Chapter 8

The Dynamics of Jump Intensity in Stock Prices: BIST 100 Example

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Abstract

This paper is concerned with the estimation of the time-varying jump intensity of the Borsa Istanbul 100 (BIST 100) index. In the estimation phase, we utilize a new two-step method. In the first step, we employ wavelet filters to compute the number of jumps as a counting process. Next, we apply an integer-valued generalized autoregressive conditional heteroscedasticity model to examine the deterministic and stochastic components of the jump dynamics. Our results indicate not only deterministic diurnal patterns but also an autoregressive mechanism in BIST 100 jump dynamics.

1. Introduction

Understanding the jump dynamics of financial time series helps traders to realize the risk and profitability profile of the traded securities. In this regard, the literature is rich in theoretical and empirical studies on the estimation of jump models. For instance, Duffie et al. (2000) provide an extensive analysis of jump-diffusion models. After the study of Duffie et al. (2000), Andersen et al. (2002) propose a jump-diffusion model endowed with the Poisson distribution that is derived by time-varying intensity. Moreover, in one of the recent empirical studies on the time-varying jump intensity, Danis et al. (2015) estimate a Dynamic Conditional Jump Model for Mexico, Indonesia, South Korea, and Turkey. Their findings indicate that the jump intensity is significantly linked to the past intensity. In our study, for Borsa Istanbul

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100 (BIST100 hereafter) index, we estimate a time-varying jump intensity, which is decomposed into deterministic and stochastic parts.

In our estimation procedure, we follow a two-step procedure. In the first stage, we employ a jump detection method to identify the location and the number of the intraday/intra-seance jumps. This method is based on wavelet theory. In the second stage, we estimate an inhomogeneous dynamic count regression model, which consists of both deterministic and stochastic components. Our methodology differs from the existing jump intensity literature in two crucial ways. First, for estimating the number of jumps, we rely on the wavelet methods, which have become a preferred tool in the finance literature (see, Gençay et al. (2001); Misiti et al. (2013); Rua and Nunes (2009)). This method has two critical advantages over the other jump detection techniques in the literature. First, Xue et al. (2014) claim that wavelets can decompose noisy financial data into different time-scale components, which can be utilized to distinguish jumps from continuous price changes and microstructure effects. Second, Fan and Wang (2007) argue that the estimation of the integrated volatility with wavelets can improve the efficiency of the estimation of jump size. Furthermore, we investigate the diurnal patters of the jump intensity by adding séance, policy day, and year dummies. To the best of our knowledge, this is the first study that examines diurnal jump dynamics for the Turkish financial system.

Additional to the technical novelty of the paper, we aim to answer three basic questions regarding the jump dynamics in the BIST 100 stock exchange. These are 1) Is there any year effect?; 2) Is there any séance effect?; and 3) Is there any impact of policy announcements on the jump dynamics? All these three questions can be examined in the deterministic part of the jump intensity. Moreover, we also investigate the stochastic patterns, which link the past intensity and number of jumps to current jump intensity. Our method does not aim a forecasting exercise for the jump dynamics. Nevertheless, the current toolsets allow us to predict future jump rates and we leave the forecast performance of our approach to a future study.

Our result demonstrates that the jumps in the BIST 100 index exhibit diurnal patterns. Notably, we find that the morning seances are more nonresilient to the jumps than the afternoon séance. Moreover, we can observe the policy announcements are mostly ineffective to trigger extreme price movements. Finally, our findings indicate that in the year 2018, jump intensity was lower relative to other years in our sample.

The rest of the article is organized as follows. In section 2, we describe the two-stage estimation methodology and introduce the data characteristics.

Section 3 presents the estimation results. Finally, in Section 4, we discuss our findings and conclude the paper.

2. Methodology and Data

In this study, we combine two major toolsets of financial econometrics. On the one hand, we utilize the first toolset to detect the location and the number of jumps within a given time interval in the stock price series of the BIST 100 index. This detection technique is built on the wavelet theory, and we mostly follow Xue et al.'s (2014) wavelet-based jump detection test. In this test, a practitioner can both detect the presence and the location of the jumps, thus we can construct a counting process based on this testing framework. On the other hand, we model the number of jumps in a trading season as a nonhomogeneous counting process with deterministic terms. This type of model is also known as the Generalized Linear Model (GLM) or Integer-valued Generalized Autoregressive Conditional Heteroscedasticity model (IN-GARCH). To estimate the model, we utilize the R package "tscount," written by Liboshcik et al. (2015).

2.1. Wavelet-Based Jump Detection Test

This section follows mostly from Xue et al. (2014). In this paper, the authors propose a jump detection method, which relies on the wavelet transform of the observed stock price series[3]. Let the $\{S_t\}_{t=T_{k-1}+1}^{T_k}$ be the sequence of the logarithm of the observed stock price for BIST 100, where T_k is the number of observation in the k^{th} subsample for each $k \in \{1, \dots, K\}$ for some positive integer K. Since our objective is to investigate the jump intensity dynamics through time, we require to divide the sample into equal-length intervals and constitute a times series of jump counts.

To apply the jump detection test, we need to extract the high-frequency component with wavelet filters. Wavelet filters are useful in decomposing a time series data into its short- and long-run components through the use of wavelet coeffiecients that are constructed based on wavelet filters. In the detection of jumps we utilize the short-run wavelet coefficient (the noise component). To this end, we define the vector $h = [h_0, \dots, h_{L-1}]$ as the high pass wavelet filter with filter length L. This filter length defines the lag-length that needs to be colved in the original data. That is, we convolve the vector *h* with S_t and obtain the first level wavelet short-run coefficients $\{W_{1,t}\}_{t=T_{k-1}+1}^{T_k}$ for the k^{th} subsample as

3 A comprehensive introduction to wavelet analysis is given in Xue et al. (2014). We refer the readers to this study for excellent guide for the wavelet analysis.

$$W_{1,t} = \sum_{l=0}^{L-1} h_l S_{t-l \, modT_k},$$

which is the short-run (noise) component. Second, we compute the recursive variance at time t, for each $t \in \{T_{k-1} + 3, \dots, T_k\}$, as

$$\hat{\sigma}_{t-1}^2 = (1/(t-2))\,))\, \sum_{i=T_{k-1}+2}^{T_{k-1}+t} |W_{1,t}||W_{1,t-1}|.$$

In the computation of the recursive variance, we lose the first two observations. Third, we define the test statistic for the presence of jumps for each $t \in \{T_{k-1} + 3, \dots, T_k\}$ as

$$\tau(t) = W_{1,t}/\hat{\sigma}_{t-1}^2.$$

Xue et al. (2014) shows that under the null of no jump at period t $\tau(t) \sim \mathrm{U_i}/d$, where $U_i = B_i - B_{i-\Delta s}$ for $\Delta s \to 0$ and B_i is Brownian motion, d is a fixed constant that depends on the high pass filter h. Finally, we reject the null of no jump if $|\tau(t)| \geq CV(1-\eta)$ for each $t \in \{T_{k-1} + 3, \dots, T_k\}$, where $CV(1-\eta)$ is the $(1-\eta)\%$ quantile of $\mathrm{U_i}/d$. Overall, after constructing the noise component, we aim to capture the extreme/singular values throught the test aforementioned test statistics.

The above testing procedure, in turn, gives us the information on whether there is a jump at time t. Accordingly, we can count the number of times that we reject the null hypothesis for the subsample period. We denote the total number of the estimated jumps as J_k for each $k \in \{1, \dots, K\}$. As a result, we obtain a sequence of the counting process $\{J_k\}_{k=3}^{K}$.

2.2. Estimating Nonhomogeneous Count Process Model

The next stage of our methodology is to fit a nonhomogeneous count process, which can be estimated by the method described in Section 2.1. In the estimation procedure, we assume that the counting process J_k has a discrete distribution conditional on the deterministic terms denoted by the n_x dimensional vector process X_k, the past values of J_k and the past jump intensity, which we define as λ_k. Formally, we can write $J_k \sim \mathrm{f}(\kappa_k \mid X_k, \mathcal{F}_{k-1}, \theta)$, where $\mathcal{F}_{k-1}$ is the information set that contains the past information about J_k and κ_k up to $k-1$, f is a distribution function, which can be selected as some famous example such as Poisson and Negative binomial distributions, and θ is the vector of unknown parameters. We can further decompose the jump intensity parameter at subsample k as $\kappa_k = \lambda_k + \delta' X_k$, where λ_k is the stochastic part of the conditional mean of J_k. Under this specification, we define the dynamics that govern the jump intensity λ_k under *INGARCH(p,q)* with deterministic components as

$$g(\kappa_k) = \alpha_0 + \delta' X_k + \sum_{j=1}^{p} \alpha_j \left(g(\kappa_{k-j}) - \delta' X_{k-j} \right) + \sum_{j=1}^{q} \beta_j J_{k-j}, \quad (1)$$

where p and q are the lag length of autoregressive and moving average terms, respectively.

In another alternative specification, we may omit the deterministic part $\delta' X_{k-j}$ from $\alpha_j \left(g(\kappa_{k-j}) - \delta' X_{k-j} \right)$. However, the model we employ is more flexible, and our estimation exercise demonstrates more consistent results under the model (1). To predict the conditional mean process κ_k, we need to estimate the unknown population parameters collected in the vector $\theta = [\alpha_0, \alpha_1, \dots, \alpha_p, \beta_1, \dots, \beta_q, \delta']$. For this purpose, we first write the log-likelihood as

$$ln\left(l(\theta, \boldsymbol{J}) \right) = \sum_{k=1}^{K} ln \left(\mathrm{f}(\kappa_k | X_k, \mathcal{F}_{k-1}, \theta) \right), \quad (2)$$

where we define the vector of the observed jump counts as $\boldsymbol{J} = [\mathrm{J}_1, \dots, \mathrm{J}_\mathrm{K}]$. Maximizing the log-likelihood in Equation (2) with respect to θ yields the (conditional) maximum likelihood (CML) estimates of the model. We denote the estimated parameter values as $\hat{\theta}$. Given these estimated parameters, we can calculate the asymptotic variance of $\hat{\theta}$ as follows,

$$Avar(\hat{\theta}) = [I(\hat{\theta})]^{-1} = \left[\sum_{k=1}^{K} cov \left(\frac{\partial ln(l(\theta, J))}{\partial \theta} \middle| X_k, \mathcal{F}_{k-1} \right) |_{\theta = \hat{\theta}} \right]^{-1}.$$

Using these objects obtained from CML estimation, Fokianos and Fried (2010) show that

$$\sqrt{K}(\hat{\theta} - \theta_0) \xrightarrow{d} N \left(\mathbf{0}_{p+q+n_x+1}, Avar(\hat{\theta}) \right).$$

We use the above result to construct confidence levels for our estimates.

2.3. Data

In our analysis, we utilize Borsa Istanbul 100 (BIST 100) Index dataset acquired from the official Borsa Istanbul database. This high-frequency dataset includes observations minutely for the BIST 100 index closing price, which dates from 1 April 2016 to 31 January 2019. For jump detection exercise, we divide each day into two sessions, namely, morning and afternoon. The morning session is between 10:00:00 and 13:00:00, and the afternoon session is between 14:00:00 and 17:00:00. We choose such a division because of two reasons. First, we aim to analyze whether there is an intensity difference between two trading sessions of a day. Second, there is almost no price volatility between 13:00:00 and 14:00:00. This situation renders some problems in jump detection. After clearing missing observation and non-trading periods, we have 1421 sessions; thus, we set $K = 1421$. In each trading session, we have 180 minutes. A summary of statistics of the high-frequency data is provided in Table 1.

Table 1. Return Statistics for High-Frequency (Minutely) BIST100 Returns

	Overall	2016	2017	2018	2019
Mean	-0.00012	-0.00013	0.00000	-0.00027	0.00043
Std. Dev.	0.01941	0.01706	0.01537	0.02409	0.01999
Median	0.00031	0.00020	0.00033	0.00033	0.00109
Kurtosis	32.03097	16.32362	17.11742	32.17472	5.68634
Skewness	-0.81413	-0.12264	-0.44415	-1.03542	-0.31216
Minimum	-0.61333	-0.24140	-0.34890	-0.61333	-0.12153
Maximum	0.40839	0.36062	0.36814	0.40839	0.11615
Sample Size	256376	67093	91132	90209	7942

Note: Std. Dev. is the abbreviation for the standard deviation of the returns.

From Table 1, we observe that the return levels are negatively skewed and posses fat tails given the high kurtosis levels. Thus, the existence of jumps in BIST 100 is a no-surprize event as might be expected from the indices of emerging market economies. The mean return levels are the worst in 2018, then followed by the year 2016. In those years the standard deviation of returns are somewhat higher, though in 2019 (a year with positive mean return) the standard deviation is higher than that in 2016.

Additionally, we investigate the effect of session differences and policy announcements of the Central Bank of the Republic of Turkey (CBRT). We utilize a dummy variable framework. In total, we use five dummy variables.

Accordingly, the first two dummy variables of deterministic component X are for the sessions and the policy announcement of CBRT. The first one is denoted as $\{D_{1,k}\}_{k=1}^{K}$ and $D_{1,k} = 1$ if it is the morning session and $D_{1,k} = 0$ otherwise. The second variable is the policy dummy, which is represented as $\{D_{2,k}\}_{k=1}^{K}$ and $D_{2,k} = 1$ if the day of session k is a policy announcement day for the CBRT. With this dummy, we try to investigate whether there is a jump intensity difference between policy and non-policy days. Furthermore, we also add year dummies to understand whether there is any shift in jump dynamics throughout the years. These dummies are represented with $\{D_{3,k}\}_{k=1}^{K}$, $\{D_{4,k}\}_{k=1}^{K}$ and $\{D_{5,k}\}_{k=1}^{K}$ for the years 2017, 2018, and 2019, respectively. As a result, the base year is 2016. In this case, the coefficient vector of the deterministic terms becomes $\delta = [\delta_1, \delta_2, \delta_3, \delta_4, \delta_5]$, where δ_j is the coefficient of $D_{j,k}$.

3. Results

In our empirical exercise, we consider the jumps that are detected with the help of the least symmetric wavelets of length 8 (sym8). Xue et al. (2014) recommend this filter in their methodology; thus, we follow their recommendation. Nonetheless, we also present results with other filters for robustness checks.

3.1. Descriptive Statistics for the Estimated Jump Dynamics

First, we apply the methods in Section 2.1 to estimate the number of jumps by using the sym8 filter. As we described in Section 2.1, we divide the trading day into morning and afternoon sessions. Within each session, we apply the jump test to minutely data. Accordingly, for each data point, we check the rejection decision by using a significance level of 0.05%. Next, we count the number of times we reject the null hypothesis of no jump. This number, which is denoted as J_k at session $k,$ gives us the number of jumps in that session. In Figure 1, we can observe the evolution of J_k for each year, which contains different number of observations. Moreover, in Figure 1 the red lines demonstrate the mean of J_k for each year. While the mean jump numbers is close to 8, we can observe serial correlations between consecutive observations. Such correlations then suggest the dependence of future jumps to their historical values.

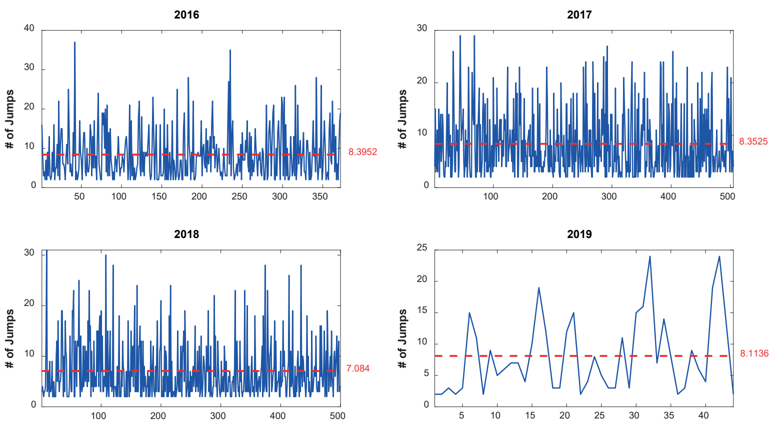

Figure 1. Estimated # of Jumps with sym8 Filter

To analyze the jump dynamics further, we present basic statistics for the series J_k. These statistics are given in Table 2. From this table, we can see few basic patterns. As previously noted, the mean jumps are very close to 8. In effect, they tend to be slightly above in years 2016, 2017 and 2019. However, th number of jumps drops to around 7 in the year 2018. Furthermore, the median of the jump counts is around 6.5, but again in 2018, it is less suggesting more tanquile periods for BIST 100 in that year. Besides, the year 2017 contains larger number of jumps. Nonetheless, this information may be misleading since we have fewer observations for the years 2016 and 2019 than we do for 2017 and 2018.

Table 2. Basic Descriptive Statistics for the Number of Jumps Series

	Overall	*2016*	*2017*	*2018*	*2019*
Mean	7.9099	8.3952	8.3525	7.0840	8.1136
Standard Error	0.1612	0.3334	0.2741	0.2519	0.9226
Median	6	7	6	5	6.5
Kurtosis	1.2243	1.5740	0.3083	2.1927	0.3020
Skewness	1.2624	1.2765	1.0439	1.5206	1.0207
Minimum	2	2	2	2	2
Maximum	37	37	29	31	24
Sum	11240	3123	4218	3542	357
Count	1421	372	505	500	44

These results shed some light on the jump dynamics in BIST 100. One of the important patterns is the instability of the jump dynamics. To illustrate this formally, we apply a regression-based technique on J_k. This regression method is presented in Section 2.2.

3.2. Estimation Results of the Inhomogeneous Count Process

As we discuss in Section 2.2, the inhomogeneous count models are excellent tools in explaining the serial linkages between the consecutive realization of a counting process. Additionally, the setup, which we utilized, also allows us to decompose the stochastic and deterministic parts of the counting process.

In this section, we work on the number of jump series that is obtained with the sym8 based jump detection algorithm. After obtaining the counting process, we utilize the regression model in Equation (1). In this regression model, we utilize the negative binomial distribution for f since its alternative Poisson Process does not generate sensible results. It also causes the MLE algorithm to suffer convergence problems. Another issue in the estimation is the selection of the link function $g(\cdot)$. We choose $g(\cdot) = log(\cdot)$, since a linear link function also suffers convergence problems. Finally, we need to choose the lag lengths q and p. We employ a Bayesian information criteria-based selection, which points an $INGARCH(1,2)$ with the log link function. We demonstrate these results in Table 3.

Table 3. Estimation Results of INGARCH(1,2) Model with Least Symmetric 8 Filter

Coefficient	Estimate	CI(lower)	CI(upper)
α_0	2.2223***	1.64356	2.801
	(0.2953)		
β_1	0.0799**	0.00819	0.15159
	(0.0366)		
β_2	-0.0679*	-0.14538	0.00967
	(0.0396)		
α_1	-0.6298***	-0.81943	-0.44023
	(0.0967)		
δ_1	0.4145**	0.095	0.73396
	(0.163)		
δ_2	-0.0179	-0.19786	0.16208
	(0.0918)		
δ_3	0.0177	-0.06979	0.10514
	(0.0446)		
δ_4	-0.1224***	-0.21424	-0.03051
	(0.0469)		
δ_5	0.0219	-0.18212	0.22585
	(0.1041)		
***: significant at 0.01, **: significant at 0.05, *: significant at 0.1. The parenthesis is for the standard deviation of the coefficient estimates. CI stands for 95% confidence interval.			

In Table 3, we observe that the intercept term is significant at the 0.01 level. This implies that the mean of the jump count is approximately 9.22 (= $e^{2.223}$) when all other variables have no effect. When we check the other deterministic terms, we see that only the coefficients of the morning session dummy and the year 2018 dummy statistically significant at the 0.05 significance level. Notably, the outcome regarding the 2018 dummy is not surprising after the results we obtain in Section 3.1. Both analyses indicate that in the year 2018, jump intensity drops by approximately 1 unit. Moreover, it is interesting that the intercept term of the morning session is approximately 1.5. This situation implies that the risk of extreme price movements is higher in the morning sessions than they are in the afternoon sessions. Another crucial result is the insignificance and negativity of the policy day dummy. Even though the coefficient of this dummy is insignificant, its negative value may indicate less risky stock behavior on the policy days. Finally, the insignificance of the coefficients δ_3, δ_5 indicates that there is no jump intensity difference among the years, excluding the year 2018. The finding is interesting because 2018 is a year when the drops in BIST 100 is substantial. Yet, the number of jumps did not differ significantly from the other years. Thus, the decline in 2018 follow no less discontinuous path than it does in other years.

Next, we examine the stochastic part of the jump intensity dynamics. Both AR(1) and MA(1) coefficients are significant at the 0.05 significance level, but the MA(2) coefficient is significant only at the 0.1 significance level. Additionally, we observe a negative and high-valued AR(1) coefficient. This type of dynamic leads to a zig-zag pattern in the stochastic component of the jump intensity. The following figure demonstrates the evolution of the jump intensity estimate $\hat{\kappa}_k$.

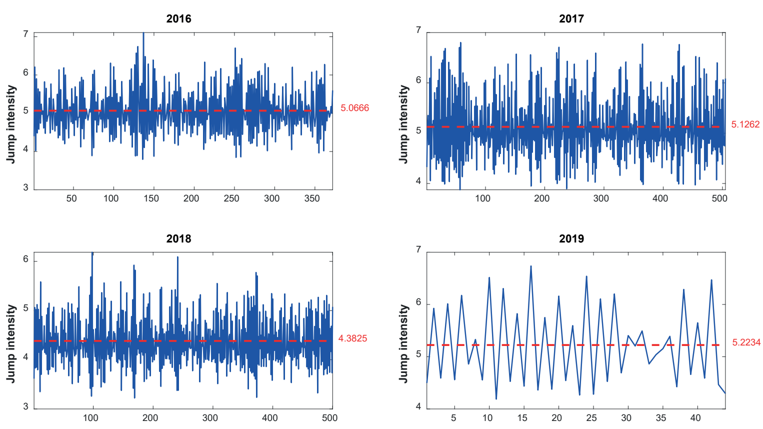

Figure 2. Evolution of Jump Intensity Estimate

In Figure 2, we can see the impact of negative AR coefficient. The other important feature of the estimated jump intensity is the level shift observed in the year 2018.

3.3. The Results with the Other Filters

In this section, we repeat the same procedures in Sections 3.1 and 3.2 by using different wavelet filters. In our list, we have 'Haar' and Daubechies 8, which are also frequently utilized filters in wavelet literature (see, Xue et al. (2014)). We first investigate Table 3, which depicts the results with the Haar filter. In this case, we have a few differences from the previously presented results. First, the coefficients of the MA terms are insignificant, while the significant AR coefficient has the same sign as the sym8 case. Second, the policy day dummy is negative and significant unlike the sym8 model. The last difference emerges about the coefficient of the year 2017 dummy, which is significant in this case. However, its coefficient has a small value.

In Tables 4 and 5, we observe the results from the Daubechies 8 wavelet filter, which shares the same filter length as sym8. These results are closer to the findings with the sym8 filter. However, there is one distinction worth noting: the AR coefficient is positive but insignificant. The other coefficients seem to have similar patterns as in the sym8 case.

Table 4. Estimation Results of INGARCH(1,2) Model with Haar Filter

Coefficient	Estimate	CI(lower)	CI(upper)
α_0	2.9117***	2.4337	3.3897
	(0.2439)		
β_1	-0.0115	-0.0663	0.0433
	(0.028)		
β_2	0.0288	-0.0275	0.085
	(0.0287)		
α_1	-0.8182***	-0.8647	-0.7717
	(0.0237)		
δ_1	0.683***	0.3717	0.9943
	(0.1588)		
δ_2	-0.2977***	-0.4984	-0.097
	(0.1024)		
δ_3	-0.1341***	-0.2272	-0.0409
	(0.0475)		
δ_4	-0.2894***	-0.387	-0.1917
	(0.0498)		
δ_5	-0.1496	-0.3697	0.0705
	(0.1123)		
***: significant at 0.01, **: significant at 0.05, *: significant at 0.1. The parenthesis is for the standard deviation of the coefficient estimates. CI stands for 95% confidence interval.			

Table 5. Estimation Results of INGARCH(1,2) Model with Daubechies 8 Filter

Coefficient	Estimate	CI(lower)	CI(upper)
α_0	2.43942***	0.9556	3.9233
	(0.7571)		
β_1	0.04075	-0.0162	0.0976
	(0.029)		
β_2	-0.09065***	-0.1505	-0.0308
	(0.0305)		
α_1	0.03983	-0.5184	0.5981
	(0.2848)		
δ_1	0.36728***	0.1807	0.5539
	(0.0952)		
δ_2	-0.12471	-0.3113	0.0619
	(0.0952)		
δ_3	0.00243	-0.0858	0.0906
	(0.045)		
δ_4	-0.17652***	-0.3041	-0.0489
	(0.0651)		
δ_5	-0.01711	-0.2239	0.1897
	(0.1055)		
***: significant at 0.01, **: significant at 0.05, *: significant at 0.1. The parenthesis is for the standard deviation of the coefficient estimates. CI stands for 95% confidence interval.			

4. Conclusion and Discussion

This paper concerns the time-varying jump intensity in BIST 100 stock exchange. We adopt a two-stage algorithm to estimate the jump intensity parameter of a negative binomial distribution. Our methodology combines two modern techniques of the literature, which are the wavelet theory and the inhomogenous counting process. The wavelet theory helps us to identify the number of jumps, which is a counting process. Then, we apply an INGARCH(p,q) model to reveal the time-varying arrival rate of this counting process.

Our results indicate that there is a significant link between the past and current jump intensity parameters. Moreover, the séance is significantly pronounced by the model. In particular, the morning sessions in BIST 100 contains more jumps than afternoon seances. However, the impact of the policy announcement seems to be weak or negative. This situation may appear because the traders avoid executing extreme actions before the policy announcement. Finally, the year effect is sounder for the year 2018 than the other years in our sample. We observe a drop in the level of the jump intensity in the year 2018.

Furthermore, our findings may attract attention to the behavioral aspects of the diurnal patterns that we found in this paper. Another future extension can be examining more diurnal or calendar effects in the jump dynamics. The authors are investigating these issues for future work.

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