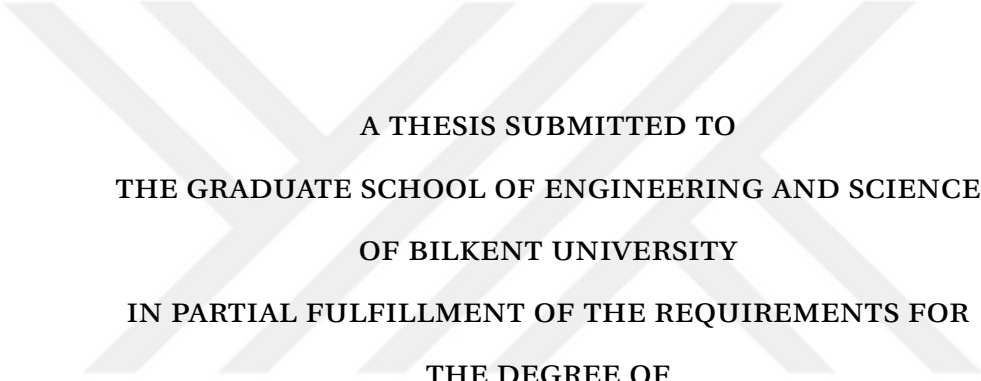


DATA ANALYTICS IN STOCK MARKETS



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By
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DATA ANALYTICS IN STOCK MARKETS

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We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

DATA ANALYTICS IN STOCK MARKETS

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One of the important strategies that is employed in finance is data analytics. Data Analytics is the science of investigating raw data with intention of drawing meaningful information and useful conclusions. Recently, organizations started to consider data analytics as a way to improve business processes and, use the collected information in operational efficiencies for achieving revenue growth. In recent years, the usage of data analytics is rapidly growing for many other reasons, such as, optimizing business processes, increasing revenue, and improving customer interactions. In this research two kinds of data analytics, order imbalances and order flow imbalances are studied and two groups of models extended according them. These regression models are based on level regressions and percentage changes, and trying to answer whether data analytics can forecast one minute a head of price return for each stock or not. Moreover, the results are analyzed and interpreted for 27 stocks of Borsa Istanbul. In the next step, for understanding the power of prediction of data analytics, Fama-Macbeth regression is considered. In the first step, each portfolio's return is regressed against one or more factor of time series. In the second step, the cross-section of portfolio returns is regressed against the factors, at each time step. Then, we discuss the Long-Short Portfolio approach which is widely used in finance literature. This method is an investing strategy that takes long positions in stocks that are expected to ascend and short positions in stocks that are expected to descend. In this part we show the number of days that are positive or negative and provide the t stats that adjusted by NW procedure for all data analytics in each day for this method. Finally, we discuss about the market efficiency and show whether according to our analysis Borsa Istanbul is an efficient market or not.

Keywords: Borsa Istanbul, Data Analytics, High Frequency Trading, Order Imbalance, Order Flow Imbalance, Market Efficiency, Fama-Macbeth Regression, Long-Short Portfolio, Newey-West Test.

ÖZET

TÜRKÇE BAŞLIK

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Finansta kullanılan önemli stratejilerden biri veri analitiğidir. Veri Analizi, anlamlı bilgileri ve faydalı sonuçları çıkarmak amacıyla ham verileri araştıran bilimdir. Son zamanlarda, kurumlar veri analizini iş süreçlerini iyileştirmenin bir yolu olarak görmeye ve toplanan bilgileri gelir artışını sağlamak için operasyonel verimlilikte kullanmaya başlamışlardır. Son yıllarda, veri analizlerinin kullanımı, iş süreçlerini optimize etmek, geliri artırmak ve müşteri etkileşimlerini iyileştirmek gibi diğer birçok nedenden dolayı hızla artmaktadır. Bu araştırmada iki tür veri analitiği, düzen dengesizlikleri ve düzen akış dengesizlikleri incelenmiş ve bunlara göre iki grup model incelenmiştir. Bu regresyon modelleri, seviye regresyonlarına ve yüzde değişikliklere dayanmaktadır ve veri analitiklerinin her hisse senedi için bir dakika başı fiyat getirisi tahmin edip edemeyeceğini yanıtlamaya çalışmaktadır. Ayrıca, 27 Borsa İstanbul hisse senedine ait sonuçlar analiz edilmiş ve yorumlanmıştır. Bir sonraki adımda, veri analitik tahmininin gücünü anlamak için, Fama-Macbeth regresyonu göz önünde bulundurulur. İlk adımda, her portföyün getirisi bir veya daha fazla zaman faktörü karşısında geri çekilir. İkinci adımda, portföy iadelerinin kesiti, her adımda, faktörlere karşı gerilemektedir. Daha sonra finans literatüründe yaygın olarak kullanılan Uzun Kısa Portföy yaklaşımını tartışıyoruz. Bu yöntem, yükselmesi beklenen hisse senetlerinde uzun pozisyon ve inmesi beklenen hisse senetlerinde kısa pozisyon alan bir yatırım stratejisidir. Bu bölümde, pozitif veya negatif olan gün sayısını gösteririz ve bu yöntem için her gün tüm veri analitiği için KB prosedürüyle ayarlanan t istatistiklerini sunarız. Son olarak, piyasa verimliliği hakkında tartışır ve analizimize göre Borsa İstanbul'un verimli bir pazar olup olmadığını gösteririz.

Anahtar sözcükler: Borsa İstanbul, Veri Analitiği, Yüksek Frekans Ticareti, Sipariş Dengesizliği, Sipariş Akışı Dengesizliği, Piyasa Verimliliği, Fama-Macbeth Regresyonu, Uzun Kısa Portföy, Newey-West Testi .

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Chapter 1

Introduction

1.1 High Frequency Trading

Algorithmic trading (AT) is defined as a system of trading which is designed to facilitate the transaction decision making in the financial markets [1]. Generally, with the recent extensive technological advances, such systems are based on advanced mathematics implemented by computer algorithms, rather than being calculated by hands, same as many other fields in science and technology [2]. High-Frequency Trading (HFT) is a broad subset of AT, in which powerful computers are used to process large number of orders in low latencies (milliseconds) to make fast decision much faster than the possible speed of a human reaction. Recent observations in order submission patterns show the sharp increase in HFT involvement in financial markets.

High Frequency Trading (HFT) is one of the major recent innovations in the financial markets. It is estimated by consultancy Tabb Group that by 2017, 50-60 percent of trades in the US, and 30-40 percent in the Europe markets are processed using HFT tools. HFT employs sophisticated computer programs to analyze market data in the search for trading opportunities and finding trading strategies. In the next step, computers enter the online market data into the concluded trading strategies to make buying and selling decisions and, send orders to the markets. HFT and traditional "quantitative investing"

method have a number of properties in common. First, in using pre-designed instructions and interpreting their effects on the market, second in identifying price patterns and third, in considering price change information to decide on trading strategies. However, the main difference is that in the HFT-based approach data are collected and processed faster than humans. The development of computer-based algorithmic trading methods reflects a recent trend towards trading automation which affects all aspects of industries, and generates productivity gains. Therefore, it reduces the operating costs of banks and financial firms by shortening the time of process and less human resources. In addition to cost saving, in some respects, it can also improve the functioning of markets.

One of the important strategies that is employed in finance is data analytics. Data Analytics is the science of investigating raw data with intention of drawing meaningful information and useful conclusions. Recently, organizations started to consider data analytics as a way to improve business processes and, use the collected information in operational efficiencies for achieving revenue growth. In recent years, the usage of data analytics is rapidly growing for many other reasons, such as, optimizing business processes, increasing revenue, and improving customer interactions. When data analytics methods are employed in business systems, the obtained outputs are more reliable and consumable, which means that more customers can use them practically. When operationalized together with business rules, effective decisions can be taken [3].

In this thesis, we test several data analytics for forecasting the return of each stock which run in HFT form, with interpreting and comparing the results [4, 1]. Also using these strategies, we want to show whether the stock market (borsa istanbul) is efficient or not. Market efficiency shows the degree of market prices reflection of all accessible information. For efficient markets, all information is integrated into prices. Market efficiency can be shown in two format. In the weak format of market efficiency, past price movements do not reflect on future rates. The strong format of market efficiency is that market prices reflect all information. In the next section, some of the terms that are used in this research are discussed.

1.2 Terminology

A stock exchange (also known as bourse), is a facility where stock brokers and traders can buy and sell securities, such as shares of stock. There is a transparent system named "central limit order book (CLOB)" that matches customer orders (e.g. bids and offers) on a "price-time priority" basis. The bid order with the highest price (best) and the offer order with the lowest price (cheapest) constitutes the best market. In the CLOB model, customers can trade directly with dealers, dealers can trade with other dealers, and importantly, customers can trade directly with other customers anonymously [1]. The most common expressions are listed as below (more details regarding the terminology and definitions can be found in Wang [5, 6]):

- Ask price, is the lowest price a seller of a stock is willing to accept for a share of given stock.
- Bid price, is the highest price that a buyer (i.e. bidder) is willing to pay.
- Bid/Ask volume (BAVOL), is the total amount of transactions occurring on both the Bid and the Ask in a given interval.
- Number of orders.
- Quantity of orders, is defined as transactions volumes.
- Number/Quantity of arrived sell orders.
- Number/Quantity of arrived buy orders.
- Number/Quantity of canceled buy orders.
- Number/Quantity of canceled sell orders.
- Number/Quantity of buyer-initiated trades, is defined as Number/Quantity of trades where a pending sell order(s) is matched with a new buy order.
- Number/Quantity of seller-initiated trades, is defined as Number/Quantity of trades where a pending buy order(s) is matched with a new sell order.

This thesis is organized as follows:

In Chapter 1, the definition of High Frequency Trading (HFT) and general information related to our work are reviewed. Besides, our motivation is briefly given.

In Chapter 2, the concept of data analytics and its applications in financial markets are described. Moreover, we investigate the significance of the problem and who can get benefit from this.

In Chapter 3, market structure of "Borsa Istanbul" and some details about the data (qualitative and quantitative, such as descriptive stats for stock returns and data analytics) and, interpretation of the quantitative statistics are explained.

Chapter 4 discusses about time series analysis, the models that we use in this chapter, estimated results and their interpretation.

In Chapter 5, the cross sectional analysis, especially Fama-Macbeth regression and the results are discussed.

In Chapter 6, we discuss about the use of long-short strategy method in our problem, and present the result of t-test (Newey-West adjustment).

Finally, the thesis ends with concluding remarks in Chapter 7.

Chapter 2

Data Analytics

Usually companies require real-time analytics for making faster and, at the same time more precise, decisions in the competitive market. Moreover, as the volume and frequency of data increase, it is often not possible to perform analytics and make decisions manually. In other word, analytic actions are needed to become more automated [7]. This process generally involves computer tools and algorithmic methods. The process of data analytics might be performed semi-automatically or automatically which is a advantage for companies [3]. For example, a preventive maintenance application, can monitor assets for issues which are based on past patterns or rules, improving performance and gaining financial benefits.

There are several areas where data analytics is applicable.

- **Health-care:** By definition, the health care industry concentrates on giving medical services to patients while acceptable quality should be provided. On the other hand, as an industry, earning financial profit is another significant concern. In recent years, usage of medical data, collected by special instruments, for optimizing health care flow, and designing more efficient medical instruments has become widespread. There are estimations of global financial gain as large as \$63 billion dollar that such data analysis can save [8].
- **Travelling:** Data analytics can be applied to optimize the user's buying experience

through the mobile devices and the social media data analysis. Previous travellings data can help optimizing requirements and preferences of the current customer [9].

- **Energy Management:** Large number of companies employ data analytics for purpose of energy management in the following fields: smart-grid management, energy optimization or distribution, and automation. In these cases, application mainly focuses on controlling and monitoring of network devices, dispatching crews, and managing service outages [10].
- **Gaming:** Digital gaming industry can also get benefit from data analytics. Game producer companies can collect and analyze user opinions, relationships, etc., to optimize their resources and costs.
- **Information , customer service and support:** IT can be a typical field for operationalizing and embedding analytics. For instance, operational analytics can be used in IT to monitor and analyze companies assets, in addition to network analysis. In 2016, verhoef shows that in US [11], 42% of companies are already employing analytics in IT function. 31% plan to do this in the coming three years. 23% of them said that they currently are using a facility or equipment monitoring solution. Similarly, another important application of operationalizing and embedding analytics is customer service and support. Besides, in call center agents analytics can be operationalized. About 38% of companies stated that they are using this sort of applications at the moment where basic or more advanced analytics like predictive analytics (explained earlier) are employed [11].
- **Finance, sales, marketing, and operations:** It is no surprise that the mentioned four fields are the most common areas for operationalizing and data analytics. Typically, use of finance and operational dashboards, are both important solution spaces for operationalizing and data analytics. Even it goes beyond and contains usage of advanced analytics in marketing and operations [11]. In the following sections we will discuss about this in more details.

2.1 Data Analytics in Finance

Big data by its own has no value unless, we can use its potential information to make decisions. For making such decisions, companies need efficient processes to turn high volumes of data into significant intuitions. Data management includes procedures and technologies to store data to prepare them for analysis. Analytics, on the other hand, refers to techniques used to analyze and interpret concepts from big data. One of the important area of data analytics is finance and stock markets [12].

Big Data, are being widely used to recognize patterns, trends and forecast the results of certain events [12]. We can say that the importance of big data can be summarize in three words: Volume, Velocity and Variety. The definition of Volume is the amount of data that being collected. Velocity is the speed of sending and receiving data and variety is about the different formats of data in the market. Based on these important words, financial organizations can extract a meaningful information that can help them in their decisions [3].

Stock market has a lot of features. Traders try to find relationships between the data that can lead to profitable financial decisions. Generally traders use two types of complementary analysis in stock market. As a first in fundamental analysis, traders focus on parameters that affected the financial trades [13]. For example, parameters such as a company's profit, market sector, or potential growth can affect the price of each company's stock.[14].

In the second way of analysis, traders consider Technical procedures. Technical analysis is the study of customers behavior that is reflected in price and amount of trades. It means that Technical analysis relies on patterns found directly in the stock data. [15, 16]. Many traditional traders don't follow and verify the assumptions made by technical traders, because they disregard the parameters of market that affect stock prices [7]. Technical analysis includes two part:

- **Visual displays:** Visual displays is known as charting because it is about visual

analysis of diagrams that show the changes of price over time. The important attributes of these charts are: Opening and closing price, maximum and minimum price for a specified period of trading time and etc [17]. Variation of price over time that is usually used by technical analysts is shown in Fig. 2.1.

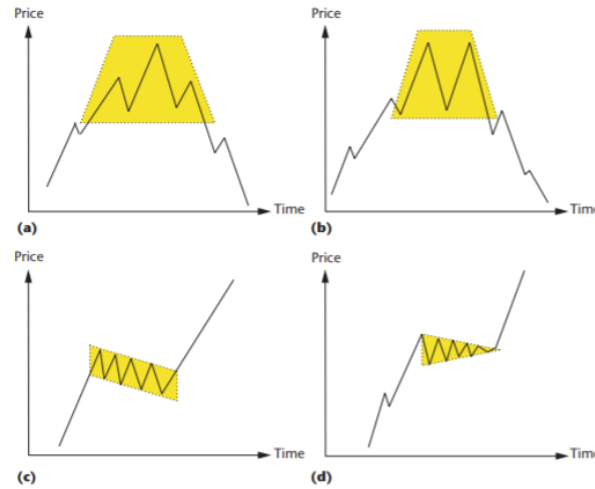


Figure 2.1: Visual analysis

- **Auditory displays:** These try to extract valuable information from sound by considering pitch and volume. In [18], author extended his audification techniques (representing a sequence of data values as sound signal) for making a sound display by converting stock market price data into a sound waveform (and then be able to process it with sound processing techniques). Nevertheless, author concludes that it was not easy to interpret such kind of sound waveforms.

2.2 Depth of Market Data

The visual displays that mentioned above let the traders to find and recognize patterns in charts. But most of the time these charts cover variations in a period of a day. For making better decisions, each transaction can be charted minute by minute and then a trader can extract valuable information from it [19].

Moreover, traders might take advantage of information prepared by the market's depth. The Depth of market is the number of buyers and sellers in each minute of a day, trying to trade in stock market [19]. A buyer might make a bid to purchase a specified volume of shares while at the same time a seller might ask a price for some specified volume. The balance of bids and asks determines the current market state.

One of the advantages of depth of market is order imbalance. Order imbalance is a situation resulting from an excess of buy or sell orders for a specific stock, making it impossible to match the buyers and sellers orders [20]. In next subsection we will talk about it in more details.

2.3 Order Imbalance (OI)

Up to now, many studies have been tried to explain the relationship between trade volume (or number) and price variations during that period and dispersion of returns of each stock called as volatility. When the traders start to register their buy (sell), at the same time they affect bid (ask) volumes and price of each stock. In this part we can understand the traders intentions and the prices changes consequently. Order imbalances is the quantification of these intentions. In the other word order imbalance is the way to show the difference between buy and sell orders. Chordia and Subrahmanyam [21], using the sample from New York stock market, showed that the relationship between order imbalance and daily return is positive. So it can be said that Order imbalance is an important concept for understanding traders intentions and market's direction [1]. If some traders have specific prior information (which other traders do not have), where the information has not been applied to asset price yet, considering being aware of that specific news (can be a negative, or positive one), the informed traders can take a long or short position, and after that increase the imbalance on the asset. Sometimes, major news like earning release or political decisions can influence order imbalances as well [22, 23].

The Fig. 2.2 allows us to see in details the respective roles of order imbalance in the

triggering of market crashes of ISBANK stock. The Blue dotted graph presents the number order imbalance changes ($\frac{\text{Number of buy orders}}{\text{Number of sell orders}} = \frac{N_b}{N_s}$), and the blue solid graph is the quantity order imbalance changes ($\frac{\text{Quantity of buy orders}}{\text{Quantity of sell orders}} = \frac{Q_b}{Q_s}$) during 9:35 AM to 5:30 PM (the left axis vs time on horizontal axis). Also the red solid graph is showing the price changes on the date 30/11/2015 (the right axis vs time on horizontal axis).

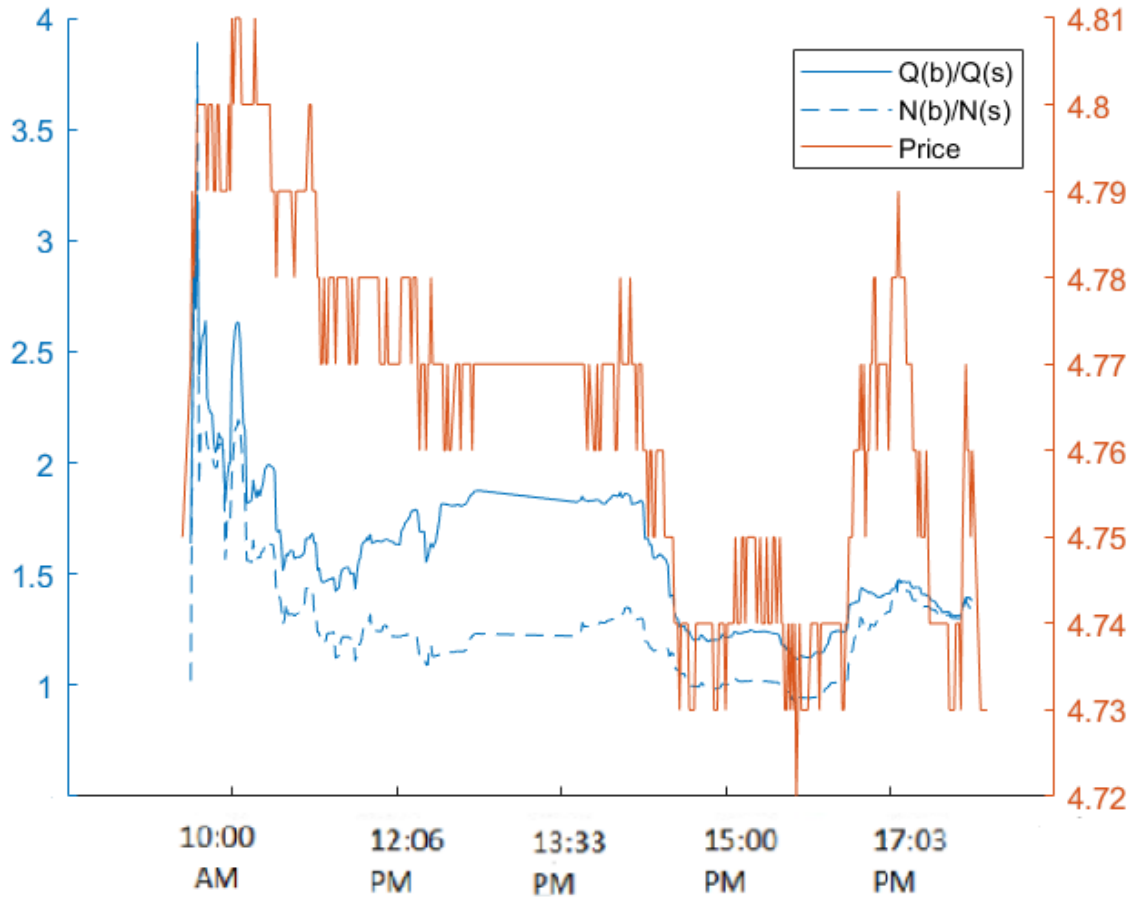


Figure 2.2: The blue dotted line and blue solid line are respectively $\frac{N_b}{N_s}$ and $\frac{Q_b}{Q_s}$ (left axis) versus time and the red solid one (right axis) is price versus time on the date 30/11/2015, for ISBANK stock.

2.3.1 Number and Quantity based Order Imbalances

In this part we are going to explain about order imbalances that we use in this thesis. The definition that are used for order imbalances are as follows:

$$OI_{t,1}^N = N_B - N_S \quad (2.1)$$

$$OI_{t,1}^Q = Q_B - Q_S \quad (2.2)$$

where,

$$N_B : \text{Number of buying orders} \quad (2.3)$$

$$N_S : \text{Number of selling orders} \quad (2.4)$$

$$Q_B : \text{Quantity of buying orders} \quad (2.5)$$

$$Q_S : \text{Quantity of buying orders} \quad (2.6)$$

Another measure for order imbalance, that we are going to use are

$$OI_{t,2}^N = \frac{N_B}{N_S} \quad (2.7)$$

$$OI_{t,2}^Q = \frac{Q_B}{Q_S} \quad (2.8)$$

Another important point that we should mention is that, The OIs that considered above only measures the magnitude of the imbalance which is not sufficient to describe the behavior of the traders in the market. For example using the order imbalance Eq. 2.1, if the number of buying order is 300 and the number of sell orders in that minute is 200 then the order imbalance would be 100, which is shown a considerable signal to buy. But another important indicator that can show the potential buyers is the ratio of number of buy and sell. Therefore the following order imbalances in Eq. 2.9 and 2.10 are defined:

$$OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S} \quad (2.9)$$

$$OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S} \quad (2.10)$$

Another equation that is used in this study with data analytics is the **percentage change** of OIs in each minute:

$$\Delta OI_t^N = \frac{OI_t^N - OI_{(t-1)}^N}{OI_{(t-1)}^N} \quad (2.11)$$

$$\Delta OI_t^Q = \frac{OI_t^Q - OI_{(t-1)}^Q}{OI_{(t-1)}^Q} \quad (2.12)$$

2.4 Order Flow Imbalance (OFI)

In 2014 cont et al. [24] introduced order flow imbalance (OFI), as a variable that accumulates the sizes of orders, and omits cancel orders to make a balance between supply and chain at the best bid and ask price. Although order flow imbalance can support important evidence for a linear relation between price variation, and OFI in stock markets. The OFI process tracks best bid and ask queues and change much faster than prices [25]. In the Fig. 2.3, Fig. 2.4 and Fig. 2.5, the order flow imbalance is illustrated with a simple example. Assume that the depth of market is four in each side (blue color). The seller initiated trades and cancellation (refer to Chapter1 section 1.2), totally remove ten stock from the bid side (gray color). Also at the same time new buy orders add three stock again to the bid side.

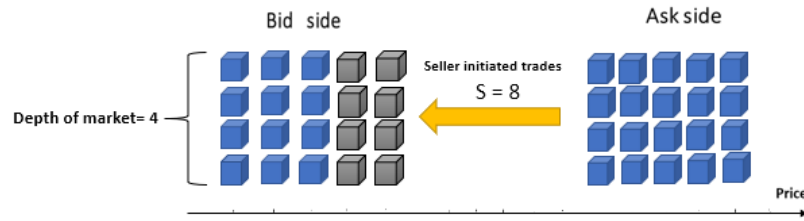


Figure 2.3: Removing the seller initiated trades from bid side

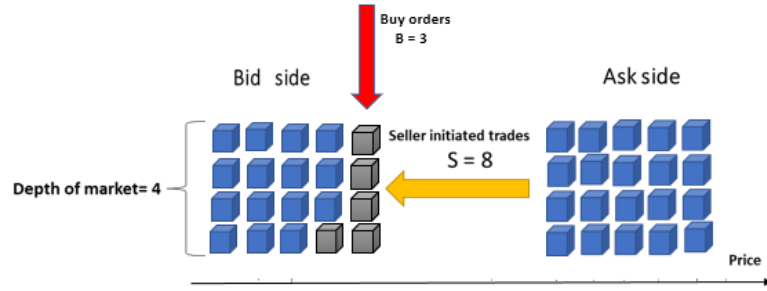


Figure 2.4: Adding new buy orders to the bid side

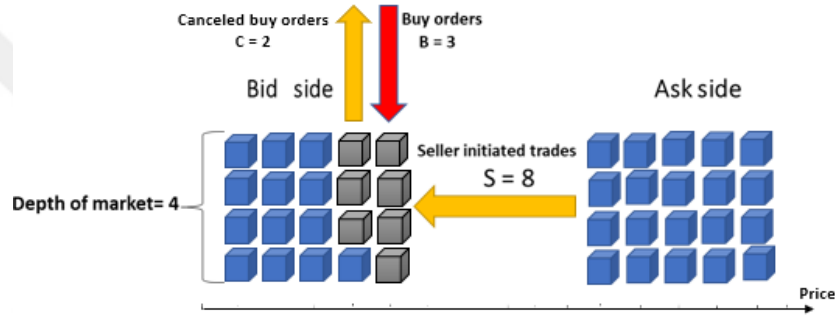


Figure 2.5: Removing buy cancellation from bid side

2.4.1 Number and Quantity based Order Flow Imbalances

The Eq. 2.13 to Eq. 2.16 and Eq. 2.17 to Eq. 2.22 are shown below for calculation of OFIs in this thesis.

$$B_N = \text{Number of arrived buy orders} - \text{Number of cancelled buy orders} - \text{Number of seller initiated trades} \quad (2.13)$$

$$B_Q = \text{Quantity of arrived buy orders} - \text{Quantity of cancelled buy orders} - \text{Quantity of seller initiated trades} \quad (2.14)$$

$$S_N = \text{Number of arrived sell orders} - \text{Number of cancelled sell orders} - \text{Number of buyer initiated trades} \quad (2.15)$$

$$S_Q = \text{Quantity of arrived sell orders} - \text{Quantity of cancelled sell orders} - \text{Quantity of buyer initiated trades} \quad (2.16)$$

$$OFI_{t,1}^N = N_B - N_S \quad (2.17)$$

$$OFI_{t,1}^Q = Q_B - Q_S \quad (2.18)$$

$$OFI_{t,2}^N = \frac{N_B}{N_S} \quad (2.19)$$

$$OFI_{t,2}^Q = \frac{Q_B}{Q_S} \quad (2.20)$$

$$OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S} \quad (2.21)$$

$$OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S} \quad (2.22)$$

The **percentage change** of OFIs will be calculated using Eq. 2.23 and Eq. 2.24:

$$\Delta OFI_t^N = \frac{OFI_t^N - OFI_{(t-1)}^N}{OFI_{t-1}^N} \quad (2.23)$$

$$\Delta OFI_t^Q = \frac{OFI_t^Q - OFI_{(t-1)}^Q}{OFI_{t-1}^Q} \quad (2.24)$$

Chapter 3

Quantitative Statistics

3.1 Literature Review

In literature, starting with definition of high frequency trading, HFT has been the subject of intense public debate and discussions. HFT or more traditional, "Quantitative Investing", have a huge impact on markets by producing efficient algorithm to make accurate decisions. Generally HFT concentrates more on the information that price movements might transfer about the trading strategies or signals of other markets [2, 4].

S. LaValle et al. [26], do a research on about 3000 company and businesses and show that big data can be the most reliable tool in making precise decisions in financial markets. Also the successful companies use data analytics based on big data five times more than others.

Karpoff [27], provides some empirical results in stock market. firstly, volume is positively related with the price variation and the absolute value of price variation in stock markets. Secondly, the variance of relationship between squared of price variation and volume, enhances with the number of traders.

Chordia and Subrahmanyam [28], investigated the relation between stock return and

order imbalances in NYSE data sets of eleven years. They showed that there is positive autocorrelation in daily order imbalances and also they have negative relation with monthly returns.

Lee et al. [29], showed the relationship between order imbalances and market efficiency in the "Taiwan Stock Exchange". The accessible data include all orders submitted to the Taiwan Stock Exchange (TWSE) from September 1996 to April 1999. They find that domestic institutions have more stable and reliable order imbalances in comparison to large companies. Also, The major orders of large individual investors had weak performance, that showed these agents act like noise traders. Although, the orders of domestic institutions have low price impact and also profitable.

Using Taiwanese stocks from 1994 to 2002, Andrade et al. [30], apply regression analysis and a sorting procedure to study the foreseeable return of price implied by the multi-asset equilibrium model. As a result they showed that stocks with more delicate order imbalances have more volatile returns.

Kaniel et al. [31], focus on the interaction between individual investors and stock returns. They examined the short-horizon dynamic relation between the buying and selling by individuals and both previous and subsequent returns using a unique data set provided by the New York Stock Exchange (NYSE) from 2000 to 2003. Their work suggests that understanding the behavior of one investor type, individuals, holds some promise for explaining observed return patterns.

Cont et al. [24], introduced order flow imbalance as the imbalance between supply and demand at the best bid and ask prices. They showed that there is a linear relation between order flow imbalance and price variation. The slope of this relationship is inversely proportional to the market depth. Also their results were robust to daily seasonality effects, and persistent across time scales and across stocks.

Hanke et al. [32], investigated effects of order flow imbalance on daily returns of German stocks. They used fixed-effects panel regressions instead of time series analysis. For the conditional relation (including concurrent order imbalance), their results confirm

those of previous studies. For the unconditional relation (which allows forecasting returns from past order imbalance), the results were qualitatively in line with the literature, but the effects were weaker.

Michael Goldstein et al. [33], showed that order imbalances are strong predictors of future prices in ASX (Australian Securities Exchange). At the same time, when the order imbalance moves in an unfavourable direction, they are quick to cancel or amend orders that are at high risk of being picked off by other traders.

Finally, our work is the extension of master thesis “Order imbalanced based strategy in high frequency trading” by Darryl Shen, [1]. Firstly they introduced the area of high frequency trading and the data that will be used to test the trading strategy. Then they extended a simple trading strategy with fitting a linear model between average price returns and order imbalances to see if the model can predict the return properly or not?. They showed that the mentioned strategy in the article, using this linear model to forecast future price changes is profitable when, the forecast is greater than 0.2.

In this thesis our analysis is based on useful information of benchmark index BIST 30. During our sample period (30th of November 2015 till end of April 2016), 27 out of 30 stocks are all included in the benchmark index. We focus on these 27 stocks because we do not want to be affected by inclusion\exclusion in\from the index. We make use of a long time series of transaction level data from the Borsa Istanbul database for answering the two questions. Firstly whether data analytics based on order imbalances and order flow imbalances can predict individual future returns (time series analysis)?. Secondly, we are trying to find out the prediction power of data analytics using cross sectional analysis like Fama-Macbeth regression and long short portfolio.

3.2 The Borsa Istanbul

The Istanbul Stock Exchange (ISE), was founded as an autonomous, professional organization for the unique exchange unit in Turkey in early 1986. Then the borsa istanbul (abbreviated as BIST) was founded on the December 30, 2012, for starting a modern stock market [34] and gathered all the exchanges operating in the Turkish capital markets together in the same place. Required documents of starting was provided by the capital markets board, and then approved by minister in charge. Formally, it was registered on April 3, 2013, and received operation permit.

The main goal of Borsa Istanbul is that, With observing the law and legislation, let to all kind of stock exchanges like foreign currencies, valuable metals, and contracts, important documents, and assets approved by the capital markets board of Turkey to trade in a free, secure and stable circumstances [34, 35].

3.2.1 Structure of Data

As one of the world's top ten biggest emerging markets, BIST successfully has absorbed considerable foreign investment. By 2015-May, average daily trade volume was 4.4 billion Turkish Lira (\$1.6 billion dollar) for around 420 listed stocks in the market [35]. The time period of this study is from 2015-November-30 to 2016-April-30 which contains 109 trading days.

Additional explanation about trading mechanisms and rules in BIST is helpful to have better understanding of AT and HFT involvement in the market. First, this should be noted that stocks of all publicly held companies in BIST, are exclusively traded, showing no market fragmentation. On the other hand, HFT strategies which are seen in BIST are most likely more diverse, leading to higher number of HFT (for instance, HF arbitrage strategies among different markets). Except those in watch list, short selling (is an trading strategy that is based on the decline in a stock price and selling it before declination.) is available for all listed stocks. In our analyses, stocks are limited to those in BIST 30 index list which can be sold short.

In BIST, trading time interval in every work day (Monday to Friday) is from 9:35 AM to 12:30 PM, and from 13:30 PM to 17:30 PM continuously. There are three call auction steps. Prices are fixed at 09:30 AM, 13:55 PM, and 17:35 PM (orders are collected from 09:15 to 09:30, from 13:00 to 13:55 and from 17:30 to 17:35), which after that, trading goes on at closing price until 17:40 PM. For our examined time period from 2015-November-30th to 2016-April-30, trading takes place within two sessions (morning and afternoon). Overall, trading mechanism is pretty similar. Both trading sessions start with single price call auctions followed by continuous auctions. At the start of our study period, first (second) session's call auction takes place between 09:30 AM and 9:50 AM (14:00 PM and 14:15 PM). Continuous auction for first (second) session is between 09:50 AM and 12:30 PM (13:30 PM and 17:30 PM). Closing call auction takes place between 17:30 PM and 17:40 PM.

The data is arranged in two tables. Table 3.1 contains the information of stocks in each day like, date, time, ID number of order, price and, etc.

Table 3.1: Sample data set for ISCTR, on date 2015/11/30.

DATE	TIME	Stock Name	ID Of Orders	Price	...
30/11/2015	9:30:08 AM	ISCTR	5C1D5181	3.75	...
30/11/2015	9:30:09 AM	ISCTR	5C1D5182	3.75	...
30/11/2015	9:30:10 AM	ISCTR	5C1D5183	3.76	...
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.

The second table 3.2 includes, time, number of arrived orders, cumulative number of arrived orders, quantity of arrived orders, cumulative quantity of arrived orders, etc.

Table 3.2: Sample data set for ISCTR, on date 2015/11/30, starting hour 9:30 AM.

TIME	Stock Name	Number Of Arrived Orders	Number Of Cum Arrived Orders	Buyer/Seller ratio	...
9:30:08 AM	ISCTR	26	26	-	...
9:30:09 AM	ISCTR	34	60	2.66	...
9:30:10 AM	ISCTR	51	111	1.43	...
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.

The data analytics which is used here is published by Borsa Istanbul on first of June, 2016. These critical analytics are usable by traders, market makers and etc. The data analytics are calculated per 60 seconds and include following categories:

- **Order arrival analytics:** Number \Quantity of orders arriving per 60 seconds.
- **Order cancellation analytics:** Number \Quantity of cancelled buy \sell orders per 60 seconds
- **Volume weighted average price analytics:** Is a trading benchmark used by traders that gives the average price a stock has traded at throughout the day, based on both volume and price.
- **Buyer-seller analytics:** Data analytics which can result from buy and sell orders.

We use all above analytics except of, volume weighted average price analytics, in this thesis.

3.3 Data Statistics

In this section, the result of statistics for all data set is presented. The Table 3.3 includes total number of buy and sell for each company, total quantity of buy and sell for each company, average of one minute return in 109 days and their standard deviation for all 27 companies.



Company Name	Total number of buy orders	Total number of sell orders	Total quantity of buy orders	Total quantity of sell orders	Avg 1-min Return 109 Day	Standard Deviation of 1-min Return
ARCLK	196457	174727	203306566	210897707	-0.00019	0.00077
BIMAS	157744	144005	100607405	102121629	-0.00024	0.00055
DOAS	225710	185614	189983193	196637008	-0.00004	0.00070
ENKAI	119709	115091	328278623	202091455	0.00008	0.00130
EREGL	253459	226533	1692718944	2047067813	-0.00007	0.00131
FROTO	144118	141268	45795997	47736261	0.00013	0.00104
GARAN	901913	901872	12731457320	12478018844	0.00001	0.00084
HALKB	681741	619802	3244629128	3346063766	-0.00045	0.00064
ISCTR	532339	454827	4777386480	5182552252	-0.00009	0.00113
KCHOL	280363	228415	447198542	446852288	0.00027	0.00075
KOZAL	342373	296349	126246448	134429175	0.00009	0.00104
KRDMD	313522	247440	5360780379	4412047814	0.00038	0.00344
OTKAR	191792	160490	25079021	25044383	-0.00003	0.00074
PETKM	219822	167853	1401413338	1495274124	0.00063	0.00115
PGSUS	268030	231209	185833359	190003901	-0.00062	0.00048
SAHOL	270933	238693	1222313452	1194185499	0.00008	0.00065
SISE	146587	146885	561210981	651752702	0.00028	0.00139
TAVHL	284126	239309	199873002	203015356	-0.00080	0.00068
TCELL	253086	229562	443080962	470889479	0.00009	0.00068
THYAO	1007486	978144	7121278038	8146725500	-0.00064	0.00094
TKFEN	166782	147041	656534724	655330440	0.00042	0.00091
TOASO	204447	190100	156869873	153210255	0.00008	0.00093
TTKOM	155703	158450	418012555	418840477	-0.00015	0.00089
TUPRS	356191	304683	178196683	175590983	-0.00002	0.00053
ULKER	20217	18725	14166608	13288852	-0.00003	0.00066
VAKBN	27429	25487	875263419	65874122	0.00009	0.00078
YKBNK	478530	428531	1187238693	1222317852	0.00003	0.00085

Table 3.3: Selected statistics of 27 companies stocks from 30th of November 2015 till the end of April 2016.

Chapter 4

Time Series Analysis

In this chapter, we aim to improve the existing strategy of generating profit by extending the linear models with new factors and, also by optimizing the regression and trading parameters. The improvements described in this section, enhance the profit value considerably. In the first section, we explain the time series analysis briefly. After that, we introduce new factors related to order imbalances. Then, we estimate the coefficients and number of significant days. Finally, in the last part, order flow imbalances and the regression models by new factors are discussed.

4.1 Time Series in Finance

Generally, continuously monitoring the price behavior to realize the probable change of the price in the future is desirable. Due to this, deeper understanding of price behavior is beneficial for everybody who is active in international commerce such as companies, investors, and etc. Many dealers face the risks related to unexpected changes in prices. Such risks can mainly be summarized by the variances of future returns, directly, or by their relationship with relevant covariance in a portfolio context. Predictions of future standard deviations can give up-to-date risk indications, where in its place, are helpful to avoid undesirable risks, possibly with hedging.

There are two major goals to study and investigate financial time series [36]. First is importance of realizing price behavior. In this case, the variance of time series is specially relevant. Tomorrow's price is uncertain and then, it should be explained with probability distribution. Therefore, statistical methods are normal ways to investigate price behavior. Usually a model is designed that describes of how successive prices are determined in details. The second goal is to use our knowledge of price behavior to decrease risk and take more suitable decisions. Typically, time series models are applicable in forecasting, risk management, and option pricing.

4.1.1 Stationarity in Time Series

High Frequency Trading and applications of their strategies are closely related to the ergodic theory of stationary processes. We explain two kind of stationary. A time-series X_t is strongly stationary if $(X_{t_1}, X_{t_2}, \dots, X_{t_n})$ has the same distribution as $(X_{t_1+a}, X_{t_2+a}, \dots, X_{t_n+a})$ for all a and any arbitrary integer $n > 0$. Another stationary definition for the time-series X_t , is weakly stationary, that is, if the first two moments do not change over time, or in another words, $E[X_t] = E[X_{t+a}] = \mu$ and $Cov(X_t; X_{t+a}) = \gamma(a)$ for all time t and arbitrary a . It is sufficient for the data to be weak stationary for traders to build an algorithmic trading strategy which generates positive expected profit.

Further theory regarding stationary processes, the strong ergodic theorem, and its applicability in high frequency trading can be found in [36]. One of the important tests in proving stationary in time series is KPSS (Kwiatkowski–Phillips–Schmidt–Shin) test (refer to [37] for more information). The usage of KPSS is testing a null hypothesis that an observable time series is stationary around a deterministic trend, against the alternative of a unit root (not to be stationary).

In this thesis, we apply KPSS on all of our variables that we want to use in regression models as predictor variable. For forecasting, we absolutely need to find the constant (time invariant) component in the series, otherwise it's impossible to forecast by definition. Stationarity is just a particular case of the invariance.

KPSS test in matlab returns value of h which can be zero or one, zero indicates failure

to reject the trend-stationary null and one indicates rejection of the trend-stationary null in favor of the unit root alternative. Also two other outputs are p value and t statistics. We define all variables including order imbalances and percentage changes in Eq. 2.1 to Eq. 2.12 and Eq. 2.17 to Eq. 2.24 respectively. According to t stats and p values, all of the variables are stationary. Instead of h values table, that all of them are one, the Tables 4.1 and 4.2 include t stats of KPSS test in the fifth lag (up to five lag of time, stationary has been checked) for all variables on 30th of November for all 27 companies.



Company Name	$OI_{t,1}^N$	$OI_{t,1}^Q$	$OI_{t,2}^N$	$OI_{t,2}^Q$	$OI_{t,3}^N$	$OI_{t,3}^Q$	$\Delta OI_{t,1}^N$	$\Delta OI_{t,1}^Q$	$\Delta OI_{t,2}^N$	$\Delta OI_{t,2}^Q$	$\Delta OI_{t,3}^N$	$\Delta OI_{t,3}^Q$
ARCLK	0.16240	0.14468	0.15714	0.18041	0.33563	0.26000	0.18816	0.07940	0.15608	0.07035	0.04746	0.04367
BIMAS	0.20456	0.09362	0.10673	0.07899	0.32341	0.27845	0.04500	0.07580	0.11480	0.05379	0.05157	0.04849
DOAS	0.12943	0.08765	0.08756	0.10364	0.27870	0.26980	0.05176	0.09090	0.11104	0.10662	0.05610	0.10954
ENKAI	0.12291	0.08767	0.11549	0.26579	0.72109	0.63102	0.21438	0.06715	0.14849	0.09046	0.12953	0.04910
EREGL	0.19821	0.13220	0.17864	0.18153	0.60189	0.48076	0.06667	0.15175	0.15568	0.40467	0.07870	0.02948
FROTO	0.11689	0.19481	0.14960	0.30300	0.41930	0.33732	0.07753	0.01274	0.14828	0.59796	0.05069	0.06113
GARAN	0.20880	0.06844	0.09854	0.10688	0.45135	0.15476	0.03742	0.05642	0.07935	0.22563	0.12000	0.25913
HALKB	0.08423	0.05164	0.15726	0.16970	0.59522	0.45370	0.07340	0.08839	0.23274	0.18901	0.66681	0.30953
ISCTR	0.10128	0.87408	0.17579	0.17565	0.33372	0.37083	0.25969	0.03530	0.11314	0.19904	0.10523	0.04663
KCHOL	0.07647	0.08376	0.10783	0.08283	0.66023	0.63680	0.10999	0.02672	0.10913	0.04357	0.08510	0.11451
KOZAL	0.20543	0.14614	0.15610	0.19146	0.45212	0.42236	0.20073	0.04062	0.15753	0.20993	0.14650	0.03215
KRDMD	0.04808	0.13625	0.13541	0.07574	0.13784	0.34586	0.76075	0.08137	0.10940	0.10729	0.14768	0.05966
OTKAR	0.07808	0.32256	0.12525	0.13488	0.06666	0.05793	0.37704	0.10952	0.09900	0.08879	0.10849	0.10077
PETKM	0.12393	0.13676	0.16345	0.03694	0.26299	0.21680	0.05276	0.07707	0.15182	0.63337	0.07632	0.02785
PGSUS	0.14668	0.12180	0.15596	0.08039	0.10508	0.21861	0.27830	0.04593	0.12905	0.06788	0.38003	0.05834
SAHOL	0.11238	0.07568	0.18628	0.17493	0.43147	0.35581	0.09458	0.04816	0.14730	0.17944	0.04459	0.06616
SISE	0.14454	0.10087	0.18818	0.04066	0.52867	0.62483	0.52330	0.04806	0.12684	0.04247	0.16115	0.04590
TAVHL	0.16952	0.09342	0.12075	0.03565	0.26275	0.27259	0.09740	0.05521	0.11428	0.03671	0.04803	0.05243
TCELL	0.13851	0.06819	0.49767	0.72001	0.43228	0.40911	0.09160	0.04332	0.38457	0.42461	0.05820	0.78360
THYAO	0.30495	0.07955	0.22851	0.33228	0.34134	0.42579	0.09366	0.04255	0.28034	0.05945	0.05310	0.04324
TKFEN	0.19531	0.12582	0.12268	0.04900	0.13351	0.40260	0.16343	0.11860	0.12930	0.03306	0.10592	0.06679
TOASO	0.18858	0.04321	0.29832	0.32433	0.36841	0.38266	0.13822	0.07257	0.16654	0.37838	0.40685	0.06218
TTKOM	0.49093	0.10045	0.18193	0.26538	0.30223	0.33204	0.28566	0.06287	0.13045	0.75055	0.06896	0.08972
TUPRS	0.14499	0.03872	0.10470	0.19184	0.24973	0.44323	0.34866	0.11367	0.17673	0.08371	0.05875	0.03105
ULKER	0.11321	0.09876	0.11998	0.11759	0.48464	0.50114	0.29104	0.09672	0.12387	0.03634	0.03846	0.10162
VAKBN	0.06873	0.07973	0.16537	0.08574	0.31059	0.29222	0.03624	0.05765	0.16549	0.07389	0.08165	0.08274

Table 4.1: t stats of KPSS test of all variables including order imbalances and their percentage changes which are defined in Eq. 2.1 to Eq. 2.12, on the date 30/11/2015 for all companies.

Company Name	$OFI_{t,1}^N$	$OFI_{t,1}^O$	$OFI_{t,2}^N$	$OFI_{t,2}^O$	$OFI_{t,3}^N$	$OFI_{t,3}^O$	$\Delta OFI_{t,1}^N$	$\Delta OFI_{t,1}^O$	$\Delta OFI_{t,2}^N$	$\Delta OFI_{t,2}^O$	$\Delta OFI_{t,3}^N$	$\Delta OFI_{t,3}^O$
ARCLK	0.16435	0.04621	0.10680	0.10699	0.15901	0.06694	0.12358	0.04343	0.08728	0.07126	0.25677	0.04896
BIMAS	0.93539	0.04227	0.10126	0.05790	0.10884	0.07084	0.66626	0.07465	0.03600	0.08633	0.05201	0.03287
DOAS	0.10397	0.06720	0.08553	0.06287	0.10833	0.10083	0.12074	0.10869	0.06201	0.05164	0.10975	0.05505
ENKAI	0.09688	0.07042	0.15815	0.08009	0.38400	0.19212	0.06452	0.06994	0.08629	0.05940	0.04803	0.03760
EREGL	0.13910	0.06946	0.09057	0.02788	0.15815	0.05166	0.06380	0.03634	0.05317	0.07841	0.12531	0.06356
FROTO	0.18748	0.11705	0.07128	0.07995	0.09702	0.05152	0.08796	0.06885	0.06896	0.04384	0.09138	0.03593
GARAN	0.20037	0.05117	0.03384	0.08360	0.04040	0.07412	0.02490	0.05080	0.05935	0.05218	0.09640	0.05895
HALKB	0.04026	0.04908	0.15640	0.07165	0.24832	0.09125	0.04842	0.04158	0.09531	0.04505	0.05995	0.06180
ISCTR	0.05900	0.05065	0.07416	0.10274	0.17357	0.12546	0.07407	0.03803	0.10097	0.08189	0.09205	0.05368
KCHOL	0.06423	0.07147	0.03603	0.04117	0.08298	0.05546	0.27832	0.06425	0.06572	0.05105	0.10675	0.02971
KOZAL	0.19805	0.06783	0.16937	0.04155	0.15594	0.14535	0.18147	0.06555	0.14301	0.12642	0.05176	0.14359
KRDMD	0.03861	0.09601	0.04298	0.04739	0.30483	0.04872	0.06359	0.10943	0.07425	0.04505	0.05977	0.03604
OTKAR	0.14155	0.12579	0.15769	0.14706	0.45032	0.08315	0.23014	0.09429	0.08769	0.04695	0.07895	0.08436
PETKM	0.15796	0.06185	0.24745	0.07381	0.48269	0.10109	0.07308	0.09882	0.15893	0.09337	0.09975	0.11248
PGSUS	0.14109	0.06920	0.18543	0.03014	0.40089	0.04094	0.05859	0.07435	0.07043	0.03461	0.02614	0.05805
SAHOL	0.05124	0.04475	0.07146	0.07977	0.04338	0.05981	0.06074	0.03926	0.09754	0.02606	0.02020	0.07665
SISE	0.12033	0.08550	0.07049	0.05701	0.07626	0.04648	0.14734	0.04548	0.05124	0.09201	0.06765	0.04537
TAVHL	0.04811	0.05730	0.11735	0.05977	0.08274	0.06830	0.07406	0.06483	0.04834	0.02122	0.04488	0.06439
TCELL	0.05904	0.08534	0.18668	0.13583	0.13555	0.15684	0.18318	0.03206	0.04888	0.08260	0.06303	0.07328
THYAO	0.11403	0.05104	0.05514	0.07160	0.06226	0.06903	0.07090	0.05293	0.17573	0.05228	0.07806	0.14729
TKFEN	0.08866	0.11300	0.09112	0.12960	0.47247	0.46843	0.16087	0.07939	0.05554	0.03594	0.10626	0.14319
TOASO	0.03670	0.06656	0.13465	0.17382	0.30730	0.03720	0.07718	0.03910	0.10953	0.14397	0.07967	0.08070
TTKOM	0.14855	0.13251	0.22822	0.06154	0.34425	0.19413	0.26118	0.04952	0.07897	0.05036	0.05521	0.04589
TUPRS	0.25740	0.03444	0.08077	0.06038	0.14124	0.05095	0.40868	0.02907	0.06169	0.04437	0.04226	0.06630
ULKER	0.10862	0.14672	0.27048	0.04422	0.27557	0.12842	0.06267	0.03573	0.12043	0.04541	0.05212	0.07092
VAKBN	0.15306	0.05392	0.07159	0.09068	0.14722	0.07283	0.06584	0.03175	0.04531	0.09694	0.03357	0.08527

Table 4.2: t stats of KPSS test of all variables including order flow imbalances and their percentage changes which are defined in Eq. 2.17 to Eq. 2.24, on the date 30/11/2015 for all companies.

4.1.2 Autocorrelation and Cross Correlation of Order Imbalances

Autocorrelation is a mathematical representation of the degree of similarity between a given time series and a lagged version of itself over successive time intervals. It is the same as calculating the correlation between two different time series, except that the same time series is actually used twice, once in its original form and once lagged one or more time periods.

Order imbalance has positive autocorrelation as presented in Fig. 4.1 for most days, the order imbalance autocorrelation is significant up to lag 15. This indicates that positive imbalances are often followed by periods of persistent positive imbalances due to traders splitting their orders across multiple periods, as explained by Chordia [28]. On the other hand, other studies argue that this phenomenon is caused by herding among investors.

We also show that the order imbalance is positively correlated with contemporary price changes. The below figures (Fig. 4.2 and Fig. 4.3) illustrate this positive relationship.

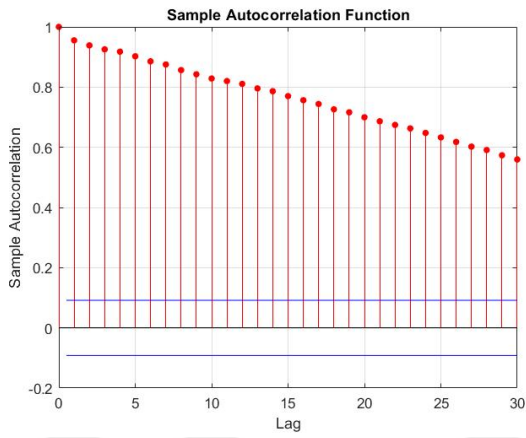


Figure 4.1: Autocorrelation of $OI_{t,2}^N = \frac{N_B}{N_S}$ on the date 30/11/2015, for ISBANK stock.

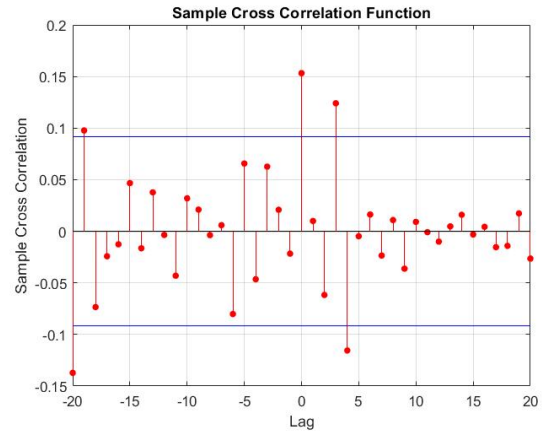


Figure 4.2: Cross correlation of price return and $OI_{t,2}^N = \frac{N_B}{N_S}$ on the date 30/11/2015, for ISBANK stock.

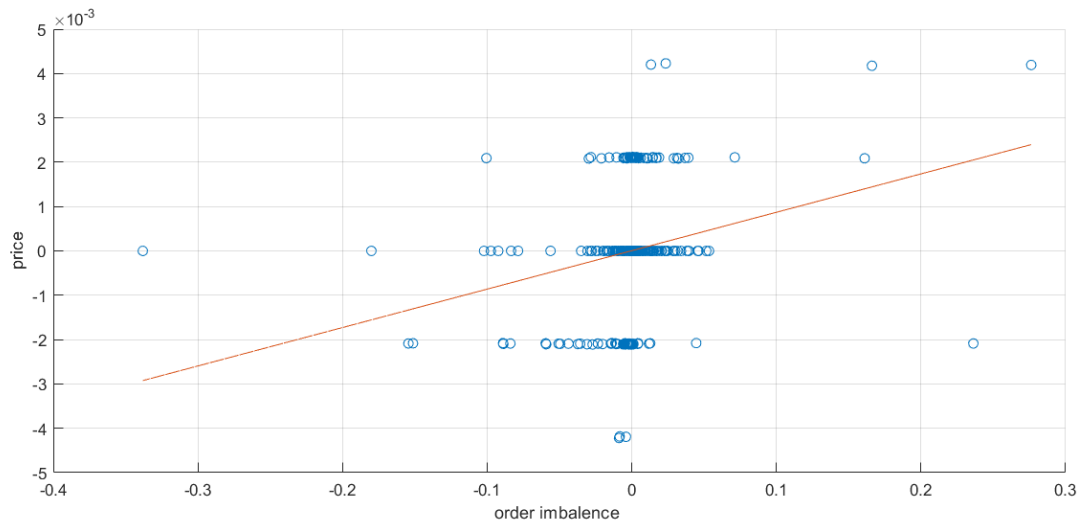


Figure 4.3: Scatter plot of $OI_{t,2}^N = \frac{N_B}{N_S}$ versus contemporary price changes on the date 30/11/2015, for ISBANK stock.

4.2 Order Imbalance-based Models

We propose some linear and nonlinear models where we predict future price change with the current (instantaneous) and lagged OIs. Chordia [28], Huang [23], and Cont [24] all build linear models with lagged order imbalances as the explanatory variable and the immediate one-period price change as the response. We also make the assumption that the errors ϵ_t are independent and normally distributed with zero mean and constant variance.

4.2.1 Models with Percentage Changes (Δ)

We present some statistical properties of the explanatory and response variables before analyzing the linear model. We define percentage return for 1 minute ahead ($t+1$) with Eq. 4.1 and we use it as the response variable.

$$r_{t+1} = \frac{price_{t+1} - price_t}{price_t} \quad (4.1)$$

The Fig. 4.4 shows the basis of constructing models for ability of prediction of 1-min ahead return, using ΔOI_t .

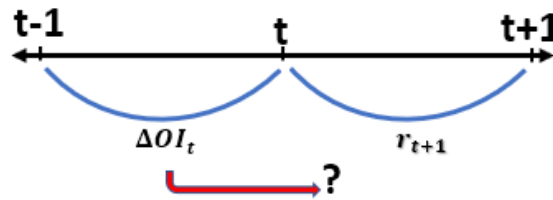


Figure 4.4: Power of prediction of ΔOI_t in 1-minute ahead return

According to above Eq. 4.1 as response variable, the **first models** are,

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^N + \epsilon_{t+1} \quad (4.2)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^Q + \epsilon_{t+1} \quad (4.3)$$

The **second models** are,

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^N + \beta_2 r_t + \epsilon_{t+1} \quad (4.4)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^Q + \beta_2 r_t + \epsilon_{t+1} \quad (4.5)$$

Where r_t is the lagged return of price. Also the **third models** listed as below,

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^N + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.6)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^Q + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.7)$$

In addition to three linear models that have been proposed in previous section, another new model is introduced. The nonlinear **fourth models** are as follows:

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^N + \beta_2 \Delta OI_t^N |\Delta OI_t^N| + \epsilon_{t+1} \quad (4.8)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_t^Q + \beta_2 \Delta OI_t^Q |\Delta OI_t^Q| + \epsilon_{t+1} \quad (4.9)$$

These models are estimated independently using the data set of Borsa Istanbul for each of the 109 trading days (30/12/2015 to 29/04/2016), using ordinary least squares linear regression. We use all $OI_{t,1}^N$, $OI_{t,1}^Q$, $OI_{t,2}^N$, $OI_{t,2}^Q$, $OI_{t,3}^N$ and $OI_{t,3}^Q$ as explanatory variables in all four models that was introduced in Eq. 4.2 to Eq. 4.9 .

In the time-series regression, we first drive information of 27 stocks on the basis of order imbalances and their percentage changes and also the return of each minute. There is a large dispersion in the average returns across the 27 companies stocks. Firstly we try to find the positive days of each coefficient and then the number of significant days on the level of 0.05. The time-series regression results in this section show that the four models, 4.10, 4.11, 4.12 and 4.13, respectively have the most positive significant days with high value of R^2 and t stats:

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,2}^N + \epsilon_{t+1} \quad (4.10)$$

In the model 4.10, **TAVHL** has 105 significant days out of 109 positive days with average $R^2 = 0.031$.

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,2}^N + \beta_2 r_t + \epsilon_{t+1} \quad (4.11)$$

In the model 4.11, **PGSUS** with 101 significant days and **ENKAI, TAVHL, TUPRS** with 100 significant days out of 109 positive days are the best ones.

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.12)$$

In the model 4.12, **PGSUS** has 100 significant days out of 109 positive days with average $R^2 = 0.06296$.

$$r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,2}^N + \beta_2 \Delta OI_{t,2}^N |\Delta OI_{t,2}^N| + \epsilon_{t+1} \quad (4.13)$$

In the model 4.13, we have the strongest results between all. for example **HALKB** has 109 significant positive days out of 109 days with $R^2 = 0.06548$.

Moreover $\Delta OI_{t,2}^N$ which $OI_{t,2}^N = \frac{N_B}{N_S}$ represents the strongest factor in explaining the Turkish stock returns and showing strong association with price return in all 27 stocks.

In the Tables 4.3 to 4.17, the average of estimated coefficients and adjusted R^2 and number of positive days (estimated coefficient of day is positive) are depicted. Also another important calculated parameter is the number of significant days that significant level is 0.05 here. It means that in that days p value is less than 0.05.

Company Name	$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta OI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta OI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.00114	1.95E-06	60	7	0.00060	-1.10E-08	51	4
BIMAS	0.00417	9.81E-06	50	15	0.00002	4.86E-08	59	4
DOAS	0.00229	1.20E-06	55	10	0.00055	4.11E-09	60	6
ENKAI	0.00218	-1.90E-06	55	6	0.00327	2.57E-08	58	11
EREGL	0.00079	5.22E-06	66	8	0.00076	7.22E-09	65	2
FROTO	0.00104	4.28E-06	58	7	0.00140	-3.17E-08	59	7
GARAN	-0.00018	1.51E-06	70	4	-0.00039	-1.04E-09	48	4
HALKB	0.00007	9.75E-07	62	5	-0.00055	2.20E-08	58	1
ISCTR	0.00101	2.23E-06	63	7	0.00012	-9.16E-09	52	2
KCHOL	0.00006	2.10E-06	66	5	-0.00019	1.46E-08	67	2
KOZAL	0.00042	3.45E-06	59	6	0.00007	-3.01E-08	59	4
KRDMD	0.00077	4.47E-06	62	6	0.00046	-4.91E-09	49	6
OTKAR	0.00132	5.76E-06	71	9	0.00208	4.59E-07	70	13
PETKM	0.00044	2.09E-06	62	4	0.00178	1.89E-08	56	11
PGSUS	0.00078	2.04E-07	55	5	-0.00046	1.74E-08	63	2
SAHOL	0.00037	-4.75E-07	59	5	-0.00013	2.46E-09	55	3
SISE	0.00234	1.00E-05	64	7	0.00121	7.98E-09	58	6
TAVHL	0.00100	-5.86E-07	49	7	0.00018	-9.87E-09	49	4
TCELL	0.00053	4.75E-07	54	4	-0.00010	-4.66E-09	52	1
THYAO	-0.00023	-1.15E-07	51	3	-0.00033	1.17E-08	54	1
TKFEN	0.00063	1.52E-06	52	6	0.00156	-3.56E-10	49	5
TOASO	0.00386	2.35E-06	51	9	0.00091	-2.65E-08	46	7
TTKOM	0.00103	-6.58E-06	35	1	0.00111	-6.48E-09	44	6
TUPRS	0.00031	1.34E-06	59	3	-0.00106	-2.16E-08	50	0
ULKER	0.00121	-2.60E-06	51	8	0.00308	-4.94E-08	58	8
VAKBN	0.00099	3.55E-06	69	8	0.00051	-7.34E-09	57	5
YKBNK	0.00158	1.74E-06	60	8	0.00017	-4.96E-10	61	4

Table 4.3: The result of first model using percentage changes of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^N + \beta_2 r_t + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^Q + \beta_2 r_t + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.02140	2.20E-06	59	8	0.02076	-1.13E-08	54	5
BIMAS	0.02347	9.33E-06	51	15	0.01988	4.47E-08	58	4
DOAS	0.02702	-3.09E-07	51	9	0.02561	-7.03E-09	59	5
ENKAI	0.04979	-2.08E-06	53	6	0.05081	2.13E-08	53	12
EREGL	0.10070	2.57E-06	60	6	0.10033	2.60E-09	57	6
FROTO	0.01554	4.01E-06	59	7	0.01580	-1.36E-08	62	7
GARAN	0.07267	1.65E-06	66	4	0.07266	-1.00E-09	53	4
HALKB	0.04172	2.50E-07	55	3	0.04124	2.82E-08	59	0
ISCTR	0.10616	1.23E-06	61	6	0.10540	-8.26E-09	48	4
KCHOL	0.01848	8.93E-07	61	4	0.01830	1.14E-08	63	3
KOZAL	0.02503	3.83E-06	57	5	0.02447	-3.97E-08	59	4
KRDMD	0.17089	-8.02E-06	53	12	0.17041	-6.08E-09	46	6
OTKAR	0.02120	5.07E-06	67	8	0.02179	3.93E-07	68	10
PETKM	0.09747	-1.03E-06	52	5	0.09841	1.63E-08	56	9
PGSUS	0.02104	-3.83E-07	54	3	0.01999	1.24E-08	60	2
SAHOL	0.03414	-1.06E-06	54	4	0.03376	-1.28E-09	51	2
SISE	0.07329	8.67E-06	59	6	0.07280	5.73E-09	55	5
TAVHL	0.02488	-2.91E-07	54	6	0.02402	-1.45E-08	49	3
TCELL	0.03381	2.13E-07	53	3	0.03309	-5.15E-09	49	1
THYAO	0.08850	-3.38E-07	48	2	0.08834	-1.04E-08	49	1
TKFEN	0.06631	-1.62E-06	46	4	0.06761	-8.22E-09	50	6
TOASO	0.02853	-3.09E-07	49	8	0.02694	-3.11E-08	46	4
TTKOM	0.04185	-7.56E-06	35	0	0.04208	-1.09E-08	41	5
TUPRS	0.02469	9.16E-07	57	5	0.02349	-3.07E-08	48	0
ULKER	0.02180	-3.75E-06	45	8	0.02333	-5.82E-08	55	8
VAKBN	0.09918	3.42E-06	64	11	0.09912	-5.74E-09	57	7
YKBNK	0.08967	3.47E-06	68	6	0.08873	-5.30E-10	62	3

Table 4.4: The result of second model using percentage changes of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.04085	2.51E-06	59	8	0.03983	-1.03E-08	53	5
BIMAS	0.03498	7.90E-06	51	15	0.03222	3.62E-08	57	3
DOAS	0.04066	-9.09E-07	51	8	0.03965	-9.45E-09	56	6
ENKAI	0.07750	-2.11E-06	51	6	0.07853	1.66E-08	54	12
EREGL	0.14294	1.23E-06	58	5	0.14222	2.21E-09	56	5
FROTO	0.03465	4.09E-06	60	8	0.03455	-1.72E-08	62	5
GARAN	0.08655	1.79E-06	69	3	0.08645	-1.47E-09	49	3
HALKB	0.05012	2.25E-07	59	3	0.04958	2.78E-08	55	0
ISCTR	0.13698	1.02E-06	59	7	0.13618	-8.13E-09	44	3
KCHOL	0.02998	8.01E-07	54	3	0.02965	1.08E-08	64	2
KOZAL	0.04588	4.91E-06	60	6	0.04507	-6.05E-08	59	3
KRDMD	0.27659	-1.62E-05	51	12	0.27555	-4.19E-09	47	6
OTKAR	0.03478	3.68E-06	68	6	0.03546	3.83E-07	68	11
PETKM	0.14003	-3.09E-06	46	6	0.14047	7.91E-09	54	10
PGSUS	0.02868	-2.67E-07	54	2	0.02770	1.11E-08	59	1
SAHOL	0.04733	-1.13E-06	51	4	0.04688	-1.42E-09	52	2
SISE	0.10906	9.49E-06	62	7	0.10899	5.51E-09	51	9
TAVHL	0.04144	1.90E-07	52	7	0.04067	-1.11E-08	53	2
TCELL	0.04651	2.84E-07	52	3	0.04566	-4.94E-09	47	1
THYAO	0.10738	-4.07E-07	51	1	0.10729	-1.71E-08	50	0
TKFEN	0.09587	-3.33E-06	42	5	0.09715	-7.74E-09	46	6
TOASO	0.04296	-2.31E-06	45	7	0.04180	-4.21E-08	42	3
TTKOM	0.05671	-7.94E-06	36	0	0.05696	-1.81E-08	37	3
TUPRS	0.03283	1.01E-06	55	5	0.03176	-3.18E-08	45	0
ULKER	0.04187	-4.18E-06	47	7	0.04308	-1.09E-07	51	8
VAKBN	0.12982	3.60E-06	67	12	0.12958	-6.40E-09	60	7
YKBNK	0.12023	4.22E-06	66	11	0.11910	-3.34E-10	59	4

Table 4.5: The result of third model using percentage changes of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^N + \beta_2 \Delta OI_{t,1}^N \Delta OI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^Q + \beta_2 \Delta OI_{t,1}^Q \Delta OI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.00321	-5.00E-07	56	8	0.00105	3.77E-07	58	2
BIMAS	0.00815	-8.00E-06	43	3	0.00071	1.61E-06	50	5
DOAS	0.00488	-5.45E-06	56	3	0.00099	9.36E-07	56	9
ENKAI	0.00540	6.23E-06	61	8	0.00589	-6.88E-07	69	13
EREGL	0.00087	3.25E-06	58	1	0.00335	4.62E-08	70	6
FROTO	0.00231	-3.63E-06	49	3	0.00124	9.73E-07	59	4
GARAN	0.00016	2.32E-06	57	7	0.00059	-4.23E-08	46	2
HALKB	0.00001	-1.66E-06	46	1	-0.00047	1.44E-07	66	0
ISCTR	0.00140	1.14E-06	63	4	0.00260	6.89E-08	58	8
KCHOL	0.00063	1.80E-06	58	6	-0.00012	-2.35E-08	56	2
KOZAL	0.00066	5.61E-06	63	2	-0.00035	-1.11E-07	55	2
KRDMD	0.00152	8.86E-07	50	3	0.00395	-2.35E-06	57	13
OTKAR	0.00367	3.47E-06	55	8	0.00195	5.43E-07	63	5
PETKM	0.00088	6.34E-07	51	4	0.00409	1.98E-07	62	7
PGSUS	0.00107	1.71E-06	58	2	-0.00049	-1.65E-07	56	4
SAHOL	0.00040	2.19E-06	58	4	0.00051	-1.47E-07	66	3
SISE	0.00452	8.10E-07	51	6	0.00440	5.43E-07	61	11
TAVHL	0.00256	-1.90E-07	48	5	0.00041	-1.58E-07	52	6
TCELL	0.00059	3.21E-06	59	4	0.00063	-2.41E-07	60	4
THYAO	0.00005	-2.84E-06	48	2	0.00009	9.23E-08	59	1
TKFEN	0.00148	-9.35E-07	56	4	0.00504	8.77E-08	56	14
TOASO	0.00647	-1.17E-05	42	3	0.00253	1.94E-06	53	9
TTKOM	0.00216	-6.81E-06	47	2	0.00216	8.72E-08	53	3
TUPRS	0.00041	-4.15E-07	53	2	-0.00138	2.62E-07	46	4
ULKER	0.00209	-7.68E-06	47	2	0.00451	4.79E-07	52	5
VAKBN	0.00184	9.50E-07	59	4	0.00248	8.90E-08	57	5
YKBNK	0.00195	7.50E-06	65	6	0.00216	-9.08E-07	57	4

Table 4.6: The result of fourth model using percentage changes of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^N + \beta_2 \Delta OI_{t,1}^N \Delta OI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,1}^Q + \beta_2 \Delta OI_{t,1}^Q \Delta OI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig Positive β_2	Avg of R^2	Avg of β_2	# of Positive β_2	# of Sig Positive β_2
ARCLK	0.00321	-8.25E-08	58	7	0.00105	6.29E-10	50	4
BIMAS	0.00815	1.35E-07	60	5	0.00071	-3.63E-10	63	2
DOAS	0.00488	1.22e-07	54	5	0.00099	-1.62e-10	53	0
ENKAI	0.00540	7.51e-08	43	8	0.00589	2.43e-11	44	4
EREGL	0.00087	7.91E-08	60	2	0.00335	-1.19e-11	39	3
FROTO	0.00231	-7.26E-08	66	11	0.00124	6.25E-10	51	1
GARAN	0.00016	3.00E-09	51	4	0.00059	-3.65E-12	62	1
HALKB	0.00001	1.59E-07	63	5	-0.00047	-3.74E-10	46	1
ISCTR	0.00140	-6.93E-09	48	3	0.00260	3.18E-12	53	2
KCHOL	0.00063	1.98E-08	51	6	-0.00012	-1.90E-11	52	5
KOZAL	0.00066	-6.13E-08	48	3	-0.00035	-6.35E-12	54	3
KRDMD	0.00152	7.97E-08	59	7	0.00395	-2.28E-11	55	10
OTKAR	0.00367	7.03E-07	62	8	0.00195	-7.86E-10	52	2
PETKM	0.00088	1.11E-08	57	3	0.00409	1.17E-10	43	8
PGSUS	0.00107	-3.67E-08	56	4	-0.00049	1.69E-10	61	4
SAHOL	0.00040	2.15E-08	48	2	0.00051	-3.62E-12	47	0
SISE	0.00452	3.89E-08	57	7	0.00440	-3.51E-12	49	8
TAVHL	0.00256	-8.31E-08	52	5	0.00041	1.04E-10	62	2
TCELL	0.00059	1.59E-08	53	0	0.00063	-6.07E-12	47	2
THYAO	0.00005	-8.72E-08	62	4	0.00009	1.21E-10	52	5
TKFEN	0.00148	6.10E-08	56	8	0.00504	-6.76E-12	51	7
TOASO	0.00647	-1.19E-08	63	13	0.00253	-2.01E-11	50	6
TTKOM	0.00216	2.82E-08	60	6	0.00216	-3.30E-11	52	5
TUPRS	0.00041	-1.05E-07	60	4	-0.00138	1.25E-11	56	2
ULKER	0.00209	-9.95E-09	68	6	0.00451	-6.28E-10	59	9
VAKBN	0.00184	3.89E-09	59	10	0.00248	-9.71E-13	55	2
YKBNK	0.00195	-6.65E-09	48	4	0.00216	3.77E-13	56	1

Table 4.7: The result of fourth model using percentage changes of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Sig Positive β_1	# of Sig Positive β_1
ARCLK	0.03428	4.75E-05	109	100	0.00288	5.36E-08	82	20
BIMAS	0.02521	3.32E-05	107	91	0.00535	1.13E-07	85	24
DOAS	0.03716	4.67E-05	109	103	0.00160	3.12E-08	85	16
ENKAI	0.01651	3.64E-05	102	64	0.00271	2.05E-08	65	16
EREGL	0.01931	2.78E-05	104	74	0.00174	2.73E-09	74	13
FROTO	0.02684	4.00E-05	108	91	0.00326	1.85E-07	88	18
GARAN	0.03068	1.70E-05	109	88	0.00121	2.94E-10	87	10
HALKB	0.03880	1.91E-05	109	101	0.00119	1.32E-09	84	14
ISCTR	0.02901	2.53E-05	109	87	0.00119	4.52E-10	71	6
KCHOL	0.03447	3.50E-05	109	102	0.00296	2.25E-08	98	21
KOZAL	0.03355	6.41E-05	107	101	0.00310	3.31E-07	88	20
KRDMD	0.01681	0.000106	97	73	0.00124	9.64E-10	62	10
OTKAR	0.03908	5.25E-05	108	97	0.00640	4.60E-07	93	32
PETKM	0.01764	2.93E-05	104	72	0.00127	2.46E-09	72	9
PGSUS	0.03880	2.68E-05	108	101	0.00317	5.34E-08	92	24
SAHOL	0.03327	2.40E-05	108	93	0.00212	2.15E-09	81	18
SISE	0.02899	5.68E-05	108	93	0.00253	2.10E-09	62	17
TAVHL	0.03115	2.88E-05	109	105	0.00201	4.08E-08	91	15
TCELL	0.03053	3.22E-05	109	96	0.00109	8.98E-09	77	10
THYAO	0.03307	2.14E-05	109	98	0.00100	1.25E-08	84	8
TKFEN	0.01491	2.46E-05	100	65	0.00266	5.39E-09	76	15
TOASO	0.03198	4.58E-05	108	96	0.00221	8.73E-08	91	16
TTKOM	0.02022	3.11E-05	108	84	0.00410	2.42E-08	76	21
TUPRS	0.03451	2.18E-05	109	103	0.00255	2.62E-08	93	20
ULKER	0.02702	6.05E-05	108	87	0.00500	2.03E-07	85	31
VAKBN	0.04215	4.27E-05	106	93	0.00178	2.51E-09	79	13
YKBNK	0.03231	4.24E-05	109	97	0.00226	7.84E-10	76	14

Table 4.8: The result of first model using percentage changes of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,2}^N + \beta_2 \mathbf{r_t} + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,2}^Q + \beta_2 \mathbf{r_t} + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Sig Positive β_1	# of Sig Positive β_1
ARCLK	0.05180	4.60E-05	109	98	0.02268	5.21E-08	83	19
BIMAS	0.04309	3.19E-05	106	86	0.02569	1.07E-07	86	21
DOAS	0.05896	4.44E-05	109	100	0.02669	2.99E-08	84	14
ENKAI	0.06292	3.49E-05	100	61	0.05047	1.30E-08	61	15
EREGL	0.11521	2.42E-05	102	63	0.10117	2.57E-09	70	14
FROTO	0.03940	3.87E-05	108	91	0.01767	1.73E-07	88	18
GARAN	0.09643	1.47E-05	109	85	0.07394	2.54E-10	72	10
HALKB	0.07474	1.76E-05	109	99	0.04271	1.18E-09	81	13
ISCTR	0.12694	2.18E-05	106	79	0.10579	3.73E-10	58	5
KCHOL	0.04990	3.34E-05	109	99	0.02118	2.14E-08	90	21
KOZAL	0.05582	6.30E-05	108	99	0.02741	3.41E-07	86	18
KRDMD	0.18404	0.000101	97	70	0.17090	1.02E-09	63	10
OTKAR	0.05649	5.09E-05	108	98	0.02638	4.53E-07	92	29
PETKM	0.11200	2.63E-05	104	65	0.09810	1.70E-09	68	9
PGSUS	0.05550	2.53E-05	108	101	0.02347	4.93E-08	87	23
SAHOL	0.06315	2.26E-05	108	92	0.03577	1.83E-09	78	17
SISE	0.09693	5.22E-05	108	87	0.07409	1.34E-09	60	14
TAVHL	0.05191	2.75E-05	109	100	0.02584	3.75E-08	85	15
TCELL	0.05989	3.01E-05	109	96	0.03415	9.04E-09	78	11
THYAO	0.11465	1.87E-05	109	97	0.08927	1.07E-08	75	6
TKFEN	0.07858	2.32E-05	100	64	0.06796	5.16E-09	72	13
TOASO	0.05486	4.32E-05	107	93	0.02807	8.37E-08	85	14
TTKOM	0.05931	2.94E-05	108	81	0.04477	2.25E-08	74	21
TUPRS	0.05517	2.06E-05	109	100	0.02678	2.53E-08	89	17
ULKER	0.04643	5.88E-05	108	87	0.02543	1.85E-07	85	31
VAKBN	0.13072	3.72E-05	106	90	0.09905	1.75E-09	70	11
YKBNK	0.11448	3.77E-05	109	94	0.09008	4.79E-10	71	9

Table 4.9: The result of second model using percentage changes of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1}}$					$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1}}$				
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1		Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	
ARCLK	0.06974	4.43E-05	109	96		0.04159	4.75E-05	83	18	
BIMAS	0.05466	3.11E-05	105	84		0.03841	3.32E-05	87	23	
DOAS	0.07228	4.32E-05	109	98		0.04061	4.67E-05	84	13	
ENKAI	0.08963	3.25E-05	98	57		0.07825	3.64E-05	64	14	
EREGL	0.15569	2.18E-05	98	61		0.14296	2.78E-05	68	13	
FROTO	0.05759	3.71E-05	108	86		0.03637	4.00E-05	85	18	
GARAN	0.10869	1.41E-05	108	84		0.08776	1.70E-05	72	9	
HALKB	0.08239	1.73E-05	109	99		0.05113	1.91E-05	77	13	
ISCTR	0.15590	2.07E-05	103	74		0.13659	2.53E-05	59	7	
KCHOL	0.06059	3.28E-05	109	97		0.03250	3.50E-05	89	21	
KOZAL	0.07616	6.11E-05	108	99		0.04837	6.41E-05	89	17	
KRDMD	0.28703	8.98E-05	94	63		0.27543	1.06E-05	62	7	
OTKAR	0.07000	4.99E-05	108	97		0.03950	5.25E-05	91	28	
PETKM	0.15286	2.44E-05	102	63		0.14021	2.93E-05	65	10	
PGSUS	0.06296	2.50E-05	107	100		0.03127	2.68E-05	85	24	
SAHOL	0.07461	2.18E-05	107	89		0.04888	2.40E-05	76	18	
SISE	0.13061	4.85E-05	107	83		0.10999	5.68E-05	58	15	
TAVHL	0.06779	2.68E-05	108	99		0.04262	2.88E-05	86	16	
TCELL	0.07141	2.89E-05	109	94		0.04668	3.22E-05	79	11	
THYAO	0.13233	1.81E-05	109	93		0.10829	2.14E-05	71	8	
TKFEN	0.10713	2.18E-05	100	59		0.09740	2.46E-05	68	13	
TOASO	0.06870	4.19E-05	106	91		0.04296	4.58E-05	84	15	
TTKOM	0.07349	2.83E-05	107	77		0.05945	3.11E-05	74	22	
TUPRS	0.06288	2.01E-05	108	98		0.03513	2.18E-05	90	18	
ULKER	0.06565	5.82E-05	109	89		0.04542	6.05E-05	85	29	
VAKBN	0.15818	3.51E-05	105	87		0.12937	4.27E-05	63	11	
YKBNK	0.14274	3.65E-05	109	91		0.12048	4.24E-05	68	8	

Table 4.10: The result of third model using percentage changes of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^N + \beta_2 \Delta \mathbf{OI}_{t,2}^N \Delta \mathbf{OI}_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^Q + \beta_2 \Delta \mathbf{OI}_{t,2}^Q \Delta \mathbf{OI}_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.04980	0.00011	108	94	0.03637	-2.45E-06	93	32
BIMAS	0.03920	0.00009	107	89	0.08776	-2.06E-06	88	32
DOAS	0.05377	0.00010	109	99	0.05113	-1.96E-06	91	31
ENKAI	0.02736	0.00011	106	70	0.04837	-2.60E-06	74	25
EREGL	0.03166	0.00008	107	83	0.14021	-8.84E-07	81	47
FROTO	0.03962	0.00011	109	95	0.13233	-1.25E-05	94	38
GARAN	0.05454	0.00005	109	107	0.10713	-4.21E-07	97	65
HALKB	0.06548	0.00005	109	109	0.06870	-4.92E-07	90	50
ISCTR	0.04653	0.00006	107	97	0.06288	-6.07E-07	88	63
KCHOL	0.05607	0.00009	109	104	0.06565	-1.62E-06	93	36
KOZAL	0.05254	0.00016	109	101	0.15818	-2.56E-06	99	25
KRDMD	0.02915	0.00031	104	79	0.01767	-7.14E-06	80	53
OTKAR	0.05523	0.00012	108	100	0.07394	-2.56E-06	97	42
PETKM	0.02747	0.00007	105	82	0.04271	-8.98E-07	78	29
PGSUS	0.05809	0.00006	108	100	0.10579	-1.10E-06	100	31
SAHOL	0.05307	0.00006	109	102	0.08927	-7.77E-07	86	46
SISE	0.04253	0.00014	108	90	0.06796	-2.52E-06	77	39
TAVHL	0.05136	0.00008	109	104	0.02807	-1.24E-06	100	33
TCELL	0.04742	0.00008	109	104	0.04477	-1.40E-06	86	38
THYAO	0.05515	0.00005	109	107	0.02678	-7.81E-07	94	42
TKFEN	0.02518	0.00007	103	72	0.06059	-1.15E-06	83	44
TOASO	0.04716	0.00011	107	97	0.07616	-1.90E-06	87	27
TTKOM	0.03336	0.00008	106	79	0.07349	-1.49E-06	84	30
TUPRS	0.05523	0.00005	109	105	0.06288	-7.92E-07	96	33
ULKER	0.03921	0.00014	108	92	0.06565	-8.59E-06	87	20
VAKBN	0.06256	0.00010	108	103	0.14021	-1.22E-06	89	63
YKBNK	0.04891	0.00010	109	104	0.03127	-1.29E-06	92	59

Table 4.11: The result of fourth model using percentage changes of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^N + \beta_2 \Delta \mathbf{OI}_{t,2}^N \Delta \mathbf{OI}_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^Q + \beta_2 \Delta \mathbf{OI}_{t,2}^Q \Delta \mathbf{OI}_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of Positive β_2	# of Sig Positive β_2	Avg of R^2	Avg of β_2	# of Positive β_2	# of Sig Positive β_2
ARCLK	0.04980	-6.27E-06	5	2	0.03637	-8.78E-11	24	3
BIMAS	0.03920	-4.23E-07	6	0	0.08776	-7.90E-10	22	2
DOAS	0.05377	-1.98E-05	5	0	0.05113	-3.72E-11	23	0
ENKAI	0.02736	-2.4E-07	12	2	0.04837	-3.15E-09	39	12
EREGL	0.03166	-4.00E-06	5	0	0.14021	5.28E-13	30	7
FROTO	0.03962	-1.13E-06	7	0	0.13233	-4.48E-10	20	0
GARAN	0.05454	-1.17E-07	0	0	0.10713	-4.3E-07	16	3
HALKB	0.06548	-7.42E-08	1	0	0.06870	-9.67E-07	21	4
ISCTR	0.04653	-3.37E-08	4	0	0.06288	-3.85E-07	23	4
KCHOL	0.05607	-2.72E-05	2	0	0.06565	-3.14E-12	26	4
KOZAL	0.05254	-1.45E-06	2	0	0.15818	-9.88E-10	12	2
KRDMD	0.02915	-1.99E-06	8	1	0.01767	-2.4E-07	32	10
OTKAR	0.05523	-1.66E-06	4	1	0.07394	-2.16E-09	14	1
PETKM	0.02747	-1.03E-07	10	0	0.04271	-2.7E-07	31	7
PGSUS	0.05809	-1.95E-07	4	1	0.10579	-3.11E-11	12	1
SAHOL	0.05307	-3.48E-08	2	0	0.08927	-4.96E-07	27	2
SISE	0.04253	-1.35E-05	7	0	0.06796	-2.24E-06	35	8
TAVHL	0.05136	-2.78E-06	0	0	0.02807	-4.58E-11	10	1
TCELL	0.04742	-6.53E-05	1	0	0.04477	-1.01E-09	23	5
THYAO	0.05515	-6.94E-05	1	0	0.02678	-7.78E-09	18	1
TKFEN	0.02518	-1.05E-06	9	0	0.06059	-1.60E-05	30	2
TOASO	0.04716	-3.81E-07	7	1	0.07616	-4.42E-10	25	5
TTKOM	0.03336	-7.35E-05	12	2	0.07349	-2.67E-07	25	6
TUPRS	0.05523	5.38E-06	1	0	0.06288	-9.89E-12	18	0
ULKER	0.03921	-4.19E-06	9	0	0.06565	9.60E-09	28	2
VAKBN	0.06256	-2.08E-05	2	0	0.14021	6.40E-07	21	9
YKBNK	0.04891	-9.53E-04	3	0	0.03127	9.74E-08	21	3

Table 4.12: The result of fourth model using percentage changes of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.00128	-4.9E-06	48	3	0.00142	-1.81E-07	56	8
BIMAS	0.00187	-4.1E-06	49	5	0.00149	1.52E-06	54	7
DOAS	0.00096	-8E-06	43	2	0.00052	-7.12E-07	51	3
ENKAI	0.00117	-6.8E-06	49	4	0.00283	4.01E-06	63	11
EREGL	-0.00008	-6.2E-06	49	2	0.00072	-1.82E-06	52	2
FROTO	0.00127	-4E-06	53	4	0.00201	-2.43E-06	47	6
GARAN	0.00019	2.11E-06	60	3	-0.00014	1.96E-07	51	2
HALKB	0.00089	5.66E-07	57	8	-0.00050	-1.31E-07	59	1
ISCTR	0.00098	-7.9E-06	49	2	0.00056	9.43E-07	58	5
KCHOL	0.00140	-3.7E-06	56	4	-0.00017	-1.14E-06	40	2
KOZAL	0.00114	-2.5E-06	47	6	-0.00077	-1.21E-06	47	0
KRDMD	0.00193	3.53E-05	65	8	0.00048	-5.15E-06	52	5
OTKAR	0.00129	-8E-06	45	1	0.00083	-2.55E-06	50	3
PETKM	0.00079	-1E-05	42	5	0.00091	-1.45E-06	52	2
PGSUS	0.00075	-4.8E-06	40	3	0.00033	-4.22E-07	43	1
SAHOL	0.00144	-4.2E-06	52	6	0.00070	3.20E-07	56	2
SISE	0.00386	6.93E-06	53	7	0.00143	4.11E-06	55	8
TAVHL	0.00127	-6.3E-06	42	4	0.00044	-5.80E-07	52	2
TCELL	0.00114	-4.5E-06	45	3	0.00166	-3.65E-07	56	4
THYAO	0.00060	-3.1E-06	42	5	0.00025	-2.82E-07	53	3
TKFEN	0.00131	-1.4E-05	45	3	0.00027	-2.91E-06	52	3
TOASO	0.00152	-6.3E-06	49	5	0.00065	-1.59E-06	50	3
TTKOM	0.00220	-1.4E-05	41	6	0.00132	-5.40E-07	52	3
TUPRS	0.00045	-1.4E-06	54	1	0.00019	-5.05E-07	47	3
ULKER	0.00233	-6.8E-06	50	6	0.00066	1.66E-06	58	6
VAKBN	0.00141	4.09E-06	59	7	0.00032	-1.27E-06	55	6
YKBNK	0.00210	-8.5E-06	45	7	0.00129	-1.76E-06	49	5

Table 4.13: The result of first model using percentage changes of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^N + \beta_2 \mathbf{r_t} + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^Q + \beta_2 \mathbf{r_t} + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.02205	-5.37E-06	44	3	0.02208	-3.76E-07	56	8
BIMAS	0.02210	-4.14E-06	48	6	0.02144	1.11E-06	55	5
DOAS	0.02647	-8.19E-06	41	2	0.02606	-8.63E-07	46	4
ENKAI	0.04926	-4.70E-06	50	5	0.05070	4.88E-06	67	10
EREGL	0.10062	-9.56E-06	46	4	0.10080	-2.89E-06	53	1
FROTO	0.01616	-4.24E-06	52	4	0.01656	-2.45E-06	46	6
GARAN	0.07363	2.52E-06	59	4	0.07311	9.02E-08	52	2
HALKB	0.04287	1.84E-08	54	8	0.04162	8.92E-09	57	3
ISCTR	0.10688	-7.32E-06	47	1	0.10609	8.25E-07	59	5
KCHOL	0.02001	-3.74E-06	55	5	0.01863	-1.07E-06	46	2
KOZAL	0.02629	-2.84E-06	45	8	0.02438	-1.27E-06	48	1
KRDMD	0.17123	1.15E-06	58	6	0.17040	-2.92E-06	47	8
OTKAR	0.02189	-8.78E-06	39	1	0.02138	-2.50E-06	52	3
PETKM	0.09856	-1.56E-05	37	4	0.09809	-1.31E-06	52	2
PGSUS	0.02159	-5.25E-06	40	3	0.02098	-2.85E-07	47	1
SAHOL	0.03559	-4.83E-06	48	5	0.03460	1.23E-07	62	2
SISE	0.07503	4.86E-06	58	7	0.07311	3.50E-06	56	6
TAVHL	0.02578	-6.01E-06	43	4	0.02482	-6.40E-07	52	2
TCELL	0.03486	-4.89E-06	44	3	0.03512	-3.93E-07	53	4
THYAO	0.08972	-3.11E-06	47	4	0.08919	1.99E-07	53	3
TKFEN	0.06764	-1.85E-05	41	2	0.06602	-4.20E-06	51	3
TOASO	0.02823	-7.54E-06	49	4	0.02708	-1.87E-06	53	3
TTKOM	0.04382	-1.46E-05	39	6	0.04264	-1.26E-06	50	3
TUPRS	0.02526	-2.25E-06	49	1	0.02495	-4.70E-07	48	4
ULKER	0.02359	-6.90E-06	47	5	0.02201	1.36E-06	54	5
VAKBN	0.10012	3.63E-06	57	8	0.09913	-1.78E-06	48	6
YKBNK	0.09070	-6.89E-06	46	9	0.09004	-1.62E-06	48	7

Table 4.14: The result of second model using percentage changes of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.04075	-4.44E-06	44	6	0.04067	-3.21E-07	55	8
BIMAS	0.03427	-4.47E-06	52	7	0.03370	4.60E-07	55	6
DOAS	0.04020	-7.98E-06	42	2	0.04007	-1.38E-06	41	3
ENKAI	0.07698	-2.54E-06	54	6	0.07832	6.01E-06	72	9
EREGL	0.14236	-9.12E-06	48	4	0.14244	-3.21E-06	53	2
FROTO	0.03509	-2.97E-06	51	6	0.03524	-1.80E-06	47	7
GARAN	0.08695	2.63E-06	59	4	0.08659	-9.05E-08	53	2
HALKB	0.05096	-1.58E-07	51	6	0.04969	-8.40E-08	54	1
ISCTR	0.13712	-7.97E-06	45	1	0.13650	6.00E-07	59	6
KCHOL	0.03134	-4.05E-06	53	5	0.02988	-8.46E-07	47	1
KOZAL	0.04692	-3.18E-06	46	8	0.04492	-1.47E-06	49	1
KRDMD	0.27615	-1.65E-05	52	8	0.27464	-2.21E-06	51	7
OTKAR	0.03538	-9.77E-06	42	2	0.03507	-2.45E-06	51	2
PETKM	0.14019	-1.77E-05	33	3	0.13967	-6.36E-07	53	3
PGSUS	0.02903	-5.27E-06	40	2	0.02860	-3.42E-07	43	2
SAHOL	0.04866	-5.06E-06	49	7	0.04754	6.42E-08	56	3
SISE	0.11047	7.39E-06	54	10	0.10870	2.72E-06	54	5
TAVHL	0.04219	-4.92E-06	43	5	0.04098	-6.74E-07	51	3
TCELL	0.04701	-5.08E-06	43	3	0.04714	-3.48E-07	54	4
THYAO	0.10822	-3.80E-06	47	3	0.10776	1.39E-07	55	2
TKFEN	0.09689	-1.99E-05	37	3	0.09512	-4.23E-06	48	2
TOASO	0.04299	-8.31E-06	46	4	0.04194	-1.99E-06	53	4
TTKOM	0.05856	-1.37E-05	40	5	0.05725	-1.47E-06	50	3
TUPRS	0.03319	-1.89E-06	52	2	0.03307	-3.96E-07	51	3
ULKER	0.04280	-7.28E-06	46	5	0.04153	1.22E-06	56	5
VAKBN	0.13006	3.02E-06	60	9	0.12907	-1.92E-06	51	6
YKBNK	0.12071	-6.61E-06	46	7	0.11976	-2.22E-06	50	5

Table 4.15: The result of third model using percentage changes of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,3}^N + \beta_2 \Delta \mathbf{OI}_{t,3}^N \Delta \mathbf{OI}_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,3}^Q + \beta_2 \Delta \mathbf{OI}_{t,3}^Q \Delta \mathbf{OI}_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.00311	9.07E-07	47	7	0.001493	1.24E-06	59	7
BIMAS	0.00289	7.94E-06	54	6	0.00212	1.53E-06	52	3
DOAS	0.00169	2.16E-06	40	4	0.001666	-4.22E-06	46	7
ENKAI	0.00407	2.08E-06	45	4	0.005615	4.38E-07	52	14
EREGL	0.00090	2.60E-07	53	3	0.001422	-3.60E-06	52	4
FROTO	0.00178	4.27E-08	55	3	0.002527	-6.89E-06	39	5
GARAN	0.00099	-1.28E-07	55	7	0.000166	2.80E-07	54	6
HALKB	0.00146	-4.71E-07	53	5	-0.00035	-1.31E-06	47	4
ISCTR	0.00233	8.36E-07	44	0	0.001198	-2.12E-06	52	8
KCHOL	0.00243	1.32E-06	47	4	0.000755	-5.55E-06	51	10
KOZAL	0.00150	1.27E-06	49	1	-0.00074	-8.21E-06	44	7
KRDMD	0.00390	-2.30E-05	67	13	0.001548	1.23E-06	55	3
OTKAR	0.00188	6.05E-07	40	2	0.001506	-5.42E-06	47	7
PETKM	0.00316	-7.57E-06	56	9	0.001613	-5.20E-06	49	6
PGSUS	0.00208	-2.92E-07	52	0	0.000853	-3.63E-07	49	9
SAHOL	0.00237	9.66E-08	53	8	0.001092	-1.41E-08	57	4
SISE	0.00560	-2.25E-06	55	5	0.003142	1.08E-05	58	6
TAVHL	0.00182	1.05E-06	41	3	0.000784	-1.01E-06	50	6
TCELL	0.00232	-3.82E-07	54	9	0.002494	1.01E-07	56	6
THYAO	0.00146	3.99E-07	40	1	0.000873	-1.15E-06	53	8
TKFEN	0.00295	-1.56E-06	47	5	0.001983	-1.18E-05	51	10
TOASO	0.00226	2.04E-06	45	1	0.001439	-3.47E-06	48	5
TTKOM	0.00300	-1.03E-06	48	5	0.003325	-1.12E-06	54	3
TUPRS	0.00151	8.48E-07	44	2	0.001164	-2.33E-06	44	11
ULKER	0.00474	1.75E-06	50	3	0.003016	-3.76E-06	44	11
VAKBN	0.00280	1.91E-07	54	7	0.000762	-5.42E-06	48	9
YKBNK	0.00416	-2.22E-06	58	7	0.002271	-8.74E-06	43	6

Table 4.16: The result of fourth model using percentage changes of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^N + \beta_2 \Delta OI_{t,3}^N \Delta OI_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OI_{t,3}^Q + \beta_2 \Delta OI_{t,3}^Q \Delta OI_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of Positive β_2	# of Sig Positive β_2	Avg of R^2	Avg of β_2	# of Positive β_2	# of Sig Positive β_2
ARCLK	0.04980	-0.0095	2	0	-0.02235	-8.78E-11	18	0
BIMAS	0.03920	-0.00489	4	0	-0.04757	-7.90E-10	19	0
DOAS	0.05377	-0.00551	1	0	-0.07670	-3.72E-11	19	0
ENKAI	0.02736	-0.0005	18	3	-0.08845	-3.15E-09	43	5
EREGL	0.03166	-0.00284	42	7	4.40006	5.28E-13	53	6
FROTO	0.03962	-0.0099	1	0	-0.02359	-4.48E-10	24	2
GARAN	0.05454	-0.00193	14	0	-0.06555	-4.35E-08	11	0
HALKB	0.06548	-0.00613	6	1	-0.09118	-9.67E-07	6	0
ISCTR	0.04653	-0.0082	25	1	-0.01154	3.85E-07	46	4
KCHOL	0.05607	-0.00458	2	0	-0.08883	3.14E-12	6	0
KOZAL	0.05254	-0.00829	2	0	-0.0294	-9.88E-10	12	1
KRDMD	0.02915	-0.00091	67	19	0.0007	0.0246	100	4
OTKAR	0.05523	-0.0070	2	0	-0.04905	-2.16E-09	20	2
PETKM	0.02747	-0.0060	48	6	0.00546	0.0278	74	2
PGSUS	0.05809	0.00076	4	0	-0.05779	-3.11E-11	17	1
SAHOL	0.05307	-0.0050	10	0	-0.01079	-4.96E-07	7	0
SISE	0.04253	-0.00109	17	0	-0.00117	-2.24E-06	36	1
TAVHL	0.05136	-0.00718	2	0	-0.02118	4.58E-11	16	2
TCELL	0.04742	-0.00657	3	0	-0.07070	-1.01E-09	11	0
THYAO	0.05515	-0.0091	35	4	-0.07505	-7.78E-09	24	3
TKFEN	0.02518	-0.00835	32	4	-9.87005	-1.60E-05	59	1
TOASO	0.04716	-0.00710	5	0	-0.00730	-4.42E-10	25	4
TTKOM	0.03336	-0.00668	12	1	-0.02083	2.67E-07	28	5
TUPRS	0.05523	-0.00293	1	0	-0.09788	-9.89E-12	9	0
ULKER	0.03921	-0.0027	3	0	-0.01921	9.60E-09	29	1
VAKBN	0.06256	-0.00821	16	0	-0.09339	6.40E-07	15	2
YKBNK	0.04891	-0.00572	14	0	-0.05415	9.74E-08	27	2

Table 4.17: The result of fourth model using percentage changes of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

4.2.2 Models with Level Regression

In this subsection we analysis the models based on order imbalances, that their coefficients are calculated without percentage changes formula that introduced in Eq. 2.11 and Eq. 2.12. The Fig. 4.5 shows the basis of constructing models for ability of prediction of 1-min ahead return, using OI_t .

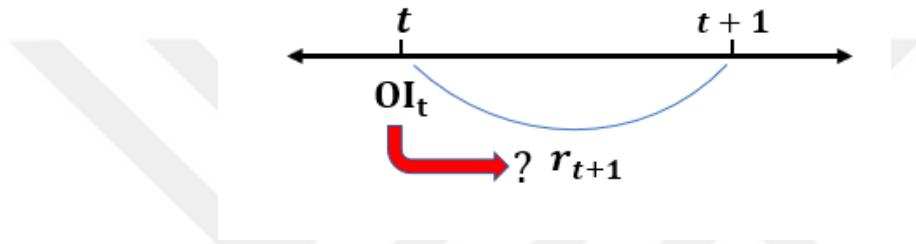


Figure 4.5: Power of prediction of OI_t in 1-minute ahead return

Then we have:

$$r_{t+1} = \beta_0 + \beta_1 OI_t^N + \epsilon_{t+1} \quad (4.14)$$

$$r_{t+1} = \beta_0 + \beta_1 OI_t^Q + \epsilon_{t+1} \quad (4.15)$$

$$r_{t+1} = \beta_0 + \beta_1 OI_t^N + \beta_2 r_t + \epsilon_{t+1} \quad (4.16)$$

$$r_{t+1} = \beta_0 + \beta_1 OI_t^Q + \beta_2 r_t + \epsilon_{t+1} \quad (4.17)$$

$$r_{t+1} = \beta_0 + \beta_1 OI_t^N + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.18)$$

$$r_{t+1} = \beta_0 + \beta_1 OI_t^Q + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.19)$$

$$r_{t+1} = \beta_0 + \beta_1 OI_t^N + \beta_2 OI_t^N |OI_t^N| + \epsilon_{t+1} \quad (4.20)$$

$$r_{t+1} = \beta_0 + \beta_1 OI_t^Q + \beta_2 OI_t^Q |OI_t^Q| + \epsilon_{t+1} \quad (4.21)$$

By applying these models using three order imbalances that were introduced by Eq. 2.1 to Eq. 2.22 on the data set, we get the Tables 4.18 to 4.32.

In the models of this section, again we drive information of 27 stocks on the basis of order imbalances and based on level regression.

The time-series regression results in this section show that almost all of the models represent brilliant and strong results. In the most of them the significant positive days are equal to 109 (all days). It seems that $OI_{t,2}^N$ has much more weak results comparison to other order imbalances.



company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,1}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,1}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.21464	8.23E-05	109	109	0.11135	6.19441E-08	108	107
BIMAS	0.20463	6.98E-05	109	109	0.10700	1.12221E-07	109	107
DOAS	0.23398	8.27E-05	109	109	0.17457	1.10794E-07	109	109
ENKAI	0.14584	8.72E-05	109	109	0.10098	4.08742E-08	109	107
EREGL	0.10988	4.92E-05	109	109	0.10087	8.43284E-09	109	109
FROTO	0.18108	7.28E-05	109	108	0.11284	2.51056E-07	108	103
GARAN	0.14904	1.17E-05	109	109	0.18467	1.51007E-09	109	108
HALKB	0.19072	1.97E-05	109	109	0.21916	6.78182E-09	109	109
ISCTR	0.10206	2.31E-05	109	109	0.12420	3.24854E-09	109	109
KCHOL	0.21374	6.14E-05	109	109	0.18356	3.71255E-08	109	108
KOZAL	0.25820	0.000106	109	109	0.14319	2.55075E-07	108	105
KRDMD	0.02103	4.82E-05	108	86	0.02210	2.22492E-09	104	77
OTKAR	0.25223	8.19E-05	109	109	0.17055	6.96838E-07	108	108
PETKM	0.10927	5.13E-05	109	109	0.08024	8.82029E-09	108	106
PGSUS	0.25811	4.8E-05	109	109	0.20703	8.933E-08	109	109
SAHOL	0.20681	4.46E-05	109	108	0.16796	1.52084E-08	109	108
SISE	0.14117	9.99E-05	109	109	0.11294	2.69047E-08	109	108
TAVHL	0.26076	6.4E-05	109	109	0.19241	1.09081E-07	109	108
TCELL	0.19548	5.78E-05	109	109	0.15141	3.18428E-08	109	109
THYAO	0.11840	1.1E-05	109	109	0.14898	2.23258E-09	109	109
TKFEN	0.10751	5.52E-05	109	109	0.09447	2.01195E-08	109	109
TOASO	0.18556	7.97E-05	109	108	0.10170	1.07491E-07	109	107
TTKOM	0.16926	6.59E-05	109	109	0.12379	3.19189E-08	109	108
TUPRS	0.25715	3.87E-05	109	109	0.17826	9.3711E-08	109	109
ULKER	0.16731	8.38E-05	109	109	0.07460	8.18038E-08	108	103
VAKBN	0.09584	2.69E-05	109	108	0.14670	4.79526E-09	108	108
YKBNK	0.10460	4.08E-05	109	109	0.11876	6.67491E-09	109	109

Table 4.18: The result of first model based on level regression of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^N + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^N + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.25668	8.77E-05	109	109	0.14045	6.50952E-08	109	108
BIMAS	0.24515	7.44E-05	109	109	0.13477	1.16762E-07	109	107
DOAS	0.28653	8.87E-05	109	109	0.21151	1.1541E-07	109	109
ENKAI	0.22203	9.72E-05	109	109	0.16239	4.42204E-08	109	107
ERGL	0.22930	5.4E-05	109	109	0.21101	8.89928E-09	109	109
FROTO	0.21418	7.77E-05	109	108	0.13482	2.61378E-07	108	103
GARAN	0.25254	1.3E-05	109	109	0.27185	1.57877E-09	109	109
HALKB	0.26347	2.15E-05	109	109	0.27474	7.00838E-09	109	109
ISCTR	0.22303	2.5E-05	109	109	0.23183	3.29692E-09	109	109
KCHOL	0.25024	6.45E-05	109	109	0.21019	3.80691E-08	109	108
KOZAL	0.30824	0.000114	109	109	0.17211	2.60695E-07	109	106
KRDMD	0.19349	5.23E-05	109	95	0.19284	2.29813E-09	105	86
OTKAR	0.30203	8.86E-05	109	109	0.20476	7.38181E-07	108	108
PETKM	0.22789	5.66E-05	109	109	0.18908	9.48914E-09	108	108
PGSUS	0.30472	5.12E-05	109	109	0.24167	9.29874E-08	109	109
SAHOL	0.26860	4.81E-05	109	108	0.21469	1.58281E-08	109	108
SISE	0.23661	0.000109	109	109	0.19581	2.84065E-08	109	108
TAVHL	0.30862	6.77E-05	109	109	0.22561	1.12426E-07	109	108
TCELL	0.25069	6.15E-05	109	109	0.19430	3.30696E-08	109	109
THYAO	0.23548	1.23E-05	109	109	0.25262	2.34248E-09	109	109
TKFEN	0.19527	6.12E-05	109	109	0.17450	2.17556E-08	109	109
TOASO	0.23200	8.49E-05	109	108	0.13516	1.11179E-07	109	108
TTKOM	0.23562	7.14E-05	109	109	0.17629	3.35167E-08	109	109
TUPRS	0.30305	4.07E-05	109	109	0.21090	9.60505E-08	109	109
ULKER	0.20731	9E-05	109	109	0.10289	8.69348E-08	108	105
VAKBN	0.20930	2.91E-05	109	108	0.24734	4.85579E-09	108	108
YKBNK	0.21078	4.42E-05	109	109	0.21292	6.84905E-09	109	109

Table 4.19: The result of second model based on level regression of $\mathbf{OI}_{t,1}^N = N_B - N_S$ and $\mathbf{OI}_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OI_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OI_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.28724	8.97E-05	109	108	0.16318	6.58E-08	109	109
BIMAS	0.26876	7.63E-05	109	107	0.15104	1.17E-07	109	109
DOAS	0.31770	9.16E-05	109	109	0.23069	1.17E-07	109	109
ENKAI	0.26933	1.03E-04	109	107	0.19712	4.56E-08	109	109
EREGL	0.28215	5.68E-05	109	109	0.25541	9.02E-09	109	109
FROTO	0.24075	7.87E-05	109	103	0.15653	2.61E-07	108	108
GARAN	0.28360	1.38E-05	109	109	0.29077	1.61E-09	109	109
HALKB	0.28744	2.25E-05	109	109	0.28864	7.10E-09	109	109
ISCTR	0.27029	2.7E-05	109	109	0.26633	3.35E-09	109	109
KCHOL	0.26951	6.55E-05	109	108	0.22293	3.79E-08	109	109
KOZAL	0.35010	1.17E-04	109	103	0.19618	2.61E-07	108	109
KRDMD	0.30292	5.84E-05	109	88	0.29790	2.36E-09	106	104
OTKAR	0.33621	9.22E-05	109	108	0.22506	7.53E-07	108	109
PETKM	0.28624	6.09E-05	109	108	0.23836	9.96E-09	108	109
PGSUS	0.32403	5.26E-05	109	109	0.25246	9.36E-08	109	109
SAHOL	0.29692	5.03E-05	109	109	0.23254	1.60E-08	109	109
SISE	0.29185	0.000116	109	109	0.23676	2.90E-08	109	109
TAVHL	0.33576	6.95E-05	109	108	0.24613	1.12E-07	109	109
TCELL	0.27348	6.3E-05	109	109	0.20984	3.31E-08	109	109
THYAO	0.27142	1.32E-05	109	109	0.27672	2.39E-09	109	109
TKFEN	0.23994	6.55E-05	109	109	0.21155	2.27E-08	109	109
TOASO	0.25787	8.71E-05	109	107	0.15641	1.15E-07	109	109
TTKOM	0.26381	7.41E-05	109	109	0.19561	3.40E-08	109	109
TUPRS	0.31962	4.13E-05	109	109	0.21944	9.55E-08	109	109
ULKER	0.24121	9.3E-05	109	103	0.12635	8.77E-08	109	109
VAKBN	0.25415	3.11E-05	109	108	0.27936	4.90E-09	109	108
YKBNK	0.25693	4.74E-05	109	109	0.24573	6.93E-09	109	109

Table 4.20: The result of third model based on level regression of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^N + \beta_2 \mathbf{OI}_{t,1}^N \mathbf{OI}_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^Q + \beta_2 \mathbf{OI}_{t,1}^Q \mathbf{OI}_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# of Sig Positive β_1
ARCLK	0.22906	9.68E-05	109	108	0.15869	2.82E-08	109	109
BIMAS	0.22063	7.85E-05	108	105	0.14600	-2.88E-07	109	107
DOAS	0.24978	1.01E-05	109	109	0.20122	7.20E-08	109	109
ENKAI	0.15853	1.1E-04	109	107	0.12230	1.42E-07	108	104
EREGL	0.12459	7.6E-05	109	109	0.11245	1.35E-07	109	103
FROTO	0.19757	8.74E-05	109	107	0.14732	-7.30E-08	109	106
GARAN	0.16227	1.65E-05	109	109	0.19300	-3.70E-08	109	107
HALKB	0.20564	2.7E-05	109	109	0.23276	2.61E-08	109	109
ISCTR	0.11680	3.65E-05	109	109	0.14001	1.27E-07	109	106
KCHOL	0.23687	7.7E-05	109	107	0.22441	1.76E-07	109	109
KOZAL	0.27105	1.32E-04	109	109	0.20221	2.23E-07	109	109
KRDMD	0.03086	1.2E-04	109	83	0.02607	-7.84E-08	91	34
OTKAR	0.26481	9.8E-05	109	108	0.20110	1.01E-07	109	108
PETKM	0.11898	7.32E-05	109	105	0.09441	-3.43E-07	108	99
PGSUS	0.27591	6.05E-05	109	109	0.23577	-3.14E-09	109	109
SAHOL	0.22399	5.91E-05	109	108	0.19519	1.75E-08	109	108
SISE	0.15382	1.41E-04	109	108	0.13249	-1.06E-06	109	106
TAVHL	0.27809	7.81E-05	109	108	0.22499	-4.36E-08	109	108
TCELL	0.21219	7.2E-05	109	106	0.18655	7.69E-08	109	109
THYAO	0.13033	1.55E-05	108	106	0.15625	-6.91E-09	109	106
TKFEN	0.12627	8.37E-05	109	108	0.10654	5.50E-07	109	106
TOASO	0.20230	9.7E-05	109	107	0.14767	-4.01E-08	109	108
TTKOM	0.18153	8.53E-05	109	109	0.14686	2.13E-07	109	109
TUPRS	0.27416	4.87E-05	109	108	0.22489	1.60E-07	109	109
ULKER	0.17805	9.98E-05	109	109	0.11243	1.33E-07	109	108
VAKBN	0.11126	4.33E-05	109	107	0.16146	9.02E-08	108	106
YKBNK	0.11467	5.97E-05	109	109	0.13575	8.02E-07	109	106

Table 4.21: The result of fourth model based on level regression of $OI_{t,1}^N = N_B - N_S$ and $OI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^N + \beta_2 \mathbf{OI}_{t,1}^N \mathbf{OI}_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^Q + \beta_2 \mathbf{OI}_{t,1}^Q \mathbf{OI}_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of Positive β_2	# of Sig Positive β_2	Avg of R^2	Avg of β_2	# of Positive β_2	# of Sig Positive β_2
ARCLK	0.22906	-7.72E-07	33	9	0.15869	-2.87E-12	5	0
BIMAS	0.22063	1.51E-08	32	14	0.14600	-1.20E-11	5	2
DOAS	0.24978	-9.60E-07	17	3	0.20122	-4.29E-12	5	0
ENKAI	0.15853	-1.14E-06	27	8	0.12230	-4.99E-13	20	3
EREGL	0.12459	-6.53E-07	8	2	0.11245	-1.62E-14	22	3
FROTO	0.19757	-5.98E-07	30	13	0.14732	-4.65E-11	7	1
GARAN	0.16227	-4.83E-08	17	1	0.19300	-5.60E-16	29	5
HALKB	0.20564	-1.20E-07	5	0	0.23276	-1.28E-14	12	1
ISCTR	0.11680	-2.22E-07	8	1	0.14001	-4.46E-15	10	1
KCHOL	0.23687	-5.62E-07	18	7	0.22441	-5.82E-13	6	0
KOZAL	0.27105	-1.04E-06	21	6	0.20221	-1.92E-11	3	1
KRDMD	0.03086	-1.75E-06	12	0	0.02607	-3.78E-15	41	7
OTKAR	0.26481	-7.45E-07	27	6	0.20110	-2.54E-10	8	4
PETKM	0.11898	-7.27E-07	19	6	0.09441	-2.95E-14	16	4
PGSUS	0.27591	-4.84E-07	13	3	0.23577	-3.82E-12	12	5
SAHOL	0.22399	-5.27E-07	14	2	0.19519	-1.13E-13	7	2
SISE	0.15382	-1.99E-06	9	3	0.13249	-1.68E-13	15	1
TAVHL	0.27809	-5.37E-07	20	5	0.22499	-4.13E-12	7	2
TCELL	0.21219	-5.87E-07	27	9	0.18655	-4.56E-13	7	1
THYAO	0.13033	-4.35E-08	12	5	0.15625	-1.22E-15	25	3
TKFEN	0.12627	-1.06E-06	11	3	0.10654	-1.61E-13	19	3
TOASO	0.20230	-6.69E-07	25	9	0.14767	-5.56E-12	9	1
TTKOM	0.18153	-8.74E-07	16	3	0.14686	-3.77E-13	15	2
TUPRS	0.27416	-3.79E-07	16	3	0.22489	-6.34E-12	6	2
ULKER	0.17805	-9.47E-07	24	4	0.16146	-7.33E-12	8	1
YKBNK	0.11467	-2.83E-07	16	1	0.13575	-7.47E-15	12	2

Table 4.22: The result of fourth model based on level regression of $\mathbf{OI}_{t,1}^N = N_B - N_S$ and $\mathbf{OI}_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,2}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,2}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of Positive	# Sig Positive	Avg of R^2	Avg of β_1	# of Positive	# Sig Positive
ARCLK	0.03401	8.39E-05	108	101	0.00221	5.31E-05	94	19
BIMAS	0.03175	6.83E-05	108	91	0.00363	9.90E-07	95	18
DOAS	0.04999	9.92E-05	109	103	0.00305	5.90E-07	100	22
ENKAI	0.01741	6.35E-05	107	79	0.00067	5.53E-07	80	5
EREGL	0.02184	6.75E-05	109	87	0.00011	3.93E-08	79	8
FROTO	0.03451	8.23E-05	109	97	0.00440	1.49E-06	102	24
GARAN	0.03857	3.92E-05	109	103	0.00173	7.21E-09	92	19
HALKB	0.05725	5.08E-05	109	108	0.00267	2.08E-08	94	19
ISCTR	0.02912	4.87E-05	109	97	0.00438	1.15E-08	92	27
KCHOL	0.04691	7.58E-05	109	107	0.00446	1.65E-07	101	33
KOZAL	0.06178	1.75E-04	109	100	0.00496	2.74E-06	105	29
KRDMD	0.00372	7.65E-05	101	26	-0.00016	2.03E-08	68	6
OTKAR	0.05410	1.05E-04	109	96	0.00927	3.41E-06	104	49
PETKM	0.01614	5.17E-05	108	71	0.00043	3.36E-08	81	13
PGSUS	0.06138	6.66E-05	109	104	0.00405	4.42E-07	103	28
SAHOL	0.04531	5.56E-05	109	105	0.00189	1.07E-07	96	10
SISE	0.02050	8.47E-05	108	81	0.00149	9.05E-08	86	16
TAVHL	0.05962	8.59E-05	109	105	0.00602	6.36E-07	103	33
TCELL	0.04010	7.14E-05	109	104	0.00438	1.81E-07	93	28
THYAO	0.02972	3.81E-05	109	98	0.00080	7.88E-08	77	8
TKFEN	0.01726	5.06E-05	109	72	0.00170	1.23E-07	88	18
TOASO	0.03806	9.09E-05	109	101	0.00625	6.91E-07	100	45
TTKOM	0.02894	6.32E-05	109	98	0.00166	1.18E-07	83	12
TUPRS	0.06730	6.57E-05	109	107	0.00615	4.34E-07	103	42
ULKER	0.02391	7.75E-05	108	84	0.00206	1.05E-06	88	21
VAKBN	0.02621	5.43E-05	109	91	0.00450	2.30E-08	94	30
YKBNK	0.02186	5.81E-05	109	92	0.00611	4.34E-08	92	34

Table 4.23: The result of first model based on level regression of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,2}^N + \beta_2 r_t + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,2}^Q + \beta_2 r_t + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1
ARCLK	0.05946	9.08E-05	108	101	0.02307	6.78E-07	94	22
BIMAS	0.05651	7.43E-05	108	95	0.02380	1.04E-06	96	19
DOAS	0.08247	1.07E-04	109	104	0.02908	6.33E-07	99	26
ENKAI	0.07095	7.30E-05	107	89	0.04918	5.91E-07	78	8
EREGL	0.12850	7.79E-05	109	101	0.10044	5.29E-08	82	12
FROTO	0.05411	8.90E-05	109	101	0.01980	1.57E-06	102	28
GARAN	0.12096	4.38E-05	109	108	0.07516	7.48E-09	93	25
HALKB	0.10700	5.44E-05	109	109	0.04476	2.08E-08	95	18
ISCTR	0.14066	5.35E-05	109	105	0.10936	1.19E-08	90	29
KCHOL	0.07139	8.10E-05	109	107	0.02343	1.69E-07	101	35
KOZAL	0.09312	1.84E-04	109	101	0.03039	2.72E-06	105	30
KRDMD	0.17574	9.40E-05	103	45	0.17014	1.63E-08	66	11
OTKAR	0.08037	1.12E-04	109	100	0.03075	3.56E-06	104	54
PETKM	0.11947	6.06E-05	108	84	0.09789	3.36E-08	90	12
PGSUS	0.08931	7.10E-05	109	106	0.02528	4.71E-07	102	33
SAHOL	0.08825	6.11E-05	109	105	0.03591	1.18E-07	96	13
SISE	0.09961	9.73E-05	108	92	0.07392	8.67E-08	84	19
TAVHL	0.09136	9.19E-05	109	107	0.03080	6.71E-07	107	37
TCELL	0.08067	7.82E-05	109	108	0.03842	2.16E-07	95	33
THYAO	0.12495	4.22E-05	109	104	0.08948	8.32E-08	80	7
TKFEN	0.08867	5.88E-05	108	83	0.06825	1.38E-07	89	21
TOASO	0.07091	9.92E-05	109	105	0.03351	7.21E-07	101	46
TTKOM	0.07787	7.13E-05	109	100	0.04360	1.42E-07	84	18
TUPRS	0.09834	6.91E-05	109	108	0.03126	4.48E-07	104	47
ULKER	0.04906	8.43E-05	108	87	0.02366	1.16E-06	87	22
VAKBN	0.13157	6.13E-05	109	98	0.10274	2.00E-08	93	35
YKBNK	0.11837	6.72E-05	109	97	0.09520	4.02E-08	91	40

Table 4.24: The result of second model based on level regression of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OI_{t,2}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OI_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1
ARCLK	0.08188	9.45E-05	108	101	0.04221	6.86E-07	92	24
BIMAS	0.07095	7.72E-05	109	96	0.03561	1.07E-06	94	21
DOAS	0.10012	1.11E-04	109	106	0.04365	6.53E-07	101	37
ENKAI	0.10542	8.40E-05	107	97	0.07716	6.80E-07	80	10
EREGL	0.17565	8.61E-05	109	104	0.14238	6.96E-08	78	11
FROTO	0.07547	9.16E-05	109	103	0.03914	1.62E-06	102	32
GARAN	0.13967	4.62E-05	109	107	0.08912	7.63E-09	93	27
HALKB	0.11915	5.58E-05	109	109	0.05332	2.05E-08	94	22
ISCTR	0.17870	5.91E-05	109	107	0.14054	1.33E-08	91	34
KCHOL	0.08551	8.31E-05	109	107	0.03486	1.55E-07	102	38
KOZAL	0.11928	1.88E-04	109	107	0.05162	2.74E-06	103	31
KRDMD	0.28380	1.2E-04	108	65	0.27579	9.10E-09	70	15
OTKAR	0.09858	1.16E-04	109	103	0.04544	3.62E-06	105	56
PETKM	0.16706	6.84E-05	108	97	0.14003	3.11E-08	86	13
PGSUS	0.09874	7.18E-05	109	106	0.03271	4.63E-07	101	34
SAHOL	0.10583	6.41E-05	109	106	0.04906	1.18E-07	98	13
SISE	0.14349	1.1E-04	109	99	0.11019	7.89E-08	84	20
TAVHL	0.11090	9.42E-05	109	108	0.04734	6.66E-07	107	41
TCELL	0.09739	8.16E-05	109	109	0.05120	2.33E-07	95	34
THYAO	0.14776	4.46E-05	109	107	0.10872	9.26E-08	79	11
TKFEN	0.12302	6.64E-05	108	90	0.09805	1.58E-07	86	22
TOASO	0.08941	1.04E-04	109	106	0.04860	7.37E-07	101	46
TTKOM	0.09784	7.62E-05	109	100	0.05855	2.12E-07	84	20
TUPRS	0.10922	6.96E-05	109	108	0.03971	4.41E-07	103	45
ULKER	0.07212	8.94E-05	108	92	0.04365	1.18E-06	88	22
VAKBN	0.16940	6.79E-05	109	103	0.13333	1.78E-08	91	32
YKBNK	0.15637	7.58E-05	108	102	0.12582	3.97E-08	92	38

Table 4.25: The result of third model based on level regression of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,2}^N + \beta_2 \mathbf{OI}_{t,2}^N \mathbf{OI}_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,2}^Q + \beta_2 \mathbf{OI}_{t,2}^Q \mathbf{OI}_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1
ARCLK	0.04444	1.68E-04	104	88	0.00358	2.30E-06	94	18
BIMAS	0.03778	1.19E-04	107	82	0.00621	3.45E-06	98	23
DOAS	0.06010	1.74E-04	108	97	0.00600	2.69E-06	103	27
ENKAI	0.02047	1.04E-04	98	48	0.00103	3.66E-06	87	7
EREGL	0.02877	1.35E-04	106	78	0.00172	2.62E-07	77	9
FROTO	0.03925	1.27E-04	104	78	0.00939	7.24E-06	102	41
GARAN	0.06066	9.47E-05	109	106	0.00519	2.18E-08	87	20
HALKB	0.07997	1.12E-04	109	108	0.00547	8.70E-08	97	25
ISCTR	0.03791	9.96E-05	108	96	0.00690	3.66E-08	86	17
KCHOL	0.05791	1.4E-04	108	99	0.00619	5.37E-07	96	26
KOZAL	0.08009	3.66E-04	109	95	0.00937	1.27E-05	102	43
KRDMD	0.00349	1.16E-04	97	10	0.00207	3.30E-08	56	5
OTKAR	0.06280	1.69E-04	107	89	0.01615	9.97E-06	104	55
PETKM	0.02062	1.06E-04	106	66	0.00167	2.42E-07	68	9
PGSUS	0.07798	1.25E-04	108	99	0.00839	2.04E-06	105	44
SAHOL	0.05717	1.09E-04	109	101	0.00391	4.05E-07	96	17
SISE	0.02664	1.7E-04	106	69	0.00388	3.98E-07	73	11
TAVHL	0.07120	1.53E-04	109	100	0.00988	3.02E-06	102	35
TCELL	0.05076	1.42E-04	109	100	0.00721	6.31E-07	93	24
THYAO	0.04613	9.36E-05	109	105	0.00383	4.57E-07	84	18
TKFEN	0.02073	8.46E-05	106	51	0.00315	4.46E-07	85	12
TOASO	0.04610	1.58E-04	108	82	0.00730	1.32E-06	98	21
TTKOM	0.03231	1E-04	106	70	0.00344	9.09E-07	87	19
TUPRS	0.08448	1.27E-04	109	107	0.01003	1.71E-06	106	40
ULKER	0.02821	3.89E-07	102	56	0.00451	4.45E-06	92	19
VAKBN	0.03755	1.21E-04	105	95	0.00814	1.06E-07	85	17
YKBNK	0.02841	1.21E-04	108	87	0.00853	8.90E-08	80	20

Table 4.26: The result of fourth model based on level regression of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,2}^N + \beta_2 \mathbf{OI}_{t,2}^N \mathbf{OI}_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,2}^Q + \beta_2 \mathbf{OI}_{t,2}^Q \mathbf{OI}_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of Positive β_2	# Sig Positive β_2	Avg of R^2	Avg of β_2	# of Positive β_2	# Sig Positive β_2
ARCLK	0.04444	-8.41E-06	13	4	0.00358	-1.55E-08	20	0
BIMAS	0.03778	-4.79E-06	17	5	0.00621	-6.44E-09	24	1
DOAS	0.06010	-6.60E-06	13	1	0.00600	-8.19E-09	12	0
ENKAI	0.02047	-2.67E-06	30	4	0.00103	-3.84E-08	27	0
EREGL	0.02877	-3.59E-06	10	1	0.00172	-2.70E-10	42	0
FROTO	0.03925	-4.28E-06	23	4	0.00939	-6.38E-08	13	0
GARAN	0.06066	-2.16E-06	1	0	0.00519	-6.52E-13	29	1
HALKB	0.07997	-3.21E-06	1	0	0.00547	-8.70E-12	21	1
ISCTR	0.03791	-2.22E-06	6	1	0.00690	-2.23E-12	36	2
KCHOL	0.05791	-5.39E-06	11	1	0.00619	-3.74E-10	26	1
KOZAL	0.08009	-1.47E-05	11	0	0.00937	-4.94E-08	15	1
KRDMD	0.00349	-1.97E-06	29	0	0.00207	1.691E-12	56	4
OTKAR	0.06280	-5.80E-06	20	2	0.01615	-5.77E-08	16	2
PETKM	0.02062	-2.92E-06	16	1	0.00167	-9.90E-11	48	0
PGSUS	0.07798	-4.76E-06	9	1	0.00839	-3.97E-09	12	1
SAHOL	0.05717	-3.34E-06	7	0	0.00391	-6.91E-10	22	0
SISE	0.02664	-5.91E-06	21	0	0.00388	-4.32E-11	47	5
TAVHL	0.07120	-5.32E-06	12	1	0.00988	-5.93E-09	17	1
TCELL	0.05076	-5.77E-06	6	1	0.00721	-2.39E-09	25	2
THYAO	0.04613	-2.55E-06	2	0	0.00383	-3.08E-10	31	0
TKFEN	0.02073	-2.22E-06	26	5	0.00315	-5.93E-10	31	2
TOASO	0.04610	-5.16E-06	20	2	0.00730	-9.14E-10	25	1
TTKOM	0.03231	-2.90E-06	28	3	0.00344	-5.25E-10	26	1
TUPRS	0.08448	-4.67E-06	2	0	0.01003	-2.24E-09	13	0
ULKER	0.02821	7.686E-05	30	6	0.00451	-3.42E-08	22	3
VAKBN	0.03755	-3.17E-06	12	0	0.00814	-1.80E-11	32	4
YKBNK	0.02841	-3.34E-06	11	0	0.00853	-2.28E-11	45	1

Table 4.27: The result of fourth model based on level regression of $OI_{t,2}^N = \frac{N_B}{N_S}$ and $OI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r_{t+1}} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive	# Sig Positive	Avg of R^2	Avg of β_1	# of Positive	# Sig Positive
ARCLK	0.13621	5.05E-04	109	109	0.12145	4.37E-04	109	109
BIMAS	0.12759	4.21E-04	109	109	0.11521	3.73E-04	109	109
DOAS	0.15302	5.63E-04	109	109	0.13739	4.69E-04	109	109
ENKAI	0.12091	6.02E-04	109	109	0.10739	5.33E-04	109	109
EREGL	0.12995	8.43E-04	109	109	0.09977	6.35E-04	109	109
FROTO	0.11798	4.10E-04	109	108	0.11278	3.75E-04	109	108
GARAN	0.10646	5.23E-04	109	109	0.07975	3.39E-04	109	109
HALKB	0.13279	5.03E-04	109	109	0.11939	3.81E-04	109	109
ISCTR	0.08890	5.93E-04	109	109	0.06538	3.97E-04	109	108
KCHOL	0.14885	4.83E-04	109	109	0.15053	4.33E-04	109	109
KOZAL	0.14633	1.13E-03	109	109	0.12583	9.14E-04	109	109
KRDMD	0.09400	2.03E-03	109	109	0.04472	1.09E-03	109	104
OTKAR	0.13480	4.76E-04	109	109	0.12503	4.17E-04	109	109
PETKM	0.12271	6.94E-04	109	109	0.09299	5.20E-04	109	109
PGSUS	0.16028	3.89E-04	109	109	0.14635	3.28E-04	109	109
SAHOL	0.16012	4.81E-04	109	108	0.14397	4.04E-04	109	108
SISE	0.13538	8.59E-04	109	109	0.10213	6.63E-04	109	109
TAVHL	0.16324	5.37E-04	109	109	0.14612	4.57E-04	109	109
TCELL	0.13467	4.75E-04	109	109	0.12174	3.97E-04	109	109
THYAO	0.08453	4.96E-04	109	109	0.06896	3.45E-04	109	108
TKFEN	0.13666	5.96E-04	109	109	0.10539	4.63E-04	109	109
TOASO	0.13050	5.47E-04	109	109	0.11782	4.64E-04	109	109
TTKOM	0.13420	5.16E-04	109	109	0.12067	4.51E-04	109	109
TUPRS	0.16370	4.43E-04	109	109	0.14780	3.62E-04	109	109
ULKER	0.10562	4.25E-04	109	109	0.09464	3.77E-04	109	109
VAKBN	0.08856	6.85E-04	109	109	0.06901	4.72E-04	109	109
YKBNK	0.08997	6.35E-04	109	109	0.07356	4.76E-04	109	109

Table 4.28: The result of first model based on level regression of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,3}^N + \beta_2 r_t + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 OI_{t,3}^Q + \beta_2 r_t + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of Positive	# Sig Positive	Avg of R^2	Avg of β_1	# of Positive	# Sig Positive
ARCLK	0.17042	5.33E-04	109	109	0.15261	4.58E-04	109	109
BIMAS	0.16056	4.46E-04	109	109	0.14555	3.93E-04	109	109
DOAS	0.19137	5.90E-04	109	109	0.17168	4.85E-04	109	109
ENKAI	0.19269	6.64E-04	109	109	0.17513	5.84E-04	109	109
EREGL	0.25220	9.16E-04	109	109	0.21459	6.82E-04	109	109
FROTO	0.14438	4.35E-04	109	108	0.13719	3.94E-04	109	108
GARAN	0.19669	5.66E-04	109	109	0.15622	3.47E-04	109	109
HALKB	0.18760	5.29E-04	109	109	0.16317	3.85E-04	109	109
ISCTR	0.20458	6.28E-04	109	109	0.17096	3.98E-04	109	109
KCHOL	0.17903	5.03E-04	109	109	0.17775	4.47E-04	109	109
KOZAL	0.18341	1.16E-03	109	109	0.15894	9.37E-04	109	109
KRDMD	0.28012	2.20E-03	109	109	0.22187	1.18E-03	109	109
OTKAR	0.16784	4.99E-04	109	109	0.15558	4.34E-04	109	109
PETKM	0.24336	7.60E-04	109	109	0.20624	5.64E-04	109	109
PGSUS	0.19190	4.04E-04	109	109	0.17512	3.38E-04	109	109
SAHOL	0.21087	5.07E-04	109	108	0.18936	4.20E-04	109	108
SISE	0.23225	9.40E-04	109	109	0.18992	7.14E-04	109	109
TAVHL	0.20028	5.60E-04	109	109	0.17976	4.72E-04	109	109
TCELL	0.18143	5.00E-04	109	109	0.16417	4.12E-04	109	109
THYAO	0.18608	5.34E-04	109	109	0.16010	3.51E-04	109	108
TKFEN	0.22863	6.55E-04	109	109	0.18963	5.04E-04	109	109
TOASO	0.17151	5.81E-04	109	109	0.15467	4.87E-04	109	109
TTKOM	0.19599	5.58E-04	109	109	0.17846	4.85E-04	109	109
TUPRS	0.19817	4.57E-04	109	109	0.17887	3.70E-04	109	109
ULKER	0.13978	4.55E-04	109	109	0.12678	4.02E-04	109	109
VAKBN	0.19945	7.33E-04	109	109	0.16749	4.70E-04	109	109
YKBNK	0.19419	6.90E-04	109	109	0.16755	4.92E-04	109	109

Table 4.29: The result of second model based on level regression of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1
ARCLK	0.19695	5.41E-04	109	109	0.17744	4.63E-04	109	109
BIMAS	0.17988	4.53E-04	109	109	0.16311	3.97E-04	109	109
DOAS	0.21245	5.96E-04	109	109	0.19016	4.87E-04	109	109
ENKAI	0.24018	7.10E-04	109	109	0.21854	6.19E-04	109	109
EREGL	0.30893	9.60E-04	109	109	0.26601	7.08E-04	109	109
FROTO	0.16897	4.39E-04	109	108	0.16020	3.96E-04	109	108
GARAN	0.22121	5.94E-04	109	109	0.17250	3.51E-04	109	109
HALKB	0.20316	5.42E-04	109	109	0.17300	3.84E-04	109	109
ISCTR	0.24904	6.75E-04	109	109	0.20482	4.05E-04	109	109
KCHOL	0.19537	5.07E-04	109	109	0.19158	4.46E-04	109	109
KOZAL	0.21348	1.17E-03	109	109	0.18482	9.31E-04	109	109
KRDMD	0.40735	2.42E-03	109	109	0.33713	1.28E-03	109	109
OTKAR	0.19043	5.04E-04	109	109	0.17574	4.36E-04	109	109
PETKM	0.30481	8.06E-04	109	109	0.26129	5.93E-04	109	109
PGSUS	0.20207	4.04E-04	109	109	0.18362	3.35E-04	109	109
SAHOL	0.23081	5.17E-04	109	109	0.20646	4.25E-04	109	109
SISE	0.29250	1.01E-03	109	109	0.24056	7.55E-04	109	109
TAVHL	0.22058	5.61E-04	109	109	0.19870	4.71E-04	109	109
TCELL	0.20084	5.08E-04	109	109	0.18052	4.14E-04	109	109
THYAO	0.21250	5.55E-04	109	109	0.18016	3.52E-04	109	108
TKFEN	0.27884	6.98E-04	109	109	0.23291	5.31E-04	109	109
TOASO	0.19316	5.89E-04	109	109	0.17440	4.91E-04	109	109
TTKOM	0.22137	5.77E-04	109	109	0.20100	4.97E-04	109	109
TUPRS	0.21062	4.57E-04	109	109	0.18935	3.68E-04	109	109
ULKER	0.16957	4.69E-04	109	109	0.15421	4.11E-04	109	109
VAKBN	0.24345	7.86E-04	109	109	0.20008	4.75E-04	109	109
YKBNK	0.24046	7.44E-04	109	109	0.20358	5.07E-04	109	109

Table 4.30: The result of third model based on level regression of $OI_{t,3}^N = \frac{N_B - N_5}{N_B + N_5}$ and $OI_{t,3}^Q = \frac{Q_B - Q_5}{Q_B + Q_5}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^N + \beta_2 \mathbf{OI}_{t,3}^N \mathbf{OI}_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^Q + \beta_2 \mathbf{OI}_{t,3}^Q \mathbf{OI}_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1	Avg of R^2	Avg of β_1	# of Positive β_1	# Sig Positive β_1
ARCLK	0.15426	1.68E-04	109	101	0.12724	1.55E-03	106	72
BIMAS	0.14454	1.19E-04	109	97	0.12016	1.36E-03	105	64
DOAS	0.17035	1.74E-04	109	105	0.14440	1.52E-03	106	75
ENKAI	0.12764	1.04E-04	104	64	0.11072	1.47E-03	87	35
EREGL	0.13330	1.35E-04	96	54	0.10126	1.06E-03	79	27
FROTO	0.13454	1.27E-04	108	100	0.11782	1.38E-03	101	56
GARAN	0.11266	9.47E-05	109	91	0.08798	9.33E-04	107	78
HALKB	0.14568	1.12E-04	109	102	0.13461	1.03E-03	108	96
ISCTR	0.09224	9.96E-05	107	65	0.06819	9.73E-04	87	31
KCHOL	0.17029	1.40E-04	109	106	0.16312	1.44E-03	109	90
KOZAL	0.16881	3.66E-04	109	102	0.13486	3.03E-03	103	83
KRDMD	0.09670	1.16E-04	78	27	0.05087	1.38E-03	21	0
OTKAR	0.16020	1.69E-04	109	103	0.13236	1.62E-03	100	76
PETKM	0.12472	1.06E-04	94	39	0.09609	8.10E-04	61	9
PGSUS	0.17960	1.25E-04	109	103	0.15378	1.02E-03	104	78
SAHOL	0.17167	1.09E-04	108	99	0.15092	1.13E-03	109	86
SISE	0.14184	1.70E-04	106	76	0.10633	1.88E-03	95	40
TAVHL	0.17936	1.53E-04	109	103	0.15461	1.39E-03	107	84
TCELL	0.15140	1.42E-04	109	102	0.13117	1.33E-03	106	84
THYAO	0.08694	9.36E-05	103	62	0.07282	6.63E-04	101	54
TKFEN	0.14002	8.46E-05	101	54	0.10904	9.42E-04	72	19
TOASO	0.14426	1.58E-04	109	99	0.12337	1.54E-03	100	64
TTKOM	0.14311	1.00E-04	107	81	0.12540	1.31E-03	98	52
TUPRS	0.18215	1.27E-04	109	108	0.15701	1.10E-03	108	92
ULKER	0.12135	3.89E-07	108	95	0.09970	1.50E-03	99	55
VAKBN	0.09334	1.21E-04	108	76	0.07182	1.29E-03	99	47
YKBNK	0.09732	1.21E-04	108	79	0.07806	1.47E-03	93	54

Table 4.31: The result of fourth model based on level regression of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^N + \beta_2 \mathbf{OI}_{t,3}^N \mathbf{OI}_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^Q + \beta_2 \mathbf{OI}_{t,3}^Q \mathbf{OI}_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of Positive β_2	# Sig Positive β_2	Avg of R^2	Avg of β_2	# of Positive β_2	# Sig Positive β_2
ARCLK	0.15426	-1.05E-04	2	0	0.12724	-6.5E-04	18	0
BIMAS	0.14454	-2.84E-04	4	0	0.12016	-5.7E-04	19	0
DOAS	0.17035	-1.99E-04	1	0	0.14440	-6.01E-04	19	0
ENKAI	0.12764	-1.93E-04	18	3	0.11072	-4.5E-04	43	5
EREGL	0.13330	-6.13E-04	42	7	0.10126	4.4E-05	53	6
FROTO	0.13454	-1.82E-04	1	0	0.11782	-4.9E-04	24	2
GARAN	0.11266	-4.58E-04	14	0	0.08798	-7.5E-04	11	0
HALKB	0.14568	-8.29E-04	6	1	0.13461	-7.8E-04	6	0
ISCTR	0.09224	-9.1E-04	25	1	0.06819	-2.4E-04	46	4
KCHOL	0.17029	-1.7E-04	2	0	0.16312	-8.3E-04	6	0
KOZAL	0.16881	-2.6E-04	2	0	0.13486	-1.3E-04	12	1
KRDMD	0.09670	7.76E-04	67	19	0.05087	3.61E-03	100	43
OTKAR	0.16020	-1.5E-04	2	0	0.13236	-6.5E-04	20	2
PETKM	0.12472	-1.09E-04	48	6	0.09609	5.1E-04	74	23
PGSUS	0.17960	-7.18E-04	4	0	0.15378	-4.9E-04	17	1
SAHOL	0.17167	-6.57E-04	10	0	0.15092	-6.9E-04	7	0
SISE	0.14184	-1.91E-04	17	0	0.10633	-8.7E-04	36	1
TAVHL	0.17936	-8.35E-04	2	0	0.15461	-6.8E-04	16	2
TCELL	0.15140	-7.1E-04	3	0	0.13117	-7.01E-04	11	0
THYAO	0.08694	-6.68E-04	35	4	0.07282	-4.5E-04	24	3
TKFEN	0.14002	-2.93E-04	32	4	0.10904	9.87E-05	59	11
TOASO	0.14426	-1.27E-04	5	0	0.12337	-5.01E-04	25	4
TTKOM	0.14311	-8.21E-04	12	1	0.12540	-5.3E-04	28	5
TUPRS	0.18215	-5.72E-04	1	0	0.15701	-5.8E-04	9	0
ULKER	0.12135	-1.95E-04	3	0	0.09970	-5.1E-04	29	1
VAKBN	0.09334	-4.89E-04	16	0	0.07182	-6.9E-04	15	2
YKBNK	0.09732	-5.51E-04	14	0	0.07806	-7.5E-04	27	2

Table 4.32: The result of fourth model based on level regression of $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

4.3 Models Based on Order Flow Imbalances

A number of studies have been devoted on examining the relationship between stock order flow imbalance and stock returns. In particular, the stock order flow imbalance projects new information in the stock market and for this reason it is believed to have a notable impact on stock returns. In the following sections we are going to describe the models based on order flow imbalances in two approaches.

4.3.1 Models with Percentage Changes (Δ)

The Fig. 4.6 shows the basis of constructing models for ability of prediction of 1-min ahead return, using ΔOFI_t .

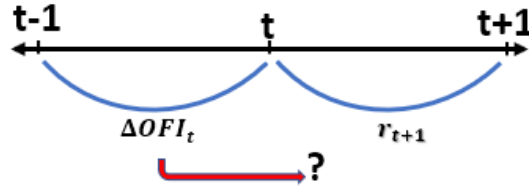


Figure 4.6: Power of prediction of ΔOFI_t in 1-minute ahead return

Then, the models with percentage changes formulas, ΔOFI^N and ΔOFI^Q , are as follows :

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^N + \epsilon_{t+1} \quad (4.22)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^Q + \epsilon_{t+1} \quad (4.23)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^N + \beta_2 r_t + \epsilon_{t+1} \quad (4.24)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^Q + \beta_2 r_t + \epsilon_{t+1} \quad (4.25)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^N + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.26)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^Q + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.27)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^N + \beta_2 \Delta OFI_t^N |\Delta OFI_t^N| + \epsilon_{t+1} \quad (4.28)$$

$$r_{t+1} = \beta_0 + \beta_1 \Delta OFI_t^Q + \beta_2 \Delta OFI_t^Q |\Delta OFI_t^Q| + \epsilon_{t+1} \quad (4.29)$$

These models are applied by MATLAB for all order flow imbalances that introduced in chapter 2. The Tables 4.33 to 4.47, are the results of models 4.22 to 4.29, in 109 days, for 27 companies stocks.

In this section except of $\Delta OFI_{t,2}^Q$, the result of other order flow imbalances are weak. For instance, In the model 4.23, **TTKOM** has 8 significant days out of 61 positive days with average $R^2 = 0.0041$.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00042	-2.48E-06	45	1	0.00118	-1.18E-08	54	0
BIMAS	0.00025	-1.95E-06	49	1	0.00155	-4.02E-08	54	0
DOAS	0.00008	-4.05E-06	38	0	0.00068	4.58E-08	54	4
ENKAI	0.00014	-2.13E-06	58	4	0.00100	7.00E-08	53	3
EREGL	0.00019	1.55E-06	51	4	0.00054	9.66E-08	56	1
FROTO	0.00049	-2.27E-06	49	1	0.00116	-2.88E-08	52	3
GARAN	0.00022	4.02E-07	53	4	0.00069	-1.10E-07	50	1
HALKB	0.00077	-1.31E-06	48	3	0.00053	-1.86E-08	51	1
ISCTR	0.00079	2.65E-06	68	6	0.00029	9.82E-08	67	3
KCHOL	0.00044	-1.06E-06	42	0	0.00133	-5.24E-08	57	0
KOZAL	0.00040	-2.05E-07	56	3	0.00113	-1.55E-07	53	0
KRDMD	0.00006	-7.17E-07	53	1	0.00067	1.45E-08	45	6
OTKAR	0.00009	-1.88E-06	43	4	0.00080	1.19E-08	64	3
PETKM	0.00011	-8.54E-08	54	2	0.00040	1.25E-07	54	3
PGSUS	0.00041	-8.34E-07	50	1	0.00123	-1.15E-08	52	1
SAHOL	0.00012	-1.48E-06	55	1	0.00121	5.06E-08	50	0
SISE	0.00035	-1.97E-06	49	3	0.00085	-2.26E-09	59	0
TAVHL	0.00021	-1.71E-06	44	3	0.00114	1.65E-07	61	1
TCELL	0.00010	-1.54E-06	50	4	0.00093	1.61E-08	62	3
THYAO	0.00044	-6.39E-07	49	4	0.00035	-2.27E-08	65	1
TKFEN	0.00045	1.60E-06	54	6	0.00035	1.11E-07	63	7
TOASO	0.00168	-3.83E-06	43	1	0.00090	1.19E-07	61	2
TTKOM	0.00032	-9.11E-07	45	2	0.00081	9.58E-08	60	0
TUPRS	0.00033	1.27E-08	56	1	0.00072	8.15E-08	54	2
ULKER	0.00010	-2.27E-06	57	2	0.00148	2.03E-08	54	1
VAKBN	0.00032	1.31E-06	56	7	0.00081	1.29E-07	56	0
YKBNK	0.00006	3.77E-06	66	7	0.00056	2.99E-08	62	1

Table 4.33: The result of first model using percentage changes of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^N + \beta_2 r_t + \epsilon_{t+1}}$			$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^Q + \beta_2 r_t + \epsilon_{t+1}}$		
	Avg of R^2	Avg of β_1	# of positive β_1	Avg of R^2	Avg of β_1	# of positive β_1
ARCLK	0.01986	-3.00E-06	40	0.01901	6.68E-09	62
BIMAS	0.01973	-2.27E-06	50	0.01843	-3.91E-08	48
DOAS	0.02544	-4.88E-06	34	0.02463	3.55E-08	52
ENKAI	0.04818	-1.49E-06	57	0.04691	1.12E-07	49
EREGL	0.10031	4.64E-07	51	0.09933	3.92E-08	58
FROTO	0.01409	-2.41E-06	51	0.01348	-2.43E-08	50
GARAN	0.07316	2.90E-07	53	0.07236	-6.66E-08	48
HALKB	0.04243	-1.51E-06	51	0.04116	-2.19E-08	48
ISCTR	0.10569	2.30E-06	69	0.10491	4.25E-08	55
KCHOL	0.01836	-1.91E-06	40	0.01733	-2.70E-08	51
KOZAL	0.02448	-1.30E-06	53	0.02353	-1.28E-07	47
KRDMD	0.16990	-1.17E-05	48	0.16996	-1.70E-08	55
OTKAR	0.02034	-2.55E-06	40	0.01947	-2.11E-08	62
PETKM	0.09777	-4.54E-06	43	0.09682	1.05E-07	52
PGSUS	0.02018	-7.98E-07	50	0.01933	-3.60E-08	49
SAHOL	0.03370	-1.48E-06	53	0.03266	3.51E-08	55
SISE	0.07157	-1.16E-06	51	0.07095	-9.77E-09	51
TAVHL	0.02389	-2.03E-06	47	0.02304	1.38E-07	63
TCELL	0.03322	-1.29E-06	51	0.03229	1.18E-08	59
THYAO	0.08915	-1.12E-06	51	0.08842	9.32E-09	61
TKFEN	0.06638	-5.12E-07	45	0.06592	9.41E-08	62
TOASO	0.02678	-3.96E-06	43	0.02534	1.15E-07	62
TTKOM	0.04171	-1.53E-06	45	0.04051	7.62E-08	61
TUPRS	0.02423	-5.21E-07	55	0.02374	7.79E-08	53
ULKER	0.02101	-2.68E-06	50	0.01933	7.09E-09	52
VAKBN	0.09854	1.22E-06	55	0.09753	1.16E-07	58
YKBNK	0.08842	3.21E-06	66	0.08779	3.65E-08	56

Table 4.34: The result of second model using percentage changes of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.03906	-2.99E-06	41	0	0.03804	-7.20E-09	52	1
BIMAS	0.03218	-1.48E-06	50	1	0.03088	-1.49E-08	51	1
DOAS	0.03960	-5.05E-06	35	1	0.03862	4.78E-08	59	2
ENKAI	0.07580	-1.47E-06	57	2	0.07482	9.10E-08	53	4
EREGL	0.14264	-5.59E-07	53	6	0.14127	4.11E-08	54	1
FROTO	0.03299	-2.52E-06	48	1	0.03240	-3.92E-09	50	3
GARAN	0.08706	2.98E-07	52	5	0.08621	-8.69E-08	52	1
HALKB	0.05084	-1.41E-06	51	2	0.04954	-2.68E-08	49	2
ISCTR	0.13629	2.35E-06	65	4	0.13576	3.44E-08	56	4
KCHOL	0.02974	-2.05E-06	43	1	0.02871	-2.75E-08	49	0
KOZAL	0.04526	-1.90E-06	54	1	0.04431	2.44E-08	52	0
KRDMD	0.27554	-1.75E-05	41	4	0.27489	-2.59E-08	52	5
OTKAR	0.03434	-3.32E-06	40	2	0.03337	-3.51E-08	61	2
PETKM	0.14032	-6.08E-06	43	2	0.13905	1.04E-07	60	4
PGSUS	0.02774	-1.01E-06	43	1	0.02712	-3.18E-08	47	0
SAHOL	0.04697	-1.83E-06	52	2	0.04585	3.59E-08	55	0
SISE	0.10774	-1.04E-06	50	3	0.10699	-2.07E-09	54	0
TAVHL	0.04056	-1.76E-06	49	3	0.03970	2.65E-08	59	1
TCELL	0.04581	-8.20E-07	53	3	0.04491	3.02E-08	57	2
THYAO	0.10821	-1.29E-06	51	2	0.10732	-5.25E-10	60	2
TKFEN	0.09584	-1.41E-06	46	6	0.09519	1.17E-07	60	4
TOASO	0.04156	-3.62E-06	44	1	0.04045	1.24E-07	59	3
TTKOM	0.05664	-1.32E-06	48	5	0.05536	7.65E-08	59	0
TUPRS	0.03259	-2.86E-07	50	2	0.03201	5.85E-08	52	2
ULKER	0.04089	-2.69E-06	51	1	0.03928	3.48E-09	47	1
VAKBN	0.12894	7.73E-07	51	6	0.12797	1.02E-07	53	1
YKBNK	0.11920	2.66E-06	59	8	0.11824	2.06E-08	57	1

Table 4.35: The result of third model using percentage changes of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^N + \beta_2 \Delta OFI_{t,1}^Q \Delta OFI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^Q + \beta_2 \Delta OFI_{t,1}^Q \Delta OFI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00078	-3.57E-06	52	1	0.00213	1.40E-07	50	1
BIMAS	0.00036	-7.38E-06	43	1	0.00278	5.02E-07	63	1
DOAS	0.00005	-7.88E-06	40	2	0.00186	2.63E-07	53	0
ENKAI	0.00061	3.55E-06	59	2	0.00183	-4.83E-07	57	0
EREGL	0.00026	3.21E-06	58	1	0.00097	-1.46E-07	55	0
FROTO	0.00001	-1.04E-06	49	3	0.00231	-1.91E-07	50	0
GARAN	0.00008	-5.19E-07	55	1	0.00113	2.29E-08	53	0
HALKB	0.00104	-2.19E-07	48	1	0.00121	-4.29E-08	68	1
ISCTR	0.00067	2.75E-06	58	3	0.00039	-2.19E-08	60	2
KCHOL	0.00047	-3.11E-06	39	2	0.00251	1.52E-07	65	0
KOZAL	0.00068	-7.19E-06	48	0	0.00204	1.20E-07	58	1
KRDMD	0.00049	5.27E-06	57	4	0.00099	-7.49E-07	49	1
OTKAR	0.00099	-1.86E-06	60	2	0.00173	5.96E-08	58	0
PETKM	0.00012	4.93E-07	53	3	0.00035	-7.82E-08	53	2
PGSUS	0.00052	-3.33E-06	50	0	0.00199	1.54E-07	55	1
SAHOL	0.00035	-6.15E-07	59	1	0.00212	-8.24E-08	57	1
SISE	0.00035	6.07E-07	57	2	0.00155	-3.12E-07	57	0
TAVHL	0.00004	-5.28E-06	42	2	0.00185	2.63E-07	61	1
TCELL	0.00038	1.07E-06	63	4	0.00182	-2.12E-07	58	1
THYAO	0.00030	-5.35E-07	54	2	0.00067	3.51E-08	40	0
TKFEN	0.00051	-1.24E-06	51	3	0.00020	2.94E-07	60	3
TOASO	0.00278	-7.42E-06	44	1	0.00155	4.26E-07	56	1
TTKOM	0.00071	5.16E-07	56	3	0.00153	-1.14E-07	63	2
TUPRS	0.00006	-3.05E-06	54	0	0.00154	1.77E-07	66	0
ULKER	0.00016	-2.67E-06	51	3	0.00259	8.14E-08	57	0
VAKBN	0.00096	1.98E-06	53	4	0.00109	2.80E-08	54	1
YKBNK	0.00002	6.10E-06	61	3	0.00087	-1.05E-07	56	1

Table 4.36: The result of fourth model using percentage changes of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^N + \beta_2 \Delta OFI_{t,1}^Q \Delta OFI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,1}^Q + \beta_2 \Delta OFI_{t,1}^Q \Delta OFI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig positive β_2	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig Positive β_2
ARCLK	0.00078	1.40E-07	61	1	0.00213	-9.17E-10	55	1
BIMAS	0.00036	5.02E-07	64	3	0.00278	-1.478E-09	54	0
DOAS	0.00005	2.63E-07	65	3	0.00186	1.84E-10	53	0
ENKAI	0.00061	-4.8E-07	46	1	0.00183	-6.23E-10	59	3
EREGL	0.00026	-1.47E-07	54	2	0.00097	-9.28E-10	44	3
FROTO	0.00001	-1.91E-07	59	2	0.00231	-2.80E-10	61	1
GARAN	0.00008	2.29E-08	57	1	0.00113	-5.74E-10	53	0
HALKB	0.00104	-4.23E-08	49	3	0.00121	-1.94E-09	54	1
ISCTR	0.00067	-2.17E-08	55	1	0.00039	-2.07E-09	56	1
KCHOL	0.00047	1.51E-07	66	4	0.00251	-3.41E-10	52	1
KOZAL	0.00068	1.19E-07	64	2	0.00204	2.22E-09	44	0
KRDMD	0.00049	-7.44E-07	52	6	0.00099	-8.29E-11	49	5
OTKAR	0.00099	5.96E-08	54	8	0.00173	3.65E-09	46	3
PETKM	0.00012	-7.89E-08	57	2	0.00035	-1.52E-09	50	0
PGSUS	0.00052	1.54E-07	62	5	0.00199	3.49E-10	58	0
SAHOL	0.00035	-8.23E-08	44	2	0.00212	-2.74E-10	49	0
SISE	0.00035	-3.14E-07	51	2	0.00155	6.68E-12	58	1
TAVHL	0.00004	2.62E-07	64	5	0.00185	-2.15E-09	53	2
TCELL	0.00038	-2.14E-07	48	7	0.00182	-1.31E-09	53	1
THYAO	0.00030	3.51E-08	46	3	0.00067	2.90E-09	53	1
TKFEN	0.00051	2.94E-07	61	5	0.00020	-1.58E-09	48	1
TOASO	0.00278	4.26E-07	63	3	0.00155	-2.21E-09	50	1
TTKOM	0.00071	-1.16E-07	49	4	0.00153	-4.22E-10	71	0
TUPRS	0.00006	1.77E-07	61	4	0.00154	-3.32E-09	50	1
ULKER	0.00016	8.13E-08	58	1	0.00259	-4.003E-10	55	0
VAKBN	0.00096	2.79E-08	58	4	0.00109	9.79E-10	49	2
YKBNK	0.00002	-1.05E-07	54	2	0.00087	-1.98E-10	45	3

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Table 4.37: The result of fourth model using percentage changes of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00048	-1.02E-07	56	0	0.00003	7.99E-08	48	6
BIMAS	0.00089	-2.71E-07	56	5	0.00028	-1.21E-08	46	1
DOAS	0.00031	-8.90E-07	45	2	0.00073	-1.68E-07	50	0
ENKAI	0.00037	1.87E-06	56	6	0.00082	-1.73E-07	42	2
EREGL	0.00042	2.22E-07	50	1	0.00003	-1.13E-07	58	4
FROTO	0.00018	-1.60E-07	54	3	0.00030	-1.93E-07	58	4
GARAN	0.00014	1.60E-08	58	1	0.00037	-1.36E-07	46	1
HALKB	0.00073	-1.46E-07	58	4	0.00031	1.95E-07	57	5
ISCTR	0.00040	-9.15E-08	56	3	0.00014	2.94E-07	64	2
KCHOL	0.00215	-3.58E-07	46	2	0.00050	1.64E-08	50	4
KOZAL	0.00006	-3.10E-06	44	2	0.00038	-2.54E-07	52	3
KRDMD	0.00007	7.81E-06	62	2	0.00013	-1.44E-08	63	5
OTKAR	0.00013	-1.31E-06	46	2	0.00126	-2.17E-07	63	4
PETKM	0.00015	-8.85E-07	57	1	0.00043	-1.55E-07	58	3
PGSUS	0.00014	-6.07E-07	44	4	0.00064	-3.62E-08	55	2
SAHOL	0.00028	3.15E-07	63	4	0.00055	4.35E-08	55	0
SISE	0.00033	1.65E-06	54	2	0.00002	-6.09E-08	55	3
TAVHL	0.00004	5.2E-07	57	5	0.00033	-1.90E-07	43	3
TCELL	0.00027	2E-07	58	4	0.00012	3.21E-08	61	6
THYAO	0.00014	3.81E-07	54	3	0.00020	-6.23E-08	54	2
TKFEN	0.00018	7.84E-07	54	4	0.00018	1.66E-07	50	3
TOASO	0.00090	3.38E-07	55	8	0.00029	1.73E-07	62	5
TTKOM	0.00071	2.41E-08	51	2	0.00034	1.44E-07	62	8
TUPRS	0.00068	-1.24E-07	56	0	0.00052	5.92E-08	57	1
ULKER	0.00083	-1.33E-06	51	2	0.00062	-7.50E-08	52	1
VAKBN	0.00118	1E-06	54	5	0.00038	7.68E-08	62	2
YKBNK	0.00023	4.01E-07	61	2	0.00006	-6.55E-08	50	3

Table 4.38: The result of first model using percentage changes of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.01983	1.23E-07	55	0	0.02016	6.52E-08	49	5
BIMAS	0.02075	4.39E-08	58	5	0.01969	-2.20E-08	49	1
DOAS	0.02502	-1.03E-06	44	1	0.02458	-1.98E-07	52	0
ENKAI	0.04808	1.77E-06	56	4	0.04711	-1.56E-07	44	1
EREGL	0.09951	6.95E-07	51	1	0.09956	-1.15E-07	57	0
FROTO	0.01439	-2.34E-07	56	4	0.01422	-1.79E-07	53	4
GARAN	0.07298	1.44E-07	60	1	0.07272	-1.58E-07	51	1
HALKB	0.04222	-8.70E-08	50	3	0.04151	1.66E-07	54	5
ISCTR	0.10542	-7.57E-08	54	3	0.10512	2.93E-07	64	2
KCHOL	0.02082	-4.15E-07	48	3	0.01814	-2.57E-09	49	3
KOZAL	0.02467	-3.01E-06	46	1	0.02434	-2.21E-07	49	4
KRDMD	0.16974	1.03E-05	68	7	0.16926	2.68E-08	60	5
OTKAR	0.02030	-1.48E-06	50	2	0.02160	-2.40E-07	62	3
PETKM	0.09737	-1.04E-06	54	3	0.09727	-1.34E-07	54	1
PGSUS	0.02033	-6.15E-07	42	4	0.01990	-6.93E-08	52	2
SAHOL	0.03367	3.84E-07	64	4	0.03332	6.33E-08	56	1
SISE	0.07147	1.46E-06	53	3	0.07167	-8.43E-08	61	2
TAVHL	0.02421	6.50E-07	56	5	0.02456	-2.14E-07	44	3
TCELL	0.03359	1.23E-08	58	5	0.03338	2.20E-08	65	7
THYAO	0.08891	2.92E-07	55	6	0.08852	-5.24E-08	57	2
TKFEN	0.06573	1.38E-07	56	5	0.06539	2.41E-07	61	3
TOASO	0.02739	5.99E-07	57	6	0.02660	1.66E-07	60	5
TTKOM	0.04062	2.35E-07	52	2	0.04129	1.77E-07	61	8
TUPRS	0.02365	-1.73E-07	55	0	0.02515	7.61E-08	59	1
ULKER	0.02145	-9.84E-07	52	3	0.02014	-9.31E-08	52	1
VAKBN	0.09885	1.81E-07	55	5	0.09786	1.58E-07	65	4
YKBNK	0.08846	2.87E-07	60	2	0.08828	-6.99E-08	50	1

Table 4.39: The result of second model using percentage changes of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.03907	5.30E-07	59	1	0.03926	-4.06E-10	51	5
BIMAS	0.03291	4.60E-07	52	4	0.03224	-4.23E-08	50	2
DOAS	0.03908	1.54E-07	51	1	0.03870	-2.42E-07	56	0
ENKAI	0.07583	1.55E-06	60	4	0.07502	-1.60E-07	48	1
EREGL	0.14171	8.00E-07	49	2	0.14166	-9.82E-08	55	2
FROTO	0.03337	5.06E-07	55	4	0.03336	-2.03E-07	54	5
GARAN	0.08676	7.54E-08	60	1	0.08662	-1.24E-07	50	2
HALKB	0.05058	-1.38E-07	48	4	0.04975	1.43E-07	56	5
ISCTR	0.13647	1.29E-07	56	4	0.13595	2.96E-07	65	2
KCHOL	0.03239	-3.97E-07	50	3	0.02957	-2.88E-09	48	2
KOZAL	0.04541	-2.63E-06	44	1	0.04521	-1.61E-07	46	4
KRDMD	0.27478	8.95E-06	60	7	0.27410	-1.03E-07	55	3
OTKAR	0.03427	-1.32E-06	50	3	0.03438	-3.22E-07	58	2
PETKM	0.13967	-7.37E-07	54	6	0.13935	-1.23E-07	56	2
PGSUS	0.02809	-5.84E-07	43	4	0.02769	-7.31E-08	55	2
SAHOL	0.04686	8.62E-08	62	4	0.04652	5.57E-08	54	1
SISE	0.10748	1.62E-06	54	1	0.10767	-8.97E-08	56	2
TAVHL	0.04091	8.07E-07	57	5	0.04113	-2.03E-07	46	2
TCELL	0.04615	2.31E-07	62	4	0.04609	1.35E-08	62	8
THYAO	0.10804	3.18E-07	58	7	0.10749	-8.07E-08	54	1
TKFEN	0.09513	-6.18E-07	56	4	0.09479	2.42E-07	59	2
TOASO	0.04248	7.10E-07	55	7	0.04164	1.95E-07	60	5
TTKOM	0.05563	3.25E-07	52	3	0.05616	1.76E-07	68	9
TUPRS	0.03183	-1.75E-08	56	0	0.03358	9.09E-08	62	1
ULKER	0.04150	-1.60E-06	51	3	0.04018	-1.36E-07	50	1
VAKBN	0.12934	2.71E-07	53	5	0.12823	1.33E-07	62	4
YKBNK	0.11878	2.24E-07	58	1	0.11882	-9.79E-08	46	1

Table 4.40: The result of third model using percentage changes of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^N + \beta_2 \Delta OFI_{t,2}^N \Delta OFI_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^Q + \beta_2 \Delta OFI_{t,2}^Q \Delta OFI_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00079	-7.65E-07	52	0	0.00022	1.59E-08	63	4
BIMAS	0.00154	-2.66E-06	56	4	0.00075	3.88E-07	51	3
DOAS	0.00040	-2.37E-06	50	4	0.00059	3.95E-08	57	1
ENKAI	0.00000	5.01E-07	53	2	0.00105	1.28E-07	61	1
EREGL	0.00041	2.04E-06	61	2	0.00014	5.28E-09	45	3
FROTO	0.00022	-3.81E-06	48	1	0.00008	1.86E-07	57	6
GARAN	0.00004	1.24E-06	58	2	0.00037	-1.91E-08	62	1
HALKB	0.00053	1.16E-07	59	3	0.00051	-1.52E-08	57	1
ISCTR	0.00035	3.58E-07	50	2	0.00033	-1.39E-08	53	2
KCHOL	0.00275	-3.03E-06	45	0	0.00021	8.66E-08	57	8
KOZAL	0.00016	-5.16E-06	41	1	0.00081	7.31E-08	54	1
KRDMD	0.00047	1.31E-05	58	6	0.00054	-6.71E-08	54	1
OTKAR	0.00007	-3.73E-06	47	2	0.00163	1.76E-07	44	3
PETKM	0.00009	6.96E-07	54	2	0.00090	-4.90E-08	48	4
PGSUS	0.00021	-1.41E-06	49	1	0.00109	-3.01E-09	53	2
SAHOL	0.00021	1.03E-06	65	5	0.00074	-3.23E-09	56	4
SISE	0.00034	3.88E-06	63	1	0.00021	1.22E-07	60	2
TAVHL	0.00005	3.66E-08	56	1	0.00031	2.20E-08	51	0
TCELL	0.00058	7.35E-07	52	3	0.00013	-6.29E-08	60	2
THYAO	0.00055	1.66E-07	54	2	0.00056	2.84E-09	58	1
TKFEN	0.00023	-4.01E-07	54	2	0.00058	1.37E-07	56	2
TOASO	0.00245	-1.54E-06	56	5	0.00059	-2.07E-08	51	0
TTKOM	0.00087	1.20E-06	49	4	0.00037	-1.00E-07	57	3
TUPRS	0.00105	-7.50E-07	56	0	0.00054	1.97E-08	43	2
ULKER	0.00242	-2.59E-06	52	3	0.00069	6.82E-09	50	2
VAKBN	0.00163	-1.19E-06	52	2	0.00049	2.25E-08	46	4
YKBNK	0.00061	4.37E-06	65	2	0.00019	-1.22E-07	56	4

Table 4.41: The result of fourth model using percentage changes of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^N + \beta_2 \Delta OFI_{t,2}^N \Delta OFI_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,2}^Q + \beta_2 \Delta OFI_{t,2}^Q \Delta OFI_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig positive β_2	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig Positive β_2
ARCLK	0.00079	8.52E-08	52	8	0.00022	1.59E-08	47	2
BIMAS	0.00154	3.58E-09	52	6	0.00075	3.88E-07	57	2
DOAS	0.00040	9.62E-07	60	8	0.00059	3.95E-08	58	4
ENKAI	0.00000	2.63E-07	62	10	0.00105	1.28E-07	45	1
EREGL	0.00041	-9.18E-08	57	2	0.00014	5.28E-09	57	2
FROTO	0.00022	3.85E-07	53	6	0.00008	1.86E-07	48	3
GARAN	0.00004	1.48E-08	57	3	0.00037	-1.91E-08	51	2
HALKB	0.00053	2.77E-08	50	2	0.00051	-1.52E-08	49	1
ISCTR	0.00035	-1.67E-08	51	4	0.00033	-1.39E-08	56	4
KCHOL	0.00275	2.28E-07	54	7	0.00021	8.66E-08	40	2
KOZAL	0.00016	-2.72E-08	60	1	0.00081	7.31E-08	59	4
KRDMD	0.00047	-1.85E-06	46	5	0.00054	-6.71E-08	59	5
OTKAR	0.00007	-9.76E-08	57	2	0.00163	1.76E-07	54	1
PETKM	0.00009	7.10E-08	56	3	0.00090	-4.90E-08	56	4
PGSUS	0.00021	-8.63E-08	54	3	0.00109	-3.01E-09	49	1
SAHOL	0.00021	-7.82E-08	51	10	0.00074	-3.23E-09	55	0
SISE	0.00034	-5.19E-07	48	6	0.00021	1.22E-07	52	7
TAVHL	0.00005	1.47E-07	51	6	0.00031	2.20E-08	59	2
TCELL	0.00058	-3.19E-07	52	3	0.00013	-6.29E-08	56	4
THYAO	0.00055	1.25E-08	57	4	0.00056	2.84E-09	51	2
TKFEN	0.00023	-5.73E-07	51	6	0.00058	1.37E-07	44	7
TOASO	0.00245	-8.67E-07	48	7	0.00059	-2.07E-08	43	1
TTKOM	0.00087	2.75E-08	54	3	0.00037	-1.00E-07	50	2
TUPRS	0.00105	-3.00E-08	59	5	0.00054	1.97E-08	56	2
ULKER	0.00242	-5.27E-07	51	4	0.00069	6.82E-09	59	7
VAKBN	0.00163	-2.20E-07	54	5	0.00049	2.25E-08	57	1
YKBNK	0.00061	-1.23E-07	54	8	0.00019	-1.22E-07	55	4

Table 4.42: The result of fourth model using percentage changes of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00048	-1.03E-07	56	0	0.00003	7.99E-08	48	6
BIMAS	0.00089	-2.72E-07	56	5	0.00028	-1.21E-08	46	1
DOAS	0.00031	-8.90E-07	45	2	0.00073	-1.68E-07	50	0
ENKAI	0.00037	1.87E-06	56	6	0.00082	-1.73E-07	42	2
EREGL	0.00042	2.23E-07	50	1	0.00003	-1.13E-07	58	4
FROTO	0.00018	-1.60E-07	54	3	0.00030	-1.93E-07	58	4
GARAN	0.00014	1.60E-08	58	1	0.00037	-1.36E-07	46	1
HALKB	0.00073	-1.46E-07	58	4	0.00031	1.95E-07	57	5
ISCTR	0.00040	-9.15E-08	56	3	0.00014	2.94E-07	64	2
KCHOL	0.00215	-3.59E-07	46	2	0.00050	1.64E-08	50	4
KOZAL	0.00006	-3.11E-06	44	2	0.00038	-2.54E-07	52	3
KRDMD	0.00007	7.81E-06	62	2	0.00013	-1.44E-08	63	5
OTKAR	0.00013	-1.32E-06	46	2	0.00126	-2.17E-07	63	4
PETKM	0.00015	-8.86E-07	57	1	0.00043	-1.55E-07	58	3
PGSUS	0.00014	-6.07E-07	44	4	0.00064	-3.62E-08	55	2
SAHOL	0.00028	3.15E-07	63	4	0.00055	4.35E-08	55	0
SISE	0.00033	1.66E-06	54	2	0.00002	-6.09E-08	55	3
TAVHL	0.00004	5.20E-07	57	5	0.00033	-1.90E-07	43	3
TCELL	0.00027	2.00E-07	58	4	0.00012	3.21E-08	61	6
THYAO	0.00014	3.82E-07	54	3	0.00020	-6.23E-08	54	2
TKFEN	0.00018	7.85E-07	54	4	0.00018	1.66E-07	50	3
TOASO	0.00090	3.38E-07	55	8	0.00029	1.73E-07	62	5
TTKOM	0.00071	2.41E-08	51	2	0.00034	1.44E-07	62	8
TUPRS	0.00068	-1.24E-07	56	0	0.00052	5.92E-08	57	1
ULKER	0.00083	-1.34E-06	51	2	0.00062	-7.50E-08	52	1
VAKBN	0.00118	1.00E-06	54	5	0.00038	7.68E-08	62	2
YKBNK	0.00023	4.01E-07	61	2	0.00006	-6.55E-08	50	3

Table 4.43: The result of first model using percentage changes of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^N + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$			$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^Q + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$		
	Avg of R^2	Avg of β_1	# of positive β_1	Avg of R^2	Avg of β_1	# of positive β_1
ARCLK	0.01983	1.23E-07	55	0.02016	6.52E-08	49
BIMAS	0.02075	4.39E-08	58	0.01969	-2.20E-08	49
DOAS	0.02502	-1.03E-06	44	0.02458	-1.98E-07	52
ENKAI	0.04808	1.77E-06	56	0.04711	-1.56E-07	44
EREGL	0.09951	6.95E-07	51	0.09956	-1.15E-07	57
FROTO	0.01439	-2.34E-07	56	0.01422	-1.79E-07	53
GARAN	0.07298	1.44E-07	60	0.07272	-1.58E-07	51
HALKB	0.04222	-8.70E-08	50	0.04151	1.66E-07	54
ISCTR	0.10542	-7.57E-08	54	0.10512	2.93E-07	64
KCHOL	0.02082	-4.15E-07	48	0.01814	-2.57E-09	49
KOZAL	0.02467	-3.01E-06	46	0.02434	-2.21E-07	49
KRDMD	0.16974	1.03E-05	68	0.16926	2.68E-08	60
OTKAR	0.02030	-1.48E-06	50	0.02160	-2.40E-07	62
PETKM	0.09737	-1.04E-06	54	0.09727	-1.34E-07	54
PGSUS	0.02033	-6.15E-07	42	0.01990	-6.93E-08	52
SAHOL	0.03367	3.84E-07	64	0.03332	6.33E-08	56
SISE	0.07147	1.46E-06	53	0.07167	-8.43E-08	61
TAVHL	0.02421	6.50E-07	56	0.02456	-2.14E-07	44
TCELL	0.03359	1.23E-08	58	0.03338	2.20E-08	65
THYAO	0.08891	2.92E-07	55	0.08852	-5.24E-08	57
TKFEN	0.06573	1.38E-07	56	0.06539	2.41E-07	61
TOASO	0.02739	5.99E-07	57	0.02660	1.66E-07	60
TTKOM	0.04062	2.35E-07	52	0.04129	1.77E-07	61
TUPRS	0.02365	-1.73E-07	55	0.02515	7.61E-08	59
ULKER	0.02145	-9.84E-07	52	0.02014	-9.31E-08	52
VAKBN	0.09885	1.81E-07	55	0.09786	1.58E-07	65
YKBNK	0.08846	2.87E-07	60	0.08828	-6.99E-08	50

Table 4.44: The result of second model using percentage changes of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.03907	5.30E-07	59	1	0.03926	-4.06E-10	51	5
BIMAS	0.03291	4.60E-07	52	4	0.03224	-4.23E-08	50	2
DOAS	0.03908	1.54E-07	51	1	0.03870	-2.42E-07	56	0
ENKAI	0.07583	1.55E-06	60	4	0.07502	-1.60E-07	48	1
EREGL	0.14171	8.00E-07	49	2	0.14166	-9.82E-08	55	2
FROTO	0.03337	5.06E-07	55	4	0.03336	-2.03E-07	54	5
GARAN	0.08676	7.54E-08	60	1	0.08662	-1.24E-07	50	2
HALKB	0.05058	-1.38E-07	48	4	0.04975	1.43E-07	56	5
ISCTR	0.13647	1.29E-07	56	4	0.13595	2.96E-07	65	2
KCHOL	0.03239	-3.97E-07	50	3	0.02957	-2.88E-09	48	2
KOZAL	0.04541	-2.63E-06	44	1	0.04521	-1.61E-07	46	4
KRDMD	0.27478	8.95E-06	60	7	0.27410	-1.03E-07	55	3
OTKAR	0.03427	-1.32E-06	50	3	0.03438	-3.22E-07	58	2
PETKM	0.13967	-7.37E-07	54	6	0.13935	-1.23E-07	56	2
PGSUS	0.02809	-5.84E-07	43	4	0.02769	-7.31E-08	55	2
SAHOL	0.04686	8.62E-08	62	4	0.04652	5.57E-08	54	1
SISE	0.10748	1.62E-06	54	1	0.10767	-8.97E-08	56	2
TAVHL	0.04091	8.07E-07	57	5	0.04113	-2.03E-07	46	2
TCELL	0.04615	2.31E-07	62	4	0.04609	1.35E-08	62	8
THYAO	0.10804	3.18E-07	58	7	0.10749	-8.07E-08	54	1
TKFEN	0.09513	-6.18E-07	56	4	0.09479	2.42E-07	59	2
TOASO	0.04248	7.10E-07	55	7	0.04164	1.95E-07	60	5
TTKOM	0.05563	3.25E-07	52	3	0.05616	1.76E-07	68	9
TUPRS	0.03183	-1.75E-08	56	0	0.03358	9.09E-08	62	1
ULKER	0.04150	-1.60E-06	51	3	0.04018	-1.36E-07	50	1
VAKBN	0.12934	2.71E-07	53	5	0.12823	1.33E-07	62	4
YKBNK	0.11878	2.24E-07	58	1	0.11882	-9.79E-08	46	1

Table 4.45: The result of third model using percentage changes of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^N + \beta_2 \Delta OFI_{t,3}^N \Delta OFI_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^Q + \beta_2 \Delta OFI_{t,3}^Q \Delta OFI_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00079	-7.65E-07	52	0	0.00022	1.59E-08	63	4
BIMAS	0.00154	-2.66E-06	56	4	0.00075	3.88E-07	51	3
DOAS	0.00040	-2.37E-06	50	4	0.00059	3.95E-08	57	1
ENKAI	0.00000	5.01E-07	53	2	0.00105	1.28E-07	61	1
EREGL	0.00041	2.04E-06	61	2	0.00014	5.28E-09	45	3
FROTO	0.00022	-3.81E-06	48	1	0.00008	1.86E-07	57	6
GARAN	0.00004	1.24E-06	58	2	0.00037	-1.91E-08	62	1
HALKB	0.00053	1.16E-07	59	3	0.00051	-1.52E-08	57	1
ISCTR	0.00035	3.58E-07	50	2	0.00033	-1.39E-08	53	2
KCHOL	0.00275	-3.03E-06	45	0	0.00021	8.66E-08	57	8
KOZAL	0.00016	-5.16E-06	41	1	0.00081	7.31E-08	54	1
KRDMD	0.00047	1.31E-05	58	6	0.00054	-6.71E-08	54	1
OTKAR	0.00007	-3.73E-06	47	2	0.00163	1.76E-07	44	3
PETKM	0.00009	6.96E-07	54	2	0.00090	-4.90E-08	48	4
PGSUS	0.00021	-1.41E-06	49	1	0.00109	-3.01E-09	53	2
SAHOL	0.00021	1.03E-06	65	5	0.00074	-3.23E-09	56	4
SISE	0.00034	3.88E-06	63	1	0.00021	1.22E-07	60	2
TAVHL	0.00005	3.66E-08	56	1	0.00031	2.20E-08	51	0
TCELL	0.00058	7.35E-07	52	3	0.00013	-6.29E-08	60	2
THYAO	0.00055	1.66E-07	54	2	0.00056	2.84E-09	58	1
TKFEN	0.00023	-4.01E-07	54	2	0.00058	1.37E-07	56	2
TOASO	0.00245	-1.54E-06	56	5	0.00059	-2.07E-08	51	0
TTKOM	0.00087	1.20E-06	49	4	0.00037	-1.00E-07	57	3
TUPRS	0.00105	-7.50E-07	56	0	0.00054	1.97E-08	43	2
ULKER	0.00242	-2.59E-06	52	3	0.00069	6.82E-09	50	2
VAKBN	0.00163	-1.19E-06	52	2	0.00049	2.25E-08	46	4
YKBNK	0.00061	4.37E-06	65	2	0.00019	-1.22E-07	56	4

Table 4.46: The result of fourth model using percentage changes of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^N + \beta_2 \Delta OFI_{t,3}^N \Delta OFI_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta OFI_{t,3}^Q + \beta_2 \Delta OFI_{t,3}^Q \Delta OFI_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig positive β_2	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig Positive β_2
ARCLK	0.00079	1.59E-08	51	2	0.00022	1.23E-09	63	5
BIMAS	0.00154	3.88E-07	53	7	0.00075	-4.67E-10	51	0
DOAS	0.00040	3.95E-08	54	2	0.00059	-3.88E-10	57	4
ENKAI	0.00000	1.27E-07	50	3	0.00105	1.16E-09	61	3
EREGL	0.00041	5.27E-09	48	2	0.00014	5.83E-10	45	3
FROTO	0.00022	1.85E-07	64	6	0.00008	7.20E-09	57	4
GARAN	0.00004	-1.91E-08	46	2	0.00037	9.86E-10	62	5
HALKB	0.00053	-1.59E-08	57	2	0.00051	4.11E-10	57	3
ISCTR	0.00035	-1.30E-08	59	4	0.00033	7.05E-10	53	0
KCHOL	0.00275	8.65E-08	59	6	0.00021	-4.18E-10	57	4
KOZAL	0.00016	7.30E-08	57	4	0.00081	-6.70E-09	54	1
KRDMD	0.00047	-6.75E-08	54	3	0.00054	7.22E-09	54	5
OTKAR	0.00007	1.76E-07	55	2	0.00163	-1.84E-09	44	2
PETKM	0.00009	-4.89E-08	51	3	0.00090	-7.49E-10	48	3
PGSUS	0.00021	-3.06E-09	62	2	0.00109	-3.07E-10	53	3
SAHOL	0.00021	-3.28E-09	46	3	0.00074	-4.14E-10	56	3
SISE	0.00034	1.22E-07	45	3	0.00021	-4.27E-09	60	5
TAVHL	0.00005	2.20E-08	55	6	0.00031	2.00E-09	51	5
TCELL	0.00058	-6.25E-08	57	2	0.00013	3.83E-10	60	3
THYAO	0.00055	2.84E-09	59	2	0.00056	-4.54E-10	58	3
TKFEN	0.00023	1.37E-07	59	2	0.00058	-3.44E-09	56	1
TOASO	0.00245	-2.06E-08	60	5	0.00059	1.77E-09	51	5
TTKOM	0.00087	-9.99E-08	52	2	0.00037	1.14E-09	57	5
TUPRS	0.00105	1.96E-08	51	0	0.00054	-1.16E-09	43	3
ULKER	0.00242	6.81E-09	59	8	0.00069	6.79E-10	50	4
VAKBN	0.00163	2.24E-08	66	5	0.00049	-1.20E-09	46	2
YKBNK	0.00061	-1.28E-07	43	2	0.00019	-2.66E-09	56	4

Table 4.47: The result of fourth model using percentage changes of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

4.3.2 Models based on Level Regression

In this part we will show the models based on order flow imbalances without using percentage changes. The Fig. 4.7 shows the basis of constructing models for ability of prediction of 1-min ahead return, using OFI_t .

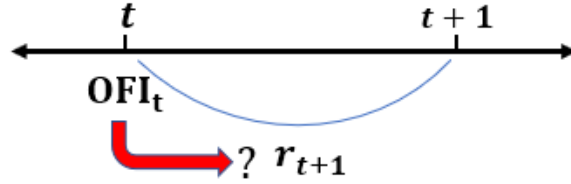


Figure 4.7: Power of prediction of OFI_t in 1-minute ahead return

Then we substitute (2.17) to (2.22) in these models to get the results.

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^N + \epsilon_{t+1} \quad (4.30)$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^Q + \epsilon_{t+1} \quad (4.31)$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^N + \beta_2 r_t + \epsilon_{t+1} \quad (4.32)$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^Q + \beta_2 r_t + \epsilon_{t+1} \quad (4.33)$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^N + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.34)$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^Q + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1} \quad (4.35)$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^N + \beta_2 OFI_t^N |OFI_t^N| + \epsilon_{t+1} \quad (4.36)$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_t^Q + \beta_2 OFI_t^Q |OFI_t^Q| + \epsilon_{t+1} \quad (4.37)$$

The Tables 4.48 to 4.62, include Average of adjusted R squared, average of coefficients, number of the days that the sign of coefficient is positive and the number of significant positive coefficients in the level of $\alpha = 0.05$.

Similar to the models based on order imbalances without applying percentage changes formula, the results are almost strong here, except of following ones which in

them even the number of positive days for all OFIs are so rare and in average around 30 days out 109 days.

$$r_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \epsilon_{t+1}$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \beta_2 r_t + \epsilon_{t+1}$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} r_{t-j} + \epsilon_{t+1}$$

$$r_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^N + \beta_2 OFI_{t,2}^N |OFI_{t,2}^N| + \epsilon_{t+1}$$

4.4 Conclusion

In this chapter, by testing OIs and OFIs in various structures we try to see whether if they can forecast 1-min ahead returns or not. Also for robustness, we estimated several models. When we use the level values of OI, with using percentage change except of $OI_{t,2}^N$, in model 4.8, all of them have acceptable performance. Moreover models without using percentage change have the better results. In OFI based models, those ones with using level regression are completely successful in comparison to models with percentage change in forecasting. However, the $OFI_{t,2}^N$ has the weakest performance in OFIs.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.21489	6.13E-05	109	109	0.14821	3.86E-08	109	109
BIMAS	0.24363	6.00E-05	109	109	0.12415	5.52E-08	107	105
DOAS	0.23565	6.03E-05	109	109	0.18523	4.56E-08	109	109
ENKAI	0.16977	8.16E-05	109	109	0.08213	1.49E-08	109	108
EREGL	0.12473	4.26E-05	109	109	0.10593	3.53E-09	109	109
FROTO	0.17666	5.29E-05	109	108	0.13214	1.24E-07	108	107
GARAN	0.15735	9.03E-06	109	109	0.25679	7.40E-10	109	109
HALKB	0.19278	1.43E-05	109	109	0.27689	3.02E-09	109	109
ISCTR	0.10581	1.73E-05	109	108	0.13953	1.33E-09	109	109
KCHOL	0.20640	4.12E-05	109	109	0.20799	1.63E-08	109	109
KOZAL	0.25642	7.50E-05	109	109	0.19478	1.40E-07	109	109
KRDMD	0.02450	3.82E-05	108	90	0.03338	7.65E-10	104	91
OTKAR	0.25632	5.95E-05	109	109	0.15558	2.43E-07	109	109
PETKM	0.11976	4.34E-05	109	109	0.07212	3.12E-09	109	104
PGSUS	0.25451	3.40E-05	109	109	0.21700	3.60E-08	109	109
SAHOL	0.22496	3.27E-05	109	107	0.19320	6.53E-09	109	108
SISE	0.16499	8.15E-05	109	109	0.12378	1.18E-08	109	109
TAVHL	0.25040	4.76E-05	109	108	0.19711	4.83E-08	109	109
TCELL	0.19117	4.06E-05	109	109	0.16304	1.44E-08	109	109
THYAO	0.12325	9.01E-06	109	109	0.19865	1.07E-09	109	109
TKFEN	0.12575	4.61E-05	109	109	0.10955	8.90E-09	109	108
TOASO	0.18676	5.82E-05	109	108	0.13676	6.27E-08	109	109
TTKOM	0.18857	5.54E-05	109	109	0.13227	1.41E-08	109	109
TUPRS	0.25438	2.85E-05	109	109	0.20022	4.16E-08	109	108
ULKER	0.17375	6.81E-05	109	109	0.09775	5.13E-08	109	106
VAKBN	0.08497	1.75E-05	109	108	0.17230	2.00E-09	109	108
YKBNK	0.10002	2.72E-05	109	109	0.14252	2.92E-09	109	109

Table 4.48: The result of first model based on level regression of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^N + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^Q + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.24002	6.21E-05	109	109	0.17055	3.90E-08	109	109
BIMAS	0.26839	6.08E-05	109	109	0.14531	5.48E-08	107	105
DOAS	0.26951	6.15E-05	109	109	0.21359	4.60E-08	109	109
ENKAI	0.22937	8.52E-05	109	109	0.13473	1.55E-08	109	108
EREGL	0.23766	4.52E-05	109	109	0.21016	3.62E-09	109	109
FROTO	0.19605	5.38E-05	109	108	0.14720	1.25E-07	108	107
GARAN	0.25628	9.82E-06	109	109	0.33606	7.52E-10	109	109
HALKB	0.25449	1.51E-05	109	109	0.32469	3.06E-09	109	109
ISCTR	0.22533	1.85E-05	109	108	0.24602	1.34E-09	109	109
KCHOL	0.23302	4.21E-05	109	109	0.22669	1.64E-08	109	109
KOZAL	0.28795	7.65E-05	109	109	0.21902	1.40E-07	109	109
KRDMD	0.19720	4.08E-05	109	97	0.20441	7.93E-10	104	98
OTKAR	0.28794	6.13E-05	109	109	0.18080	2.49E-07	109	109
PETKM	0.23159	4.62E-05	109	109	0.17351	3.23E-09	108	107
PGSUS	0.28487	3.48E-05	109	109	0.24314	3.66E-08	109	109
SAHOL	0.27284	3.39E-05	109	107	0.23062	6.60E-09	109	108
SISE	0.24780	8.45E-05	109	109	0.19811	1.20E-08	109	109
TAVHL	0.28031	4.84E-05	109	108	0.22305	4.87E-08	109	109
TCELL	0.23230	4.15E-05	109	109	0.19802	1.46E-08	109	109
THYAO	0.23552	9.87E-06	109	109	0.29516	1.09E-09	109	109
TKFEN	0.20507	4.87E-05	109	109	0.18263	9.26E-09	109	108
TOASO	0.21954	5.93E-05	109	108	0.16443	6.28E-08	109	109
TTKOM	0.24010	5.70E-05	109	109	0.17680	1.43E-08	109	109
TUPRS	0.28582	2.89E-05	109	109	0.22695	4.17E-08	109	108
ULKER	0.19958	6.94E-05	109	109	0.12010	5.19E-08	109	106
VAKBN	0.19689	1.89E-05	109	109	0.27213	2.02E-09	109	108
YKBNK	0.20337	2.92E-05	109	109	0.23350	2.96E-09	109	109

Table 4.49: The result of second model based on level regression of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.25956	6.16E-05	109	109	0.18952	3.85E-08	109	108
BIMAS	0.28213	6.03E-05	109	109	0.16013	5.39E-08	107	104
DOAS	0.28659	6.14E-05	109	109	0.22885	4.62E-08	109	109
ENKAI	0.25830	8.51E-05	109	109	0.16289	1.58E-08	109	106
EREGL	0.28264	4.59E-05	109	109	0.25039	3.59E-09	109	109
FROTO	0.21488	5.34E-05	109	108	0.16516	1.24E-07	108	106
GARAN	0.27956	1.01E-05	109	109	0.34800	7.51E-10	109	109
HALKB	0.26879	1.53E-05	109	109	0.33396	3.06E-09	109	109
ISCTR	0.26914	1.96E-05	109	108	0.27684	1.34E-09	109	109
KCHOL	0.24729	4.22E-05	109	109	0.23663	1.62E-08	109	109
KOZAL	0.30960	7.57E-05	109	109	0.23707	1.38E-07	109	109
KRDMD	0.30540	4.35E-05	109	102	0.30644	7.76E-10	104	97
OTKAR	0.30533	6.12E-05	109	109	0.19427	2.50E-07	109	109
PETKM	0.28195	4.78E-05	109	109	0.21617	3.27E-09	108	107
PGSUS	0.29451	3.49E-05	109	109	0.25123	3.67E-08	109	109
SAHOL	0.29042	3.42E-05	109	108	0.24313	6.62E-09	109	109
SISE	0.28815	8.55E-05	109	109	0.23058	1.18E-08	109	109
TAVHL	0.29749	4.83E-05	109	108	0.24238	4.88E-08	109	109
TCELL	0.24714	4.16E-05	109	109	0.21185	1.47E-08	109	109
THYAO	0.26489	1.03E-05	109	109	0.31244	1.09E-09	109	109
TKFEN	0.23977	4.98E-05	109	109	0.21245	9.37E-09	109	109
TOASO	0.23497	5.89E-05	109	109	0.18056	6.26E-08	109	109
TTKOM	0.25728	5.72E-05	109	109	0.19049	1.42E-08	109	109
TUPRS	0.29379	2.88E-05	109	109	0.23307	4.12E-08	109	108
ULKER	0.22127	6.90E-05	109	109	0.14022	5.12E-08	109	106
VAKBN	0.23948	2.01E-05	109	109	0.30082	2.01E-09	109	108
YKBNK	0.24621	3.08E-05	109	109	0.26327	2.96E-09	109	109

Table 4.50: The result of third model based on level regression of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^N + \beta_2 OFI_{t,1}^N OFI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^Q + \beta_2 OFI_{t,1}^Q OFI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.23670	7.35E-05	109	105	0.17404	5.33E-08	109	109
BIMAS	0.25976	6.81E-05	109	109	0.15523	9.23E-08	109	108
DOAS	0.25593	7.24E-05	109	109	0.20314	5.90E-08	109	109
ENKAI	0.18914	1.03E-04	109	107	0.09870	1.98E-08	107	95
EREGL	0.14055	6.26E-05	109	109	0.11452	4.40E-09	109	105
FROTO	0.20245	6.78E-05	109	108	0.15872	1.90E-07	109	106
GARAN	0.17293	1.21E-05	109	109	0.26260	8.55E-10	109	108
HALKB	0.20675	1.93E-05	109	109	0.28722	3.70E-09	109	109
ISCTR	0.11718	2.48E-05	109	108	0.90193	3.42E-09	109	107
KCHOL	0.23531	5.42E-05	109	108	0.23025	2.18E-08	109	109
KOZAL	0.27540	9.61E-05	109	109	0.22610	2.01E-07	109	108
KRDMD	0.03437	7.94E-05	109	89	0.54341	-7.05E-08	73	22
OTKAR	0.27257	6.90E-05	109	107	0.19103	3.81E-07	108	105
PETKM	0.13157	5.98E-05	109	106	0.08495	4.25E-09	108	98
PGSUS	0.27193	3.99E-05	109	108	0.23917	5.02E-08	109	109
SAHOL	0.24621	4.27E-05	109	108	0.20690	8.33E-09	109	108
SISE	0.18541	1.16E-04	109	109	0.13363	1.36E-08	109	98
TAVHL	0.26996	5.50E-05	109	108	0.21578	6.04E-08	109	107
TCELL	0.21329	5.14E-05	109	107	0.18457	1.89E-08	109	108
THYAO	0.13182	1.20E-05	107	104	0.20388	1.17E-09	109	106
TKFEN	0.15071	7.29E-05	109	108	0.11669	1.07E-08	109	102
TOASO	0.20735	6.91E-05	109	107	0.16195	8.87E-08	109	107
TTKOM	0.20592	7.10E-05	108	108	0.14366	1.62E-08	108	101
TUPRS	0.27063	3.40E-05	109	108	0.22389	5.61E-08	109	108
ULKER	0.18917	8.30E-05	109	109	0.12308	7.71E-08	108	107
VAKBN	0.10021	2.78E-05	109	106	0.18163	2.61E-09	109	104
YKBNK	0.11209	4.00E-05	109	108	0.15129	3.70E-09	109	105

Table 4.51: The result of fourth model based on level regression of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^N + \beta_2 OFI_{t,1}^N OFI_{t,1}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,1}^Q + \beta_2 OFI_{t,1}^Q OFI_{t,1}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig positive β_2	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig Positive β_2
ARCLK	0.23670	-3.90e-07	33	13	0.17404	-3.72e-13	23	4
BIMAS	0.25976	-2.22e-07	39	12	0.15523	-1.86e-12	14	4
DOAS	0.25593	-4.31e-07	21	5	0.20314	-4.16e-13	18	2
ENKAI	0.18914	-8.06e-07	23	6	0.09870	-4.90e-14	34	13
EREGL	0.14055	-4.19e-07	6	1	0.11452	-1.56e-15	33	7
FROTO	0.20245	-3.85e-07	26	9	0.15872	-7.34e-12	12	1
GARAN	0.17293	-2.48e-08	20	3	0.26260	-7.00e-17	25	5
HALKB	0.20675	-6.87e-08	13	0	0.28722	-1.82e-15	15	3
ISCTR	0.11718	-9.89e-08	10	1	0.90193	-7.88e-16	18	1
KCHOL	0.23531	-2.83e-07	13	4	0.23025	-6.58e-14	20	4
KOZAL	0.27540	-5.36e-07	18	6	0.22610	-3.08e-12	11	3
KRDMD	0.03437	-6.31e-07	8	0	0.54341	5.630-15	69	23
OTKAR	0.27257	-2.66e-07	31	11	0.19103	-2.31e-11	12	5
PETKM	0.13157	-4.69e-07	24	5	0.08495	-2.13e-15	27	4
PGSUS	0.27193	-1.47e-07	26	6	0.23917	-5.53e-13	16	5
SAHOL	0.24621	-2.43e-07	16	1	0.20690	-1.30e-14	25	10
SISE	0.18541	-1.18e-06	16	6	0.13363	-6.77e-15	40	11
TAVHL	0.26996	-1.69e-07	26	7	0.21578	-3.93e-13	19	6
TCELL	0.21329	-2.83e-07	27	5	0.18457	-4.20e-14	20	3
THYAO	0.13182	-2.82e-08	22	3	0.20388	-6.69e-17	38	2
TKFEN	0.15071	-7.92e-07	6	0	0.11669	-1.32e-14	26	5
TOASO	0.20735	-2.10e-07	31	10	0.16195	-1.12e-12	15	6
TTKOM	0.20592	-4.76e-07	17	3	0.14366	-1.55e-14	36	12
TUPRS	0.27063	-1.45e-07	26	8	0.22389	-7.73e-13	19	5
ULKER	0.18917	-6.13e-07	23	4	0.12308	-8.94e-13	13	7
VAKBN	0.10021	-1.30e-07	10	1	0.18163	-6.54e-16	23	2
YKBNK	0.11209	-2.66e-07	15	1	0.15129	-1.26e-15	26	4

Table 4.52: The result of fourth model based on level regression of $OFI_{t,1}^N = N_B - N_S$ and $OFI_{t,1}^Q = Q_B - Q_S$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00029	-1.13E-06	53	51	0.00010	-2.10E-07	36	33
BIMAS	0.00141	8.06E-06	66	64	0.00099	-1.80E-07	41	34
DOAS	0.00210	6.55E-06	64	62	0.00078	-3.69E-08	41	35
ENKAI	0.00225	2.33E-05	82	80	0.00017	8.70E-08	35	33
EREGL	0.00143	2.26E-05	83	82	0.00012	-5.45E-07	37	30
FROTO	0.00111	6.43E-06	67	65	0.00037	4.26E-07	36	34
GARAN	0.00139	7.47E-06	80	77	0.00047	-3.43E-07	46	41
HALKB	0.00171	4.32E-06	71	69	0.00082	2.35E-07	45	39
ISCTR	0.00073	1.19E-05	81	78	0.00032	-1.24E-07	41	30
KCHOL	0.00174	-4.63E-06	47	45	0.00047	-2.37E-07	34	24
KOZAL	0.00174	-2.24E-06	54	53	0.00075	-6.84E-07	51	49
KRDMD	0.00199	-1.72E-05	47	46	0.00022	-2.89E-08	36	30
OTKAR	0.00292	1.64E-05	83	82	0.00025	3.87E-07	41	36
PETKM	0.00217	1.48E-05	77	77	0.00029	-1.76E-07	32	27
PGSUS	0.00329	5.29E-06	69	68	0.00012	-3.59E-07	32	27
SAHOL	0.00062	9.45E-06	72	71	0.00001	-2.29E-07	34	29
SISE	0.00059	2.52E-05	74	70	0.00016	-4.41E-08	38	29
TAVHL	0.00134	1.60E-07	59	57	0.00045	3.33E-07	35	33
TCELL	0.00196	-3.41E-06	52	52	0.00027	-1.18E-07	30	27
THYAO	0.00200	9.59E-06	78	76	0.00054	-2.58E-07	44	40
TKFEN	0.00228	1.79E-05	76	76	0.00117	-3.34E-08	31	26
TOASO	0.00238	-7.70E-06	47	44	0.00028	-2.95E-07	31	28
TTKOM	0.00129	1.74E-05	79	78	0.00060	1.01E-07	33	26
TUPRS	0.00157	5.56E-06	70	68	0.00006	-3.52E-07	42	39
ULKER	0.00240	8.44E-06	60	58	0.00003	-3.24E-07	29	23
VAKBN	0.00207	1.63E-05	75	74	0.00047	-2.18E-07	33	25
YKBNK	0.00139	2.26E-05	82	79	0.00056	-6.33E-08	49	38

Table 4.53: The result of first model based on level regression of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^N + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.02060	7.17E-07	57	56	0.02006	2.24E-07	39	39
BIMAS	0.02155	8.66E-06	66	65	0.01889	-1.95E-07	39	36
DOAS	0.02790	7.67E-06	66	64	0.02539	9.13E-08	40	35
ENKAI	0.05029	2.55E-05	84	83	0.04792	-6.74E-08	40	37
EREGL	0.10173	2.47E-05	86	83	0.09980	-5.43E-07	33	31
FROTO	0.01583	6.77E-06	67	64	0.01477	-4.35E-07	34	30
GARAN	0.07453	7.50E-06	78	77	0.07260	-3.27E-07	53	46
HALKB	0.04385	5.13E-06	74	70	0.04089	-2.30E-07	43	36
ISCTR	0.10605	1.26E-05	80	79	0.10474	-1.20E-07	41	35
KCHOL	0.02035	-3.84E-06	49	47	0.01798	-2.20E-07	34	25
KOZAL	0.02637	-1.97E-06	51	51	0.02513	-5.70E-07	51	48
KRDMD	0.17171	-1.78E-05	45	43	0.16925	7.01E-09	35	30
OTKAR	0.02360	1.77E-05	84	84	0.02016	-4.07E-07	40	36
PETKM	0.09939	1.58E-05	80	78	0.09740	-1.53E-07	32	27
PGSUS	0.02434	6.28E-06	69	68	0.02050	-3.77E-07	29	25
SAHOL	0.03469	1.03E-05	73	71	0.03391	-2.32E-07	36	31
SISE	0.07271	2.75E-05	72	71	0.07204	-3.06E-08	40	35
TAVHL	0.02564	5.66E-07	58	57	0.02372	-3.31E-07	36	32
TCELL	0.03549	-2.31E-06	52	51	0.03273	-1.15E-07	31	25
THYAO	0.09081	9.81E-06	85	81	0.08810	2.21E-07	43	40
TKFEN	0.06821	2.06E-05	78	78	0.06698	-3.66E-08	36	32
TOASO	0.02888	-8.43E-06	44	44	0.02609	-3.01E-07	31	28
TTKOM	0.04277	1.94E-05	81	80	0.04063	-1.14E-07	32	30
TUPRS	0.02626	6.18E-06	71	69	0.02442	3.78E-07	38	35
ULKER	0.02321	8.87E-06	59	58	0.02107	3.24E-07	29	21
VAKBN	0.10023	1.49E-05	75	75	0.09852	2.01E-07	35	27
YKBNK	0.09018	2.26E-05	80	80	0.08781	6.12E-08	44	37

Table 4.54: The result of second model based on level regression of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.03973	2.58E-08	59	55	0.03949	-1.98E-07	40	40
BIMAS	0.03409	9.13E-06	68	68	0.03129	-1.75E-07	44	41
DOAS	0.04218	9.88E-06	66	66	0.03921	-1.30E-07	39	33
ENKAI	0.07836	2.83E-05	87	85	0.07605	-8.61E-08	37	35
EREGL	0.14397	2.62E-05	87	85	0.14173	-5.24E-07	37	32
FROTO	0.03492	6.96E-06	65	64	0.03366	-4.04E-07	37	35
GARAN	0.08858	8.22E-06	76	76	0.08639	-3.22E-07	45	42
HALKB	0.05229	5.56E-06	72	69	0.04925	-2.39E-07	45	39
ISCTR	0.13701	1.27E-05	78	76	0.13545	-1.31E-07	43	36
KCHOL	0.03167	-3.63E-06	49	48	0.02944	-2.18E-07	26	25
KOZAL	0.04715	1.70E-06	56	56	0.04587	-5.53E-07	50	50
KRDMD	0.27634	-1.99E-05	48	45	0.27420	-3.28E-08	40	37
OTKAR	0.03788	1.80E-05	86	84	0.03394	-4.86E-07	41	37
PETKM	0.14190	1.75E-05	78	78	0.13951	-1.53E-07	33	32
PGSUS	0.03220	7.05E-06	70	70	0.02800	-3.40E-07	27	25
SAHOL	0.04789	1.14E-05	75	74	0.04703	-2.33E-07	33	30
SISE	0.10894	3.00E-05	77	75	0.10765	3.94E-08	37	35
TAVHL	0.04190	3.04E-07	60	58	0.04043	-3.12E-07	34	32
TCELL	0.04800	-4.19E-07	55	55	0.04539	-1.18E-07	34	28
THYAO	0.11027	1.06E-05	83	83	0.10718	-2.76E-07	43	42
TKFEN	0.09755	2.21E-05	80	77	0.09643	-3.33E-08	31	29
TOASO	0.04385	-6.24E-06	48	45	0.04113	-3.11E-07	36	31
TTKOM	0.05792	2.09E-05	84	80	0.05548	-1.02E-07	33	30
TUPRS	0.03475	6.99E-06	69	69	0.03266	-3.97E-07	41	34
ULKER	0.04269	1.06E-05	64	62	0.04093	-3.29E-07	27	24
VAKBN	0.13052	1.32E-05	72	70	0.12887	-2.00E-07	34	30
YKBNK	0.12056	2.19E-05	78	74	0.11819	4.95E-08	42	38

Table 4.55: The result of third model based on level regression of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^N + \beta_2 OFI_{t,2}^N OFI_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \beta_2 OFI_{t,2}^Q OFI_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00177	9.55E-07	58	54	0.00020	4.73E-09	36	34
BIMAS	0.00414	2.68E-06	64	61	0.00103	4.20E-09	39	38
DOAS	0.00649	3.05E-06	40	37	0.00090	5.87E-09	24	22
ENKAI	0.00431	5.79E-07	66	65	0.00004	2.30E-10	34	32
EREGL	0.00281	7.16E-07	71	69	0.00098	8.29E-09	42	40
FROTO	0.00353	3.81E-06	49	48	0.00116	4.74E-09	31	29
GARAN	0.00422	-1.10E-06	80	79	0.00040	6.97E-09	42	35
HALKB	0.00272	-6.43E-07	64	61	0.00080	5.37E-09	41	39
ISCTR	0.00219	-1.43E-06	80	79	0.00011	1.42E-09	35	33
KCHOL	0.00335	8.91E-07	43	43	0.00139	1.52E-09	36	34
KOZAL	0.00606	4.05E-06	40	39	0.00038	2.27E-08	39	36
KRDMD	0.00387	9.06E-06	35	35	0.00176	3.99E-11	35	35
OTKAR	0.00603	2.19E-06	60	58	0.00021	6.47E-09	35	33
PETKM	0.00653	1.80E-06	48	47	0.00029	6.05E-10	30	28
PGSUS	0.00819	1.26E-06	51	47	0.00009	5.45E-09	32	28
SAHOL	0.00208	1.65E-07	63	61	0.00027	-4.25E-11	46	42
SISE	0.00286	6.85E-07	58	56	0.00066	4.60E-10	31	29
TAVHL	0.00357	1.15E-07	52	51	0.00047	1.17E-08	29	26
TCELL	0.00607	-1.82E-06	59	59	0.00073	4.28E-10	38	37
THYAO	0.00309	-9.23E-07	84	81	0.00058	1.03E-08	36	35
TKFEN	0.00398	1.63E-06	64	63	0.00216	3.32E-10	35	34
TOASO	0.00449	3.12E-07	50	49	0.00047	2.69E-09	29	25
TTKOM	0.00384	-9.37E-07	65	65	0.00150	4.94E-10	36	34
TUPRS	0.00502	6.30E-07	54	51	0.00020	8.13E-09	34	32
ULKER	0.00682	2.50E-06	53	50	0.00028	1.13E-09	37	33
VAKBN	0.00363	-1.37E-06	75	74	0.00113	-3.07E-10	36	34
YKBNK	0.00318	5.47E-07	72	71	0.00002	2.90E-10	52	50

Table 4.56: The result of fourth model based on level regression of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^N + \beta_2 OFI_{t,2}^N OFI_{t,2}^N + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,2}^Q + \beta_2 OFI_{t,2}^Q OFI_{t,2}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig positive β_2	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig Positive β_2
ARCLK	0.00177	-3.53E-06	58	56	0.00020	4.72E-09	68	62
BIMAS	0.00414	1.88E-05	49	47	0.00103	4.19E-09	73	69
DOAS	0.00649	-1.28E-05	67	67	0.00090	5.86E-09	82	79
ENKAI	0.00431	2.15E-05	58	56	0.00004	2.30E-10	68	63
EREGL	0.00281	2.10E-05	57	56	0.00098	8.29E-09	64	62
FROTO	0.00353	-9.32E-06	66	66	0.00116	4.73E-09	75	73
GARAN	0.00422	2.16E-05	39	37	0.00040	6.96E-09	67	65
HALKB	0.00272	8.69E-06	47	46	0.00080	5.36E-09	71	68
ISCTR	0.00219	2.43E-05	34	34	0.00011	1.42E-09	72	70
KCHOL	0.00335	-1.08E-05	60	60	0.00139	1.51E-09	67	65
KOZAL	0.00606	-2.98E-05	68	68	0.00038	2.27E-08	68	64
KRDMD	0.00387	-9.17E-05	71	69	0.00176	3.99E-11	73	70
OTKAR	0.00603	4.37E-06	61	60	0.00021	6.46E-09	71	69
PETKM	0.00653	-5.21E-06	73	72	0.00029	6.05E-10	70	66
PGSUS	0.00819	-3.82E-06	63	62	0.00009	5.44E-09	75	70
SAHOL	0.00208	7.99E-06	59	56	0.00027	-4.20E-11	63	59
SISE	0.00286	2.06E-05	61	58	0.00066	4.59E-10	75	69
TAVHL	0.00357	7.83E-07	62	60	0.00047	1.17E-08	76	76
TCELL	0.00607	5.16E-06	49	49	0.00073	4.28E-10	68	64
THYAO	0.00309	2.00E-05	36	35	0.00058	1.02E-08	67	67
TKFEN	0.00398	6.52E-06	67	65	0.00216	3.31E-10	65	64
TOASO	0.00449	-8.68E-06	63	58	0.00047	2.69E-09	75	71
TTKOM	0.00384	2.09E-05	56	54	0.00150	4.93E-10	69	67
TUPRS	0.00502	-6.82E-07	65	64	0.00020	8.13E-09	73	70
ULKER	0.00682	2.32E-06	59	55	0.00028	1.12E-09	63	61
VAKBN	0.00363	3.10E-05	45	43	0.00113	-3.05E-10	70	68
YKBNK	0.00318	2.82E-05	56	53	0.00002	2.90E-10	56	52

Table 4.57: The result of fourth model based on level regression of $OFI_{t,2}^N = \frac{N_B}{N_S}$ and $OFI_{t,2}^Q = \frac{Q_B}{Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1} = \beta_0 + \beta_1 OFI_{t,3}^N + \epsilon_{t+1}}$				$\mathbf{r_{t+1} = \beta_0 + \beta_1 OFI_{t,3}^Q + \epsilon_{t+1}}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00266	3.99E-06	67	65	0.00383	4.17E-06	83	80
BIMAS	0.00425	-7.30E-06	38	36	0.00179	2.20E-06	86	85
DOAS	0.00196	2.63E-06	56	53	0.00248	2.29E-06	83	81
ENKAI	0.00252	-1.44E-05	31	30	0.00156	1.78E-06	72	66
EREGL	0.00160	3.80E-06	61	59	0.00125	3.49E-06	89	85
FROTO	0.00307	-2.48E-06	52	52	0.00427	4.10E-06	84	81
GARAN	0.00073	-1.08E-06	43	43	0.00217	3.51E-06	92	86
HALKB	0.00119	4.67E-07	56	53	0.00698	6.54E-06	92	90
ISCTR	0.00125	1.83E-06	61	60	0.00124	2.73E-06	80	74
KCHOL	0.00511	5.78E-06	77	76	0.00344	3.26E-06	86	84
KOZAL	0.00241	3.07E-06	62	59	0.00432	1.41E-05	91	90
KRDMD	0.00223	6.11E-05	94	93	-0.00015	1.15E-06	71	55
OTKAR	0.00221	-2.34E-06	46	45	0.00535	4.75E-06	95	94
PETKM	0.00018	5.59E-06	71	69	0.00090	1.27E-06	77	68
PGSUS	0.00280	1.46E-06	54	54	0.00316	1.61E-06	96	95
SAHOL	0.00283	-5.04E-07	53	52	0.00278	2.36E-06	79	77
SISE	0.00224	4.60E-07	57	56	0.00036	1.80E-06	79	69
TAVHL	0.00232	2.53E-06	70	69	0.00277	4.49E-06	87	85
TCELL	0.00167	1.04E-06	55	54	0.00255	2.87E-06	95	93
THYAO	0.00156	-1.66E-06	48	46	0.00349	5.74E-06	84	79
TKFEN	0.00153	1.33E-06	57	56	0.00074	7.65E-07	76	70
TOASO	0.00244	3.83E-06	64	62	0.00373	4.65E-06	90	89
TTKOM	0.00332	-5.28E-06	41	41	0.00245	2.21E-06	86	79
TUPRS	0.00155	-1.97E-07	64	61	0.00522	4.44E-06	91	90
ULKER	0.00344	-6.51E-07	54	52	0.00282	3.89E-06	86	84
VAKBN	0.00074	-6.76E-07	54	52	0.00100	2.69E-06	86	78
YKBNK	0.00088	-1.81E-06	54	52	0.00080	2.41E-06	87	78

Table 4.58: The result of first model based on level regression of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,3}^N + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,3}^Q + \beta_2 \mathbf{r}_t + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.02293	3.38E-06	63	61	0.02406	4.19E-06	82	81
BIMAS	0.02464	-8.09E-06	35	34	0.02185	2.24E-06	88	85
DOAS	0.02743	1.30E-06	54	51	0.02815	2.37E-06	83	83
ENKAI	0.05085	-1.62E-05	35	32	0.04934	1.78E-06	72	67
EREGL	0.10189	3.93E-06	59	57	0.10120	3.62E-06	90	87
FROTO	0.01771	-2.81E-06	52	51	0.01897	4.14E-06	83	82
GARAN	0.07397	-1.45E-06	45	45	0.07526	3.59E-06	90	88
HALKB	0.04310	3.80E-07	57	57	0.04891	6.58E-06	93	91
ISCTR	0.10628	9.44E-07	58	56	0.10623	2.57E-06	80	76
KCHOL	0.02386	5.70E-06	76	75	0.02199	3.21E-06	84	84
KOZAL	0.02728	1.65E-06	58	56	0.02931	1.45E-05	91	90
KRDMD	0.17172	6.12E-05	96	95	0.16934	1.20E-06	70	60
OTKAR	0.02270	-3.21E-06	42	41	0.02593	4.78E-06	94	93
PETKM	0.09753	5.88E-06	72	70	0.09777	1.37E-06	80	73
PGSUS	0.02347	6.49E-07	54	53	0.02377	1.60E-06	97	94
SAHOL	0.03663	-9.19E-07	50	50	0.03654	2.32E-06	78	76
SISE	0.07392	-4.84E-07	50	47	0.07220	1.82E-06	77	68
TAVHL	0.02651	2.09E-06	73	69	0.02701	4.53E-06	84	83
TCELL	0.03504	4.54E-07	54	53	0.03571	2.81E-06	91	89
THYAO	0.09051	-2.00E-06	47	47	0.09241	5.84E-06	83	82
TKFEN	0.06748	2.08E-07	58	56	0.06628	8.13E-07	78	76
TOASO	0.02896	3.34E-06	62	60	0.03003	4.64E-06	93	91
TTKOM	0.04489	-6.98E-06	40	40	0.04347	2.29E-06	84	81
TUPRS	0.02600	-4.80E-07	62	59	0.02953	4.38E-06	91	91
ULKER	0.02426	-1.16E-06	52	50	0.02386	3.99E-06	85	85
VAKBN	0.09891	-8.02E-07	56	55	0.09895	2.51E-06	82	77
YKBNK	0.08982	-1.86E-06	54	53	0.08915	2.33E-06	82	78

Table 4.59: The result of second model based on level regression of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$				$\mathbf{r}_{t+1} = \beta_0 + \beta_1 OFI_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.04209	1.63E-06	62	60	0.04310	3.98E-06	79	77
BIMAS	0.03754	-8.83E-06	34	31	0.03451	2.21E-06	88	86
DOAS	0.04138	-5.09E-07	45	45	0.04214	2.49E-06	81	81
ENKAI	0.07956	-1.91E-05	32	28	0.07736	1.76E-06	71	67
EREGL	0.14376	1.75E-06	57	56	0.14303	3.50E-06	93	89
FROTO	0.03682	-3.86E-06	50	49	0.03798	4.05E-06	83	82
GARAN	0.08782	-1.49E-06	44	43	0.08916	3.60E-06	88	88
HALKB	0.05138	1.09E-07	56	55	0.05711	6.47E-06	92	91
ISCTR	0.13710	6.88E-07	63	61	0.13705	2.55E-06	78	76
KCHOL	0.03507	5.52E-06	76	76	0.03333	3.21E-06	83	82
KOZAL	0.04809	-5.44E-07	50	49	0.05030	1.43E-05	89	88
KRDMD	0.27709	6.42E-05	98	97	0.27434	1.35E-06	76	72
OTKAR	0.03695	-4.69E-06	42	39	0.04004	4.91E-06	95	93
PETKM	0.13975	4.64E-06	68	66	0.13971	1.34E-06	75	73
PGSUS	0.03133	-3.35E-07	50	50	0.03165	1.62E-06	97	92
SAHOL	0.04986	-1.77E-06	46	44	0.04966	2.30E-06	79	76
SISE	0.11001	-1.87E-06	47	45	0.10795	1.65E-06	70	67
TAVHL	0.04306	1.62E-06	68	65	0.04375	4.41E-06	86	83
TCELL	0.04782	-1.02E-07	56	49	0.04839	2.80E-06	90	88
THYAO	0.10940	-2.14E-06	46	45	0.11135	5.77E-06	82	80
TKFEN	0.09678	-2.50E-07	58	56	0.09548	7.91E-07	79	78
TOASO	0.04412	3.07E-06	59	58	0.04507	4.59E-06	91	90
TTKOM	0.05998	-8.67E-06	37	36	0.05838	2.29E-06	81	79
TUPRS	0.03430	-8.55E-07	57	55	0.03789	4.33E-06	93	90
ULKER	0.04421	-2.40E-06	53	49	0.04359	3.94E-06	86	85
VAKBN	0.12949	-4.98E-07	55	55	0.12935	2.49E-06	81	79
YKBNK	0.12038	-1.26E-06	58	56	0.11948	2.25E-06	80	78

Table 4.60: The result of third model based on level regression of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1}} = \beta_0 + \beta_1 OFI_{t,3}^N + \beta_2 OFI_{t,3}^N OFI_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r_{t+1}} = \beta_0 + \beta_1 OFI_{t,3}^Q + \beta_2 OFI_{t,3}^Q OFI_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig positive β_1	Avg of R^2	Avg of β_1	# of positive β_1	# of Sig Positive β_1
ARCLK	0.00780	1.43E-05	72	70	0.01408	2.20E-05	102	102
BIMAS	0.00927	-3.10E-06	48	46	0.00818	1.31E-05	103	103
DOAS	0.00453	1.11E-05	66	64	0.01039	1.36E-05	98	98
ENKAI	0.00565	-2.53E-05	38	36	0.00545	1.17E-05	90	87
EREGL	0.00319	1.77E-05	64	63	0.00528	1.56E-05	93	93
FROTO	0.00718	2.10E-06	63	58	0.01315	1.90E-05	106	106
GARAN	0.00216	-3.83E-06	40	40	0.01395	2.12E-05	105	104
HALKB	0.00197	3.87E-06	62	60	0.02699	2.89E-05	106	106
ISCTR	0.00199	3.24E-06	57	55	0.00652	1.48E-05	95	95
KCHOL	0.00967	1.18E-05	73	71	0.01477	1.64E-05	98	97
KOZAL	0.00663	2.22E-05	71	69	0.01692	6.29E-05	104	104
KRDMD	0.00484	0.000155	97	94	0.00119	6.48E-06	75	73
OTKAR	0.00793	-7.91E-06	39	39	0.01835	2.21E-05	107	107
PETKM	0.00184	2.83E-05	81	80	0.00285	6.29E-06	81	75
PGSUS	0.00582	5.81E-06	67	64	0.01391	1.07E-05	105	105
SAHOL	0.00570	-2.96E-06	46	44	0.00984	1.21E-05	95	93
SISE	0.00450	6.09E-06	56	55	0.00208	9.62E-06	90	86
TAVHL	0.00579	7.26E-06	67	64	0.01883	2.77E-05	105	105
TCELL	0.00404	8.56E-06	73	73	0.01034	1.43E-05	93	92
THYAO	0.00297	-4.89E-06	47	46	0.01497	2.54E-05	101	100
TKFEN	0.00301	1.24E-05	71	70	0.00342	6.72E-06	90	89
TOASO	0.00582	1.16E-05	70	69	0.01049	1.79E-05	102	101
TTKOM	0.00653	-9.73E-06	44	42	0.00691	1.15E-05	96	96
TUPRS	0.00467	2.92E-06	57	56	0.02122	2.19E-05	104	104
ULKER	0.00843	6.23E-06	63	63	0.01032	1.77E-05	97	95
VAKBN	0.00158	-2.57E-06	56	51	0.00539	1.44E-05	93	93
YKBNK	0.00232	-6.70E-06	45	43	0.00498	1.22E-05	95	92

Table 4.61: The result of fourth model based on level regression of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Company Name	$\mathbf{r_{t+1}} = \beta_0 + \beta_1 OFI_{t,3}^N + \beta_2 OFI_{t,3}^N OFI_{t,3}^N + \epsilon_{t+1}$				$\mathbf{r_{t+1}} = \beta_0 + \beta_1 OFI_{t,3}^Q + \beta_2 OFI_{t,3}^Q OFI_{t,3}^Q + \epsilon_{t+1}$			
	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig positive β_2	Avg of R^2	Avg of β_2	# of positive β_2	# of Sig Positive β_2
ARCLK	0.00780	-7.98E-07	39	38	0.01408	-2.68E-07	8	7
BIMAS	0.00927	-1.54E-07	53	52	0.00818	-9.17E-08	10	9
DOAS	0.00453	-8.19E-07	46	43	0.01039	-9.11E-08	12	12
ENKAI	0.00565	1.72E-06	62	60	0.00545	-8.38E-08	22	22
EREGL	0.00319	-1.24E-06	43	42	0.00528	-1.00E-07	19	18
FROTO	0.00718	-4.15E-07	48	46	0.01315	-1.64E-07	6	5
GARAN	0.00216	-3.37E-09	59	58	0.01395	-2.05E-07	5	5
HALKB	0.00197	-1.99E-07	45	43	0.02699	-3.58E-07	3	3
ISCTR	0.00199	-1.15E-07	54	53	0.00652	-1.07E-07	16	16
KCHOL	0.00967	-5.99E-07	40	40	0.01477	-1.23E-07	14	13
KOZAL	0.00663	-1.42E-06	40	39	0.01692	-7.32E-07	4	3
KRDMD	0.00484	-7.39E-06	21	18	0.00119	-3.53E-08	36	36
OTKAR	0.00793	5.30E-07	62	61	0.01835	-1.92E-07	6	6
PETKM	0.00184	-2.52E-06	29	28	0.00285	-4.50E-08	32	30
PGSUS	0.00582	-4.24E-07	44	42	0.01391	-8.53E-08	6	6
SAHOL	0.00570	2.29E-07	67	64	0.00984	-1.00E-07	12	11
SISE	0.00450	-8.05E-07	47	45	0.00208	-6.22E-08	20	20
TAVHL	0.00579	-5.09E-07	51	51	0.01883	-3.74E-07	3	3
TCELL	0.00404	-7.64E-07	44	43	0.01034	-1.34E-07	17	16
THYAO	0.00297	1.21E-07	61	61	0.01497	-3.53E-07	12	11
TKFEN	0.00301	-1.30E-06	40	40	0.00342	-5.29E-08	19	18
TOASO	0.00582	-5.72E-07	41	40	0.01049	-1.44E-07	8	8
TTKOM	0.00653	3.60E-07	62	58	0.00691	-6.10E-08	17	13
TUPRS	0.00467	-2.46E-07	54	53	0.02122	-2.22E-07	7	6
ULKER	0.00843	-7.59E-07	48	47	0.01032	-1.67E-07	13	12
VAKBN	0.00158	-5.10E-08	56	53	0.00539	-1.01E-07	17	17
YKBNK	0.00232	1.29E-07	64	61	0.00498	-6.61E-08	14	14

Table 4.62: The result of fourth model based on level regression of $OFI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ and $OFI_{t,3}^Q = \frac{Q_B - Q_S}{Q_B + Q_S}$ for 27 companies since 30/11/2015 until 29/04/2016.

Chapter 5

Fama-Macbeth Regression

In this chapter, firstly a brief introduction of the general structure of cross sectional analysis will be introduced. Then, *Fama-Macbeth Regression* which aim to use in this chapter will be define. Finally, the results of this regression on the data set and the interpretation of result will be discussed.

5.1 Cross Sectional Analysis

In economics, cross-sectional studies typically involve the use of cross-sectional regression, in order to sort out the existence and magnitude of causal effects of one or more independent variables upon a dependent variable of interest at **a given point in time**. They differ from time series analysis, in which the behavior of one or more economic aggregates is traced **through time**. The most important advantages of this method are:

- The analysis takes place at a single point in time.
- It allows researchers to look at numerous characteristics of a sample at once.
- It is often used to look at the prevailing characteristics in a given sample.
- It can provide information about what is happening in a current sample.

5.1.1 Fama-Macbeth Regression

Fama-Macbeth regression is an alternative way to estimate the regression coefficients and standard errors when the residuals are not independent [38]. In other words The **Fama-MacBeth two-step regression** is a practical way of estimating different factors in asset pricing [38].

In the first step, each portfolio's return is regressed against one or more factor of time series. In the second step, the cross-section of portfolio returns is regressed against the factors, at each time step. [39].

For implementing this regression, firstly we construct a **panel data** with all minutes of each day and also data analytics, then by applying the MATLAB codes, the following tables are generated for each order imbalance and order flow imbalance and their percentage changes. The Tables 5.1 and 5.2 are the result of Fama-Macbeth regression that each of them contains the average of estimated β_1 and average of t stats.

Models	Avg of β_1	Avg of t stats
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.046	13.94***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.00001	72.35***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,2}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.054	39.29***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.001	-0.28
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.565	16.03***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OI}_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.448	15.78***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.062	6.21***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.007	0.88
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.0005	0.02
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.037	6.98***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.002	-0.79
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OI}_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.0009	-0.25

Table 5.1: The results of Fama-Macbeth regression for order imbalance based models. The *** indicates significance at the level of 0.01 (P-value < 0.01).

Models	Avg of β_1	Avg of t stats
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OFI}_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.565	16.11***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OFI}_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.448	15.78***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OFI}_{t,2}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.009	1.02
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OFI}_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.001	-0.43
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OFI}_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.027	13.46***
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \mathbf{OFI}_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.00002	0.22
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OFI}_{t,1}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.0008	-0.15
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OFI}_{t,1}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	0.0008	0.43
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OFI}_{t,2}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.003	-0.49
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OFI}_{t,2}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.001	-0.44
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OFI}_{t,3}^N + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.0002	-0.05
$\mathbf{r}_{t+1} = \beta_0 + \beta_1 \Delta \mathbf{OFI}_{t,3}^Q + \sum_{j=0}^4 \beta_{j+2} \mathbf{r}_{t-j} + \epsilon_{t+1}$	-0.013	-0.61

Table 5.2: The results of Fama-Macbeth regression for order imbalance based models. The *** indicates significance at the level of 0.01 (P-value < 0.01).

In this chapter, we used data analytics, OIs and OFIs, to see if they are useful in forecasting 1-min ahead returns by using the cross sectional analysis. Almost similar to our earlier findings in time series regression, $OI_{t,1}^N$, $OI_{t,1}^Q$, $OI_{t,2}^N$, $OI_{t,3}^N$, $OI_{t,3}^Q$, $\Delta OI_{t,1}^N$, $\Delta OI_{t,1}^Q$, $\Delta OI_{t,2}^N$, $\Delta OI_{t,2}^Q$, $\Delta OI_{t,3}^N$, $OFI_{t,1}^N$, $OFI_{t,1}^Q$, $OFI_{t,2}^N$, $OFI_{t,2}^Q$, $OFI_{t,3}^N$, $OFI_{t,3}^Q$, $\Delta OFI_{t,1}^Q$, $\Delta OFI_{t,2}^Q$ show significant predictive power for 1-min ahead returns in the Fama–MacBeth regression. The most positive estimated power is 0.56 for $OI_{t,3}^N = \frac{N_B - N_S}{N_B + N_S}$ per 109 days with average t stats 16.03 Fama–MacBeth regressions (with adjusted covariances); and the most negative estimated power -0.01 for $\Delta OFI_{t,3}^Q$ with average t stats of -0.61 using the standard Fama–MacBeth regressions.

On the other hand, we also test the robustness of the OIs and OFIs by expanding our model with five lagged return variables. The estimated coefficients of all these variable were negative that implies on no effect of previous return on the current one. Also all above mentioned positive coefficient were robust with high average t stats.

At the end, among all 22 data analytics; $OI_{t,3}^N$ is the most important in terms of capturing cross-sectional variations in Turkish stock returns.

Chapter 6

Long-Short Portfolio Approaches

In this chapter, we discuss the **Long-Short Portfolio** approach which is widely used in finance literature. This method is an investing strategy that takes long positions in stocks that are expected to ascend and short positions in stocks that are expected to descend [40]. Also this strategy seeks to minimize market exposure (market exposure refers to the percentage of a portfolio, invested in a particular type of security, market sector or industry, which is usually expressed as a percentage of total portfolio holdings. Market exposure, also known as exposure, represents the amount an investor can lose from the risks unique to a particular investment.), while profiting from stock gains in the long positions, along with price declines in the short positions [40].

We first summarize the main findings in long-short method on the data set of 27 stocks for each minute in 109 days. Then we discuss the number of days that are positive or negative. Finally, we provide the t stats that adjusted by NW procedure (for more information see [41]) for all data analytics in each day for long-short method.

6.1 Description of Implemented Algorithm

Long-Short strategy is both long and short stocks simultaneously in the market. Just like pairs trading identifies which stock is cheap and which is expensive in a pair, a Long-Short strategy will rank all stocks in a basket to identify which stocks are relatively cheap and expensive. It will then go long (buys) the top n equities based on the ranking, and short (sells) the bottom n stock [40, 42].

Also the quality of ranking scheme is so important. A ranking scheme is any model that can assign each stock a number based on how they are expected to perform, where higher is better or worse. Examples could be value factors, technical indicators, pricing models, or a combination of all of the above. For example, you could use a momentum indicator to give a ranking to a basket of trend following stocks: stocks with highest momentum are expected to continue to do well and get the highest ranks; stocks with lowest momentum will perform the worst and get lowest ranks [43, 44].

The success of this strategy depends on almost entirely in the ranking scheme used (the better separate high performing stocks from low performing stocks), better the returns of a long-short strategy.

Once we have determined a ranking scheme, we would obviously like to be able to profit from it. We do this by investing an equal amount of money into buying stocks at the top of the ranking, and selling stocks at the bottom. This ensures that the strategy will make money proportionally to the quality of the ranking only, and will be market neutral [42].

We describe the algorithm that we use for our problem setting as follows:

1. At the beginning of each minute, find the stocks with highest and lowest data analytics that we consider (totally we have 22 data analytics).
2. After that, construct a long (short) portfolio, buying (selling) the stocks with highest (lowest) data analytics.
3. Hold this portfolio for a minute, and then repeat step one up to step three again.

4. At the end we report the mean of the portfolio return that we hold for a minute.
5. Test whether this mean is significantly positive by using t test (Newey-West adjustment).

6.1.1 t test (Newey-West Adjustment)

The Newey–West (1987) variance estimator [41], is an extension that produces consistent estimates when there is auto-correlation in addition to possible variability. The Newey–West test handles auto-correlation up to and including a lag of m , where m is specified by stipulating the `lag()` option. Thus, it assumes that any auto-correlation at lags greater than m , can be ignored.

The following Table 6.1, are the results of t stats (NW adjustment) for described algorithm, "Long-Short Strategy", for order imbalances that are calculated with Eq. 2.1 to Eq. 2.12 and order flow imbalances, which discussed in Eq. 2.19 to Eq. 2.24. According to the result all of data analytics except of $\Delta OI_{t,2}^Q, \Delta OI_{t,3}^N, \Delta OI_{t,3}^Q$ and $OIF_{t,1}^N, OIF_{t,1}^Q, \Delta OIF_{t,2}^N, \Delta OIF_{t,2}^Q, \Delta OIF_{t,3}^N, \Delta OIF_{t,3}^Q$ are able to produce a long short portfolio with a significant positive 1-min return. A long-short portfolio algorithm in our data set earns at most an average return of 0.006 per minute in 109 days using $OIF_{t,1}^N$. It is not only economically large but also strongly significant at the 0.01 and 0.05 level with t stat of 11.34. In contrast, $\Delta OIF_{t,1}^Q$ with 1-min return of -0.00016 is the lowest one and also t stats is not significant as well.

Order Imbalance	$OI_{t,1}^N$	$OI_{t,1}^Q$	$OI_{t,2}^N$	$OI_{t,2}^Q$	$OI_{t,3}^N$	$OI_{t,3}^Q$	$\Delta OI_{t,1}^N$	$\Delta OI_{t,1}^Q$	$\Delta OI_{t,2}^N$	$\Delta OI_{t,2}^Q$	$\Delta OI_{t,3}^N$	$\Delta OI_{t,3}^Q$
Avg of 1-Min Return t stats	0.0061 11.34***	0.00048 9.27***	0.00117 16.40***	0.00095 14.001***	0.00091 15.73***	0.00086 15.32***	0.00056 10.05***	0.00035 6.61***	0.00005 0.07	0.00002 0.35	-0.00002 -0.46	0.00003 0.69
Order Flow Imbalance	$OFI_{t,1}^N$	$OFI_{t,1}^Q$	$OFI_{t,2}^N$	$OFI_{t,2}^Q$	$OFI_{t,3}^N$	$OFI_{t,3}^Q$	$\Delta OFI_{t,1}^N$	$\Delta OFI_{t,1}^Q$	$\Delta OFI_{t,2}^N$	$\Delta OFI_{t,2}^Q$	$\Delta OFI_{t,3}^N$	$\Delta OFI_{t,3}^Q$
Avg of 1-Min Return t stats	0.00004 0.83	-0.00016 -3.17***	0.00112 15.95***	0.00077 11.17***	0.00007 1.33	0.00059 10.12***	-0.00001 -0.13	0.00004 0.77	-0.00002 -0.32	0.00001 0.23	0.0000 0.06	-0.00001 -0.32

Table 6.1: The results of t stats (NW adjustment) for average of return in one minute for order imbalances and order flow imbalances and their first differences, that is calculated using long-short analysis for 27 stocks since 30/11/2015 until 29/04/2016. The * and *** indicates significance at the level of 0.05 and 0.01 respectively (p-value < 0.05 and 0.01).

Chapter 7

Conclusion

In this study, we investigated whether the order imbalances (OI), and order flow imbalances (OFI), are useful in forecasting 1-min ahead returns of 27 stocks in the Borsa Istanbul at Turkish market or not.

In Chapter 1, we discussed about high frequency trading in financial markets and related information to our work. After that, the concept of data analytics and their applications in financial markets, the structure of data sets that we used in this thesis, and a brief statistics of them is discussed in Chapter 2 and 3. We apply time series regression using four different models for all data analytics in Chapter 4. Then we answer to above question by the cross sectional analysis and applying the Fama–MacBeth regression in Chapter 5. Finally, in Chapter 6, we try to produce a long short portfolio with a significant positive 1-min return ahead and the most profitable OIs and OFIs are introduced.

According to our data and consistent to the previous works, there is positive autocorrelation in order imbalance. Also this autocorrelation is significant up to lag 15 and it is a sign of persistent positive imbalances. Moreover order imbalance is in a positive relationship with daily stock return. In the literature, three major approaches are introduced for calculating the order imbalances and order flow imbalances. All these approaches are firstly based on number of buy and sell orders and then on quantity (size) of buy and

sell orders. Also we define a percentage change formula and apply it on above calculation as well. In time series regression, we test four model for finding the association of calculated OIs and OFIs with daily return stock. Additionally by adding the lagged daily return to the models and nonlinear terms, it is tried to prove robustness of models and the effect of these variables on daily stock return.

We demonstrate that, level based regression models are more successful in forecasting 1-min ahead and the number of significant days is in the best position. In comparison between OIs and OFIs, OIs have shown better results. Finally, consistent with previous findings, the coefficient of current order imbalances and order flow imbalances in most cases are positive and significant. Except of $OI_{t,2}^N$ and $OFI_{t,2}^N$ the performance of strategies based on order imbalances and order flow imbalances are profitable. In cross sectional analysis specially Fama-Macbeth, the coefficients of most of the OIs and OFIs are positive and significant. The highest positive return is 0.56 per 109 days for $OI_{t,3}^N$. Along to this issue we apply long-short strategy on our data. Most of the average return of coefficient are positive and significant and the best return per minute in 109 days is 0.006 and belongs to $OI_{t,1}^N$.

Finally, in this study, we consider the effects of order flow imbalance and order imbalances on daily price returns of Turkey. We used fixed-effects panel regressions and time series analysis for understanding the efficiency of market. For forecasting one minute a head returns from past order imbalances and order flow imbalances, based on level regression models, our results are qualitatively in line with the previous findings, but in the models with percentage change, the average of returns are small and insignificant. Other point is that the R-squared of models are small which shows the weakness of data analytics prediction power. Same is true for cross sectional analysis and because of small average of coefficients, the effects are so weak.

According to the definition of weak and strong efficiency, that is shown in Chapter 1, the Borsa Istanbul can be weakly efficient. The reason is that in our models, the coefficients of lagged version of returns, all the time were negative and they have not any effect on future returns. However, due to that mentioned results, the price impact coefficients are not all significant and positive, and the prices do not reflect all information of the market, so the Borsa Istanbul is not strongly efficient.

7.1 Further Works

Two interesting directions for further works would be as follows:

- Applying our analysis to other stock exchange markets which publicly publish their data analytics, such as Deutsche Börse and Nasdaq Stockholm.
- We can use more advanced techniques such as machine learning to utilize the data analytics provided by the stock exchanges.

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