SKIPPING ACROSS THE BOSPHORUS:

POST-JUMP RETURNS
AT ULTRA-HIGH FREQUENCY

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To my dear wife,

ABSTRACT

This study rigorously investigates intraday jumps in highly liquid stocks listed on Borsa Istanbul (BIST) using two common jump test methods and ultra-high frequency data. Additionally, three purely price-based jump methods, referred to as Price Skipping, were developed to improve jump detection accuracy. The findings reveal the presence of reversal post-jump returns, irrespective of the jump direction. A profitable trading strategy was established, exploiting this market behavior by taking long positions after down jumps and short positions after up jumps. The strategy's performance was compared across different jump detection methods and confidence intervals.

Logistic regression analyses demonstrate a significant negative correlation between relative tick size and jump occurrence. Additional analyses using Ordinary Least Squares (OLS) and Locally Estimated Scatterplot Smoothing (LOESS) consider factors such as relative tick size, volume, pre-jump returns, sector affiliation, jump timing, index jumps, and alternative jump detection methods.

Importantly, a positive correlation was discovered between relative tick size and the magnitude of reversal post-jump returns. Another significant finding suggests a positive correlation between trading volume during jumps and the magnitude of reversal post-jump returns. These results indicate that high volumes, potentially resulting from large market orders, induce stock price jumps involving multiple ticks, and when the relative tick size is large, these movements trigger an overreaction, subsequently leading to a reversal within a defined time period.

These findings suggest that the tick size is excessive for the small priced stocks and suboptimal for the middle range. Therefore, it is recommended that Borsa Istanbul's management consider revising their tick size policy to enhance market liquidity, considering the implications of this study.

Keywords:

Ultra-high frequency data, Intraday jumps, Price Skipping, Jump detection methods, Price reversal, Trading strategy, Relative tick size, Stock market liquidity, Borsa Istanbul.

ÖZETÇE

Bu çalışma, Borsa İstanbul'da (BIST) işlem gören yüksek likiditeye sahip hisse senetlerinde gün içi sıçramaları iki yaygın kullanılan sıçrama test yöntemi ve ultra yüksek frekanslı veri kullanarak titizlikle araştırmaktadır. Ayrıca, sıçrama tespit doğruluğunu artırmak için fiyat sekmesi adında tamamen fiyat bazlı üç sıçrama yöntemi geliştirilmiştir. Bulgular, sıçrama yönünden bağımsız olarak sıçrama sonrası ters yönlü getirilerin varlığını ortaya koymaktadır. Bu piyasa davranışını, aşağı sıçramalardan sonra uzun, yukarı sıçramalardan sonra kısa pozisyon alarak kullanan karlı bir ticaret stratejisi oluşturulmuştur. Stratejinin performansı, farklı sıçrama tespit yöntemleri ve güven aralıklarında karşılaştırılmıştır.

Lojistik regresyon analizleri, göreceli adım büyüklüğü ile sıçrama olasılığı arasında anlamlı bir negatif korelasyon olduğunu göstermektedir. Göreceli adım büyüklüğü, hacim, sıçrama öncesi getiriler, sektör, sıçrama zamanlaması, endeks sıçramaları ve alternatif sıçrama tespit yöntemleri gibi faktörleri dikkate alan Olağan En Küçük Kareler (OLS) ve Yerel Tahminli Dağılım Grafiği Düzleştirme (LOESS) kullanılarak yapılan ek analizler de bulunmaktadır.

Önemli olarak, göreceli adım büyüklüğü ile sıçrama sonrası ters yönlü getirilerin büyüklüğü arasında pozitif bir korelasyon keşfedilmiştir. Başka bir önemli bulgu, sıçrama esnasındaki işlem hacmi ile sıçrama sonrası ters yönlü getirilerin büyüklüğü arasında pozitif bir korelasyon olduğunu göstermektedir. Bu sonuçlar, potansiyel olarak büyük piyasa emirlerinden kaynaklanan yüksek hacimlerin, birden fazla adım içeren hisse senedi fiyatı artışlarına neden olduğunu ve göreceli adım boyutu büyük olduğunda, bu

hareketlerin bir aşırı tepkiyi tetiklediğini ve ardından belirli bir süre içinde bir tersine dönüşe yol açtığını göstermektedir.

Bu bulgular, küçük fiyatlı hisse senetleri için adım büyüklüğünün aşırı olduğunu ve orta aralık için de idealden büyük olduğunu önermektedir. Bu nedenle, Borsa İstanbul yönetiminin bu çalışmanın sonuçlarını dikkate alarak piyasa likiditesini iyileştirmek için adım büyüklüğü politikasını gözden geçirmesi önerilmektedir.

Anahtar Kelimeler:

Ultra yüksek frekanslı veri, Gün içi sıçramalar, Fiyat sekmesi, Sıçrama tespit yöntemleri, Ters yönlü fiyat hareketi, Ticaret stratejisi, Göreceli adım büyüklüğü, Hisse senedi piyasası likiditesi, Borsa İstanbul.

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CHAPTER I

INTRODUCTION

Tick data can be analogized as the subatomic world of finance, and ultra-high frequency stands on the shores of it. Recent years, with the availability of tick data and increasing computer power, there has been more and more studies on these not well known shores.

Price jumps, which are discontinuous price movement has been on the focus of science literature. Detecting jumps has high value due to their dire consequences in risk management and derivatives pricing [1]. Early studies used GARCH-jump or SV-jump models, which needed arrangement of complex parameters that decreased accuracy of the tests [2]. [3] and [4] defined a more efficient non-parametric jump test. [5], [6], [7], [8], [9] and many others tried to improve this method. However, these tests only give information about the existence or absence of jumps in a day. [10] developed a test, which also states the exact timing of jumps by comparing standardized intraday returns and using normal distribution. [11] improved it by using Gumbel distribution instead.

Ever since, there has been numerous studies on almost all markets using some form of non-parametric jump tests. However, rather than ultra-high frequency, most of the research is on lower frequencies. [12], [1] are among exceptions. The main deterrent is the microstructure noise which [13] analyzed in detail. Intraday zero returns and microstructure noise leads to bias for tests [10]. There has been attempts to tackle microstructure noise like [9], [14], [12] using pre-averaging and subsampling, however by design this method increases the frequency and although it is somewhat used in the average, still less information is used. Additionally, [15] these data processing methods may cause distortion of jump characteristics of data. [16] also suggest using subsampling on only lower frequencies, because it has negligible or negative effect on accuracy on higher frequencies.

When selecting the frequency, there is a trade-off between exposure of microstructure noise and discarding of useful data [17], [1]. Microstructure noise can cause spurious jumps, however even if lower frequency is used to avoid microstructure noise, spurious jumps still do exist, as [12] shoves that most of the jumps detected at 5-minute frequency are overestimated and actually are not jumps but volatility bursts. [18] confirms that most detected jumps are actually spurious. [1] also finds that jump numbers from ultra-high frequency are much smaller than jumps from 5-minute frequency. [19] on the other hand claims that volatility bursts alone are not enough to explain the frequency effect on number of jumps.

In many studies the empirical results seem to be highly sensitive data series, price measurements, frequency and data preparation methods [20]. The chosen test method and the frequency cause major variation on the jump number, timing, average size and ratio of direction [19]. Though [10] suggests using volatility signature plots, there is not a clear guideline for ideal frequency [21]. Besides volatility signature plots do not resolve extreme sensitivity to frequency [19].

In this study ultra-high frequency (1 second) data is used combining it with some elements of the tick data. The goal is to study time-series and cross-sectional properties and also return predictabilities of discontinuous price movements, namely realized jumps. Another goal is to try to understand the microstructural relationship between properties and return predictabilities of jumps and other factors, like tick size, volume, sector and timing. Though microstructure noise can obscure jumps, for this study, the severity of type II error is much less than type I errors, if there are return predictabilities of jumps. Also to reduce the impact of type II errors, great emphasis is placed on maximizing data usage, hence using a wide range of time period and not discarding any usable data.

Despite the wide literature on other markets, the studies of intraday jumps on Turkish stock market is limited. Some, like [22] focuses on indices, rather than stocks. To the best of my knowledge, this study will be a first, in terms of ultra-high frequency data usage and post-jump stock return analysis, for Turkish stocks. Being an unfragmented market with strict tick rules and adequate volume, Turkish stock market is very convenient for this study.

Demystifying the dynamics of intradaily return jumps is important for policy makers, as it is they, who are under the responsibility of the regulating the rules such as price ticks, order types, matching rules, circuit breakers, uptick rules, algorithmic trading procedures, market maker incentives, and many others; for creating a fair, transparent, and efficient marketplace, ensuring investor protection, maintaining market stability, and fostering economic growth. Understanding the predictability of post-jump intradaily returns is important for traders, as they try to make gains out of those. Comprehending the relationship between jumps and other factors is very useful for the risk management of investors' portfolios.

In order to prevent the study branching out too much, limit order book data is excluded and the liquidity aspect of jumps is mostly left out for another study. Almost half of the transactional data is timestamped with milliseconds. Though data frugality is the one of the concepts of this study, there are computational limitations to be considered.

Working on data with number of rows over a billion, is a challenge even for the fastest computers, unless big data programs are used, which have their own limitations. On the verge of big data, a choice between using millisecond frequency with much narrower time period or using 1 second frequency with wider time period has to be made. The latter is chosen, as that is thought to be potentially more descriptive, considering that some of the tick data dynamics is still being used.

Rather than individual stocks, mainly indices are in the center of the wide literature on jumps of stock market, and return predictability is mostly out of the focus. Albeit tick size has been widely studied, there is a lack of studies on the relationship between relative tick sizes and intraday jumps, possibly due to flexible tick rules and fragmentation of some stock markets in the world. This study contributes the literature by proving evidence of return predictability of intraday jumps on Turkish stock market, by developing three purely price based jump methods to improve jump detection accuracy, by providing evidence for understanding the relationship between intraday jumps and relative tick sizes, and by giving insight for other researches for unraveling the dynamics of intraday jumps. Also, this study illuminates all stock market managements, especially Borsa İstanbul, in making their decisions for tick size regulations.

The remainder of the thesis is structured as follows. **Chapter 2** summarizes the various usage of jumps tests in literature. **Chapter 3** describes the Turkish stock market and the data. **Chapter 4** defines the methodology. **Chapter 5** demonstrate the results. **Chapter 6** concludes.

CHAPTER II

LITERATURE REVIEW

After non-parametric jumps tests entered the literature with [3] and [4], many new jump test methods followed. [10] based their test on bi-power variation. [11] improved it by detecting large increments. [6] used threshold bi-power variations. [7] used swap variance. [5] used power variations sampled at different frequencies. [23] used neighborhood truncation estimators. [9], [12] and [14] used pre-averaging. [18] used thresholding. [24] used differenced returns. [25] used normalized kernel-smoothed U-statistic. [26] used option-implied volatility index.

Albeit there is a consensus on the presence of jumps in asset prices, the causes are still not clearly understood [27]. There are many papers focusing on news in search of this causality. Linkage to information shocks or liquidity shocks are common [22], [28]. [29] and [30] detected jumps after scheduled macroeconomic news, while [11] after unscheduled news. [31] matched only a third of jumps to macroeconomic news. [31] and [32] found that firm specific news is also the cause of some jumps, though less in number. Contrarily [18] found neither macroeconomic nor company specific news increases probability of jumps. [31], [33] and [34] shoved abnormal liquidity dynamics causing jumps. [35] and [2] used liquidity dynamics to predict jumps via machine learning. [36] detected jumps related to technical indicators and showed endogenous technical trading carries information. [28] introduced a framework for stock specific pre-jump trading patterns using technical indicators and liquidity measures.

[12] showed that, though severe shocks to liquidity are common, price

discontinuities are rare. [1] confirmed that, the number and magnitude of jumps decline notably with higher frequencies. [19] showed inconsistencies of the number of jumps, the ratio of jumps in direction, the size of jumps, and cross sectional ordering by number of jumps, with changing frequencies and test methods.

[21] and [37] compared jump tests. [38] and [39] investigated co-jumps. [40] investigated idiosyncratic jumps. [41] compared co-jumps and idiosyncratic jumps. [42] studied contagion of jumps across two markets. [22] compared jump dynamics across several markets. [27] studied trends in jump activity over many years. [43] compared jump risk premia for various components of the market. [35] and [2] used machine learning to predict jumps while [44] and [45] used it to detect jumps. [46] studied high frequency trader activity around jumps. [47] demonstrated how to apply jump test using “highfrequency” package of R.

CHAPTER III

DATA

3.1 *Borsa İstanbul*

Türkiye is one of the ten largest emerging economies of the world and its stock market, Borsa İstanbul (BIST) is one of the ten largest emerging markets. BIST has been a notable attraction for foreign investors since late 90's. By December 2022, mean daily trading volume was 116.36 billion TRY (6.24 billion USD) and maximum daily trading volume was 158.88 billion TRY (8.54 billion USD). Its daily trading volume is sufficient enough for this study. [22] underlines that when price jump arrivals are concerned, BIST behaves as a stable developed market rather than its economically and geographically similar counterparts.

BIST doesn't reflect any market fragmentation. All publicly held firm stocks are solely traded in BIST, which is one of the reasons why this market is chosen for this study. It has three main indices, Bist100 Bist50 and Bist30, which respectively consist of 100, 50 and 30 most liquid stocks, selected by Borsa İstanbul management quarterly. The indices are calculated by free-float adjusted market-capitalization weighting method. There are also market makers and liquidity providers, that are appointed by Borsa İstanbul management.

Up to 3 October 2019, BIST had two continuous trading sessions in a day. Morning continuous trading session was starting at 10:00 (TRT, which has been GMT+3 for the time period we study) and ending at 13:00 (TRT). Evening continuous trading session was starting at 14:00 (TRT) and ending at 18:00 (TRT). Since 4 October 2019, there has been one continuous trading session in a day, starting at 10:00 (TRT) and ending at 18:00 (TRT). The day before some holidays are acknowledged as half-days. Continuous trading session on half-days start at 10:00 (TRT) and ends at 12:30 (TRT). There are opening and closing sessions, as single price call auctions, before and after each continuous trading sessions. Stock based and also index based circuit breakers for falling prices are applied with certain conditions. After circuit breaker is activated, a single price call auction is implemented.

The tick rule for stock market is very strict, which is another reason why this market is chosen for this study. As **Table 1** shows, up to 20 TRY the tick size is 0.01 TRY. Between 20 TRY and 50 TRY, the tick size is 0.02 TRY. Between 50 TRY and 100 TRY, the tick size is 0.05 TRY. For share prices more than 100 TRY, the tick size is 0.1 TRY. The tick rule is valid on every stock and has not been changed during the time period chosen for this study. Various order types are used in BIST. However, the most common types are limit orders, market orders and market to limit orders.

Table 1: Tick rule of Borsa İstanbul for stock market

Price Range (TRY)			Price Tick (TRY)
0.01	-	20.00	0.01
20.00	-	50.00	0.02
50.00	-	100.00	0.05
100.00	and	over	0.10

3.2 Data Description

The data used in this study is shared by Borsa İstanbul. It consists of realized returns of all the indices with 1 second frequency, and all the realized transactions of all stocks traded on BIST with timestamps. The time period of the data is from January 2017 to December 2022, covering 6 years. Up to September 2019, the timestamps of the transactions are with second accuracy and after October 2019 they are with millisecond accuracy. For consistency, all the data is treated as if the transactions are with second accuracy, by cutting the millisecond part and flooring it to second level.

3.2.1 Data Selection

When studying the intradaily dynamics of stock prices, liquidity is an important factor. [33] argues that, due to the substantial difference between liquid and illiquid stocks a complete analysis on both would not be informative. Due to their selection methods, the main indices are appropriate filters for liquidity. In this study, Bist30 index is chosen for that filter. Only the stocks which has been in Bist30 across all the chosen time period, are selected. The number of stocks is 20. Representing the diversity of Turkish economy, selected stocks are also well diversified among sectors. Out of 20 stocks; 6 of them are industry firms (2 steel producers, 2 petrochemical companies, 1 glass manufacturer, 1 household appliances manufacturer), 4 of them are banks, 3 of them are conglomerates, 2 of them are telecommunication companies, 2 of them are transportation firms (1 airline company, 1 airport service company), 1 of them is a retail company, 1 of them is a mining company and 1 of them is a real estate developer. Among indices, Bist100 is used for benchmark.

3.2.2 Data Transformation

Transactions which took place outside the continuous trading sessions are omitted. Transactional stock data is converted to 1 second frequency data. While converting, the last price of a second is taken as the closing price. Also the highest, the lowest and the number of share weighted price of that second are calculated. The total number of intradaily continuous transactions for 20 stocks, is 1,073,180,263 actualized in 161,692,714 seconds. The empty seconds are filled, which is %80.12 of the seconds. Observing numerous zero returns is very common in practice [21]. The data consists of 1506 days (687 full days with two continuous sessions, 807 full days with one continuous session, 12 half days), 40,664,193 seconds. After returns are calculated the data has 40,662,000 seconds in it. [46] emphasizes that, for NASDAQ daily mean number of trades is 59,824 for large stocks and 1,491 for small stocks. Daily mean number of trades of the 20 selected stocks is 36,377.15 and intradaily mean number of trades is 35,630.15, which lies close to the large stocks of NASDAQ. This is also proof that liquid stocks of BIST are adequate for this study.

CHAPTER IV

METHODOLOGY

4.1 Price Process

Finance literature generally agrees on the assumption that realized log prices are generated by a continuous time Brownian semi-martingale with finite jump process, as shown below:

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

where p_t is the logarithmic price of a stock, μ_t is the predictable drift term, σ_t is the càdlàg positive spot volatility process, W_t is standard Brownian motion and dJ_t is the jump term, which is defined as;

$$dJ_t = c_t dN_t \tag{2}$$

where dN_t is Poisson type counting process and c_t is the jump size.

Quadratic variation (QV) is the cumulative variation of the return process [10]. QV of this process up to a fixed point in time t (for example a trading day), can be defined as;

$$QV_t = \int_0^t \sigma_s^2 \, ds + \sum_{j=1}^{N_t} c_{t_j}^2 \tag{3}$$

where the first part is the integrated variance (IV) which is caused by the spot volatility process, and the second part is caused by the jump process. In the absence of jumps QV is equal to IV. This is the main concept of most jump detection tests. QV can be estimated by realized variance (RV);

$$RV_t = \sum_{j=1}^{n} r_j^2 \tag{4}$$

where n is the equal subinterval of the interval [0,t], and r_j is the return of that subinterval. When n goes to infinity, RV is equal to QV. Though there are others [16] compares QV estimators and found that the benchmark and simplest of them, RV, is difficult to beat; and shows that more sophisticated estimators are more exposed to microstructure noise.

To measure IV there are various jump robust estimators. The most popular jump robust IV estimator is the realized bipower variation (BV) defined by [3]:

$$BV_t = \frac{\pi}{2} \frac{n}{n-1} \sum_{j=2}^{n} |r_j||r_{j-1}| \tag{5}$$

When n goes to infinity BV converges to IV.

4.2 Jump Detection

The intuition of many jump tests is that, in the presence of a jump, standardized returns are too extreme to be accepted as increments of Brownian motion [33]. However, none of the jump tests actually test the presence of a jump, they just give information whether or not the price process is continuous or not [21]. The null hypothesis of jump tests is that the price process in a given time interval is continuous, and the rejection of null suggests the presence of a discontinuous component, namely a jump [37].

[37] categorizes jump tests into five categories: those that are grounded on the difference from total variation and jump robust IV estimate, those that use measure of higher order variation, those that are grounded on returns rather than variance, those that use a variance swap, and those that are specifically designed to handle microstructure noise.

[42] states that none of the jump test is preferred to others, as it depends on the time frequency and features of the price process. However, they found that LM Test has more power, confirming [21] and [38]. [48] shows that, as long as the jumps sizes are sufficiently large, LM Test is satisfactory to detect jumps. [21] shows LM Test has overall the best performance among other tests with high power, controllable size, except in the case of extreme volatility, which in those cases they suggest using tests with more conservative size such as MedRV.

4.2.1 Lee-Mykland Jump Test (LM Test)

[11] proposed a test based on returns which allows it to detect the exact time of the jump. It uses jump robust IV estimator realized measure (RM);

$$\mathcal{L}_{RM_i} = \frac{r_i}{\hat{\sigma}_{RM_{i-1}}} \tag{6}$$

where RM uses BV;

$$\hat{\sigma}_{RM_i} = \frac{\pi}{2} \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} |r_j|\,|r_{j-1}| \tag{7}$$

where K is the window size. [11] suggest the K to be selected between $\sqrt{252\,n}$ and 252 n., where is n is the daily observations. In this study among the time period chosen every year has under 252 open days, so it is appropriate to use K as $\sqrt{252\,n}$.

Instead of normal distribution. [11] proposed Gumbel distribution and a jump is detected when;

$$\mathcal{L}_{RM_i} > \frac{-\log(-\log(1-\alpha))}{\sqrt{2/\pi}\,\sqrt{2\,\log(n)}} + \frac{\sqrt{2\,\log(n)}}{\sqrt{2/\pi}} - \frac{\log(4\pi) + \log(\log(n))}{2\sqrt{2/\pi}\,\sqrt{2\log(n)}} \qquad (8)$$

[38] and [28] emphasized that in the original [11] paper, in the numerator of the last term, $\log(4\pi)$ is printed as $\log(\pi)$ mistakenly. Corrected version is used and shown. α is the significance level and is the object of a trade-off between more spurious jumps and less jump test power [27]. Literature is far from consensus on this choice [19]. [21] suggests using 0.1% significance level in the presence of microstructure noise at higher frequencies. In this study 10%, 5%, 1% and 0.1% are used for comparison. [47] demonstrated applying LM Test using “highfrequency” package of R, however caution has to be given using it, as default alpha for critical value is erroneously uses 0.95 instead of 0.05, and also the function written in code doesn’t use constants $\sqrt{2/\pi}$ in (8), which results in overestimation of jumps in [47]’s demonstration.

4.2.2 MedRV

Instead of BV, [23] proposed MedRV to estimate IV:

$$MedRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi} \frac{n}{n-2} \sum_{j=3}^{n} med(|r_j|, |r_{j-1}|, |r_{j-2}|)^2 \tag{9}$$

When n goes to infinity MedRV converges to IV. By construction MedRV is robust with two consecutive jumps, unlike BV [23]. It is also more robust to microstructure noise and outliers [16]. There are less spurious jumps with MedRV and it detects less jumps [26]. In this study MedRV is also used for robustness check.

4.2.3 Price Skipping

Using 1 second frequency data [1] defined a jump test based on purely price, differencing highest (lowest) price observed in a local window and consecutive lowest (highest) price observed in a local window of that same width when consecutive price is going up (down) and identifying the tick price gap. Similarly, leaning on the strict tick rule of BIST, three methods, namely Price Skipping, are used in this study to detect price going past ticks discontinuously. The intuition behind this is that if prices are moving in a continuous Brownian motion, the increments should not be more than tick sizes.

4.2.3.1 Weighted Mean Skipping

Using 1 second frequency data, every second is taken as a local window. The lowest price that could happen in BIST is 0.01 TRY. Starting from there, every tick is counted as the next step, assuming the prices as a staircase going to infinity. For the seconds which has more than one transactions, number of shares weighted average of prices are calculated. Weighted average price of every second is matched to the corresponding step count. For fractional numbers, it is calculated by subtracting the largest integer lower than that number, dividing the fraction into the tick size of between the integers around that fractional number, and adding the quotient to the step count of the largest integer lower than the fractional number. A jump is detected when;

$$|\,WeightedMeanTickCount_s - WeightedMeanTickCount_{s-1}| \geq 2 \tag{10}$$

meaning the weighted average price move at least more than two ticks in a second.

In order to counter the possible argument that, in a high volatility environment, more than two tick count change in a second could be a normality; daily mean absolute tick count changes and standard errors are calculated. In none of the days, mean absolute tick count change plus two standard errors are more than 2. In fact, among 30,120 days, in only 6 of them it is over 1. Those 6 days belong to the same stock which is the highest priced and relatively lowest tick sized stock; and all the days are in the same month when the price of the stock is at the peak.

4.2.3.2 Low Skipping

In this method, highest and lowest price of every transaction in a second is selected. Tick counts are matched as above. A jump is detected when;

$$\begin{gathered} ((\max_j TickCount_{s_j} - \min_j TickCount_{s-1_j}) \geq 2) \\ \cup \\ ((\max_j TickCount_{s-1_j} - \min_j TickCount_{s_j}) \geq 2) \end{gathered} \tag{11}$$

meaning the price moves at least two ticks in at most two seconds. When both statements occur at the same instance, that instance is accepted as a positive jump.

4.2.3.3 High Skipping

In this method, highest and lowest price of every transaction in a second is selected. Tick counts are matched as above. A jump is detected when;

$$\begin{gathered}((\min_j TickCount_{s_j} - \max_j TickCount_{s-1_j} \geq 2) \\ \cup \\ ((\min_j TickCount_{s-1_j} - \max_j TickCount_{s_j} \geq 2)\end{gathered} \tag{12}$$

meaning the price moves at least two ticks in consecutive increments, which happens to be also in consecutive seconds.

4.2.4 Jump Co-Exceedance

[21] shows that combining tests with high power and with another test which has less power, reduces the detection of spurious jumps. [41] compares combination of jumps using Co-exceedance. [38] showed the co-exceedance rule for two jump tests as;

$$\sum_{j=1}^{N} \mathbb{I}\{Jump_{t,i,j} > 0\} \begin{Bmatrix} \geq 2 & Cojump, \\ \leq 1 & No\ Cojump, \end{Bmatrix} \tag{13}$$

where 𝕀{ 〖Jump〗 _(t,i,j)>0} is an indicator function to be valued as 1 if there is a jump.

In this study co-exceedance of LM Test with %5 significance level and MedRV with %5 significance level (named CoEx1) and also co-exceedance of LM Test with %5 significance level, MedRV with %5 significance level and High Skipping (named CoEx2) are used.

4.3 Jaccard Index

Jaccard Index is a similarity measurement method between two sample sets. It is calculated by dividing the intersection of two sets to the union of two sets [26]. **Table 2** shows Jaccard Index results of LM Test, MedRV with four different confidence intervals each and three Price Skipping methods. There are only high similarities among LM Tests, among MedRV, except for the 0.1% significance level, and between Weighted Mean Skipping and High Skipping.

Table 2: Jaccard Index results

WM Skip	**Low Skip**	0.270
WM Skip	**High Skip**	0.753
WM Skip	**LM %10**	0.017
WM Skip	**LM %5**	0.016
WM Skip	**LM %1**	0.013
WM Skip	**LM %0.1**	0.011
WM Skip	**Med %10**	0.026
WM Skip	**Med %5**	0.026
WM Skip	**Med %1**	0.025
WM Skip	**Med %0.1**	0.009
Low Skip	**High Skip**	0.220
Low Skip	**LM %10**	0.006
Low Skip	**LM %5**	0.006
Low Skip	**LM %1**	0.005
Low Skip	**LM %0.1**	0.004
Low Skip	**Med %10**	0.009
Low Skip	**Med %5**	0.009
Low Skip	**Med %1**	0.009
Low Skip	**Med %0.1**	0.003
High Skip	**LM %10**	0.010
High Skip	**LM %5**	0.010
High Skip	**LM %1**	0.008
High Skip	**LM %0.1**	0.007
High Skip	**Med %10**	0.017
High Skip	**Med %5**	0.017
High Skip	**Med %1**	0.016
High Skip	**Med %0.1**	0.006
LM %10	**LM %5**	0.943
LM %10	**LM %1**	0.828
LM %10	**LM %0.1**	0.718
LM %10	**Med %10**	0.167
LM %10	**Med %5**	0.166
LM %10	**Med %1**	0.158
LM %10	**Med %0.1**	0.150
LM %5	**LM %1**	0.879
LM %5	**LM %0.1**	0.761

LM %5	**Med %10**	0.148
LM %5	**Med %5**	0.147
LM %5	**Med %1**	0.140
LM %5	**Med %0.1**	0.124
LM %1	**LM %0.1**	0.866
LM %1	**Med %10**	0.130
LM %1	**Med %5**	0.129
LM %1	**Med %1**	0.124
LM %1	**Med %0.1**	0.110
LM %0.1	**Med %10**	0.111
LM %0.1	**Med %5**	0.110
LM %0.1	**Med %1**	0.105
LM %0.1	**Med %0.1**	0.098
Med %10	**Med %5**	0.996
Med %10	**Med %1**	0.948
Med %10	**Med %0.1**	0.301
Med %5	**Med %1**	0.952
Med %5	**Med %0.1**	0.302
Med %1	**Med %0.1**	0.317

4.4 Tick Returns

Assuming the ticks of BIST as a staircase starting from 0.01 going to infinity; not all steps have relatively equal heights. On the contrary, the first steps are enormous compared to later steps, which limits to 0 as it goes to infinity. In order to study the relationship between relative tick size and jumps; for every tick possible in BIST up to a certain value, the return and log return of next tick up and next tick down are calculated. It is cut at a sensible number as it goes to infinity. Except for the break points 20 TRY, 50 TRY and 100 TRY; negative returns to predecessor consecutive tick are the negative of positive returns to successor consecutive tick.

Figure 1 and **Figure 2** show percentage return and log return of next tick up and next tick down, respectively.

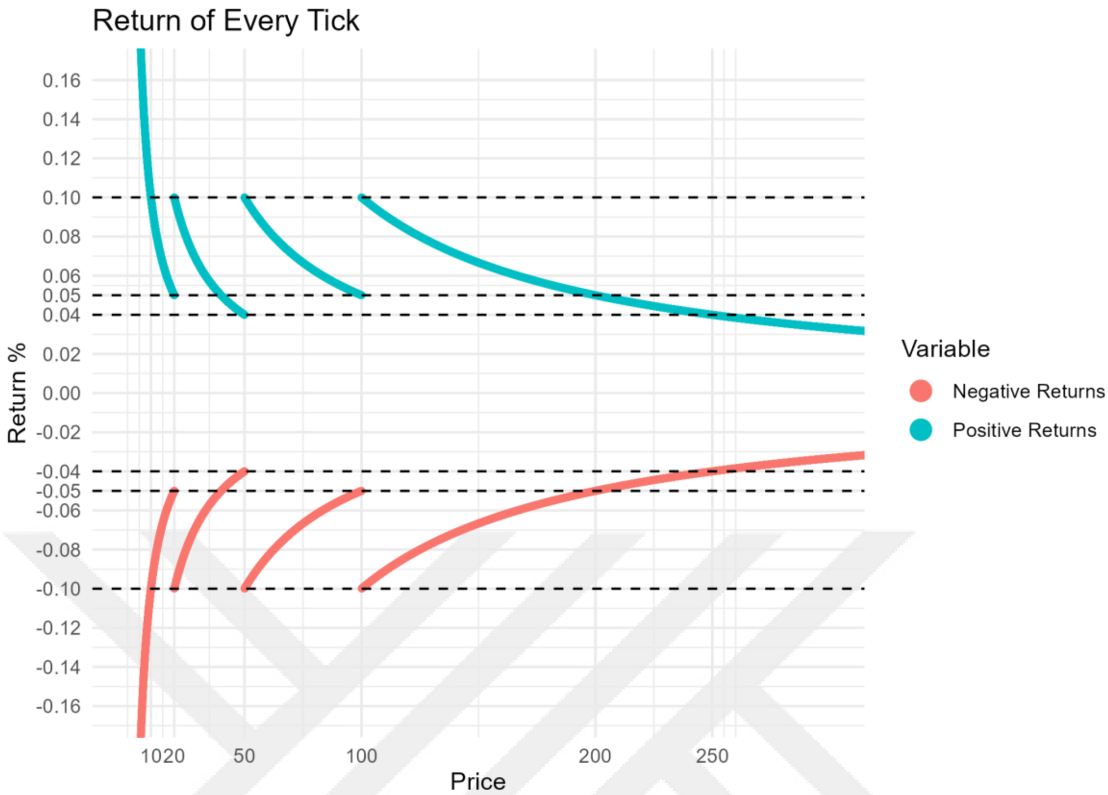


Figure 1: Percentage of returns of consecutive ticks

As a result of the tick rule of BIST, prices between 10 TRY and 250 TRY have similar relative tick sizes, tick returns ranging from 0.04% to 0.1%. When prices go below 10 TRY, relative tick sizes rapidly increase to a maximum of 100% tick return at 0.01 TRY. When prices go above 250 TRY, relative tick sizes slowly decrease, and tick returns limits to 0 as prices goes to infinity.

Stock prices on every second, are grouped to three, according to the closing prices of the prior second and current second. If they are both below 10 TRY they are grouped as small priced, if they are both above 250 TRY they are grouped as large priced and the rest is grouped as the middle range.

Figure 2: Log returns of consecutive ticks

4.5 Post-Jump Return Strategy

Every detected jump is divided into up and down jumps, according to the price movement. Expecting reversal post-jump returns, a strategy is established going on long (short) position at the exact time a down (up) jump is detected. For the time of the closure of the position 1, 5, 10, 15, 20, 30, 45, 60, 90 and 120 minutes are chosen, and each are tested separately. If there is less time left for the market to close than the chosen time, then no action is taken. Transaction fees for high-frequency traders in Türkiye, ranges between 0.0001 and 0.00001, so both ends of the spectrum are used.

CHAPTER V

RESULTS

5.1 Comparison of Number of Jumps

Table 3 and **Figure 3** display the total number of jumps of all selected stocks by year. Contrary to [26] the number of jumps associated with MedRV is more than with LM Test. The number of purely price based jump tests, namely Price Skipping, are much more than MedRV and LM Test. Among them, Low Skipping has the highest number by far and High Skipping has the lowest number, which is expected by the design. Among MedRV and LM Test, the ratio of jumps in direction are mostly consistent, though there are exceptions but not as much as [19] mentioned. There is consistency on number of jumps by year among methods and significance levels, as they increase or decrease uniformly with consecutive years. The total number of jumps in 2018 is more than the others, but the substantial increase is in 2022. in 2018 Türkiye went in to recession and suffered a currency and debt crisis, which caused high volatility in stock market. After the currency crisis at the end of 2021, Türkiye suffered very high inflation in 2022, which caused stock market nearly tripling nominally. As a results of this nominal increase, the relative tick sizes of stocks decreased, which may explain the increase in jumps, as the relationship will be shown later.

Table 3: Total number of jumps by year

Year	2017	2018	2019	2020	2021	2022
Seconds	6359400	6292800	6462000	7218000	7111800	7218000
LM %10 Down	1539	3188	1104	2300	3032	10041
LM %10 Up	1370	2893	903	2111	2637	7598
LM %5 D	1420	2999	1040	2153	2860	9557
LM %5 U	1267	2698	845	1986	2487	7190
LM %1 D	1178	2587	925	1903	2513	8578
LM %1 U	1067	2329	747	1715	2160	6366
LM %0.1 D	982	2198	799	1664	2197	7535
LM %0.1 U	886	1970	657	1488	1862	5541
Med %10 D	3376	6098	2618	3946	4146	12888
Med %10 U	3148	5631	2330	3646	3905	9836
Med %5 D	3356	6063	2615	3937	4117	12848
Med %5 U	3125	5602	2324	3629	3884	9793
Med %1 D	3230	5806	2553	3760	3898	12121
Med %1 U	3003	5379	2246	3467	3665	9242
Med %0.1 D	1111	1804	733	1214	1269	3762
Med %0.1 U	1028	1750	600	1231	1231	2782
CoEx1 D	593	1127	386	759	941	3068
CoEx1 U	520	1015	329	728	860	2222
CoEx2 D	432	613	207	356	357	735
CoEx2 U	368	577	190	399	394	583
WM Skip D	124742	182148	99318	119242	93702	261750
WM Skip U	127459	182646	97120	124273	94203	253488
Low Skip D	222907	442469	265025	395852	434075	1353412
Low Skip U	224471	438812	249708	417811	462696	1497271
High Skip D	115574	161515	90029	99290	64895	159599
High Skip U	119654	164713	89012	107000	68287	166456

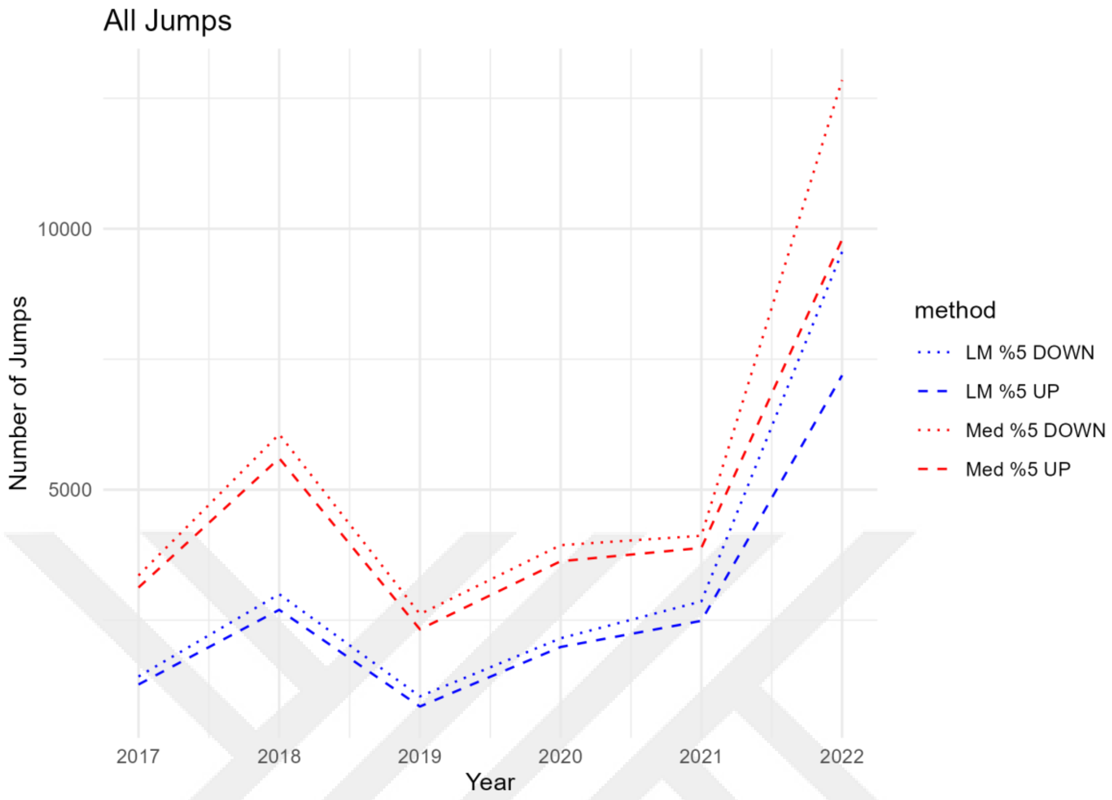


Figure 3: Total number of jumps by year

Figure 4 displays the total number of jumps of all selected stocks by minute. Around the open and close of the market, trading day volatility is expected to be highest [10]. As expected jumps are more concentrated just after the market opens. There is also a peak just before the close but not as much as the morning. The lowest numbers of jumps are around noon, with the exception of peak just after 14:00, which is caused by the opening of the evening session when there were two continuous trading sessions in a day. Also note that jumps between 13:00 and 14:00 are sparser due to the same reason.

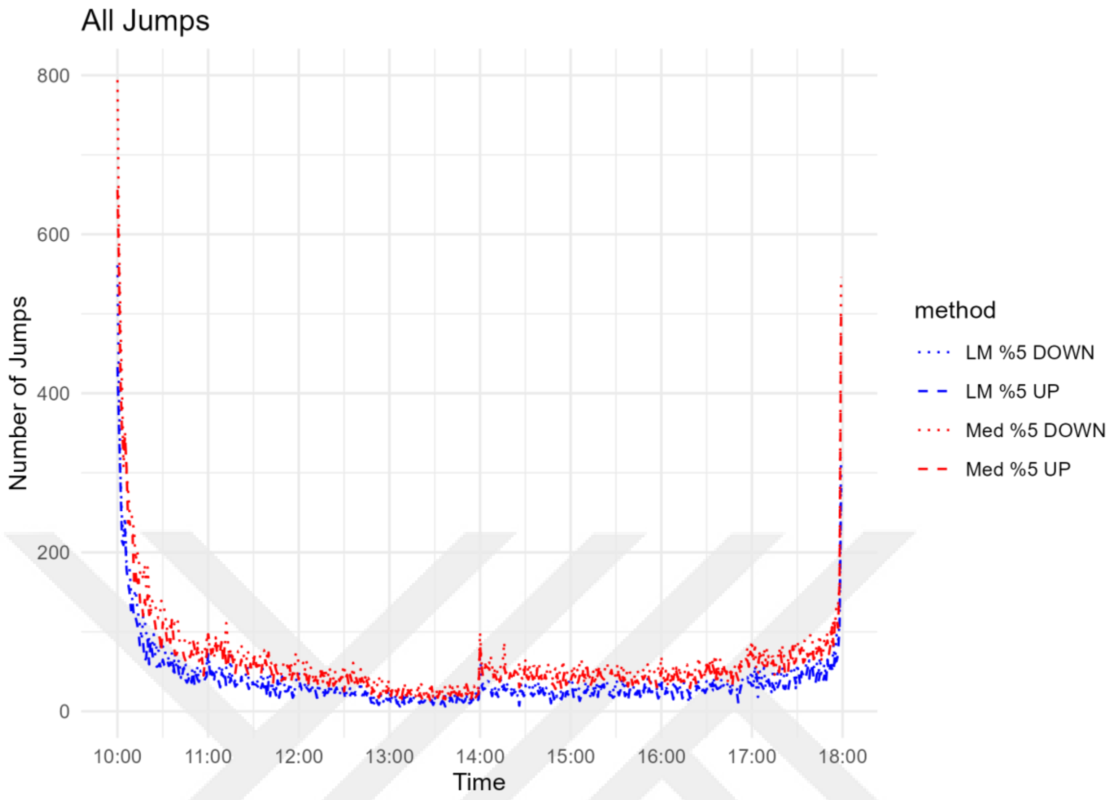


Figure 4: Total number of jumps by minute

Table 4 displays the total number of jumps of all selected stocks and **Figure 5** displays the number of jumps per 1,000,000 seconds by price group. There are much less large priced stocks in Borsa İstanbul, hence much less seconds in the data. Stocks tend to split after prices go up [49]. When the number of jumps is proportioned to the number of the seconds, the picture appears: Middle range on average has more jumps than the small priced, but the substantial increase happen going from middle range to large priced. This result raises the question of whether the probability of jumps increases with decreasing relative tick prices.

Table 4: Total number of jumps by price group

Price Group	< 10	>= 10 , <= 250	> 250
Seconds	368930053	438828073	5481874
LM %10 Down	684	16019	4501
LM %10 Up	531	13428	3553
LM %5 D	653	15163	4213
LM %5 U	512	12642	3319
LM %1 D	603	13471	3610
LM %1 U	456	11118	2810
LM %0.1 D	544	11801	3030
LM %0.1 U	401	9652	2351
Med %10 D	1007	26255	5810
Med %10 U	814	23282	4400
Med %5 D	1005	26151	5780
Med %5 U	812	23173	4372
Med %1 D	965	25108	5295
Med %1 U	781	22197	4024
Med %0.1 D	255	7545	2093
Med %0.1 U	222	6902	1498
CoEx1 D	199	5042	1633
CoEx1 U	173	4267	1234
CoEx2 D	59	2132	509
CoEx2 U	60	2067	384
WM Skip D	42049	730962	107891
WM Skip U	43039	732298	103852
Low Skip D	242151	2571439	300150
Low Skip U	226111	2689158	375500
High Skip D	37345	596655	56902
High Skip U	39533	617802	57787

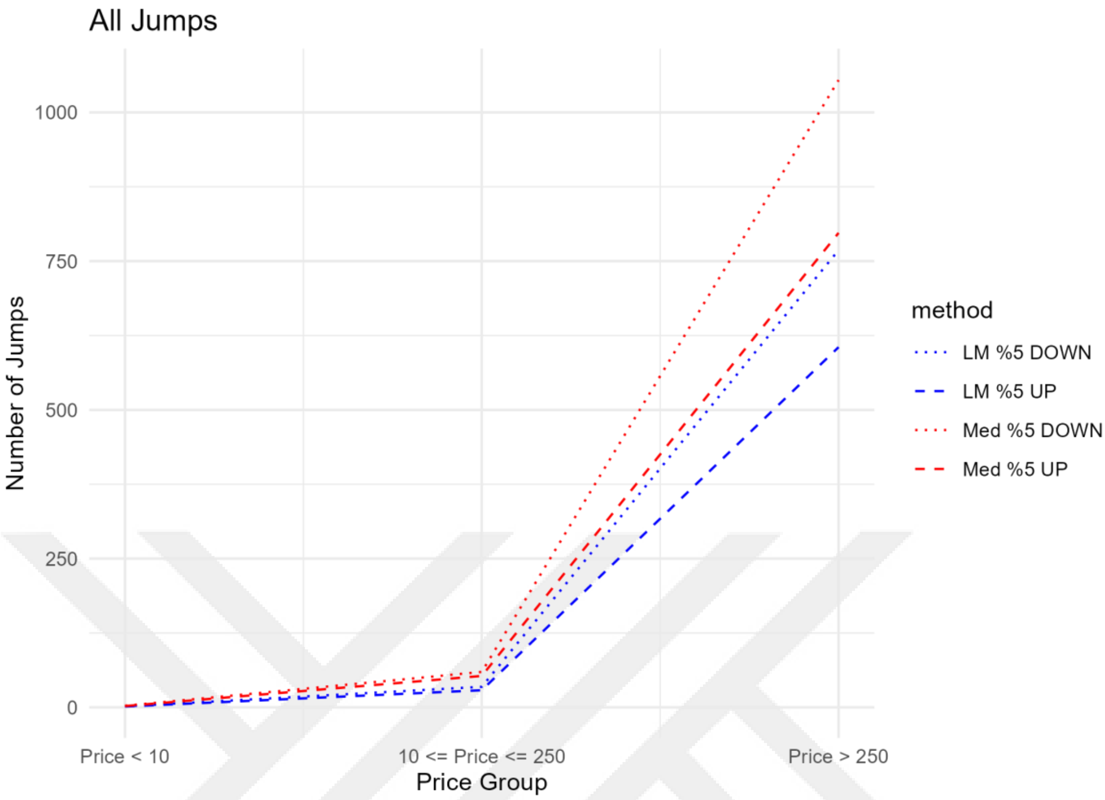


Figure 5: Total number of jumps by price group in 1,000,000 secs

5.1.1 Logistic Regression Analyses

To answer that question, logistic regression analyzes are applied using both logit and probit functions. As the number of jumps are much sparse than no-jumps, undersampling method is used. In order to mitigate the impact of randomness due to sampling variability, repeated cross validation method is used. Repeat number is 10. Then the coefficients (parameter estimates, standard errors, t statistics and p values) are averaged. The regressions are done separately to up and down jumps. For up jumps log positive returns to successor consecutive tick, and for down jumps log negative returns to predecessor consecutive tick are used.

The results show highly statistically significant relationship between relative tick sizes and the occurrence of jumps, regardless of jump test method and significance level. Uniformly very large absolute T statistic values suggest that relative tick sizes have a substantial and meaningful impact on the likelihood of jumps. They are negatively correlated, meaning as the absolute relative tick size increases, a decrease in the number of jumps is to be expected. The results are displayed in **Table 5.**

Table 5: Logistic Regression Coefficients (jump test ~ log tick return)

		Estimate	Std. Err.	T value	p value
LM %10 Down Logit	α β	3.18491 4145.24671	0.03686 50.12526	86.39937 82.69752	0 0
LM %10 Down Probit	α β	1.77532 2261.32459	0.01944 25.89899	91.32717 87.31322	0 0
LM %10 Up Logit	α β	3.21277 -4186.70926	0.04087 55.71864	78.59970 -75.14029	0 0
LM %10 Up Probit	α β	1.79087 -2284.11804	0.02156 28.79702	83.05575 -79.31808	0 0
LM %5 Down Logit	α β	3.17264 4128.92746	0.03787 51.47694	83.76580 80.20886	0 0
LM %5 Down Probit	α β	1.76601 2248.93391	0.01997 26.58497	88.43893 84.59405	0 0
LM %5 Up Logit	α β	3.20069 -4166.63300	0.04205 57.27612	76.10668 -72.74603	0 0
LM %5 Up Probit	α β	1.78292 -2271.03288	0.02219 29.60431	80.33878 -76.71299	0 0
LM %1 Down Logit	α β	3.14729 4078.77117	0.04012 54.37667	78.44193 75.00888	0 0
LM %1 Down Probit	α β	1.75365 2223.81061	0.02120 28.12395	82.73175 79.07154	0 0
LM %1 Up Logit	α β	3.18634 -4139.09793	0.04499 61.15499	70.82256 -67.68162	0 0
LM %1 Up Probit	α β	1.76487 -2241.38134	0.02368 31.49671	74.51626 -71.16222	0 0
LM %0.1 Down Logit	α β	3.09267 3985.26112	0.04257 57.35025	72.65183 69.48956	0 0
LM %0.1 Down Probit	α β	1.72085 2169.30480	0.02254 29.69621	76.35817 73.05019	0 0
LM %0.1 Up Logit	α β	3.15427 -4082.82254	0.04813 65.19702	65.53711 -62.62212	0 0
LM %0.1 Up Probit	α β	1.74599 -2209.56189	0.02536 33.58439	68.83964 -65.79106	0 0
Med %10 Down Logit	α β	3.21229 4156.80984	0.03006 40.79029	106.87856 101.90653	0 0
Med %10 Down Probit	α β	1.79582 2276.88700	0.01595 21.21468	112.62156 107.32605	0 0
Med %10 Up Logit	α β	3.22582 -4166.09644	0.03263 44.26636	98.87027 -94.11350	0 0
Med %10 Up Probit	α β	1.81691 -2302.50180	0.01743 23.19144	104.26464 -99.28204	0 0

Med %5 Down	α	3.22802	0.03020	106.89343	0
Logit	β	4172.56307	40.94292	101.91132	0
Med %5 Down	α	1.80792	0.01603	112.76866	0
Probit	β	2290.43073	21.31660	107.44827	0
Med %5 Up	α	3.24259	0.03281	98.84138	0
Logit	β	-4182.60349	44.46792	-94.05833	0
Med %5 Up	α	1.82529	0.01751	104.25890	0
Probit	β	-2310.06240	23.28072	-99.22616	0
Med %1 Down	α	3.21572	0.03092	103.99131	0
Logit	β	4148.43361	41.85586	99.11189	0
Med %1 Down	α	1.80194	0.01644	109.60704	0
Probit	β	2278.87458	21.81800	104.44901	0
Med %1 Up	α	3.24733	0.03374	96.23663	0
Logit	β	-4189.02866	45.77131	-91.52012	0
Med %1 Up	α	1.82569	0.01800	101.43917	0
Probit	β	-2310.42309	23.93915	-96.51186	0
Med %0.1 Down	α	3.41097	0.05696	59.88467	0
Logit	β	4516.87967	78.83810	57.29164	0
Med %0.1 Down	α	1.91376	0.03001	63.77520	0
Probit	β	2486.29466	40.88049	60.81767	0
Med %0.1 Up	α	3.35669	0.06076	55.24696	0
Logit	β	-4410.31662	83.81318	-52.61957	0
Med %0.1 Up	α	1.86229	0.03190	58.37240	0
Probit	β	-2394.04983	43.11972	-55.52039	0
WM Skip Down	α	2.59816	0.00511	508.36720	0
Logit	β	3146.71310	6.47363	486.08193	0
WM Skip Down	α	1.44043	0.00275	523.50834	0
Probit	β	1704.59426	3.37126	505.62476	0
WM Skip Up	α	2.56812	0.00508	505.22855	0
Logit	β	-3101.16384	6.41753	-483.23330	0
WM Skip Up	α	1.42031	0.00274	519.05756	0
Probit	β	-1674.98045	3.33772	-501.83379	0
Low Skip Down	α	1.95680	0.00231	848.51600	0
Logit	β	2216.84645	2.69681	822.02399	0
Low Skip Down	α	1.00185	0.00123	811.61085	0
Probit	β	1092.35646	1.35756	804.64703	0
Low Skip Up	α	2.16116	0.00236	914.49942	0
Logit	β	-2506.58604	2.84126	-882.20968	0
Low Skip Up	α	1.14427	0.00127	902.48189	0
Probit	β	-1284.94322	1.44904	-886.75757	0
High Skip Down	α	2.42596	0.00559	433.65360	0
Logit	β	2865.11212	6.91229	414.49547	0
High Skip Down	α	1.34562	0.00304	442.47883	0
Probit	β	1553.26494	3.62137	428.91640	0
High Skip Up	α	2.40115	0.00547	439.24418	0
Logit	β	-2829.53380	6.73588	-420.06886	0
High Skip Up	α	1.33054	0.00297	447.56259	0
Probit	β	-1531.94754	3.52782	-434.24710	0

5.2 Comparison of Post-Jump Returns

5.2.1 OLS Regression between Jumps and Post-Jump Returns

For comparing post jumps returns, OLS method is used. Returns of 1, 5, 10, 15, 20, 30, 45, 60, 90 and 120 minutes are regressed onto jump test results as indicator variables, separately. If there is less time left for the market to close than the chosen time, the data is omitted.

The results show highly statistically significant relationship between jumps and post-jump returns, regardless of jump test method and significance level. Uniformly very large absolute T statistic values provides strong evidence that jumps have a substantial and meaningful impact on the returns. They are negatively correlated, meaning when a jump occurs in one direction, a statistically significant reversal return is to be expected. The results are displayed in **Table 6.**

Table 6: OLS Regression Coefficients (log reversal return ~ jump test)

		Estimate	Std. Err.	T value	p value
WM Skip 1m	α	0.00000	0.00000	-34.24169	0
	β	-0.00039	0.00000	-332.30201	0
WM Skip 5m	α	-0.00001	0.00000	-106.82492	0
	β	-0.00041	0.00000	-214.97411	0
WM Skip 10m	α	-0.00002	0.00000	-190.10131	0
	β	-0.00042	0.00000	-164.59905	0
WM Skip 15m	α	-0.00004	0.00000	-257.65268	0
	β	-0.00042	0.00000	-140.20268	0
WM Skip 20m	α	-0.00005	0.00000	-312.03955	0
	β	-0.00042	0.00000	-120.84865	0
WM Skip 30m	α	-0.00008	0.00000	-394.36293	0
	β	-0.00041	0.00000	-96.64612	0
WM Skip 45m	α	-0.00012	0.00000	-483.09365	0
	β	-0.00040	0.00001	-77.54803	0
WM Skip 60m	α	-0.00015	0.00000	-529.49845	0
	β	-0.00040	0.00001	-64.72157	0
WM Skip 90m	α	-0.00021	0.00000	-558.18124	0
	β	-0.00040	0.00001	-50.44461	0
WM Skip 120m	α	-0.00025	0.00000	-552.78536	0
	β	-0.00040	0.00001	-42.21416	0
Low Skip 1m	α	0.00000	0.00000	-33.44186	0
	β	-0.00020	0.00000	-325.13502	0

Low Skip 5m	α	-0.00001	0.00000	-106.37521	0
	β	-0.00019	0.00000	-188.63445	0
Low Skip 10m	α	-0.00002	0.00000	-189.77427	0
	β	-0.00019	0.00000	-140.24356	0
Low Skip 15m	α	-0.00004	0.00000	-257.36690	0
	β	-0.00020	0.00000	-123.92631	0
Low Skip 20m	α	-0.00005	0.00000	-311.80663	0
	β	-0.00019	0.00000	-103.25351	0
Low Skip 30m	α	-0.00008	0.00000	-394.17435	0
	β	-0.00019	0.00000	-85.71122	0
Low Skip 45m	α	-0.00012	0.00000	-482.92842	0
	β	-0.00020	0.00000	-72.46180	0
Low Skip 60m	α	-0.00015	0.00000	-529.34723	0
	β	-0.00020	0.00000	-62.87803	0
Low Skip 90m	α	-0.00021	0.00000	-558.01565	0
	β	-0.00025	0.00000	-61.25195	0
Low Skip 120m	α	-0.00025	0.00000	-552.65172	0
	β	-0.00021	0.00000	-42.63048	0
High Skip 1m	α	0.00000	0.00000	-33.98312	0
	β	-0.00045	0.00000	-344.12960	0
High Skip 5m	α	-0.00001	0.00000	-106.66064	0
	β	-0.00047	0.00000	-219.80254	0
High Skip 10m	α	-0.00002	0.00000	-189.97718	0
	β	-0.00047	0.00000	-165.97375	0
High Skip 15m	α	-0.00004	0.00000	-257.54746	0
	β	-0.00047	0.00000	-140.39575	0
High Skip 20m	α	-0.00005	0.00000	-311.94885	0
	β	-0.00047	0.00000	-120.84380	0
High Skip 30m	α	-0.00008	0.00000	-394.29025	0
	β	-0.00046	0.00000	-96.69931	0
High Skip 45m	α	-0.00012	0.00000	-483.03573	0
	β	-0.00045	0.00001	-76.95692	0
High Skip 60m	α	-0.00015	0.00000	-529.44954	0
	β	-0.00045	0.00001	-64.94066	0
High Skip 90m	α	-0.00021	0.00000	-558.14183	0
	β	-0.00045	0.00001	-51.09956	0
High Skip 120m	α	-0.00025	0.00000	-552.75209	0
	β	-0.00045	0.00001	-41.92493	0
LM %10 1m	α	0.00000	0.00000	-34.26850	0
	β	-0.00058	0.00001	-73.94282	0
LM %10 5m	α	-0.00001	0.00000	-106.84188	0
	β	-0.00068	0.00001	-51.91390	0
LM %10 10m	α	-0.00002	0.00000	-190.11470	0
	β	-0.00073	0.00002	-42.68531	0
LM %10 15m	α	-0.00004	0.00000	-257.66693	0
	β	-0.00080	0.00002	-39.43772	0
LM %10 20m	α	-0.00005	0.00000	-312.05032	0
	β	-0.00074	0.00002	-32.01064	0
LM %10 30m	α	-0.00008	0.00000	-394.37300	0
	β	-0.00077	0.00003	-26.95008	0
LM %10 45m	α	-0.00012	0.00000	-483.10131	0
	β	-0.00073	0.00004	-20.73601	0
LM %10 60m	α	-0.00015	0.00000	-529.50599	0
	β	-0.00076	0.00004	-18.46656	0
LM %10 90m	α	-0.00021	0.00000	-558.18739	0
	β	-0.00071	0.00005	-13.63633	0
LM %10 120m	α	-0.00025	0.00000	-552.79238	0
	β	-0.00083	0.00006	-13.41057	0
LM %5 1m	α	0.00000	0.00000	-34.26578	0

	β	-0.00057	0.00001	-70.32651	0
LM %5 5m	α	-0.00001	0.00000	-106.83996	0
	β	-0.00066	0.00001	-49.33570	0
LM %5 10m	α	-0.00002	0.00000	-190.11334	0
	β	-0.00072	0.00002	-40.90454	0
LM %5 15m	α	-0.00004	0.00000	-257.66568	0
	β	-0.00079	0.00002	-37.72674	0
LM %5 20m	α	-0.00005	0.00000	-312.04957	0
	β	-0.00074	0.00002	-30.99783	0
LM %5 30m	α	-0.00008	0.00000	-394.37238	0
	β	-0.00076	0.00003	-26.06521	0
LM %5 45m	α	-0.00012	0.00000	-483.10121	0
	β	-0.00075	0.00004	-20.69186	0
LM %5 60m	α	-0.00015	0.00000	-529.50621	0
	β	-0.00080	0.00004	-18.90968	0
LM %5 90m	α	-0.00021	0.00000	-558.18773	0
	β	-0.00076	0.00005	-14.19540	0
LM %5 120m	α	-0.00025	0.00000	-552.79275	0
	β	-0.00089	0.00006	-13.94503	0
LM %1 1m	α	0.00000	0.00000	-34.26280	0
	β	-0.00058	0.00001	-66.37858	0
LM %1 5m	α	-0.00001	0.00000	-106.83683	0
	β	-0.00064	0.00001	-45.10085	0
LM %1 10m	α	-0.00002	0.00000	-190.11049	0
	β	-0.00070	0.00002	-37.07431	0
LM %1 15m	α	-0.00004	0.00000	-257.66274	0
	β	-0.00076	0.00002	-33.73313	0
LM %1 20m	α	-0.00005	0.00000	-312.04723	0
	β	-0.00071	0.00003	-27.88794	0
LM %1 30m	α	-0.00008	0.00000	-394.37033	0
	β	-0.00073	0.00003	-23.33086	0
LM %1 45m	α	-0.00012	0.00000	-483.09899	0
	β	-0.00068	0.00004	-17.65598	0
LM %1 60m	α	-0.00015	0.00000	-529.50423	0
	β	-0.00073	0.00005	-16.26272	0
LM %1 90m	α	-0.00021	0.00000	-558.18616	0
	β	-0.00069	0.00006	-12.21273	0
LM %1 120m	α	-0.00025	0.00000	-552.79153	0
	β	-0.00085	0.00007	-12.47331	0
LM %0.1 1m	α	0.00000	0.00000	-34.25787	0
	β	-0.00057	0.00001	-60.74154	0
LM %0.1 5m	α	-0.00001	0.00000	-106.83300	0
	β	-0.00062	0.00002	-40.56728	0
LM %0.1 10m	α	-0.00002	0.00000	-190.10682	0
	β	-0.00066	0.00002	-32.56111	0
LM %0.1 15m	α	-0.00004	0.00000	-257.65901	0
	β	-0.00070	0.00002	-28.98881	0
LM %0.1 20m	α	-0.00005	0.00000	-312.04461	0
	β	-0.00068	0.00003	-24.64283	0
LM %0.1 30m	α	-0.00008	0.00000	-394.36797	0
	β	-0.00068	0.00003	-20.41837	0
LM %0.1 45m	α	-0.00012	0.00000	-483.09701	0
	β	-0.00063	0.00004	-15.17996	0
LM %0.1 60m	α	-0.00015	0.00000	-529.50285	0
	β	-0.00071	0.00005	-14.75871	0
LM %0.1 90m	α	-0.00021	0.00000	-558.18548	0
	β	-0.00072	0.00006	-11.72268	0
LM %0.1 120m	α	-0.00025	0.00000	-552.79091	0
	β	-0.00089	0.00007	-12.15956	0

Med %10 1m	α	0.00000	0.00000	-34.28542	0
	β	-0.00063	0.00001	-101.16914	0
Med %10 5m	α	-0.00001	0.00000	-106.85070	0
	β	-0.00068	0.00001	-65.96723	0
Med %10 10m	α	-0.00002	0.00000	-190.12147	0
	β	-0.00073	0.00001	-53.94589	0
Med %10 15m	α	-0.00004	0.00000	-257.67232	0
	β	-0.00077	0.00002	-47.65449	0
Med %10 20m	α	-0.00005	0.00000	-312.05630	0
	β	-0.00075	0.00002	-40.76703	0
Med %10 30m	α	-0.00008	0.00000	-394.37673	0
	β	-0.00073	0.00002	-32.37955	0
Med %10 45m	α	-0.00012	0.00000	-483.10527	0
	β	-0.00073	0.00003	-26.15869	0
Med %10 60m	α	-0.00015	0.00000	-529.50922	0
	β	-0.00074	0.00003	-22.72544	0
Med %10 90m	α	-0.00021	0.00000	-558.18947	0
	β	-0.00067	0.00004	-16.08327	0
Med %10 120m	α	-0.00025	0.00000	-552.79306	0
	β	-0.00069	0.00005	-13.84946	0
Med %5 1m	α	0.00000	0.00000	-34.28534	0
	β	-0.00063	0.00001	-100.84591	0
Med %5 5m	α	-0.00001	0.00000	-106.85043	0
	β	-0.00068	0.00001	-65.42067	0
Med %5 10m	α	-0.00002	0.00000	-190.12122	0
	β	-0.00073	0.00001	-53.43025	0
Med %5 15m	α	-0.00004	0.00000	-257.67209	0
	β	-0.00077	0.00002	-47.22021	0
Med %5 20m	α	-0.00005	0.00000	-312.05621	0
	β	-0.00075	0.00002	-40.55173	0
Med %5 30m	α	-0.00008	0.00000	-394.37666	0
	β	-0.00073	0.00002	-32.20586	0
Med %5 45m	α	-0.00012	0.00000	-483.10524	0
	β	-0.00073	0.00003	-26.07774	0
Med %5 60m	α	-0.00015	0.00000	-529.50930	0
	β	-0.00075	0.00003	-22.81668	0
Med %5 90m	α	-0.00021	0.00000	-558.18954	0
	β	-0.00067	0.00004	-16.15145	0
Med %5 120m	α	-0.00025	0.00000	-552.79312	0
	β	-0.00069	0.00005	-13.89480	0
Med %1 1m	α	0.00000	0.00000	-34.28173	0
	β	-0.00063	0.00001	-97.75430	0
Med %1 5m	α	-0.00001	0.00000	-106.84831	0
	β	-0.00067	0.00001	-63.71772	0
Med %1 10m	α	-0.00002	0.00000	-190.11907	0
	β	-0.00072	0.00001	-51.33247	0
Med %1 15m	α	-0.00004	0.00000	-257.67017	0
	β	-0.00075	0.00002	-45.28653	0
Med %1 20m	α	-0.00005	0.00000	-312.05436	0
	β	-0.00073	0.00002	-38.66171	0
Med %1 30m	α	-0.00008	0.00000	-394.37533	0
	β	-0.00071	0.00002	-30.85515	0
Med %1 45m	α	-0.00012	0.00000	-483.10412	0
	β	-0.00071	0.00003	-25.02909	0
Med %1 60m	α	-0.00015	0.00000	-529.50823	0
	β	-0.00073	0.00003	-21.82365	0
Med %1 90m	α	-0.00021	0.00000	-558.18855	0
	β	-0.00065	0.00004	-15.19629	0
Med %1 120m	α	-0.00025	0.00000	-552.79202	0

	β	-0.00066	0.00005	-12.81019	0
Med %0.1 1m	α	0.00000	0.00000	-34.25161	0
	β	-0.00112	0.00001	-97.76412	0
Med %0.1 5m	α	-0.00001	0.00000	-106.82929	0
	β	-0.00123	0.00002	-65.39820	0
Med %0.1 10m	α	-0.00002	0.00000	-190.10327	0
	β	-0.00125	0.00002	-50.19393	0
Med %0.1 15m	α	-0.00004	0.00000	-257.65574	0
	β	-0.00128	0.00003	-43.27606	0
Med %0.1 20m	α	-0.00005	0.00000	-312.04144	0
	β	-0.00122	0.00003	-36.01587	0
Med %0.1 30m	α	-0.00008	0.00000	-394.36548	0
	β	-0.00124	0.00004	-30.08760	0
Med %0.1 45m	α	-0.00012	0.00000	-483.09542	0
	β	-0.00114	0.00005	-22.52077	0
Med %0.1 60m	α	-0.00015	0.00000	-529.50105	0
	β	-0.00125	0.00006	-20.90681	0
Med %0.1 90m	α	-0.00021	0.00000	-558.18439	0
	β	-0.00131	0.00008	-17.27516	0
Med %0.1 120m	α	-0.00025	0.00000	-552.78842	0
	β	-0.00133	0.00009	-14.62604	0

5.2.2 OLS Regression between Test Statistics of Jump Tests and Post-Jump Returns

In order to add more proof to the relationship, post-jump returns are regressed onto test statistic values of both LM Test and MedRV separately with OLS method.

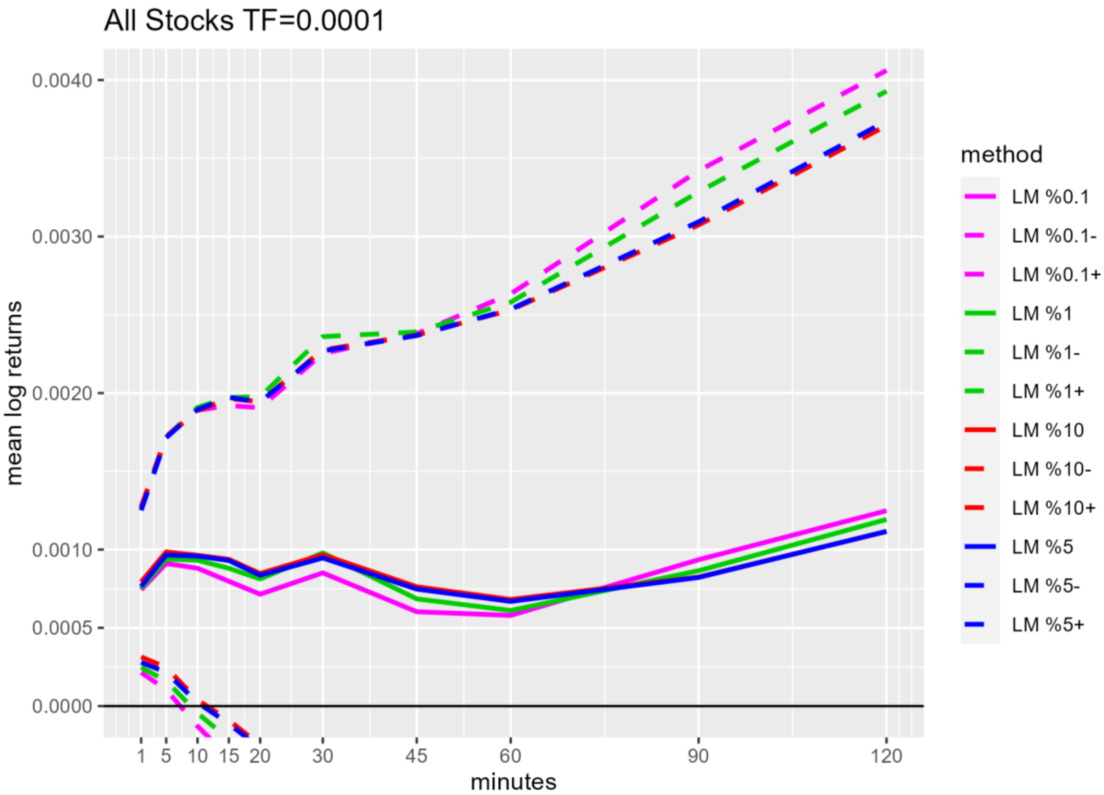
The results add solid proof to highly statistically significant relationship between jumps and post-jump returns. With both tests, very large absolute T statistics values provide strong evidence that T statistic values of jumps tests have a substantial and meaningful impact on the returns. They are again negatively correlated, meaning as the T statistics of a jump test increases, the magnitude of reversal return increases. The results are displayed in **Table 7.**

Table 7: OLS Regression Coefficients (log reversal return ~ jump test t statistic)

		Estimate	Std. Err.	T value	p value
LM 1m	α	0.00000	0	-24.59025	0
	β	-0.00023	0	-1364.71462	0
LM 5m	α	-0.00001	0	-100.92466	0
	β	-0.00023	0	-842.52532	0
LM 10m	α	-0.00002	0	-185.61963	0
	β	-0.00023	0	-644.22947	0
LM 15m	α	-0.00004	0	-253.88701	0
	β	-0.00023	0	-541.86301	0
LM 20m	α	-0.00005	0	-308.75415	0
	β	-0.00023	0	-472.84487	0
LM 30m	α	-0.00008	0	-391.65938	0
	β	-0.00023	0	-386.22588	0
LM 45m	α	-0.00012	0	-480.87256	0
	β	-0.00023	0	-312.88531	0
LM 60m	α	-0.00015	0	-527.58320	0
	β	-0.00023	0	-265.58958	0
LM 90m	α	-0.00020	0	-556.62669	0
	β	-0.00023	0	-209.32538	0
LM 120m	α	-0.00025	0	-551.44246	0
	β	-0.00023	0	-173.83819	0
Med 1m	α	0.00000	0	-19.96739	0
	β	-0.00025	0	-1579.70992	0
Med 5m	α	-0.00001	0	-98.06564	0
	β	-0.00026	0	-978.66570	0
Med 10m	α	-0.00002	0	-183.42575	0
	β	-0.00026	0	-750.13851	0
Med 15m	α	-0.00004	0	-252.03028	0
	β	-0.00026	0	-632.40094	0
Med 20m	α	-0.00005	0	-307.13028	0
	β	-0.00026	0	-551.78279	0
Med 30m	α	-0.00008	0	-390.31562	0
	β	-0.00026	0	-451.77648	0
Med 45m	α	-0.00012	0	-479.76362	0
	β	-0.00026	0	-366.73494	0
Med 60m	α	-0.00015	0	-526.61792	0
	β	-0.00026	0	-312.20249	0
Med 90m	α	-0.00020	0	-555.84341	0
	β	-0.00026	0	-246.05057	0
Med 120m	α	-0.00025	0	-550.76618	0
	β	-0.00026	0	-204.37392	0

5.2.3 Analyses on Post-Jump Return Strategy

In finance a statistically significant return, doesn't always mean an economically significant return. Also transaction fees have to be taken in consideration. **Figure 6** displays mean of post-jump return strategies on selected 20 stocks with margins of error (2 SE), using LM Test with various significance levels, with two different transaction fee costs.



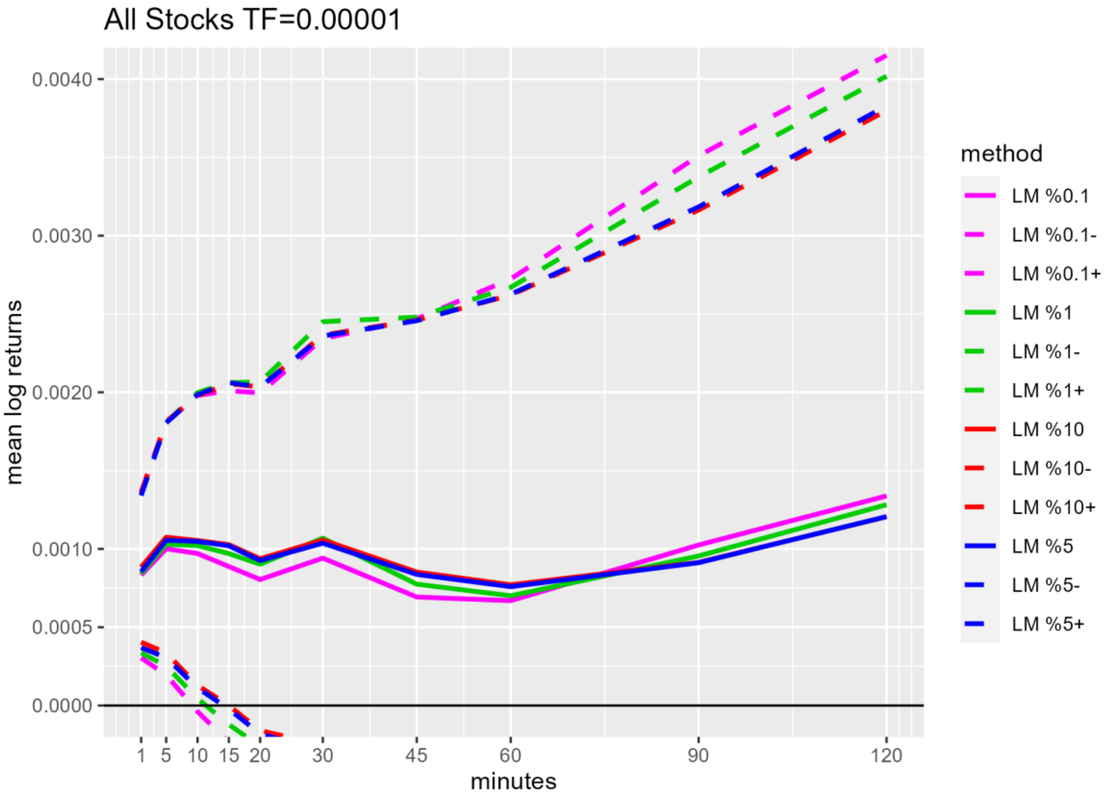


Figure 6: Post-jump return LM Test

The primary jump test for this study is the LM Test. With LM Test even after 1 minute there is remarkable return and it peaks at 5 minute before lower margin of error goes negative. This results suggests after a jump occurs, the market recovers but not fully, as it takes more time for the price to stabilize. Another result is that the significance levels of LM Test doesn't make much difference as the returns almost overlap, though widest range of significance levels are used. For LM Test the optimal post-jump return is 5 minutes.

Figure 7 displays the results for MedRV. For the %10, %5 and %1 significance levels, the level of return is very similar to LM Test, but with 20 minutes peak instead of 5 minutes; and the returns overlap. However, the %0.1 significance level differs by peaking at 5 minutes just like LM Test, but more than doubling the returns. Also note that MedRV with %0.1 significance level had much less total number of jumps.

Figure 8 displays the results for Price Skipping. Though they are designed as purely price based and not using volatility, the results are intriguing, as they all give positive returns with lower margins of error on the positive side. Still, the returns are less than LM Test. The highest return is with High Skipping which had the lowest number of jumps among the three, and the lowest return is with Low Skipping which had the highest number of jumps. This result may be the consequence of spurious jumps.

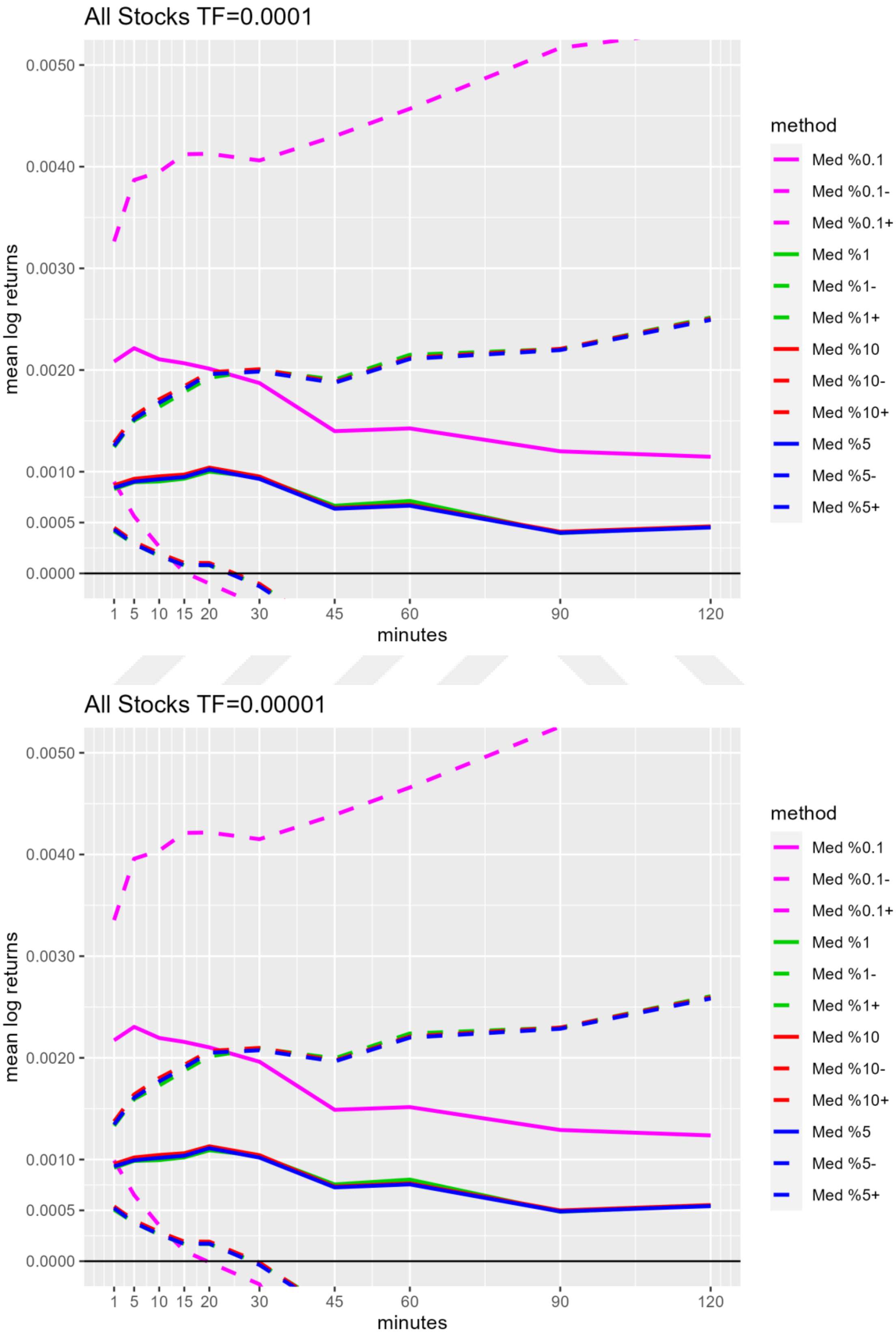


Figure 7: Post-jump return MedRV

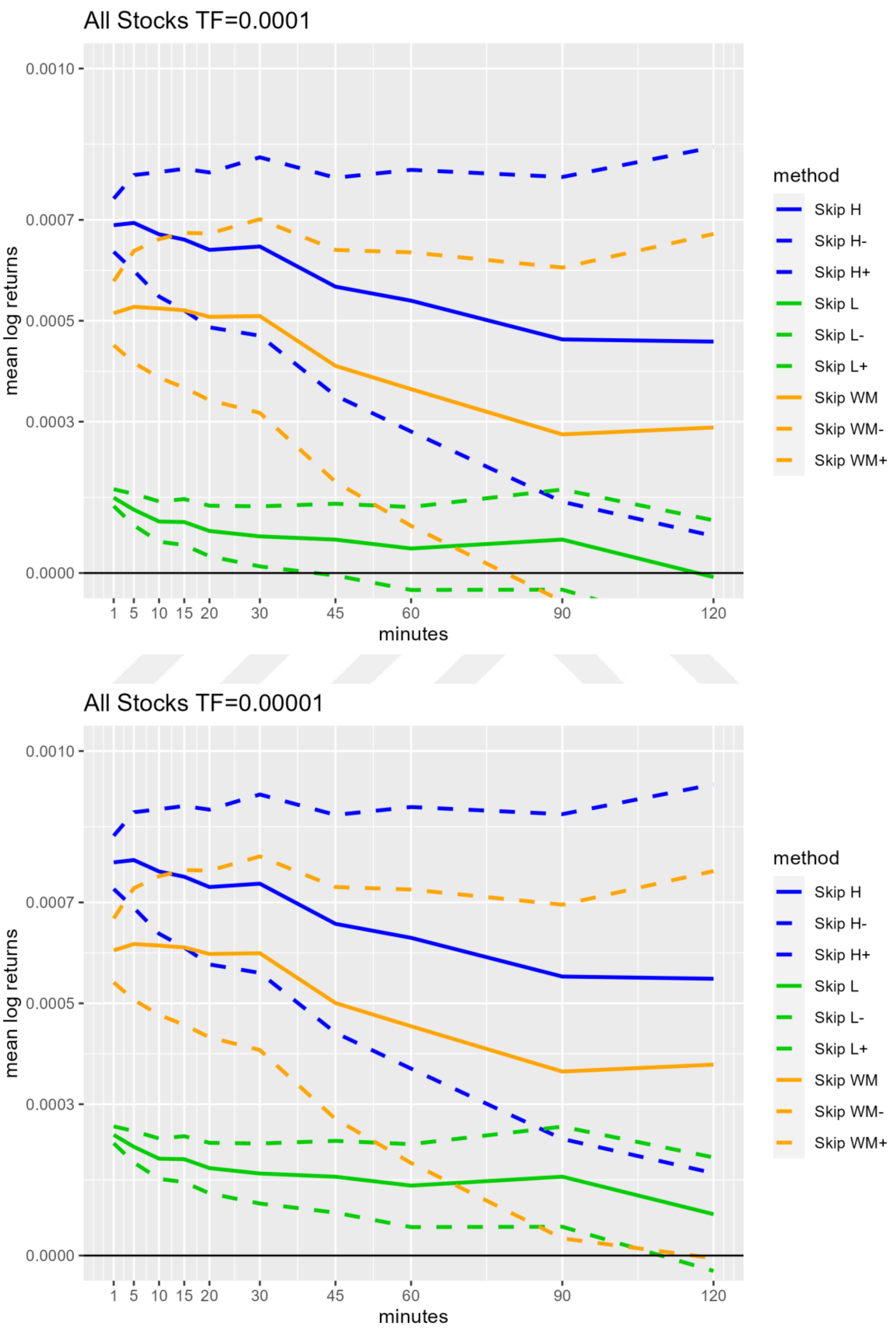


Figure 8: Post-jump return Price Skipping

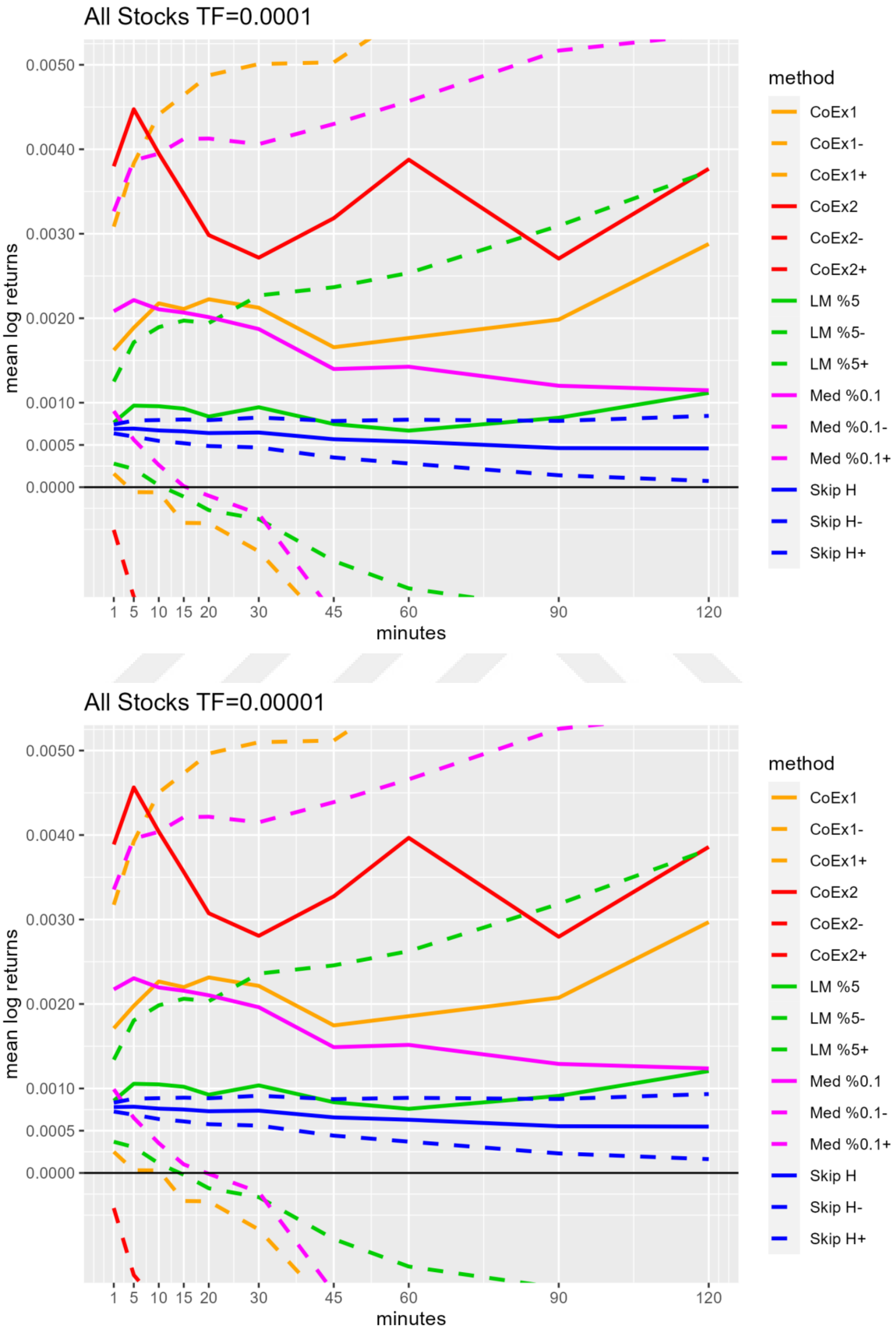


Figure 9: Post-jump return, all tests

Figure 9 displays the results for LM Test with %5 significance level, and MedRV with %0.1 significance level, High Skipping, CoEx1 and CoEx2. CoeEx1 has more returns than LM Test but the peak 20 minutes cannot be used as lower margin of error goes negative. With CoEx2 lower margin of error goes negative all the way.

Figure 10 displays the results of post-jump return strategy on selected 20 stocks, using LM Test with various significance levels, with 0.00001 transaction fee costs. With a few exceptions, most stocks have similar returns. This raises the question whether there is common mechanism behind post-jump returns.

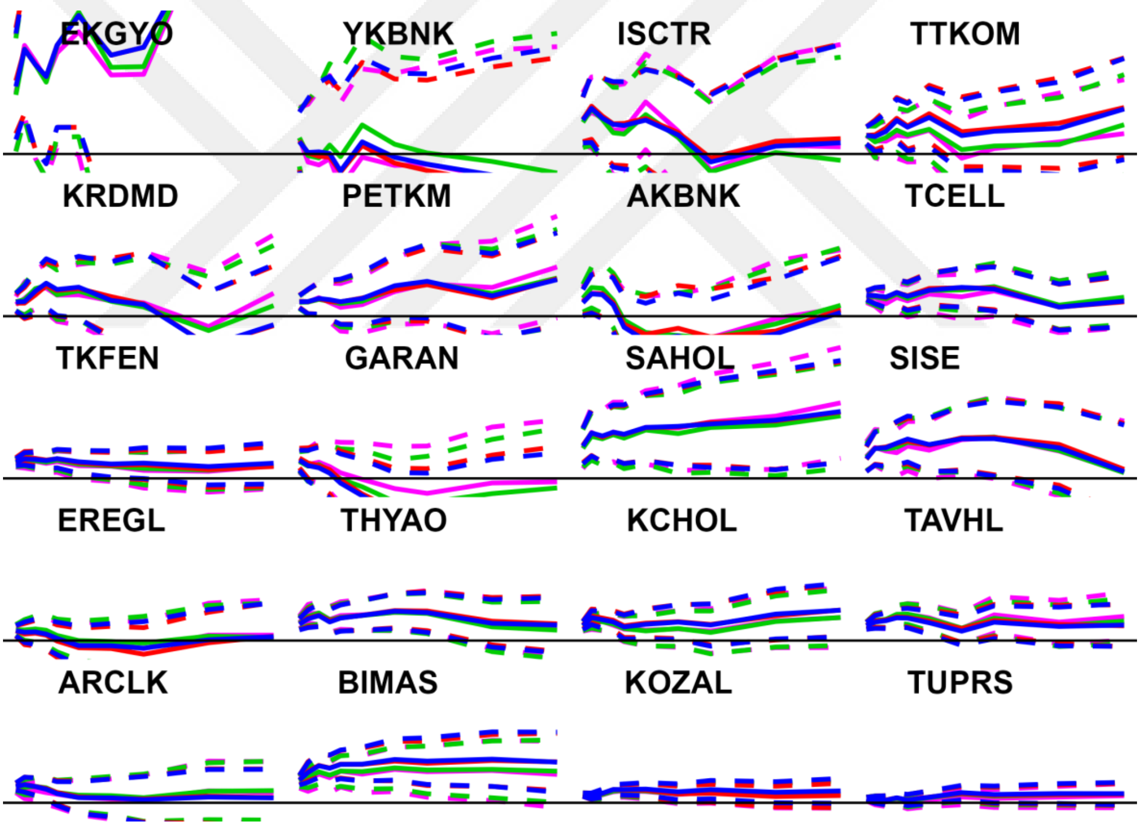


Figure 10: Post-jump return LM Test 0.00001 TF, sorted by mean of price

In search of that common mechanism, **Figure 11**, **Figure 12** and **Figure 13** displays the results of mean of post-jump return strategy on selected 20 stocks, with 0.00001 transaction fee costs, using LM Test, MedRV and Price Skipping respectively, grouped by price group. The story of those results is the same: Small priced group has the highest post-jump returns, middle range has some, and large priced group has little to none. Note that for LM Test and MedRV, if there is a positive return, lower margin of error goes negative at 5 or 10 minutes; whereas for Price Skipping it stays positive much longer. Though Price Skipping provides less returns, the variation of those returns seems less than other methods.

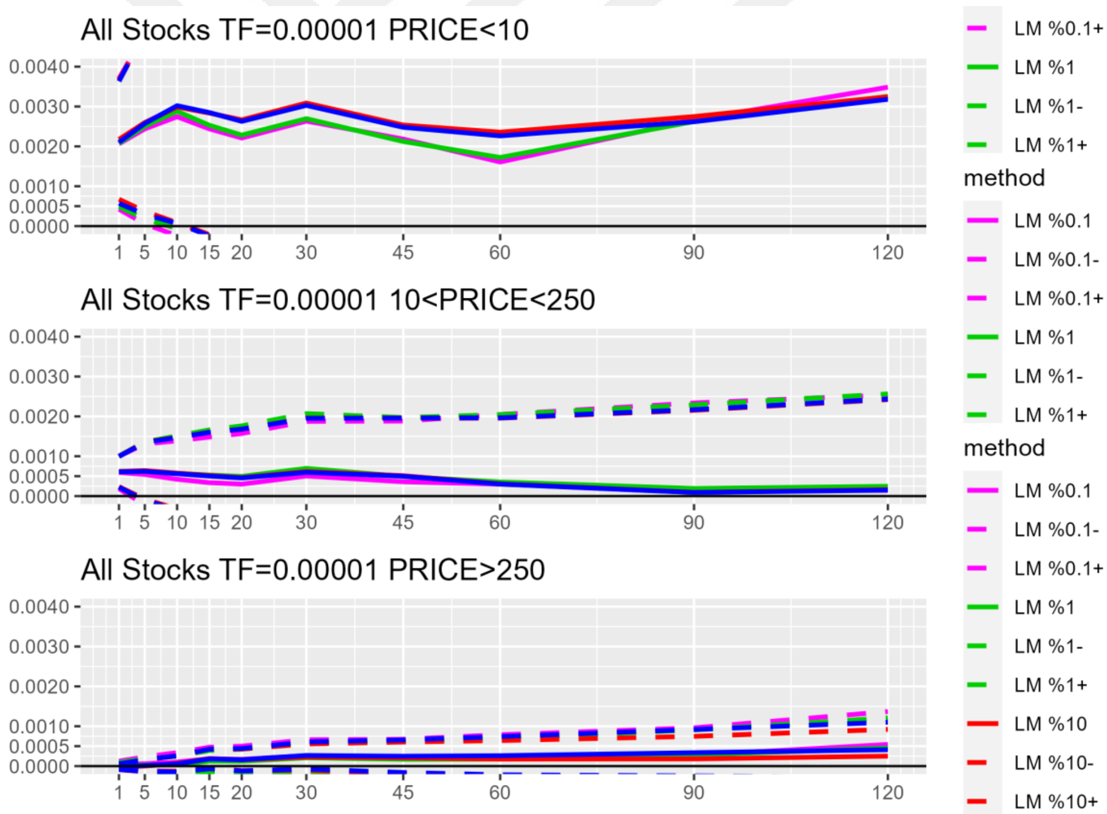


Figure 11: Post-jump return LM Test 0.00001 TF, grouped by price group

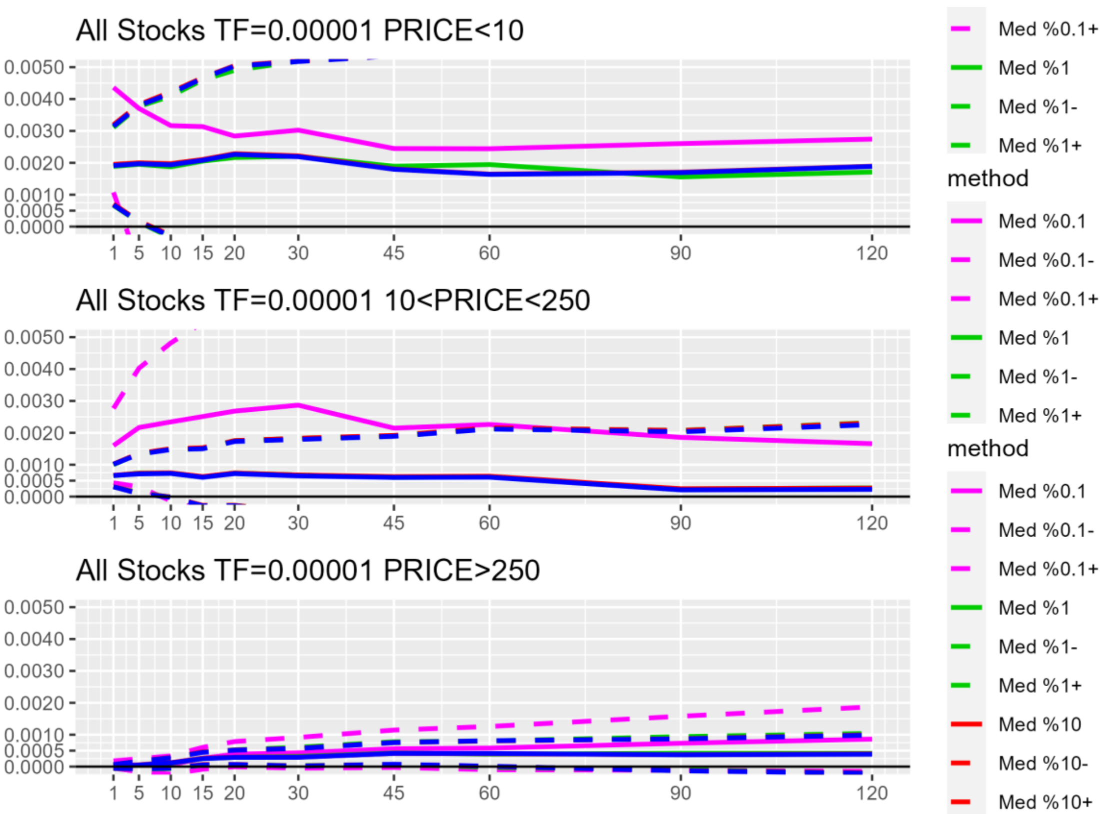


Figure 12: Post-jump return MedRV 0.00001 TF, grouped by price group

5.3 *Relationship with Jumps and other Factors*

Up to this point, the study was on the whole data. In order to understand the relationship between jumps and other factors and build a model for the strategy, focusing on the seconds with only jumps is needed. Before focusing, factors need to be determined.

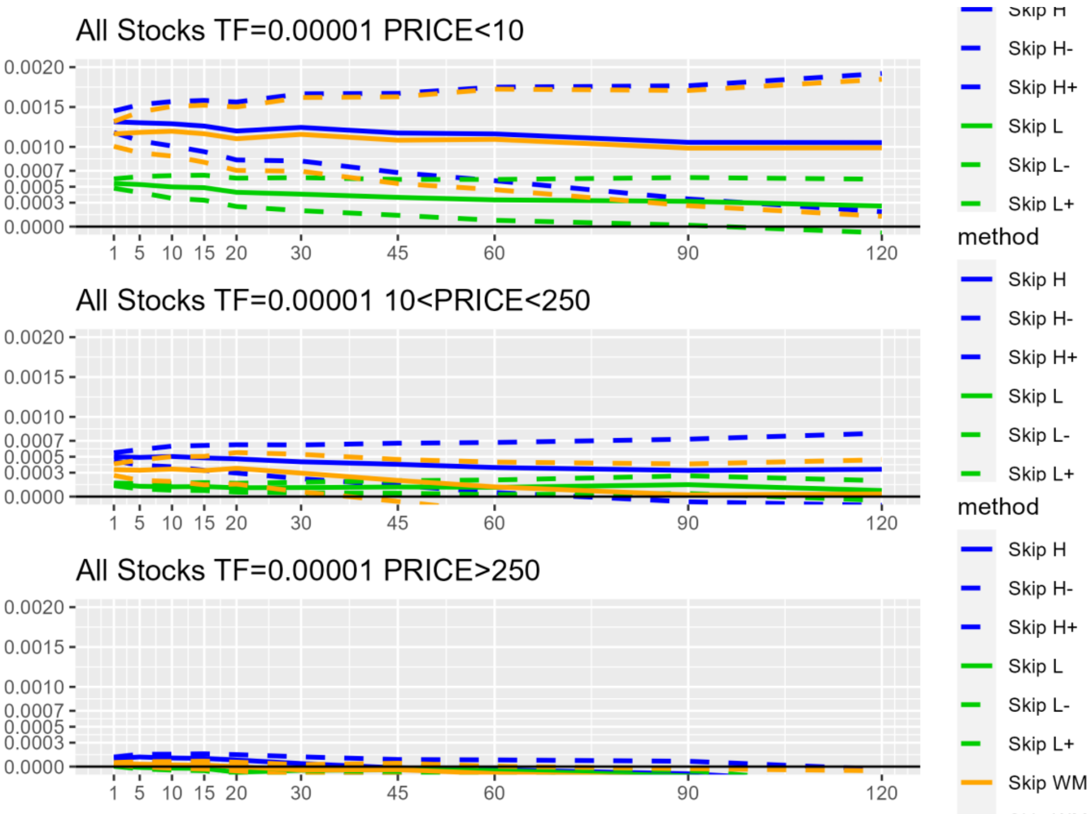


Figure 13: Post-jump return Price Skipping 0.00001 TF, grouped by price group

5.3.1 Factors for the Model

The factors used are as follows;

- the closing price of prior second,
- log positive returns to successor consecutive tick for the closing price of prior second,
- log negative returns to predecessor consecutive tick, for the closing price of prior second,
- dummy variables for price group,
- order of hours, counting the opening hour as 1,
- dummy variables for hours,
- order of minutes, counting the opening minute as 1,

- ex post standardized daily volume (number of shares in transactions),
- dummy variables for sector affiliation,
- pre-jump returns of 1, 5, 10, 15, 20, 30, 45, 60, 90 and 120 minutes, (If there is less time since the market opened than the chosen time, the data is omitted.)
- dummy variables for co-exceedance with other test methods,
- order of High Skipping, (using High Skipping of Price Skipping method, subtracting 1 from positive skipped tick counts and adding 1 to negative skipped tick counts)
- dummy variable for jump test results of Bist100 index, using the same test method and significance level

5.3.2 Analyzes on Reversal Post-Jump 5 Minute Returns with LM Test %5 Significance Level

From this point on, the study is focused on post-jump 5 minute returns with LM Test %5 significance level. These are chosen because the return plots suggested that the peak to be at 5 minutes for LM Test and the significance levels do not differ much. If there is less than 5 minutes for the market to close, the data is omitted.

Before building a model, the relationship between reversal post-jump returns and factors are investigated separately, using Ordinary Least Squares (OLS) and Locally Estimated Scatterplot Smoothing (LOESS) methods. Seconds with no jumps are omitted. Data is divided in to two by up jumps and down jumps. Post-jump returns after up jumps are multiplied by -1, as the strategy is to take short position after up jumps.

5.3.2.1 *Price and Relative Tick Size*

Using the both up jump and down jump data together, reversal post-jump returns are regressed onto the closing prices of prior seconds. **Table 8** shows the coefficients. **Figure 14** displays both fitted OLS line and LOESS lines. There is statistically significant evidence for the negative correlation between the closing prices of prior seconds and the magnitude of reversal post-jump returns.

Table 8: OLS Regression Coefficients (log reversal return ~ price)

	Estimate	Std. Err.	T value	p value
Intercept	0.0008984863	0.0000483658	18.576883927	0
Prics	-0.0000020833	0.0000002279	-9.140839483	0

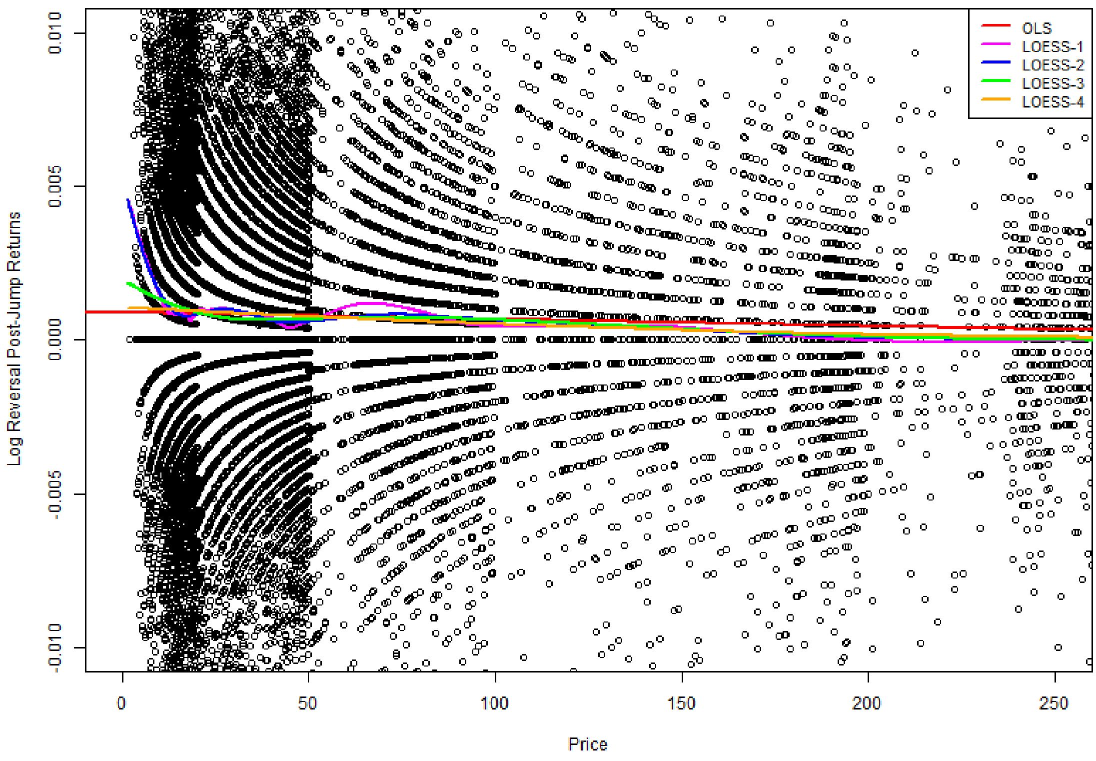


Figure 14: Log reversal post-jump return and price

Reversal post up jump returns are regressed onto log positive returns to successor consecutive tick for the closing price of prior second. Reversal post down jump returns are regressed onto log negative returns to predecessor consecutive tick, for the closing price of prior second. **Table 9** and **Table 10** show the coefficients and **Figure 15** and **Figure 16** display both fitted OLS line and LOESS lines, respectively. There is statistically significant evidence for the positive correlation between absolute relative tick size and the magnitude of reversal post-jump returns, regardless of the direction of the jump.

Table 9: OLS Regression Coefficients (log reversal return ~ log pos. tick return)

	Estimate	Std. Err.	T value	p value
Intercept	-0.0005072053	0.0001379517	-3.676687801	0.0002370628
Log Pos Tick Ret	1.3357178845	0.2206889187	6.052491863	0.0000000015

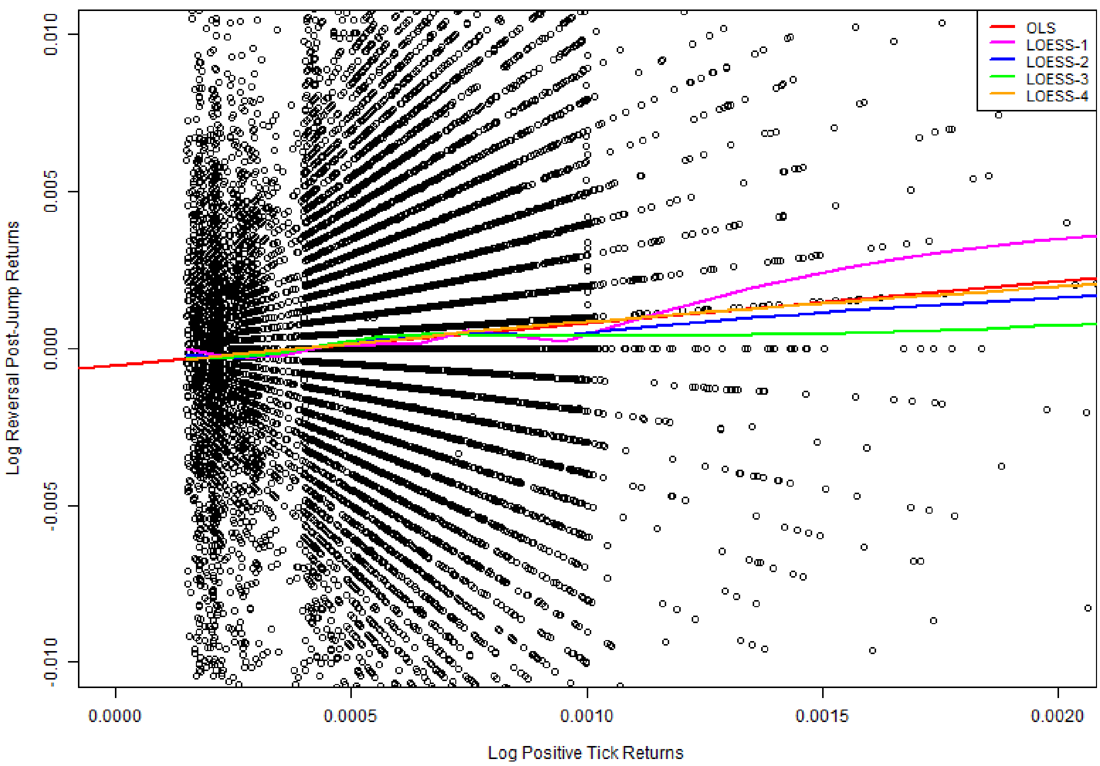


Figure 15: Log reversal post up jump return and log positive tick return

Table 10: OLS Regression Coefficients (log reversal return ~ log neg. tick return)

	Estimate	Std. Err.	T value	p value
Intercept	-0.0002222742	0.0001244247	-1.786415239	0.0740477159
Log Neg Tick Ret	-2.0695274728	0.1986504270	-10.417936189	0.0000000000

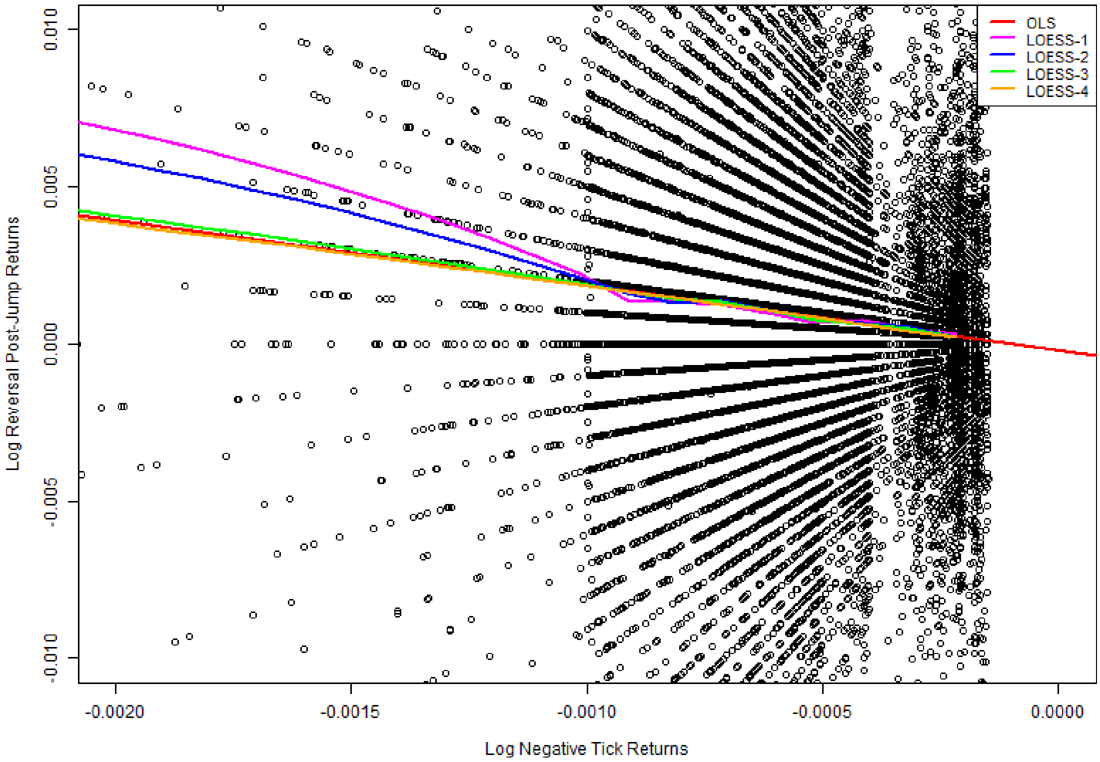


Figure 16: Log reversal post down jump return and log negative tick return

Reversal post up jump returns and reversal post down jump returns are regressed onto dummy variables for price group. The middle range is chosen as the reference category, as it is the most common one. **Table 11** shows the coefficients. Results suggest that, regardless of the direction of the jump, average of reversal post-jump returns of small priced stocks are significantly higher than average of reversal post-jump returns of middle range, whereas average of reversal post-jump returns of large priced stocks are significantly lower than it. Reversal post up jump returns of large priced stocks are actually negative.

Table 11: OLS Regression Coefficients (log reversal return ~ price group)

	Estimate	Std. Err.	T value	p value
Intercept	0.0003429357	0.0000655122	5.234685869	0.0000001674
Up Jump Pr >10	0.0014899223	0.0003357166	4.438035668	0.0000091396
Up Jump Pr<250	-0.0006648192	0.0001427166	-4.658316313	0.0000032140
Intercept	0.0010571187	0.0000608985	17.358687815	0.0000000000
Down Jump Pr>10	0.0018438933	0.0003030810	6.083830207	0.0000000012
Down Jump	-0.0007710109	0.0001297165	-5.943816095	0.0000000028

5.3.2.2 Timing

Reversal post up jump returns and reversal post down jump returns are regressed onto order of hours, dummy variables for hours and order of minutes, separately. The first hour is chosen as the reference category, as it has the highest number of jumps. **Table 12**, **Table 13** and **Table 14** show the coefficients. **Figure 17** and **Figure 18** display fitted OLS lines and LOESS lines for regressions onto order of minutes. The results suggest that average of reversal post up jump returns between 15:00 and 16:00 are significantly higher than average of reversal post up jump returns between 10:00 and 11:00; and average of reversal post down jump returns between 10:00 and 11:00 are significantly higher than average of reversal post down jump returns between 13:00 and 17:00 with %99 confidence intervals. There is statistically significant evidence for the positive correlation between the passing time and average of reversal post up jump returns and negative correlation between the passing time and average of reversal post down jump returns. LOESS lines differ with OLS line, just before the market closes, and they suggest slight increase at that time.

Table 12: OLS Regression Coefficients (log reversal return ~ hour order)

	Estimate	Std. Err.	T value	p value
Intercept	-0.0000209606	0.0000992799	-0.211126771	0.8327910667
Up J Hour Ord	0.0000724325	0.0000214817	3.371832179	0.0007484852
Intercept	0.0013687397	0.0000922494	14.837390153	0.0000000000
Down J Hour Ord	-0.0001102889	0.0000199454	-5.529554328	0.0000000325

Table 13: OLS Regression Coefficients (log reversal return ~ minute order)

	Estimate	Std. Err.	T value	p value
Intercept	0.0000207330	0.0000879246	0.2358041874	0.8135876673
Up J Minute Ord	0.0000012041	0.0000003465	3.4746142958	0.0005129566
Intercept	0.001297535	0.0000818068	15.860965485	0.0000000000
Down J Minute Ord	-0.000001791	0.0000003223	-5.556778368	0.0000000278

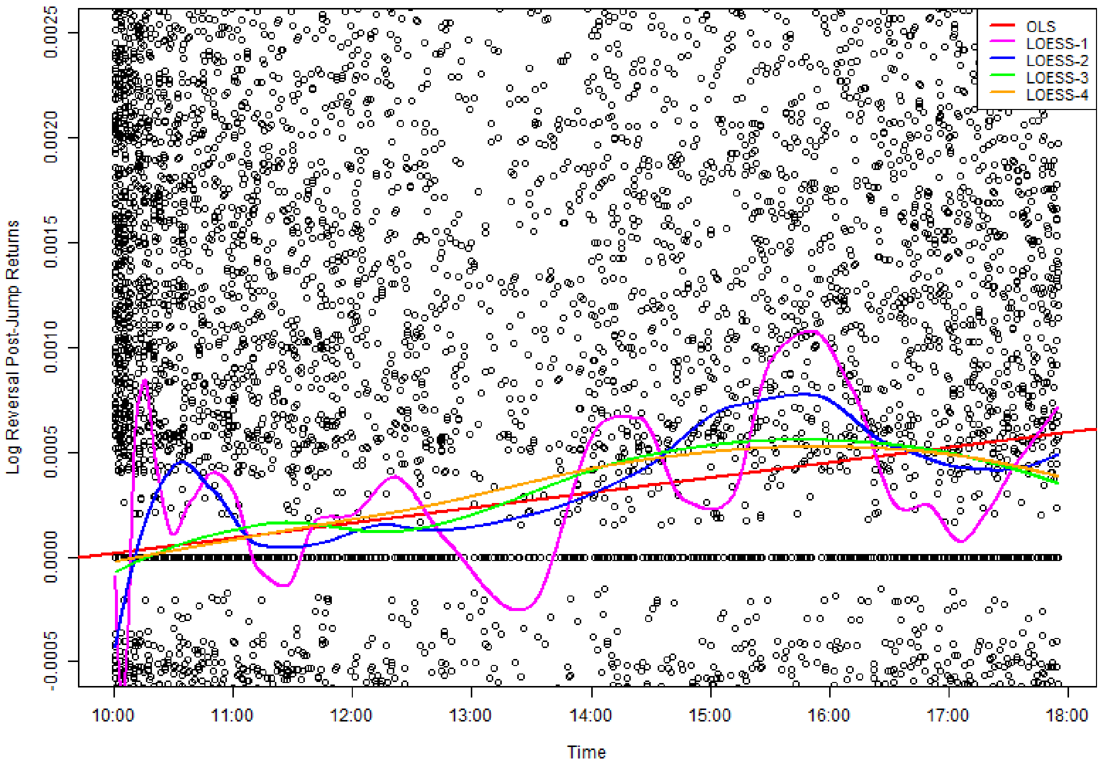


Figure 17: Log reversal post up jump return and minutes

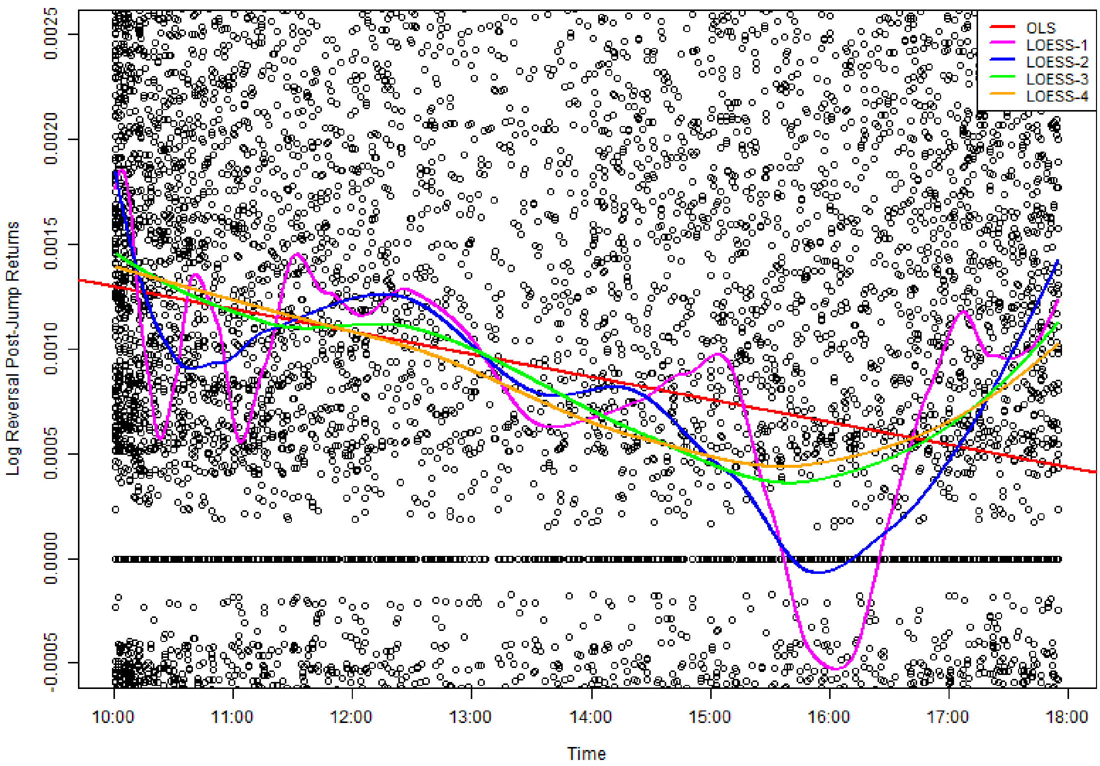


Figure 18: Log reversal post down jump return and minutes

Table 14: OLS Regression Coefficients (log reversal return ~ hour)

	Estimate	Std. Err.	T value	p value
Intercept Up J	0.0000758046	0.0000984717	0.7698109930	0.4414235018
11:00 – 12:00	-0.0001075154	0.0001890338	-0.5687627373	0.5695252322
12:00 – 13:00	0.0002840886	0.0002310951	1.2293144633	0.2189721938
13:00 – 14:00	-0.0005016049	0.0002852392	-1.7585412565	0.0786747738
14:00 – 15:00	0.0005082755	0.0002189095	2.3218520544	0.0202535243
15:00 – 16:00	0.0008671409	0.0002163449	4.0081408472	0.0000614789
16:00 – 17:00	0.0001098369	0.0002054719	0.5345593868	0.5929620793
17:00 – 18:00	0.0004357802	0.0001832918	2.3775216379	0.0174412237
Intercept Down J	0.0013098890	0.0000918869	14.2554503965	0.0000000000
11:00 – 12:00	-0.0001294757	0.0001745535	-0.7417533214	0.4582458207
12:00 – 13:00	-0.0001516231	0.0002121768	-0.7146071791	0.4748604388
13:00 – 14:00	-0.0007102746	0.0002583186	-2.7496064388	0.0059722329
14:00 – 15:00	-0.0005254956	0.0001996662	-2.6318704839	0.0084983687
15:00 – 16:00	-0.0010515535	0.0001971331	-5.3342305329	0.0000000970
16:00 – 17:00	-0.0010785669	0.0001926740	-5.5978843804	0.0000000220
17:00 – 18:00	-0.0003454472	0.0001701307	-2.0304809063	0.0423213446

These results are intriguing for behavioral financial aspect. It seems like in the morning down jump reversals are more vigorous, which can be explained downside overreaction of prices possibly caused by ongoing fear from past news, but then sharp returns possibly caused by traders who try to take advantage of that overreaction. Strong down jump reversal just before the market closure can also be explained by the same mechanism, however instead of past news, the cause of the downside overreaction is possibly fear of an upcoming macroeconomic events, as some investors may choose to increase their cash amount before such an event in the fear of possible bad news. Weak down jump reversal at the afternoon can be explained by weak reversals of down jumps caused by bad macroeconomics news either from Turkish Central Bank at 14:00 TST or the US at around 15:30 and 17:00 TST (08:30-10:00 ET).

It seems like there are minimal to no reversal up jump returns in the morning, which can be explained by the power of positive overnight news and high risk appetite giving less opportunities to reversals. Note that these are intraday jumps, not jumps of opening session. The slightly increase in power of reversals after up jumps in the afternoon can be explained by traders taking advantage of the overreaction after up jumps caused by good macroeconomic news, which can sometimes be interpreted more positively initially but then interpreted less positively with a more realistic approach.

5.3.2.3 Volume and Sector

Reversal post up jump returns and reversal post down jump returns are regressed onto ex post standardized daily volume, which is calculated by using number of shares in transactions. [36] used standardized volume as an indicator but here it is used as a vector. **Table 15** shows the coefficients, **Figure 19** and **Figure 20** displays both fitted OLS line and LOESS lines. There is statistically significant evidence for the positive correlation between the volume and the magnitude of reversal post-jump returns, regardless of the direction of the jump. Overlapping LOESS lines clearly suggest the relationship is actually quadratically positive, rather than linearly. These results are illuminating, as they suggest the cause of the post-jump reversals being lack of liquidity possibly caused by large market orders. When a large buying (selling) market order arrives and exceeds all the orders at the current ask (bid) price, limit orders beyond that price try to cover it. If the market order is too large, the price can move multiple ticks, and this movement in the price may be accepted as an overreaction by the market, hence market starting a reversal to an optimal price for that time.

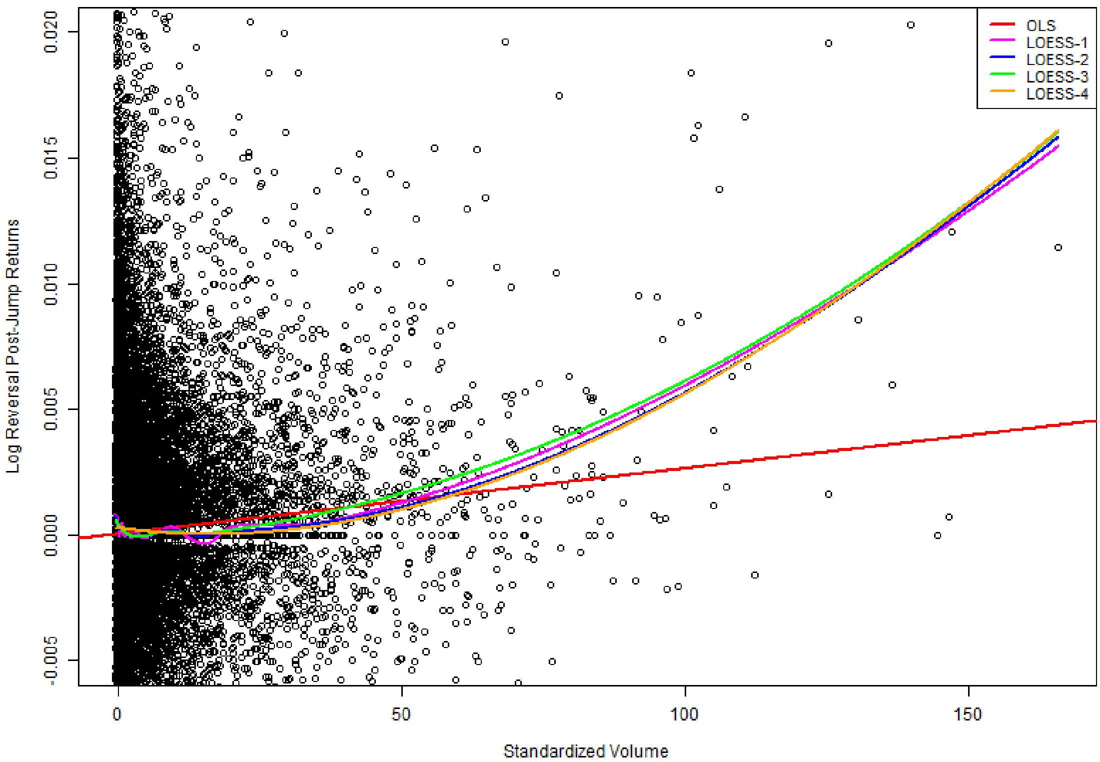


Figure 19: Log reversal post up jump return and volume

Table 15: OLS Regression Coefficients (log reversal return ~ volume)

	Estimate	Std. Err.	T value	p value
Intercept	0.0000730392	0.0000657749	1.110441805	0.2668255482
Up J Volume	0.0000261002	0.0000046941	5.560204832	0.0000000274
Intercept	0.0007334130	0.0000623641	11.760175952	0.0000000000
Down J Volume	0.0000330963	0.0000050066	6.610494745	0.0000000000

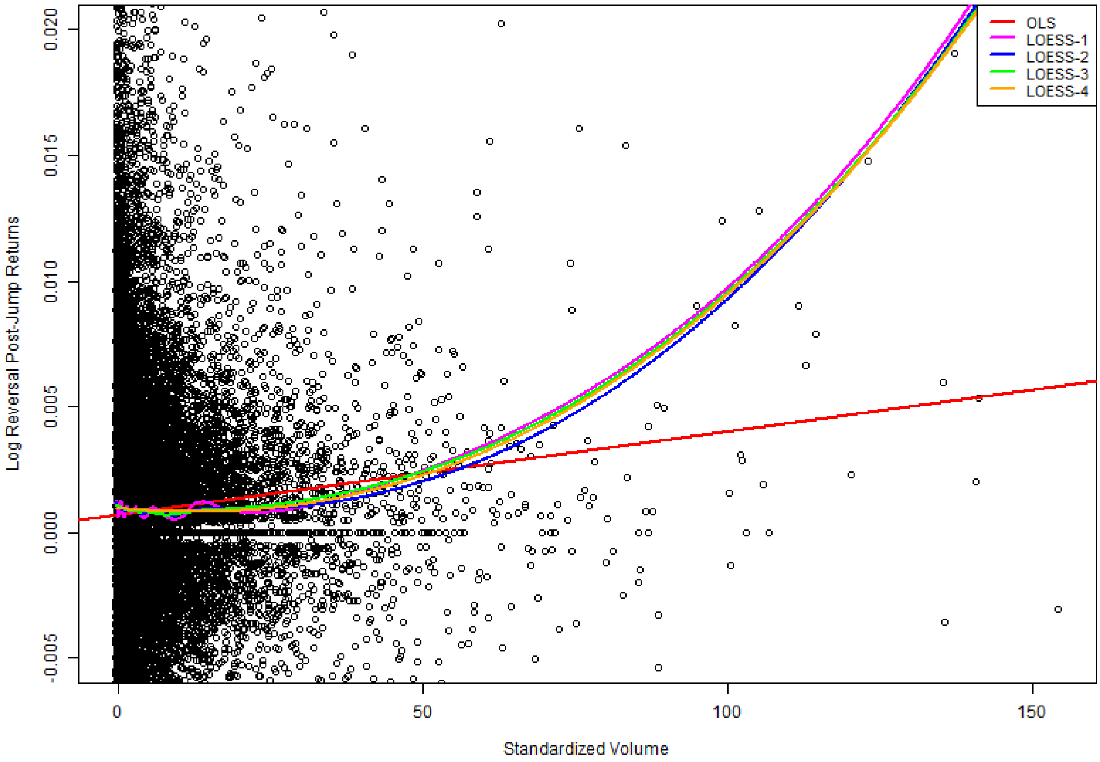


Figure 20: Log reversal post down jump return and volume

Reversal post up jump returns and reversal post down jump returns are regressed onto dummy variables for sector affiliation. The industry is chosen as the reference category, as it the most common one. **Table 16** shows the coefficients. The results suggest that average of reversal post up jump returns of conglomerate stocks are significantly higher than average of reversal post up jump returns of industry stocks; and average of reversal post down jump returns of conglomerate, retail and transportation stocks are significantly higher than average of reversal post down jump returns of industry stocks with %99 confidence intervals. Note that average of reversal post down jump returns of industry stocks is also significantly positive. These results suggest that reversal jump returns of conglomerate stocks are more vigorous. The cause may be the affinity of large fund managers to conglomerate stocks, due to their larger size and more stable income, as large market orders are executed mostly by large fund managers.

Table 16: OLS Regression Coefficients (log reversal return ~ sector)

	Estimate	Std. Err.	T value	p value
Intercept Up J	0.0001673539	0.0001100834	1.5202460111	0.1284691246
Bank	0.0007371230	0.0003109520	2.3705363782	0.0177742017
Real Estate	0.0053811039	0.0025542559	2.1067207924	0.0351574787
Conglomerate	0.0005392090	0.0001852957	2.9099919578	0.0036194130
Mining	-0.0002177427	0.0001522551	-1.4301176649	0.1527029825
Retail	0.0004200390	0.0003021471	1.3901804733	0.1644936225
Transportation	-0.0000632452	0.0001890353	-0.3345684798	0.7379550568
Telecom	0.0004711602	0.0002533045	1.8600550246	0.0628962703
Intercept Down J	0.0006428179	0.0000982242	6.5443936866	0.0000000001
Bank	0.0002576195	0.0002672440	0.9639861528	0.3350649300
Real Estate	0.0036821236	0.0014753262	2.4958029316	0.0125755090
Conglomerate	0.0007204252	0.0001730691	4.1626460634	0.0000315943
Mining	-0.0000284802	0.0001393477	-0.2043823275	0.8380568915
Retail	0.0013647959	0.0002848104	4.7919450681	0.0000016640
Transportation	0.0008807795	0.0001735784	5.0742457965	0.0000003926
Telecom	0.0004285735	0.0002339978	1.8315277253	0.0670371975

5.3.2.4 Momentum Effect

In order to understand the momentum effect, reversal post up jump returns and reversal post down jump returns are regressed onto pre-jump returns of 1, 5, 10, 15, 20, 30, 45, 60, 90 and 120 minutes, separately. **Table 17** and **Table 18** show the coefficients. **Figure 21** and **Figure 22** display both fitted OLS line and LOESS lines for 1-minute. There is statistically significant evidence for the positive (negative) correlation between the pre-jump momentum and the average of reversal post-jump returns, when the direction of the jump opposes (coincides) the direction of the momentum. If the jump is in the same direction with the momentum, which denotes a very vigorous movement, then the reversal seems to be weak. If the jump is in the opposite direction with the momentum, then the reversal seems to be strong. The effect is most prominent with momentum of shorter time periods before down jumps.

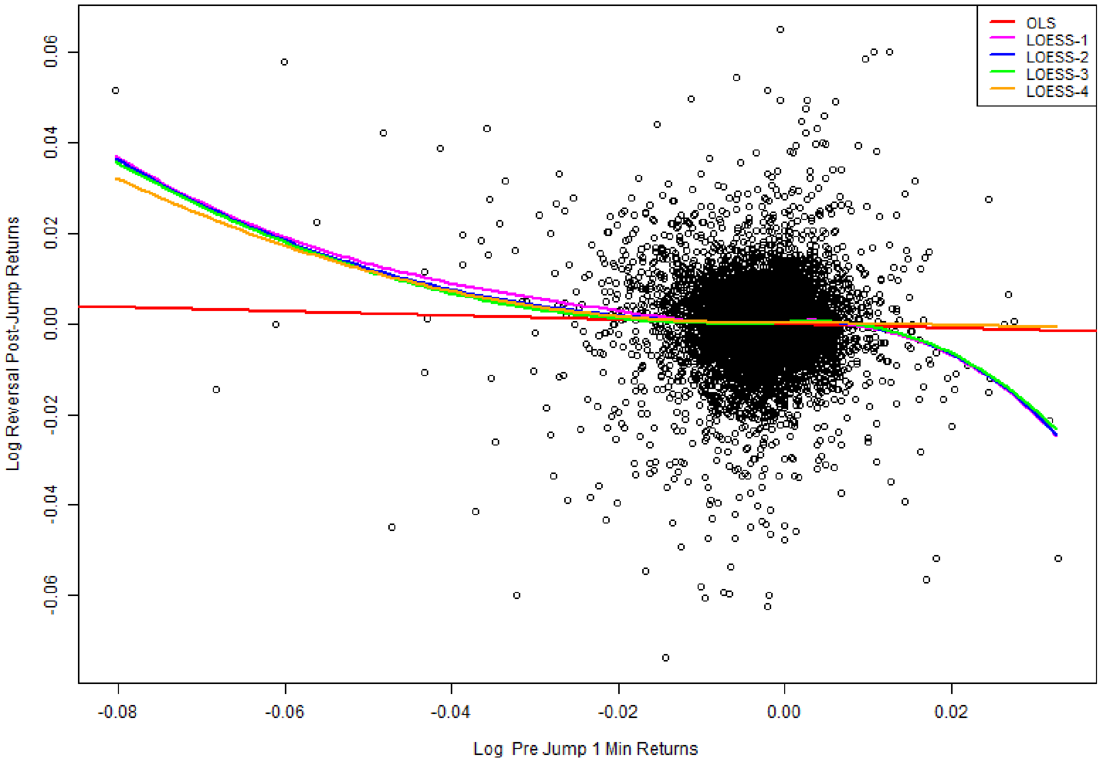


Figure 21: Log reversal post up jump return and log 1-minute pre-jump return

Table 17: OLS Regression Coefficients (log up jump reversal return ~ log pre-jump return)

	Estimate	Std. Err.	T value	p value
Intercept Up J	0.0001393541	0.0000640565	2.175487810	0.0296087343
Mom 1 min	-0.0462843602	0.0124688230	-3.712007161	0.0002063466

	0.0002469469	0.0000584334	4.226128956	0.0000239222
Mom 5 min	-0.0366705557	0.0060261562	-6.085231523	0.0000000012
	0.0002701192	0.0000596565	4.527907688	0.0000060085
Mom 10 min	-0.0312798619	0.0047490339	-6.586573696	0.0000000000
	0.0002787084	0.0000606885	4.592441810	0.0000044228
Mom 15 min	-0.0229970595	0.0042419697	-5.421316347	0.0000000602
	0.0002615508	0.0000617593	4.235004394	0.0000230205
Mom 20 min	-0.0196923181	0.0039474760	-4.988584588	0.0000006165
	0.0002968214	0.0000639908	4.638497898	0.0000035478
Mom 30 min	-0.0123556105	0.0035229332	-3.507194091	0.0004545694
	0.0003014526	0.0000671364	4.490150849	0.0000071917
Mom 45 min	-0.0088854815	0.0031761878	-2.797530246	0.0051586922
	0.0003119158	0.0000696780	4.476531821	0.0000076705
Mom 60 min	-0.0072463142	0.0029763466	-2.434633888	0.0149242289
	0.0003583858	0.0000743645	4.819312813	0.0000014651
Mom 90 min	-0.0093313562	0.0026656867	-3.500545062	0.0004666498
	0.0003768940	0.0000790717	4.766484087	0.0000019095
Mom 120 min	-0.0085289372	0.0025737828	-3.313775095	0.0009247608

Table 18: OLS Regression Coefficients (log down jump reversal return ~ log pre-jump return)

	Estimate	Std. Err.	T value	p value
Intercept Down J	0.0002129212	0.0000578545	3.680288379	0.0002336232
Mom 1 min	0.2943509963	0.0104083366	28.280310936	0.0000000000
	0.0006439438	0.0000542375	11.872658634	0.0000000000
Mom 5 min	0.0839061791	0.0057049830	14.707524692	0.0000000000
	0.0006990905	0.0000545287	12.820589011	0.0000000000
Mom 10 min	0.0526319088	0.0044279077	11.886406165	0.0000000000
	0.0006835420	0.0000554294	12.331750879	0.0000000000
Mom 15 min	0.0441580848	0.0040039067	11.028749653	0.0000000000
	0.0007306453	0.0000564235	12.949305155	0.0000000000
Mom 20 min	0.0304111625	0.0037238242	8.166648261	0.0000000000
	0.0007701141	0.0000583936	13.188329229	0.0000000000
Mom 30 min	0.0179231168	0.0032876991	5.451568459	0.0000000508
	0.0007309746	0.0000607211	12.038227059	0.0000000000
Mom 45 min	0.0110639831	0.0029589102	3.739208789	0.0001853796
	0.0007319131	0.0000634258	11.539682267	0.0000000000
Mom 60 min	0.0071651610	0.0027685968	2.588011726	0.0096644664
	0.0007071007	0.0000686141	10.305465878	0.0000000000
Mom 90 min	0.0068744123	0.0025698765	2.674997145	0.0074843460
	0.0006265239	0.0000715085	8.761530306	0.0000000000
Mom 120 min	0.0052226129	0.0024017533	2.174500133	0.0296924246

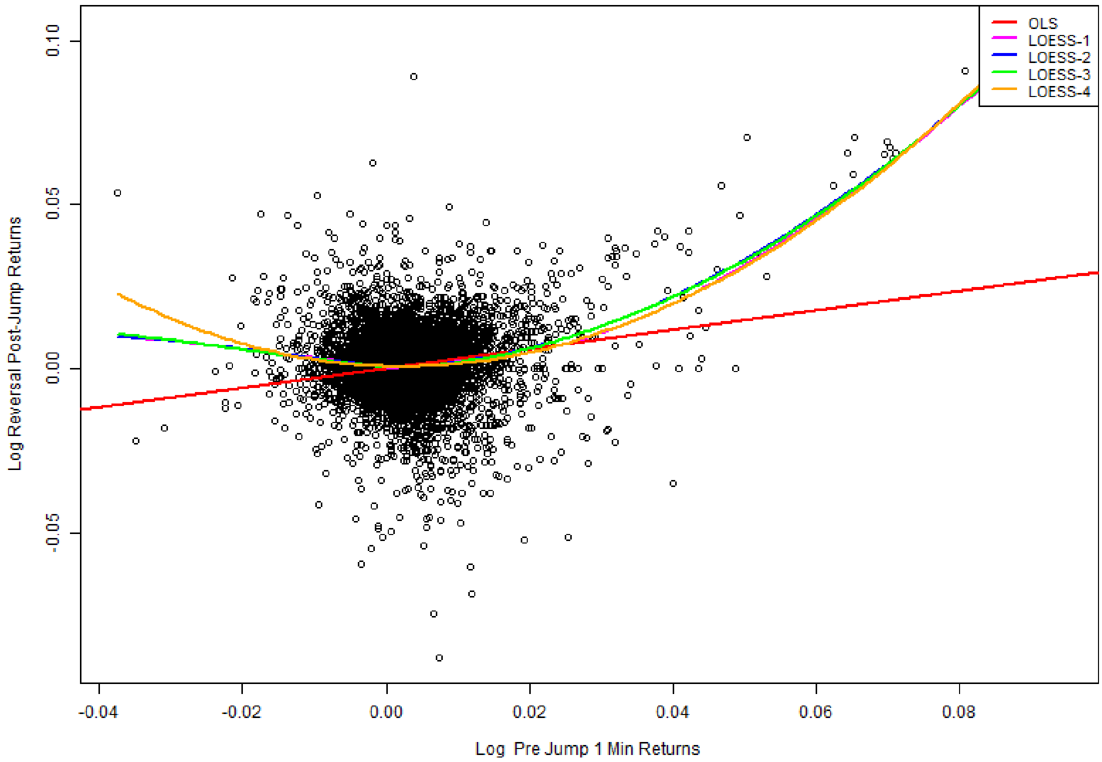


Figure 22: Log reversal post down jump return and log 1-minute pre-jump return

5.3.2.5 Co-exceedance

Reversal post up jump returns and reversal post down jump returns are regressed onto dummy variables for co-exceedance with other test methods and order of High Skipping, separately. Order of High Skipping uses the High Skipping of Price Skipping method, but instead of giving and indicator whether price moves at least two ticks or not, it calculates the excess tick movement, assuming that one or zero tick movements are the normal. **Table 19** and **Table 20** show the coefficients. **Figure 23** and **Figure 24** display the fitted OLS lines for regression onto order of High Skipping.

Table 19: OLS Regression Coefficients (log up jump reversal return ~ co-exceedance)

	Estimate	Std. Err.	T value	p value
Intercept Up J	0.0000625385	0.0000709402	0.8815653855	0.3780252571
Med %10	0.0005477936	0.0001205507	4.5440920492	0.0000055580
	0.0000752783	0.0000707716	1.0636790985	0.2874903110
Med %5	0.0005157997	0.0001208271	4.2689067273	0.0000197576
	0.0000806350	0.0000695023	1.1601785389	0.2459936088
Med %1	0.0005381056	0.0001230757	4.3721514355	0.0000123812
	0.0001352242	0.0000629213	2.1491025319	0.0316413778
Med %0.1	0.0006921985	0.0001530372	4.5230723594	0.0000061391
	-0.0001399068	0.0001135560	-1.2320519390	0.2179479713
WM Skip	0.0005244689	0.0001310707	4.0014187488	0.0000632502
	0.0005734318	0.0012575167	0.4560033571	0.6483938156
Low Skip	-0.0003218658	0.0012588285	-0.2556868093	0.7981960013
	0.0000366676	0.0000748367	0.4899681759	0.6241632044
High Skip	0.0005224972	0.0001165101	4.4845662642	0.0000073576
	0.0001420565	0.0000599071	2.3712796102	0.0177385054
Order of High Skip	0.0000913476	0.0000144340	6.3286457299	0.0000000003

Table 20: OLS Regression Coefficients (log down jump reversal return ~ co-exceedance)

	Estimate	Std. Err.	T value	p value
Intercept Down J	0.0007135324	0.0000654145	10.907854687	0.0000000000
Med %10	-0.0006898719	0.0001114630	-6.189245935	0.0000000006
	0.0007248548	0.0000653171	11.097481926	0.0000000000
Med %5	-0.0006609683	0.0001116327	-5.920922459	0.0000000033
	0.0007356243	0.0000641734	11.463068205	0.0000000000
Med %1	-0.0006761978	0.0001136724	-5.948651969	0.0000000028
	0.0007108943	0.0000577579	12.308176596	0.0000000000
Med %0.1	-0.0014825604	0.0001434802	-10.332857813	0.0000000000
	0.0008164069	0.0001058413	7.713503284	0.0000000000
WM Skip	-0.0001789435	0.0001216687	-1.470743958	0.1413766490
	0.0013334847	0.0001388070	9.606757128	0.0000000000
Low Skip	0.0004138795	0.0001388680	2.980379963	0.0028824918
	0.0008635929	0.0000664105	13.003863267	0.0000000000
High Skip	-0.0002412811	0.0001102513	-2.188464919	0.0286476773
	0.0005028461	0.0000530052	9.486731303	0.0000000000
Order of High Skip	-0.0004724335	0.0000135436	-34.882326824	0.0000000000

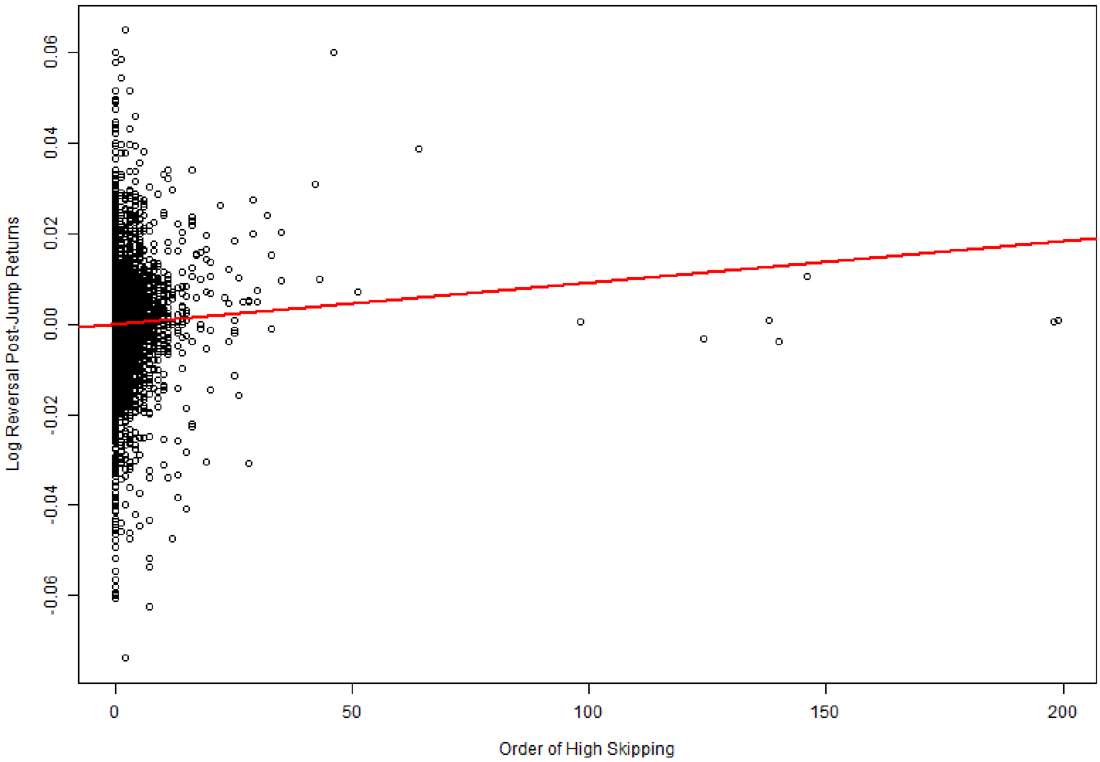


Figure 23: Log reversal post up jump return and order of High Skipping

For all significance levels of MedRV, High Skipping and order of High Skipping, there is statistically significant evidence for the positive correlation between the co-exceedance and the average of reversal post-jump returns, regardless of the direction of the jump. For Weighted Mean Skipping, there is statistically significant evidence for the positive correlation only for up jumps. There is no positive correlation for Low Skipping. The positive correlation is most prominent with order of High Skipping with down jumps. This may be the consequence of large selling market orders pushing the price downwards and then triggering a reversal.

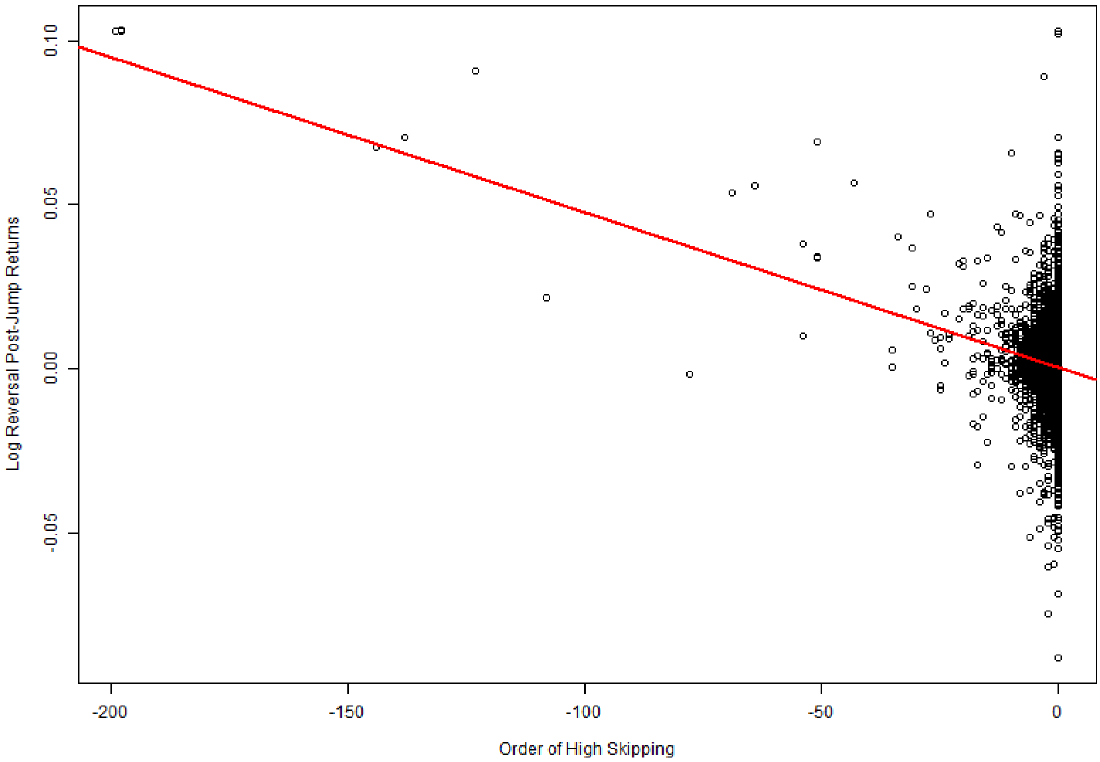


Figure 24: Log reversal post down jump return and order of High Skipping

Reversal post up jump returns and reversal post down jump returns are regressed onto dummy variable for LM jump test results of Bist100 index with %5 significance level. **Table 21** shows the coefficients. The results give no evidence for any correlation. This finding is in line with [39] who also found that index jumps are uncorrelated with constitutive stocks.

Table 21: OLS Regression Coefficients (log reversal return ~ Bist100 jump)

	Estimate	Std. Err.	T value	p value
Intercept Up J	0.0002521545	0.0000573951	4.3933074453	0.0000112364
Bist100 Jump	0.0002164581	0.0009830672	0.2201864705	0.8257287706
Intercept Down J	0.0009526280	0.0000530352	17.962187491	0.0000000000
Bist100 Jump	0.0008732494	0.0008403875	1.039103284	0.2987696997

5.3.2.6 Analyzes on Excess Returns

In order to understand whether the relationships mentioned above are idiosyncratic or systematic, all the regressions are repeated but with the excess reversal post-jump returns. Excess returns are calculated by subtracting corresponding 5 minute Bist100 index returns from 5 minute returns of stocks, and then multiplying post up jump returns by -1, as the strategy is to take short position after up jumps.

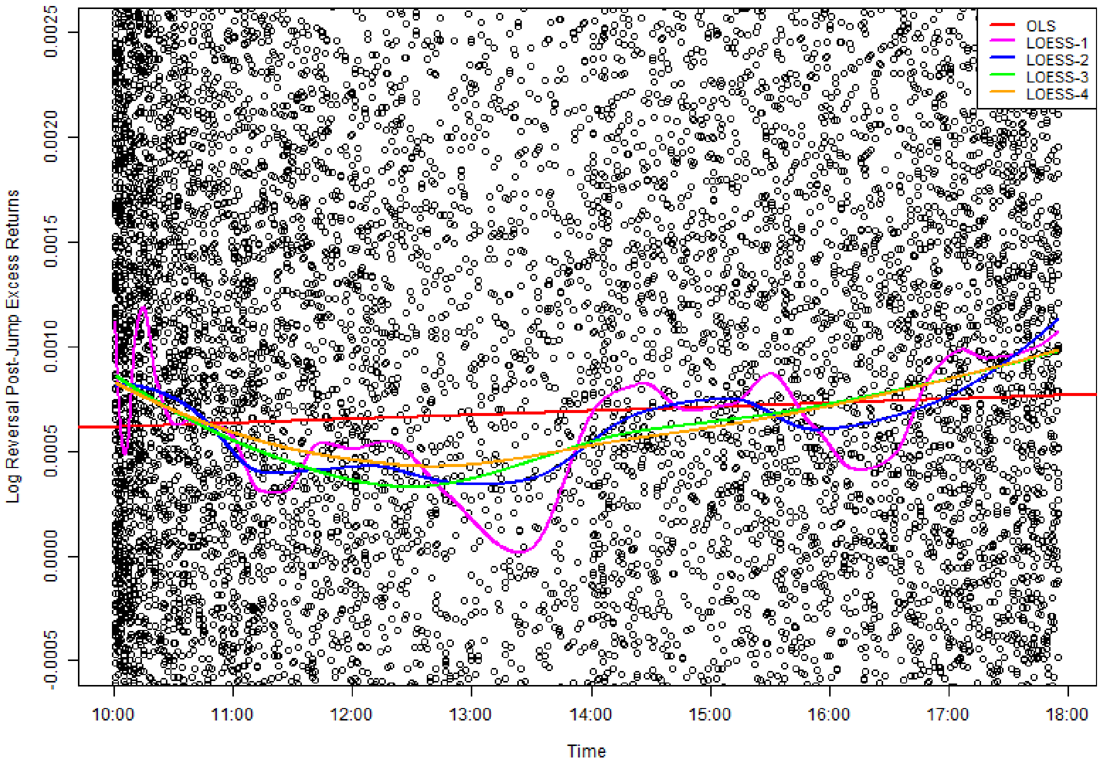


Figure 25: Log reversal post up jump excess return and minutes

Many of the relationships doesn't change as **Table 22**, **Table 23**, **Table 24**, **Table 25**, **Table 26**, **Figure 25**, **Figure 26**, **Figure 27** and **Figure 28** display. There are slight changes in timing, as LOESS lines show. There seems to be positive reversal post up jump returns, which suggests that market's high risk of appetite is responsible for the weak post up jump reversals in the morning. Also the afternoon effects on reversal post down jump returns are smoothened. This suggests that the market's fear possibly after macroeconomic news is responsible for the weak post down jump reversals in the afternoon. Momentum effect before an up jump for more than 1 hour disappears, which suggests that some of the momentum effect comes from the market. The relationships between tick size, volume and co-exceedance stays the same. This finding suggests the effects are idiosyncratic and based on the microstructures and order books of the stocks.

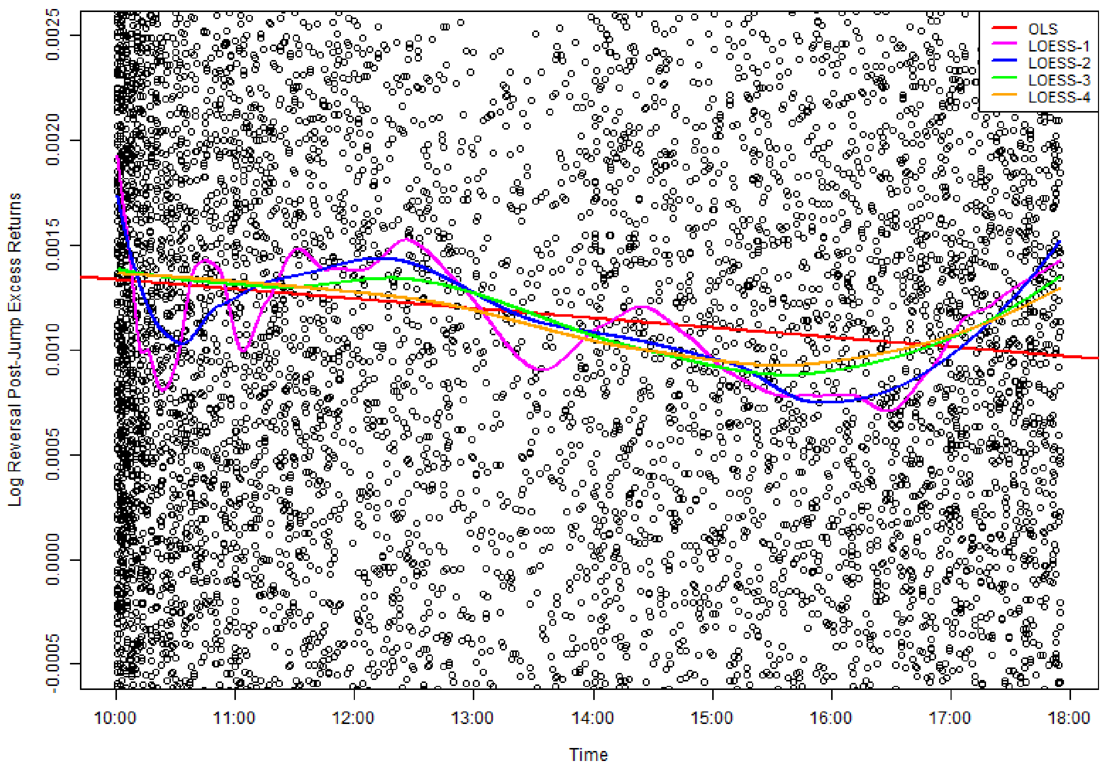


Figure 26: Log reversal post down jump excess return and minutes

Table 22: OLS Regression Coefficients (log reversal excess return ~ log tick return)

	Estimate	Std. Err.	T value	p value
Intercept	-0.0005072053	0.0001379517	-3.676687801	0.0002370628
Log Pos Tick Ret	1.3357178845	0.2206889187	6.052491863	0.0000000015
Intercept	-0.0002222742	0.0001244247	-1.786415239	0.0740477159
Log Neg Tick Ret	-2.0695274728	0.1986504270	-10.417936189	0.0000000000

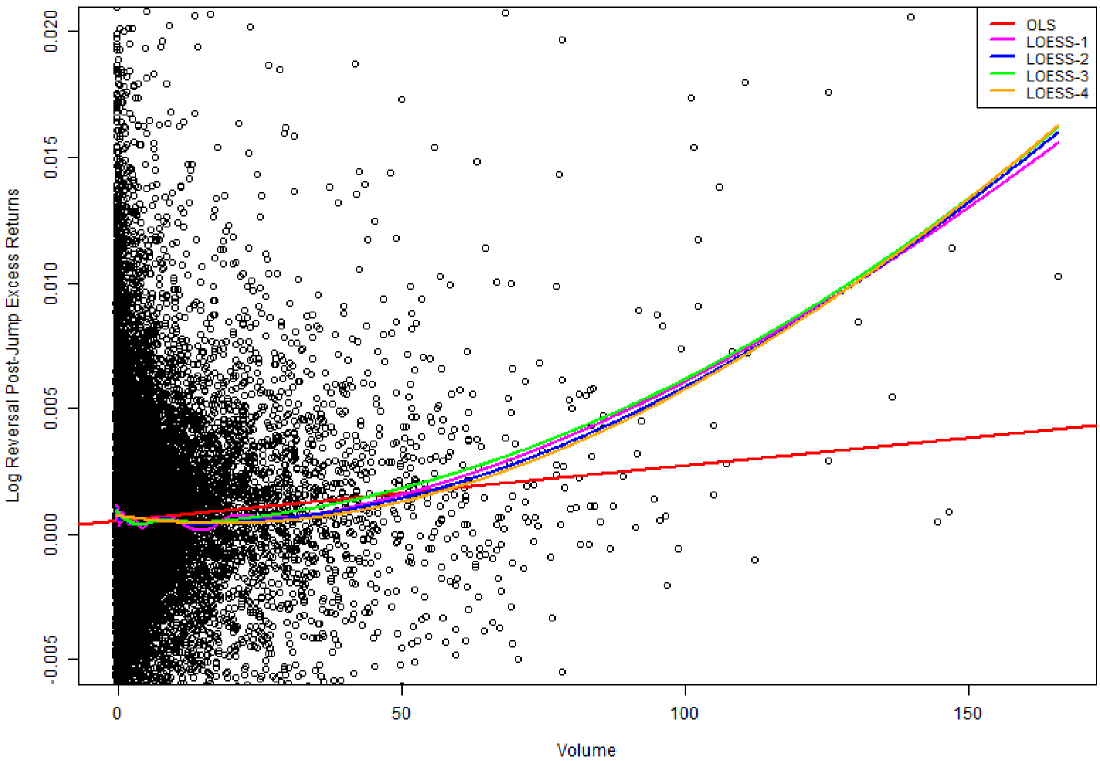


Figure 27: Log reversal post up jump excess return and volume

Table 23: OLS Regression Coefficients (log up jump reversal excess return ~ log pre-jump return)

	Estimate	Std. Err.	T value	p value
Intercept Up J	0.0003502572	0.0000509181	6.8788416486	0.0000000000
Mom 1 min	-0.1374290852	0.0099113825	-13.8657836908	0.0000000000
	0.0005860736	0.0000477313	12.2785876565	0.0000000000
Mom 5 min	-0.0355836570	0.0049224712	-7.2288196963	0.0000000000
	0.0005841569	0.0000486749	12.0011999567	0.0000000000
Mom 10 min	-0.0323414768	0.0038748257	-8.3465628757	0.0000000000

Mom 15 min	0.0005786236 -0.0215047914	0.0000494543 0.0034567301	11.7001620482 -6.2211369811	0.0000000000 0.0000000005
Mom 20 min	0.0005719100 -0.0182342480	0.0000502164 0.0032096883	11.3889105237 -5.6810027552	0.0000000000 0.0000000137
Mom 30 min	0.0005931130 -0.0122214971	0.0000517603 0.0028495947	11.4588476457 -4.2888544456	0.0000000000 0.0000181049
Mom 45 min	0.0006011583 -0.0057207397	0.0000540770 0.0025583522	11.1167190553 -2.2361032275	0.0000000000 0.0253655362
Mom 60 min	0.0006172082 -0.0045654769	0.0000559203 0.0023886775	11.0372794267 -1.9112989879	0.0000000000 0.0559947143
Mom 90 min	0.0006549681 -0.0021081048	0.0000589929 0.0021146735	11.1024848680 -0.9968937272	0.0000000000 0.3188440115
Mom 120 min	0.0006526095 0.0007514353	0.0000620662 0.0020202534	10.5147355266 0.3719510254	0.0000000000 0.7099396847

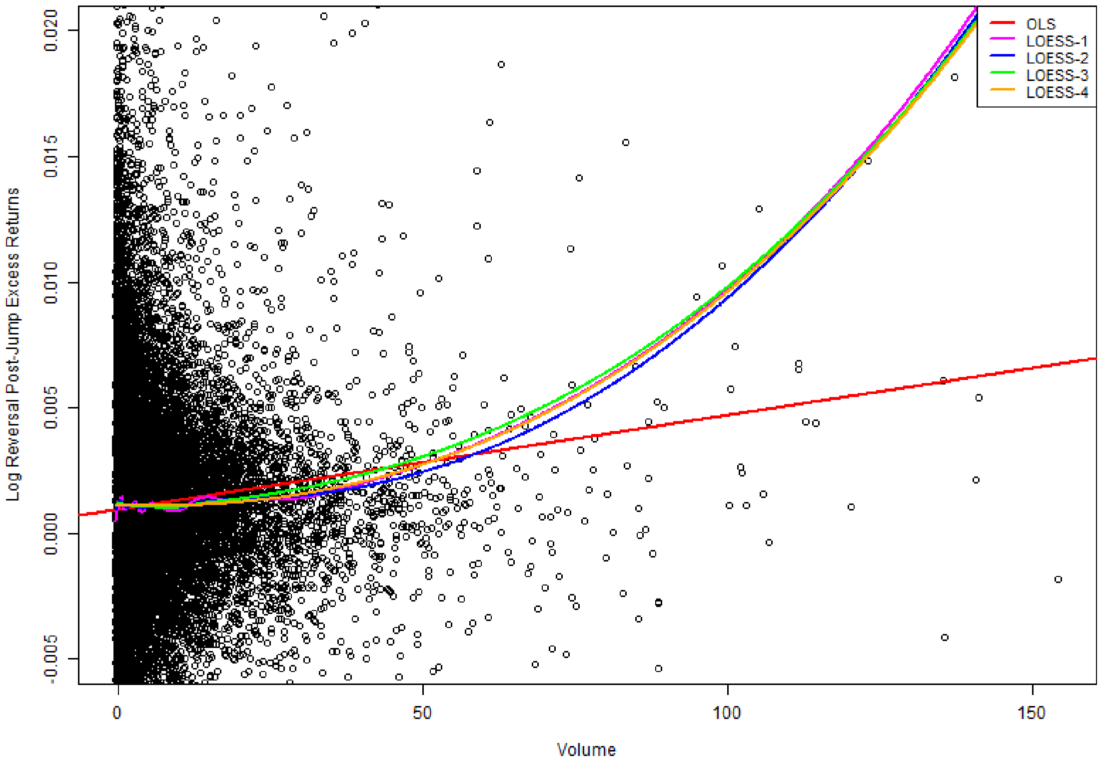


Figure 28: Log reversal post down jump excess return and volume

Table 24: OLS Regression Coefficients (log down jump reversal excess return ~ log pre-jump return)

	Estimate	Std. Err.	T value	p value
Intercept Down J	0.0002940278	0.0000451270	6.515554639	0.0000000001
Mom 1 min	0.3551564156	0.0081186002	43.746016436	0.0000000000
	0.0008448234	0.0000434094	19.461752684	0.0000000000
Mom 5 min	0.1125812989	0.0045660253	24.656301916	0.0000000000
	0.0009327859	0.0000434905	21.448035001	0.0000000000
Mom 10 min	0.0748106727	0.0035315683	21.183413953	0.0000000000
	0.0009782131	0.0000443090	22.077079942	0.0000000000
Mom 15 min	0.0585078283	0.0032006290	18.280103422	0.0000000000
	0.0010057213	0.0000450873	22.306087856	0.0000000000
Mom 20 min	0.0469701229	0.0029756600	15.784774828	0.0000000000
	0.0010611126	0.0000465620	22.789230259	0.0000000000
Mom 30 min	0.0342807136	0.0026215526	13.076492907	0.0000000000
	0.0010559001	0.0000478597	22.062426335	0.0000000000
Mom 45 min	0.0227921608	0.0023321776	9.772909679	0.0000000000
	0.0010625591	0.0000498796	21.302494574	0.0000000000
Mom 60 min	0.0166754381	0.0021772921	7.658797062	0.0000000000
	0.0010595343	0.0000530288	19.980374309	0.0000000000
Mom 90 min	0.0139081693	0.0019861408	7.002609932	0.0000000000
	0.0010215246	0.0000536570	19.038047681	0.0000000000
Mom 120 min	0.0111296308	0.0018021758	6.175663255	0.0000000007

Table 25: OLS Regression Coefficients (log up jump reversal excess return ~ co-exceedance)

	Estimate	Std. Err.	T value	p value
Intercept Up J	0.0004262826	0.0000568571	7.4974337945	0.0000000000
Med %10	0.0007317950	0.0000966189	7.5740360776	0.0000000000
	0.0004451496	0.0000567311	7.8466579724	0.0000000000
Med %5	0.0006836682	0.0000968560	7.0586049851	0.0000000000
	0.0004616051	0.0000557183	8.2846270100	0.0000000000
Med %1	0.0006838971	0.0000986668	6.9313818667	0.0000000000
	0.0005092735	0.0000504135	10.1019185177	0.0000000000
Med %0.1	0.0010081721	0.0001226159	8.2221942544	0.0000000000
	0.0002956671	0.0000910955	3.2456837616	0.0011741223
WM Skip	0.0005136208	0.0001051460	4.8848357008	0.0000010453
	0.0010284085	0.0010090376	1.0191974098	0.3081248222
Low Skip	-0.0003494372	0.0010100902	-0.3459464821	0.7293875297
	0.0004976656	0.0000600453	8.2881642068	0.0000000000
High Skip	0.0004412144	0.0000934821	4.7197764962	0.0000023812
	0.0005657065	0.0000480296	11.7782957198	0.0000000000
Order of High Skip	0.0000945087	0.0000115722	8.1668617891	0.0000000000

Table 26: OLS Regression Coefficients (log reversal excess return ~ co-exceedance)

	Estimate	Std. Err.	T value	p value
Intercept Down J	0.0009181715	0.0000521674	17.600494696	0.0000000000
Med %10	-0.0007930493	0.0000888905	-8.921644844	0.0000000000
	0.0009280600	0.0000520920	17.815804165	0.0000000000
Med %5	-0.0007689577	0.0000890298	-8.637083878	0.0000000000
	0.0009427491	0.0000511811	18.419867780	0.0000000000
Med %1	-0.0007798982	0.0000906587	-8.602571065	0.0000000000
	0.0009455613	0.0000460285	20.542935041	0.0000000000
Med %0.1	-0.0015165530	0.0001143425	-13.263242597	0.0000000000
	0.0010248826	0.0000844905	12.130146377	0.0000000000
WM Skip	-0.0002210457	0.0000971252	-2.275884422	0.0228638174
	0.0015088829	0.0001108128	13.616502818	0.0000000000
Low Skip	0.0003437601	0.0001108616	3.100805009	0.0019327286
	0.0011395624	0.0000530210	21.492661685	0.0000000000
High Skip	-0.0001426291	0.0000880228	-1.620366209	0.1051699441
	0.0007636963	0.0000417427	18.295315415	0.0000000000
Order of High Skip	-0.0004506453	0.0000106659	-42.251030172	0.0000000000

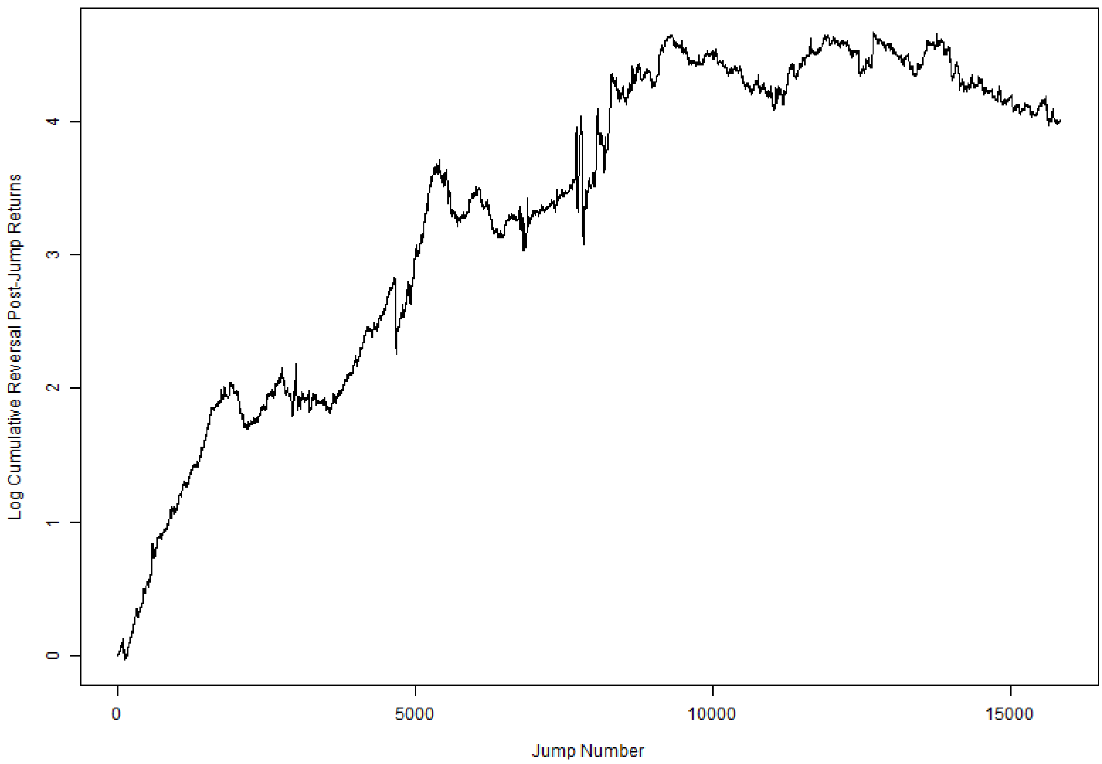


Figure 29: Log cumulative reversal post up jump return

5.3.2.7 *Cumulative Returns*

The number of up jumps is 15842, and the number of down jumps is 19334. **Figure 29** and **Figure 30** show cumulative returns for reversal post-jump returns, without the transaction fee costs. Incomparably, the cumulative reversal post down jump returns are larger. This result suggests that the market is more resilient to large buying market orders, but less resilient to large selling market orders, as they cause more overreactions, hence stronger reversals.

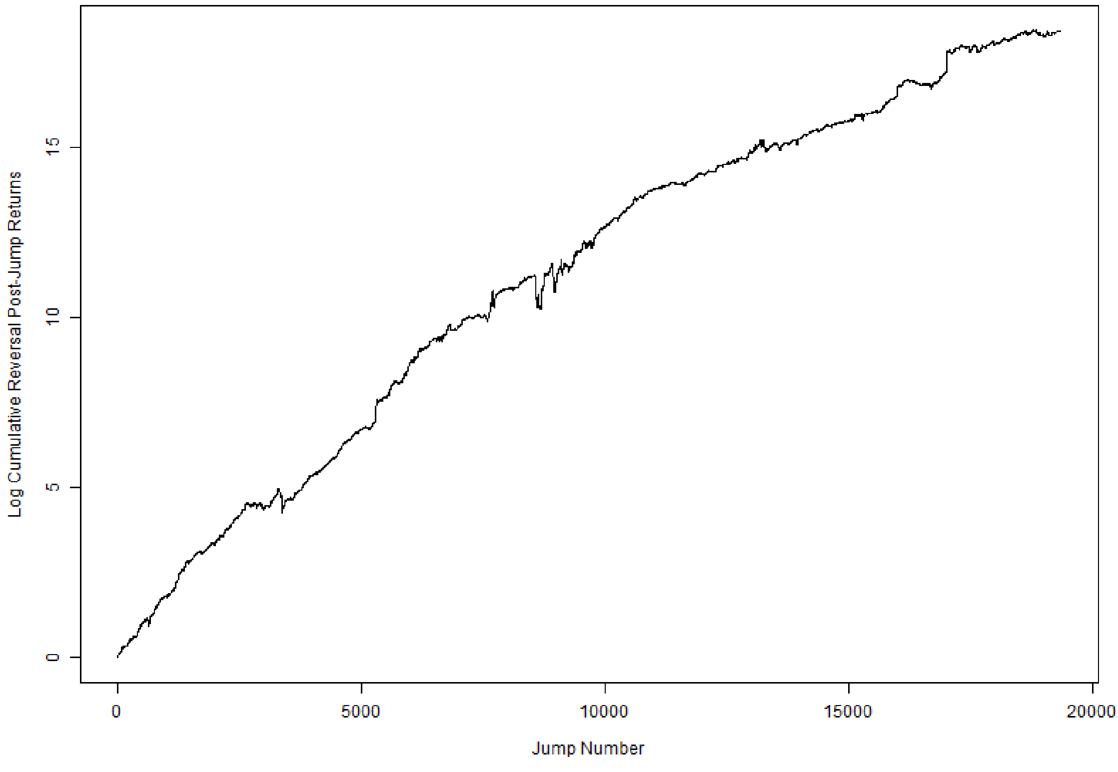


Figure 30: Log cumulative reversal post down jump return

5.3.3 Modelling

A multivariate linear regression is modelled for both up and down jumps, but to assess multicollinearity variance inflation factor (VIF) is used. **Table 27** displays the correlation matrix of the factors used. Starting from adding everything in the model, VIF values are calculated and the factor with highest value is discarded from the model. The process is repeated until all the VIF values are under 5. The factors of the resulting model are; log positive tick returns, price groups dummies, volume, Med %10, Med%0.1, WM Skipping, Low Skipping, High Skipping, Order of High Skipping, Bist Jumps, 1, 5, 10, 20, 60, 120 minutes pre-jump returns, order of minute, sector dummies for up jumps; and log negative tick returns, price groups dummies, volume, Med %10, Med%0.1, WM Skipping, Low Skipping, High Skipping, Order of High Skipping, Bist Jumps, 1, 5, 10, 30, 60, 120 minutes pre-jump returns, order of minute, sector dummies for down jumps.

Table 27: Correlation Matrix of Factors

	Tick	Tick	P10	PM	P25	Vol	Med1	Med	Med	Med0.	WM	LS	HS	OH	Bist	1M	5M
TickN	1.00	-1.00	-	-	0.67	-	0.00	0.00	0.00	-0.01	-0.01	0.0	-	0.00	-	-	-
TickP	-1.00	1.00	0.5	0.45	-	0.2	0.00	0.00	0.00	0.01	0.01	-	0.0	0.00	0.0	0.0	0.0
P10	-0.55	0.54	1.0	-	-	0.1	0.00	0.00	-0.01	0.00	0.00	0.0	0.0	0.01	0.0	0.0	0.0
PMR	-0.45	0.45	-	1.00	-	0.1	0.01	0.01	0.01	0.01	0.01	0.0	0.0	0.00	0.0	0.0	0.0
P250	0.67	-0.67	-	-	1.00	-	-0.01	-0.01	-0.01	-0.02	-0.02	0.0	-	-	-	-	-
Vol	-0.21	0.21	0.1	0.13	-	1.0	-0.01	-0.01	-0.01	0.00	-0.01	0.0	-	-	0.0	0.0	-
Med10	0.00	0.00	0.0	0.01	-	-	1.00	1.00	0.96	0.69	0.59	0.5	0.3	0.25	0.0	-	-
Med5	0.00	0.00	0.0	0.01	-	-	1.00	1.00	0.96	0.70	0.58	0.5	0.3	0.25	0.0	-	-
Med1	0.00	0.00	-	0.01	-	-	0.96	0.96	1.00	0.72	0.56	0.5	0.3	0.25	0.0	-	-
Med0.	-0.01	0.01	0.0	0.01	-	0.0	0.69	0.70	0.72	1.00	0.44	0.3	0.2	0.25	0.0	-	-
WMS	-0.01	0.01	0.0	0.01	-	-	0.59	0.58	0.56	0.44	1.00	0.8	0.6	0.35	0.0	-	-
LS	0.01	-0.01	0.0	0.00	0.00	0.0	0.56	0.55	0.54	0.38	0.84	1.0	0.6	0.30	0.0	-	-
HS	-0.01	0.01	0.0	0.01	-	-	0.37	0.36	0.35	0.26	0.69	0.6	1.0	0.50	0.0	-	-
OHS	0.00	0.00	0.0	0.00	-	-	0.25	0.25	0.25	0.25	0.35	0.3	0.5	1.00	0.0	-	-
Bist	-0.01	0.01	0.0	0.00	-	0.0	0.02	0.02	0.01	0.02	0.01	0.0	0.0	0.00	1.0	-	0.0
1M	-0.05	0.05	0.0	0.02	-	0.0	-0.36	-0.36	-0.35	-0.32	-0.40	-	-	-	-	1.0	0.6
5M	-0.04	0.04	0.0	0.02	-	-	-0.22	-0.22	-0.21	-0.20	-0.24	-	-	-	0.0	0.6	1.0
10M	-0.04	0.04	0.0	0.01	-	-	-0.17	-0.17	-0.16	-0.15	-0.19	-	-	-	0.0	0.5	0.8
15M	-0.04	0.04	0.0	0.02	-	-	-0.15	-0.14	-0.14	-0.13	-0.17	-	-	-	0.0	0.4	0.7
20M	-0.05	0.04	0.0	0.03	-	-	-0.14	-0.14	-0.13	-0.12	-0.16	-	-	-	0.0	0.4	0.6
30M	-0.05	0.05	0.0	0.04	-	-	-0.12	-0.12	-0.12	-0.11	-0.14	-	-	-	0.0	0.3	0.5
45M	-0.07	0.07	0.0	0.05	-	-	-0.11	-0.10	-0.10	-0.09	-0.12	-	-	-	0.0	0.3	0.5
60M	-0.07	0.07	0.0	0.06	-	-	-0.10	-0.10	-0.09	-0.09	-0.11	-	-	-	0.0	0.3	0.4
90M	-0.10	0.10	0.0	0.09	-	-	-0.08	-0.08	-0.08	-0.07	-0.10	-	-	-	0.0	0.2	0.3

120M	-0.11	0.11	0.0	0.10	-	-	-0.07	-0.07	-0.07	-0.06	-0.08	-	-	-	0.0	0.2	0.3
Min	-0.06	0.06	0.0	0.10	-	0.0	0.01	0.01	0.00	0.00	0.01	0.0	0.0	0.00	0.0	0.0	0.0
Ind	0.08	-0.08	-	-	0.16	0.0	0.00	0.00	0.00	0.01	-0.02	-	0.0	0.00	0.0	0.0	0.0
Bnk	-0.27	0.27	0.3	0.02	-	0.0	-0.01	-0.01	-0.01	0.00	-0.01	-	0.0	-	0.0	0.0	0.0
RE	-0.23	0.23	0.2	-	-	0.0	0.00	0.00	0.00	0.00	0.00	-	0.0	0.00	0.0	0.0	0.0
Cg	-0.12	0.12	-	0.25	-	0.0	0.01	0.01	0.01	0.01	0.02	0.0	0.0	0.01	-	-	0.0
Mng	0.38	-0.38	-	-	0.40	-	0.00	0.00	0.00	-0.01	0.00	0.0	-	0.00	-	-	-
Rtl	-0.09	0.09	-	0.13	-	-	0.01	0.01	0.00	0.00	0.02	0.0	0.0	0.00	0.0	0.0	0.0
Trp	-0.12	0.12	-	0.24	-	0.0	0.00	0.00	-0.01	0.00	0.00	-	-	-	0.0	0.0	0.0
Tel	-0.20	0.20	0.0	0.12	-	0.0	-0.01	-0.01	-0.01	0.00	0.00	0.0	0.0	0.01	0.0	0.0	0.0

	10M	15M	20M	30M	45M	60M	980M	120M	Min	Ind	Bnk	RE	Cg	Mng	Rtl	Trp	Tel
TickN	-0.04	-0.04	-	-	-	-	-0.10	-0.11	-0.06	0.08	-0.27	-	-	0.38	-	-	-
TickP	0.04	0.04	0.04	0.05	0.07	0.07	0.10	0.11	0.06	-0.08	0.27	0.23	0.12	-	0.09	0.12	0.20
P10	0.04	0.03	0.03	0.03	0.04	0.04	0.05	0.05	0.00	-0.03	0.31	0.22	-	-	-	-	0.09
PMR	0.01	0.02	0.03	0.04	0.05	0.06	0.09	0.10	0.10	-0.14	0.02	-	0.25	-	0.13	0.24	0.12
P250	-0.03	-0.03	-	-	-	-	-0.11	-0.13	-0.11	0.16	-0.14	-	-	0.40	-	-	-
Vol	-0.03	-0.03	-	-	-	-	-0.06	-0.06	0.03	0.03	0.08	0.04	0.01	-	-	0.07	0.07
Med10	-0.17	-0.15	-	-	-	-	-0.08	-0.07	0.01	0.00	-0.01	0.00	0.01	0.00	0.01	0.00	-
Med5	-0.17	-0.14	-	-	-	-	-0.08	-0.07	0.01	0.00	-0.01	0.00	0.01	0.00	0.01	0.00	-
Med1	-0.16	-0.14	-	-	-	-	-0.08	-0.07	0.00	0.00	-0.01	0.00	0.01	0.00	0.00	-	-
Med0.1	-0.15	-0.13	-	-	-	-	-0.07	-0.06	0.00	0.01	0.00	0.00	0.01	-	0.00	0.00	0.00
WMS	-0.19	-0.17	-	-	-	-	-0.10	-0.08	0.01	-0.02	-0.01	0.00	0.02	0.00	0.02	0.00	0.00
LS	-0.21	-0.19	-	-	-	-	-0.10	-0.08	0.02	-0.03	-0.01	-	0.01	0.03	0.01	-	0.00
HS	-0.07	-0.05	-	-	-	-	-0.02	-0.02	0.00	0.00	0.00	0.00	0.01	-	0.01	-	0.01
OHS	-0.08	-0.07	-	-	-	-	-0.03	-0.02	0.00	0.00	-0.01	0.00	0.01	0.00	0.00	-	0.01
Bist	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	-	-	0.00	0.01	0.01
1M	0.50	0.44	0.42	0.37	0.34	0.32	0.26	0.23	0.01	0.00	0.04	0.01	-	-	0.01	0.02	0.01
5M	0.82	0.71	0.65	0.57	0.50	0.47	0.36	0.31	0.02	0.01	0.04	0.00	0.00	-	0.00	0.00	0.01
10M	1.00	0.89	0.80	0.70	0.60	0.56	0.42	0.36	0.03	0.02	0.04	0.00	0.01	-	0.00	0.00	0.01
15M	0.89	1.00	0.92	0.79	0.69	0.63	0.49	0.41	0.04	0.02	0.04	0.00	0.01	-	0.00	0.00	0.01
20M	0.80	0.92	1.00	0.88	0.78	0.70	0.56	0.47	0.06	0.02	0.04	0.00	0.02	-	0.00	0.00	0.01
30M	0.70	0.79	0.88	1.00	0.87	0.80	0.65	0.54	0.08	0.02	0.05	0.00	0.03	-	0.00	0.00	0.00
45M	0.60	0.69	0.78	0.87	1.00	0.92	0.79	0.67	0.12	0.02	0.05	0.00	0.04	-	0.00	0.01	0.01
60M	0.56	0.63	0.70	0.80	0.92	1.00	0.87	0.76	0.14	0.01	0.04	0.01	0.03	-	0.00	0.02	0.01
90M	0.42	0.49	0.56	0.65	0.79	0.87	1.00	0.92	0.17	0.02	0.04	0.01	0.04	-	-	0.03	0.02
120M	0.36	0.41	0.47	0.54	0.67	0.76	0.92	1.00	0.17	0.03	0.03	0.00	0.04	-	0.00	0.03	0.02
Min	0.03	0.04	0.06	0.08	0.12	0.14	0.17	0.17	1.00	-0.03	0.01	0.02	0.02	-	0.01	0.03	0.02
Ind	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.03	-0.03	1.00	-0.15	-	-	-	-	-	-
Bnk	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.03	0.01	-0.15	1.00	-	-	-	-	-	-
RE	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.02	-0.03	-0.01	1.00	-	-	-	-	-
Cg	0.01	0.01	0.02	0.03	0.04	0.03	0.04	0.04	0.02	-0.26	-0.09	-	1.00	-	-	-	-
Mng	-0.05	-0.05	-	-	-	-	-0.10	-0.11	-0.03	-0.42	-0.14	-	-	1.00	-	-	-
Rtl	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.01	-0.13	-0.04	-	-	-	1.00	-	-
Trp	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.03	0.03	-0.25	-0.08	-	-	-	-	1.00	-
Tel	0.01	0.01	0.01	0.00	0.01	0.01	0.02	0.02	0.02	-0.17	-0.06	-	-	-	-	-	1.00

CHAPTER VI

CONCLUSION

The main purpose of this study is to investigate properties and return predictabilities of intraday jumps of stocks of Borsa İstanbul. Another objective is to try to understand the microstructural mechanism of jumps and the relationship of jumps with other factors.

Strong evidence is found for jumps on ultra-high frequency exhibiting return predictability, in the format of reversals; contrary to [30], who found no evidence for return predictability. Conclusive evidence is found for increasing relative tick sizes decreasing the likelihood of jumps, but increasing the predictability of post-jump returns. The results also suggest that there is quadratically positive relationship between volume and magnitude of post-jump returns. Despite having low Jaccard similarity, jump tests of different methods and significance levels are mostly consistent in terms of the results.

Stock prices change because of the market orders, which are executed against limit orders [50]. The cause of extreme price changes is greater demand for liquidity, rather than weak liquidity supply [31]. The probability of jumps is positively correlated with volume [36], [28]. Large market orders cause high volume. If a market order executed against limit orders is large enough, it demands liquidity, and when it is not fulfilled, the price moves multiple ticks. If the movement is sharp enough to disrupt price continuity, then it is called a jump. The results of this study suggest that, the price movement ending on a level too far from the market equilibrium, causes the market to start a reversal.

The dimensions of liquidity can be categorized into; width (trading costs), depth (trading quantity), immediacy (trading speed) and resiliency (trading impact) [31], [51]. A resilient market absorbs sudden changes in supply and demand without causing extreme price movements. Turkish stock market seems to be more resilient to upward jumps, but less to downward jumps.

Also resiliency decreases with increasing relative tick size. If relative tick size is not small, stocks have one tick spread normally, but multi-tick spreads under low liquidity periods [52]. If the relative tick size is large, the market holds higher demand for liquidity up to a point, but when the walls are breached, stability of price is lost for some time. Trading from high frequency traders decrease around jumps, whereas trading from non-high frequency traders increase [46]. High frequency traders act as the guards on wall, when the walls are breached, they flee too. When the tick size is small, though the number of jumps increase, they don’t have much impact, and the market stays resilient.

This study contributes to the literature by giving insight to jump mechanisms on ultra-high frequency, by elucidating the relationship between relative tick size and intraday jumps, by providing evidence for jump predictability and by developing three purely price based jump test methods, namely Price Skipping. Mechanisms of intraday jumps are still not completely understood, and relative tick size is a subject many researchers ignore. This study may open doors and give ideas to other researches on this subject. Of the three Price Skipping methods, High Skipping has more return predictability than others. Though they provide lesser reversal returns, they have less variation than well-established tests. They may also be used in combinations with well-established other volatility based tests.

Another contribution of this study is to illuminate policy makers of Turkish stock market about the tick sizes of Borsa İstanbul. Large relative tick sizes and large market orders do not get along. Stocks with smaller tick sizes has higher percentage of market orders [49]. Some investors may use dark pools for large trades [44]. Sub-tick trading is also allowed in dark pools [53]. However, the dark pools are used less often in Türkiye than in the US. They operate under the supervision of the Capital Markets Board of Türkiye and follow specific regulations to ensure transparency and fair trading practices.

Tick sizes are mainly on the focus of the researchers when the regulators change them. If the spread is not at its competitive minimum, reducing tick size decreases trading costs (width) [54]. [53] showed that reduced tick size decreased width. [55] found that for small priced and high volume stocks, decline in tick size decreased width but also decreased depth. [56] found no evidence for tick size reduction changing depth, but found that it reduces width. [52] found that relative tick size effect on depth is insignificant. [54] found that reduced tick size increased depth, decreased width and decreased volatility for only heavily traded securities. [55] provided weak evidence for tick size reduction increasing market efficiency. Reduced tick size increases liquidity [57], [58], and the increase is greatest in high volume stocks [58]. The price clustering, caused by trading at round numbers, increases as the tick size decreases [54].

[59] showed that tick size reduction in BIST, which happened in 2014, increased high frequency trading. Smaller relative tick sizes increase high frequency trading [52]. Larger tick size decreases algorithmic trading [57]. When the spread is more than one tick, high frequency market makers benefit large relative tick sizes by undercutting resting limit orders, causing more adverse selection and lower depth by affecting traders' willingness to supply depth. [52]

The matter of determining the ideal tick size still lacks a conclusive answer [58]. When deciding tick sizes, there is trade-off between liquidity and price discovery [57]. So, ideally there should be a tick size, but it should be regulated by policy makers to a level that doesn’t hinder market efficiency. The role of Borsa İstanbul's management is to provide an efficient marketplace, maintain market stability, and foster economic growth. There is strong evidence that the current tick size policy is reducing market resilience, stability, and efficiency, especially for low-priced stocks, and to some extent for stocks in the mid-price range. There are quite a few studies providing proof for reducing tick sizes increasing liquidity especially on highly traded stocks. In the light of this information, Borsa İstanbul management is advised to re-evaluate their tick size policy.

This study did not fully dive into liquidity and investigate order imbalance, as these aspects are left for future research. Also repeating the research on tick data, but using a volume time clock instead of calendar time, might give further insights on the mechanism of intraday jumps.

[20] defined bounceback as a sequence of price movement to one direction and immediately preceding of a price movement on the opposite direction with the same magnitude. A sequence of price movements which contains a jump and a post-jump reversal on ultra-high frequency may be seen as a bounceback on lower frequencies. Bouncebacks are cleared by many practitioners in the data cleaning process, but it may contain valuable information in it, if looked through a magnifying glass.

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