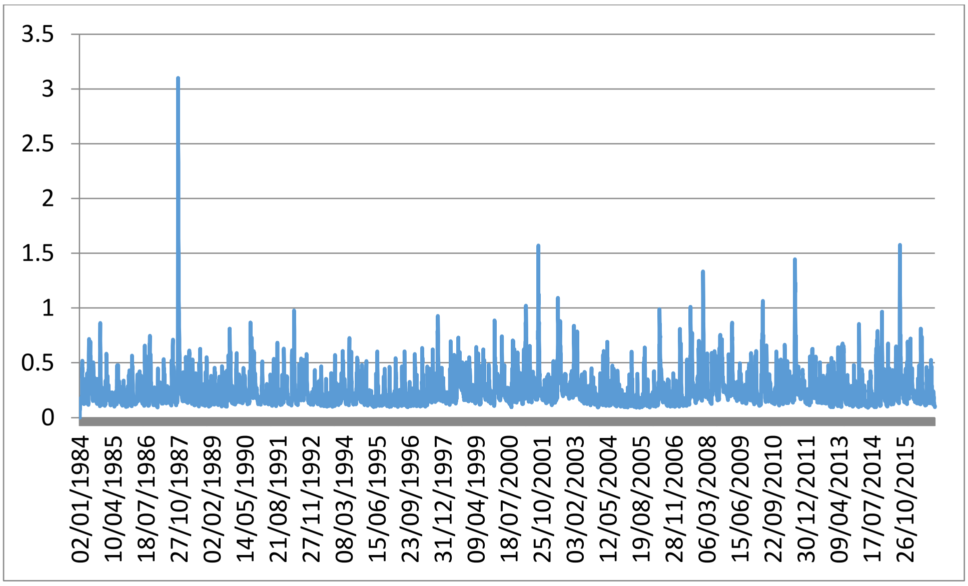
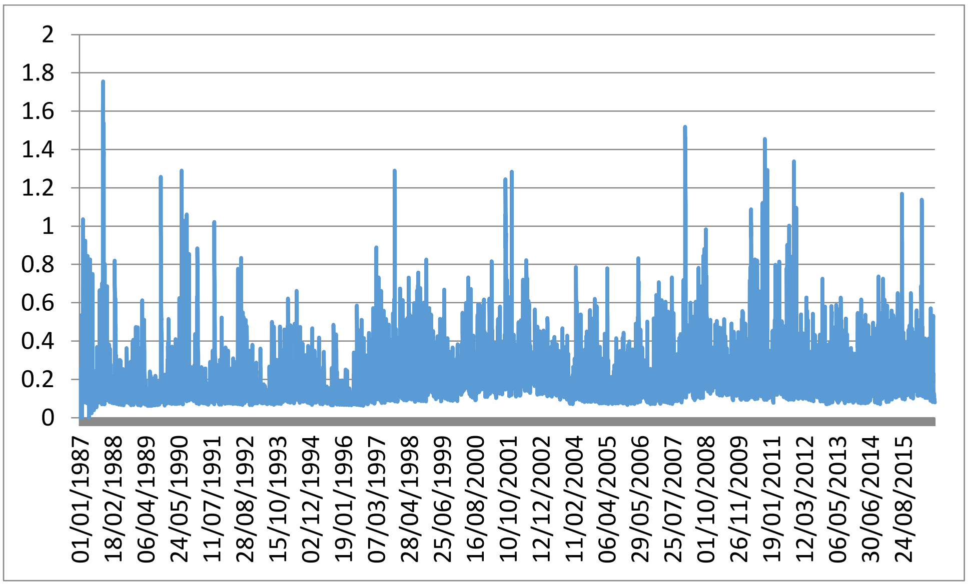
Figure 1. Jump Intensities:

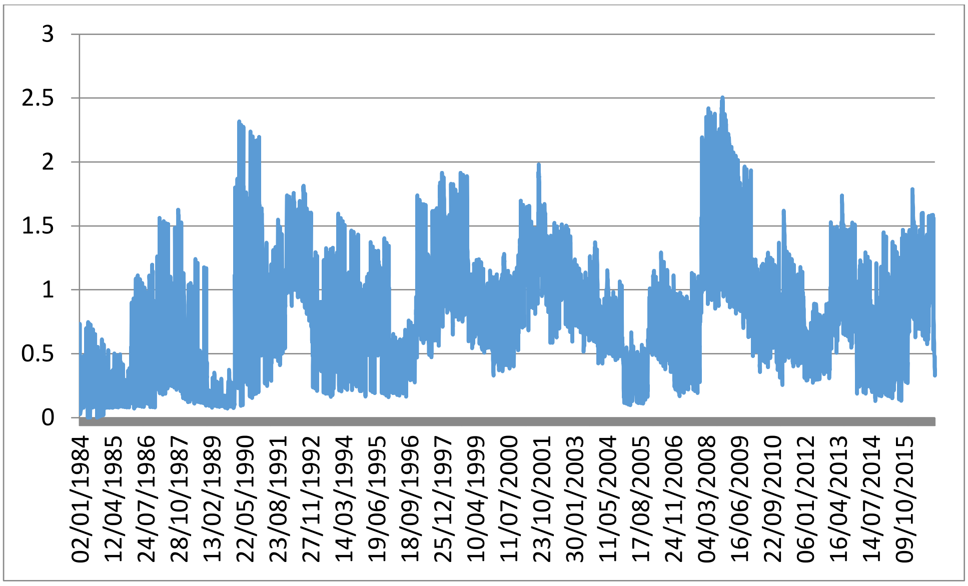
1(a). FTSE 100:



1(b). EuroStoxx50:



1(c). Nikkei225:



1(d). S&P500:

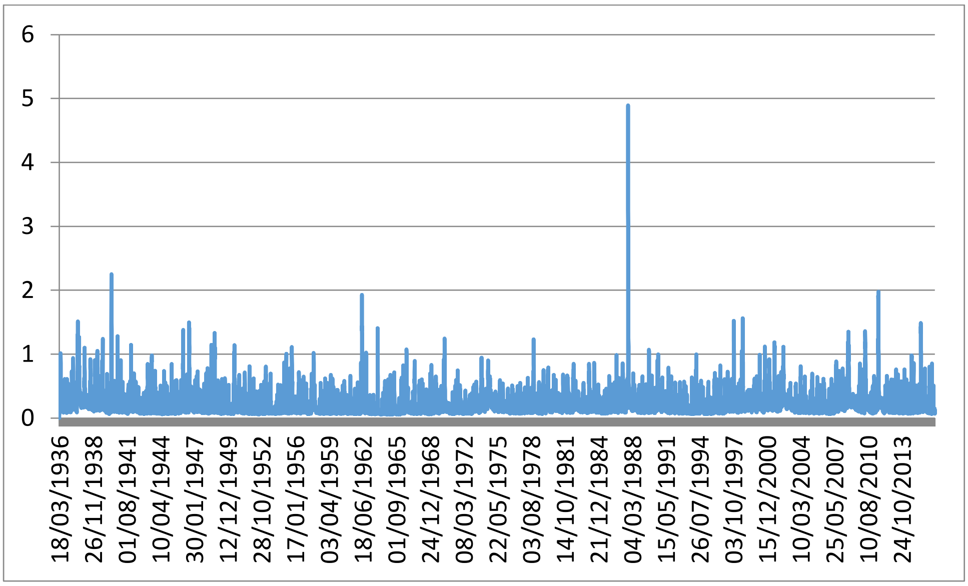


Table 1. Estimates of ARJI model.

$$R_t = \mu + \sum_{i=1}^{2} \phi_i R_{t-i} + \sqrt{h_t z_t} + \sum_{k=1}^{n_t} Y_{t,k}$$

$$z_t \sim NID(0,1), \quad Y_{t,k} \sim n(\theta_t, \delta_t^2)$$

$$h_t = \varpi + \alpha \epsilon_{t-1}^2 + \beta h_{t-1}$$

$$\lambda_t = \lambda_0 + \rho\, \lambda_{t-1} + \Upsilon \xi_{t-1}$$

$$\theta_t = \eta_0$$

$$\delta_t^2 = \xi_0^2$$

Parameter	FTSE100		Nikkei225		Eurostoxx50		S&P500	
μ	0.1154	***	0.1477	***	0.1131	***	0.0831	***
ϕ_1	-0.0039		-0.0132		-0.0237	**	0.0858	***
ϕ_2	-0.0359	***	-0.0192	*	-0.0439	***	-0.0543	***
ϖ	0.0077	***	0.0278	***	0.0071	***	0.0027	***
α	0.0629	***	0.0772	***	0.0471	***	0.0356	***
β	0.9108	***	0.8275	***	0.9305	***	0.9456	***
ξ	0.7863	***	1.0554	***	1.2713	***	0.9880	***
η_0	-0.4422	***	-0.2023	***	-0.5952	***	-0.3662	***
λ_0	0.0326	***	0.0068	**	0.0167	***	0.0231	***
ρ	0.8626	***	0.9912	***	0.9164	***	0.8866	***
γ	0.4261	***	0.1968	***	0.4501	***	0.4310	***
Q_2	24.38	*	18.34		16.08		0.4516	
$Q_{\xi t}$	14.83		10.94		6.44		0.7451	
Log-likelihood	-11378.3960		-13206.3360		-11403.6180		-24967.0380	

NOTE: *, **, and *** represents 10%, 5% and 1% significance level respectively. Q_2 is the modified Ljung–Box portmanteau test, robust to heteroscedasticity, for serial correlation in the squared standardized residuals with 15 lags for the respective models. $Q_{\xi t}$ is the same test for serial correlation in the jump intensity residuals.

Table 2. Monetary Policy Committee Meetings and Jump Intensities

Stock Markets	Full-Sample	Sub-Sample 1	Sub-Sample 2	Sub-Sample 3	Sub-Sample 4	Sub-Sample 5
			Eq.(6a) and Eq.(6b): FOMC Response (α_2)			
FTSE100	0.0212***	0.0696***	0.0170***	0.0103*		
EuroStoxx50	0.0298**	0.0970**	-0.0118	0.0029	0.0318**	0.0178
Nikkei225	0.0159	0.0354	0.0096	0.0298	0.0321	-0.0046
S&P500	0.0136***	-0.0186***	0.0221***	0.0010		
			Eq.(7a) and Eq.(7b): FOMC Response (α_2)			
FTSE100	0.0118**					
EuroStoxx50	0.0224**					
Nikkei225	0.0213	0.0200	0.0431	0.0322	-0.0036	
			Eq.(7): MPC Response (α_3)			
FTSE100	0.0083*					
EuroStoxx50	-0.0101					
Nikkei225	0.0000	0.0298	0.0278*	-0.0253	-0.0177	

Note: ***, **, * indicates significance at 1, 5 and 10 percent respectively. Eq.(6a): $JI_{i,t}=\alpha_0+\alpha_1 JI_{i,t-1}+\alpha_2 FOMC_t+\varepsilon_{it}$; Eq.(7a): $JI_{j,t}=\alpha_0+\alpha_1 JI_{j,t-1}+\alpha_2 FOMC_t+\alpha_3 MPC_{j,t} +\varepsilon_{jt}$; FOMC enters as a lag for Nikkei225 in Eq. (6b) and Eq.(7b); Eq.(6a): FTSE: Sub-Sample 1: 03/01/1984-13/12/1988, Sub-Sample 2: 14/12/1988-22/10/1997, Sub-Sample 3: 23/10/1997-30/12/2016; EuroStoxx50: Sub-Sample 1: 04/01/1987-01/09/1991, Sub-Sample 2: 04/09/1991-02/03/1997, Sub-Sample 3: 03/03/1997-13/09/2001, Sub-Sample 4: 14/09/2001-31/01/2008, Sub-Sample 5: 01/02/2008-29/12/2016; Eq.(6b): Nikkei225: Sub-Sample 1: 03/01/1984-02/02/1990, Sub-Sample 2: 03/02/1990-07/10/1997, Sub-Sample 3: 09/10/1997-06/01/2004, Sub-Sample 4: 07/01/2004-04/06/2009, Sub-Sample 5: 07/06/2009-30/12/2016; S&P500: Sub-Sample 1: 19/03/1936-15/11/1948, Sub-Sample 2: 16/11/1948-24/03/1997, Sub-Sample 3: 25/03/1997-30/12/2016. Eq.(7b): Nikkei225: Sub-Sample 1: 16/01/1998-04/12/2000, Sub-Sample 2: 05/12/2000-16/12/2003, Sub-Sample 3: 17/12/2003-04/06/2009, Sub-Sample 4: 07/06/2009-30/12/2016.

APPENDIX:

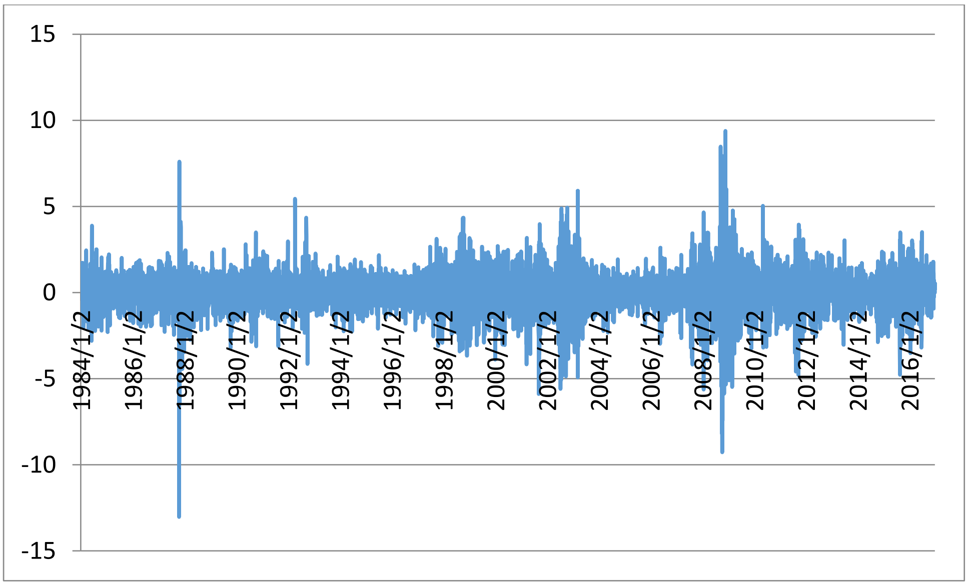
Table A1. Summary Statistics of Stock Returns

	Stock Returns			
Statistic	FTSE100	EuroStoxx50	Nikkei225	S&P500
Mean	0.0228	0.0168	0.0081	0.0239
Median	0.0204	0.0500	0.0399	0.0461
Maximum	9.3843	10.4377	13.2346	10.9572
Minimum	-13.0286	-9.0110	-16.1375	-22.8997
Std. Dev.	1.0887	1.3365	1.4683	0.9984
Skewness	-0.4750	-0.1950	-0.2692	-0.8890
Kurtosis	12.5274	8.7041	11.1463	25.0582
Jarque-Bera	32887.9700	10441.4300	22561.8900	428570.1000
Probability	0.0000	0.0000	0.0000	0.0000
Observations	8610	7666	8124	21003

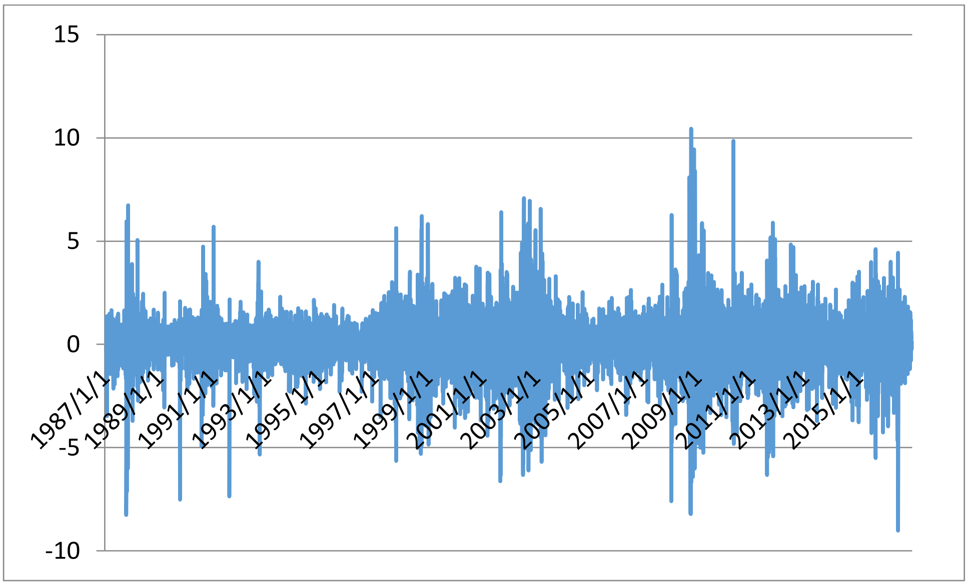
NOTE: Std. Dev. stands for standard deviation; Probability corresponds to the Jarque-Bera test with the null of normality.

Figure A1. Plots of Stock Returns

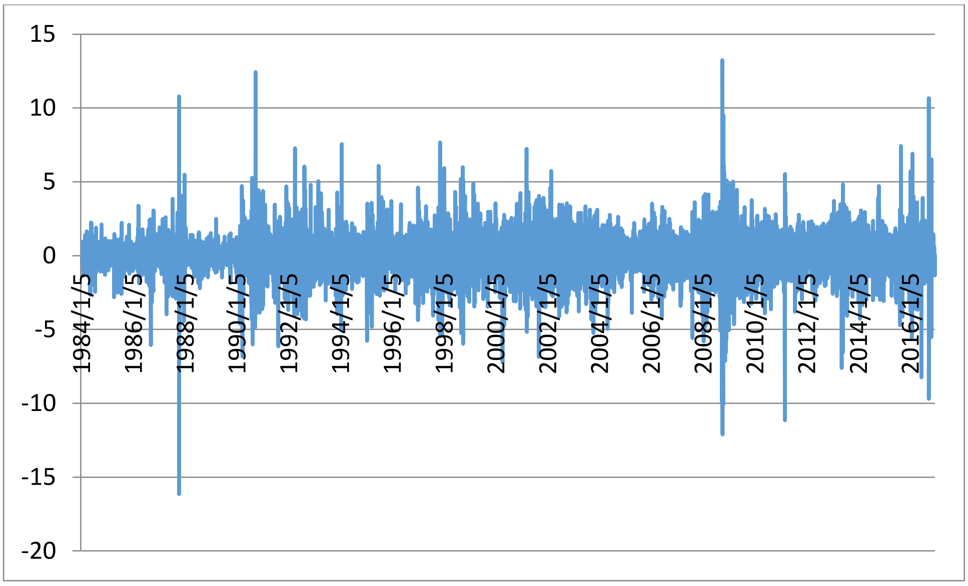
A1(a). FTSE100:



A1(b). EuroStoxx50:



A1(c). Nikkei225:



A1(d). S&P500: