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SHARE PRICE CLUSTERING IN TURKISH AND EUROPEAN BANKS

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Danışman: PROF DR. MURAT ÇİNKO

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GENEL BİLGİLER

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ÖZET

TÜRK VE AVRUPA BANKALARI HİSSE SENETLERİNDE FİYAT KÜMELENMESİ

Market anomalileri her zaman finansal piyasaların ilgi çekici ve güncel konularından biri olmuştur. Bu anomalilerden biri olan fiyat kümelenmesi fiyatların bazı sayılarda daha çok veya daha az toplanması eğilimidir. Bu bağlamda fiyat kümelenmesi, hakkında yapılan ilk çalışmadan günümüze kadar güncelliğini korumuş ve literatürde hakkında teoriler geliştirilen konulardan biri olmuştur. Bu çalışmada Türk ve Avrupa bankalarının hisse senetlerinin fiyat kümelenmesinin analiz edilmesi hedeflenmiştir. Fiyat kümelenmesinin test edikmesi ve potansiyel belirleyicilerinin analiz edilmesi amaçlanmıştır. Çalışma Avrupadan yedi Türkiyeden beş bankanın 2005 ve 2020 yılları arasındaki hisse senetleri ve hacimlerinin fiyat kümelenmesini ve bunların belirleyicilerini analiz etmiştir. Fiyat kümelenmesinin hacim ve oynaklık ile ilişkli olduğuna dair kanıtlar bulunmuştur. Genel olarak bu çalışma Türk ve Avrupa bankalarının hisse senetlerinin fiyat kümelenmesi eğilimi üzerine yapılmış olup konu hakkında geliştirilen Müzakere Hipotezini destekler niteliktedir.

GENERAL KNOWLEDGE

Name and Surname	: Merve Erşan
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ABSTRACT

SHARE PRICE CLUSTERING IN TURKISH AND EUROPEAN BANKS

Market anomalies have always been one of the interesting and current topics of financial markets. Price clustering, one of these anomalies, is the tendency of prices to aggregate more or less in certain numbers. In this context, price clustering has remained up-to-date since the first study on it and has been one of the aread on which theories have been developed in the literature. In this study, it is aimed to analyze the price clustering of the stocks of Turkish and European banks. It is aimed to test the price clustering and analyze its potential determinants. The study has analyzed the price clustering and their determinants of stocks and volumes between 2005 and 2020 of five banks from Turkey and seven from Europe. Evidence has been found that price clustering is associated with volume and volatility. In general, this study was conducted on the price clustering tendency of Turkish and European banks' stocks and supports the Negotiation Hypothesis developed on this subject.

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İstanbul, 2021 Merve Erşan

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ABBREVIATIATIONS

AM	Ante Meridiem- Before Noon
AMEX	American Stock Exchange
ASX	Australian Stock Exchange
BTC	Bitcoin
CNY	Chinese Yuan
CRSP	Center for Research in Security Prices
CSRC	Chinese Securities Regulatory Commission
DJA	Dow Jones Industrial Index
ETF	Exchange Trade Funds
EUR	Euro
FTSE100	Financial Times Stock Exchange 100
FX	Foreign Exchange
IPO	Initial Public Offering
ISSM	Institute for The Study of Securities Markets
NASDAQ	National Association of Securities Dealers Automated Quotations
NYMEX	New York Mercantile Exchange
NYSE	New York Stock Exchange
PM	Post Meridiem- After Noon
S&P 500	Standard and Poor's 500
SEATS	Stock Exchange Automated Trading System
TOQ	Trade and Quotes Database
TORQ	Trades, Orders, Reports, and Quotes
TRY	Turkish Lira
TSE	Tokyo Stock Exchange
U.S.	United States
U.S.A.	United States of America
UK	United Kingdom
USD	United States Dollar

1.INTRODUCTION

Market anomalies in financial markets have always been a subject of interest. Price clustering, one of these anomalies, has been a topic that has been keeping up to date since the first study in 1962 (Osborne 1962). According to Fama's Efficient Market Hypothesis, prices should follow a random walk (Fama 1969). However, there is evidence in the literature that certain prices are more or less traded than others. Price clustering is the tendency for prices to gather around certain numbers and escape from other numbers, as opposed to the random distribution of prices. This trend has been observed in various markets and various market instruments. There have been many studies in the literature on the determinants of price clustering. The determinants of price clustering are still a controversial area, and new studies are being carried out on these determinants every day.

Shiller stated that market traders tend to use the round numbers which are closest to the value of based transactions, in scnerios where not detailed and further information is not available (Robert J. Shiller 2000). This means that, if the price analysis hypothesis is uncertain, market traders limit price sets to cut down research costs in valuations (Harris 1991).

In addition, this statement is more common in markets where there is no limit restriction. In the ''order-based markets''; the opportunity trade against the limit order, provided by the limit order trader. If clustering pattern is observed in such a market, it may be due to psychological preferences. Or this pattern may arise depending on the habits of stock traders. If this habit occurs around round numbers, then price clustering will occur (Niederhoffer 1965).

Asset prices can take any value depending on variables in standard pricing theories. In real life, some prices are relatively more preferred than others. Price clustering is the case where asset prices are gathered more in certain numbers or certain fractions. Many studies have been researched on price clustering in diffirent geographies and dates, using various methods. Niedenhoffer and Osborne are among the pioneers of these studies. They observed that stock market ticker prices are accumulated in certain integers (26,43) and halves (261/2, 431/2), quarters and odd-eights. They found that this non-uniform order distribution makes some spesific effects. They observed that this is especially in the second hand market prices (Niederhoffer 1965) (Niederhoffer and Osborne 1966).They have studied in 60s, since then, researchers from diffirent places of the world have analyzed wheter insturments such as stocks, gold prices, foreign exchange, government bonds, future contract prices, interest rates have price clustering or not. And researchers have obtaind significant results from these studies. There are four theories in the literature for price clustering. These theories are Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985), Negotiation Hypothesis (Harris 1991), Attraction Hypothesis (Curcio and Goodhart 1991), and Collusion Hypothesis (Christie and Schultz 1994), respectively.

The Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) argued that information uncertainty of a security causes price clustering. It has stated that the uncertainty of the value of the security causes market participants to use more big tick size and this leads to clustering. In the hypothesis, it has also argued that the level of price resolution is directly proportional to the amount of information in the market. As exemplified in the article, more information should be found about companies that are widely followed in the market. This will result in a wider set of prices and a lower level of clustering. Additionally, the higher the price of an asset in the hypothesis, the bigger tick size market participants use. For this reason, the article has argued that price resolution is inversely proportional to the price level. In addition, it has suggested in the hypothesis that as the stock price volatility increases, the level of clustering will also increase. Because volatility brings along uncertainty. In the hypothesis, it has argued that high trade liquidity level is inversely proportional to clustering. Because the liquidity level increases the level of knowledge. In summary, it has suggested in the hypothesis that as the quality and amount of information in the market increases, uncertainty will decrease and the higher the level of price resolution, the less price clustering will be observed.

In The Negotiation Hypothesis (Harris 1991), it is argued that the high cost of negotiation causes price clustering. Higher negotiation costs lead to more clustering. As exemplified in the article, this is true for high volume transactions when the price level and the market volatility is high. The article has suggested that market participants use price sets as a mechanism to eliminate negotiation costs. The level of uncertainty increases in a crisis or heavy trade conditions. This leads market participants to use a less detailed price chart as they want to speed up trading and trade at the lowest cost. According to the hypothesis, it is suggested that this situation decreases the level of information and the price clustering increases. In summary, the Negotiation Hypothesis has argued that prices are clustered in round numbers in order to reduce negotiation costs and speed up transactions.

The Attraction Hypothesis (Curcio and Goodhart 1991) suggests that market participants tend to more interest in certain numbers than other numbers without rational reasons, and this causes clustering. According to the hypothesis, this tendency is natural and has no specific rational explanation. In the hypothesis, it is suggested that market participants have a natural interest in the numbers 0, 5, 2, and 8, respectively and this situation leads to greater clustering on these numbers in trade. It has also suggested that the numbers of least interest are 1 and 9, because they are followed by 0. In addition, it has argued that the level of interest and clustering of 3 and 7, 4 and 6 are equal in the article. It has also suggested that market participants tend to cluster more to even numbers than odd numbers.

The Collusion Hypothesis (Christie and Schultz 1994) suggests that there is a collusion between market participants at NASDAQ to protect their profits, and provides evidence of a deliberate cooperation between NASDAQ dealers to maintain their wide spreads. The article has argued that by avoiding odd-eight quotes, dealers encourage non-competitive trading margins, thus this avoidance leads to a price clustering.

In this study, the clustering of stocks of Turkish and European banks has analyzed. In this context, seven banks from Europe and five banks from Turkey have selected. These banks are Deutsche Bank, HSBC, Royal Bank of Scotland, Barclays, Credit Agricole, Societe General, BNP Paribas, Türkiye İş Bankası, GarantiBBVA, Akbank, Yapı Kredi and Vakıfbank, respectively. The clustering of stock prices of banks on the basis of USD, EUR and TRY has been analyzed. The motivation of this study has to measure whether price and volume, which are the determinants of price clustering in the literature, have also valid in bank stock prices.

Price clustering has been studied in the literature before, but there is no such study specifically for banking sector and European-Turkish banks. The European economy has an important place in the world economy, the banking sector being one of the most important elements of the economy and Turkey's business relationship with the European economy are the reasons of this study to be formed in this direction.With this study, it is aimed to measure the stock price clustering of Turkish and European banks, which has not been studied in the literature before. The study differs from the others in that with the time interval is wide and covers only bank stocks.

The study consists of six parts. Chapter 1 provides a general definition of the concept of price clustering and presents the scope and summary of the study.

Chapter 2 presents the theories in the literature in detail and explains the concept of price clustering and Chapter 3 summarizes the studies done in the field of price clustering so far. The data and methods used in the study explained ın Chapter 4. The results and Conclusıon ıs gıven ın Chapter 5 and 6, respectıvely.

2. PRICE CLUSTERING AND THEORIES

2.1. Theories

Price clustering is generally defined as the fact that prices are not uniformly distributed and the tendency to gather around certain numbers and avoid certain numbers. The studies carried out so far in the field of price clustering have generally been shaped around four theories. These theories differ in terms of measuring the concept of price clustering and its determinants. These theories are Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985), Negotiation Hypothesis (Harris 1991), Attraction Hypothesis (Curcio and Goodhart 1991), and Collusion Hypothesis (Christie and Schultz 1994), respectively. These theories and models are discussed in detail below. In this context, Table 1 presents the studies in the literature and the theories they support.

Table 1: Studies and Theories

Price Resoulution Hypothesis					
Writers	Study Name	Data Type	Market	Analysis	S&C
Clifford A. Ball, Walter N. Torous, Adrian E. Tschoegl (1985)	The degree of price resolution: The case of the gold market	Daily data	London Gold Market	Regression Analysis	Support
Allaudeen Hameed, Eric Terry (1998)	The Effect of Tick Size On Price Clustering And Trading Volume	Daily data	Singapore Stock Market	Regression Analysis	Support
Owain ap Gwilym, Andrew Clare , Stephen Thomas (1998)	Extreme price clustering in the London equity index futures and options markets.	Minute data	FTSE100	Regression Analysis	Support
Philip Brown, Angeline Chua, Jason Mitchell (2002)	The influence of cultural factors on price clustering: Evidence from Asia–Pacific stock markets	Daily data	Australia, Hong Kong, Indonesia, the Philippines, Singapore and Taiwan Stock Exchange	Chi-Square Analysis	Support

Ben J. Sopranzettia, Vinay Datar(2002)	Price clustering in foreign exchange spot markets	Daily data	Foreign Exchange Spot Market German mark, the Japanese yen, the UK pound, the French franc, the Italian lira and the Swedish krona)	Probit Analysis	Support
Hee-Joon Ahn, Jun Cai, Yan Leung Cheung (2005)	Price clustering on the limit-order book: Evidence from the Stock Exchange of Hong Kong	secondly data (30 seconds)	Hong Kong Stock Exchange	Regression Analysis	Support
Wataru Ohta (2006)	An analysis of intraday patterns in price clustering on the Tokyo Stock Exchange	Minute data	Tokyo Stock Exchange	Probit Analysis	Support
Aslı Aşçıoğlu, Carole Comerton-Forde, Thomas H. Mclnish (2007)	Price Clustering on the Tokyo Stock Exchange	Daily data	Tokyo Stock Exchange	T-Test Analysis	Support
David L. Ikenberry James P. Weston (2008)	Clustering in US Stock Prices after Decimalisation	Daily data	NYSE and NASDAQ	Regression Analysis	Support
Paresh Kumar Narayan, Seema Narayan, Stephan Popp, Michael D'Rosar(2011)	Share price clustering in Mexico	Daily data	The Mexican stock market	Probit Analysis	Support
Paresh Kumar Narayan, Seema Narayan, Stephan Popp (2011)	Investigating price clustering in the oil futures market	Daily data	Oil-Future Markets (NYMEX)	T-Test Analysis	Conflict
Negotiation Hypothesis					
Lawrence Harris (1991)	Stock Price Clustering and Discreteness	Daily data	NYSE	Regression Analysis	Support
Owain ap Gwilym, Andrew Clare , Stephen Thomas (1998)	Extreme price clustering in the London equity index futures and options markets.	Minute data	FTSE100	Regression Analysis	Support

Gordon J. Alexander, Mark A. Peterson (2007)	An analysis of trade-size clustering and its relation to stealth trading	Daily data	NYSE and NASDAQ	Probit Analysis	Support
David L. Ikenberry James P. Weston (2008)	Clustering in US Stock Prices after Decimalisation	Daily data	NYSE and NASDAQ	Regression Analysis	Support
Paresh Kumar Narayan, Seema Narayan, Stephan Popp, Michael D'Rosar(2011)	Share price clustering in Mexico	Daily data	The Mexican stock market	Probit Analysis	Support
Paresh Kumar Narayan, Seema Narayan, Stephan Popp (2011)	Investigating price clustering in the oil futures market	Daily data	Oil-Future Markets (NYMEX)	T-Test Analysis	Conflict
Andrew Urquhart (2017)	Price Clustering in Bitcoin	Daily data	BITSTAMP	Regression Analysis	Support
Bill Hu, Christine Jiang, Thomas McInish, Yixi Ning (2019)	Price Clustering of Chinese IPOs: The Impact of Regulation, Cultural Factors, and Negotiation	Daily data	Chinese IPOs from GTA	T-Test Analysis	Support
Ahmed Baig,Benjamin M. Blau,Nasim Sabah (2019)	Price clustering and sentiment in bitcoin	Daily data	BTC/USD parity	Ordinary Least Squares Analysis	Support
Attraction Hypothesis					
Riccardo Curcio, Charles Goodhart (1991)	The clustering of Bid/Ask Prices and The Spread In The Foreign Exchange Market	Daily data	Reuters Foreign Exchange Transactions (German Mark US Dollar)	Chi-Square Analysis	Support
Philip Brown, Angeline Chua, Jason Mitchell (2002)	The influence of cultural factors on price clustering: Evidence from Asia–Pacific stock markets	Daily data	Australia, Hong Kong, Indonesia, the Philippines, Singapore and Taiwan Stock Exchange	Chi-Square Analysis	Support
Aslı Aşçıoğlu, Carole Comerton-Forde, Thomas H. Mclnish (2007)	Price Clustering on the Tokyo Stock Exchange	Daily data	Tokyo Stock Exchange	T-Test Analysis	Support

Philip Brown, Jason Mitchell (2008)	Culture and stock price clustering: Evidence from The Peoples' Republic of China	Daily data	Shanghai, Shenzhen, Hong Kong and London Stock Exchange	Regression Analysis	Conflict
Paresh Kumar Narayan, Seema Narayan, Stephan Popp (2011)	Investigating price clustering in the oil futures market	Daily data	Oil-Future Markets (NYMEX)	T-Test Analysis	Support
Collusion Hypothesis					
William G. Christie, Paul H. Schultz (1994)	Why do NASDAQ Market Makers Avoid Odd-Eighth Quotes?	Daily data	NYSE, NASDAQ and AMEX	Regression Analysis	Support
Sanford J. Grossman, Merton H. Miller, Kenneth R. Cone, Daniel R. Fischel and David J. Ross (1997)	Clustering and Competition in Asset Markets	Daily data	London Stock Exchange, London Gold Market and London Foreign Exchange Market	Cross-sectional variation Analysis	Conflict

2.1.1. Price Resolution Hypothesis

The Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) argued that information uncertainty of a security causes price clustering. Gold prices in London are being traded in U.S. dollars with 5 cent increments. In this context, the probability of no change in price at the point where there is constant price change and non-rounding is zero. In the article, the frequency of the 20 probabilities of the last cent of the prices is first plotted. The probability ratio in the frequency tables has observed as chi-square goodness of fit statistics, with 19 degrees of freedom under the 5-cent uniform rounding null hypothesis as 561.2 and 475.4, respectively. It has been observed that the distributions are not only uniform but also sudden increases in the multiples of numbers at 100, 50 and 2, 5 and 10. It has been suggested that this is an indication of the existence of varying degrees of sensitivity in determining prices. In the equation used in the study $\{C^r(t)\colon t \, \varepsilon \, T\}$, $C^r(t)$ represents the cent digits of the price T represents the total number of observations. For each $i \, \varepsilon \, \boldsymbol{I}$, define F_i, as the observed frequency of $_i$ in the given data set. Using the dummy variable regression model to fit the observed frequency histogram and the frequency of occurrence of each rounding level of the estimated regression coefficients is shown and the equation is: $i \varepsilon I_{10}$

$$D10_i = \begin{cases} 1 & \text{if } i \,\varepsilon\, I_{10} \\ 0 & \text{otherwise} \end{cases}$$

Where, $D10_i$, = 1 when $_i$ is a multiple of ten and zero otherwise. In an analogous manner define the dummy variables D20, D25, D50, and D100. The following two regression models has used in the study: D10: represents a 10-cent round, D20: a 20-cent round, D25: a 25-cent round D50: a 50-cent round, and D100: a full dollar round.

$$F_i = \alpha_5 + \alpha_{10} D10_i + \alpha_{20} D20_i + \alpha_{25} D25_i + \alpha_{50} D50_i + \alpha_{100} D100_i + \in_i$$
$$F_i = \beta_5 + \beta_{10} D10_i + \beta_{25} D25_i + \beta_{50} D50_i + \beta_{100} D100_i + \in_i$$

Multiple linear regression analysis has used in the study to estimate alpha and beta parameters and to fit these models. If all rounding is k = 5 cents, the histogram for $\{C^r(t): t \varepsilon T\}$ will be flat. For example, the effects of 10 cent rounding will be evenly distributed over I_{10} and similar results are valid for each rounding level.As the null hypothesis, the observation of a 5 cent rounding has chosen. To be tested, it was expected to determine the frequency of occurrence of each rounding level of the estimated regression coefficients to fit the observed frequency histogram through the dummy variable regression model. The estimated coefficients have used to determine the frequency of occurrence of each rounding level. So if all rounding is k = 5 cents, the histogram is expected to be flat. An estimated frequency histogram is obtained using the least squares model. The predicted frequency histogram has associated with the specified rounding levels, and similar results have expected to be valid for each rounding level.

It has used to estimate the occurrence frequency of each level of precision using the dummy variable regression model. Three variables have determined and these variables are the probability of rounding a dollar, half dollar and quarter dollar respectively. The researcher expected the probability of being one to be a function of some basic parameters such as price level, volatility and the amount of information in the market, and estimated the parameters using the maximum likelihood logit analysis. Since the data in the article is divided into before noon (AM) and after noon (PM), there is more transaction and volume in the PM group due to the working hours of the United States. This difference is used to establish a statistical relationship between pricing precision and the number of traders in the market. Maximum likelihood logit estimation has used to measure level and uncertainty effects. The variables have chosen as alternating periods of volatility, the absolute value of the difference between the logarithms of the morning and afternoon fixing prices, the range-based relative volatility and the logarithm of the fixing price. As a result of this test, it has been determined that as the price level and volatility increase, the observed rounding also increases.

As a result of the study, It has stated that the uncertainty of the value of the security causes market participants to use more big tick size and this leads to clustering. In the hypothesis, it has also argued that the level of price resolution is directly proportional to the amount of information in the market. As exemplified in the article, more information should be found about companies that are widely followed in the market. This will result in a wider set of prices and a lower level of clustering. Additionally, the higher the price of an asset in the hypothesis, the bigger tick size market participants use. For this reason, the article has argued that price resolution is inversely proportional to the price level. In addition, it has suggested in the hypothesis that as the stock price volatility increases, the level of clustering will also increase. It is stated in the article that a high level of trading liquidity leads to a higher level of knowledge, and a higher level of knowledge leads to less clustering. In summary, it has suggested in the hypothesis that as the quality and amount of information in the market increases, uncertainty will decrease and the higher the level of price resolution, the less price clustering will be observed.

2.1.2. Negotiation Hypothesis

In The Negotiation Hypothesis (Harris 1991), it is argued that the high cost of negotiation causes price clustering. Higher negotiation costs lead to more clustering. As exemplified in the article, this is true for high volume transactions when the price level and the market volatility is high. In the article, first of all, the frequency distributions of the prices of the stocks have plotted. It has been observed that prices cluster in whole numbers, halves, odd quarters and odd eigths, respectively. In addition, in the frequency distribution, it has observed that the prices of expensive stocks cluster more than the prices of cheap stocks. The same frequency distribution has also made on bid-ask quotes. In the distribution, clustering has observed in whole numbers and halves, respectively. In frequency distributions, it has been observed that the whole ask clustering is more than the whole price clustering and the whole price clustering is more than the whole bid clustering. Researchers have also argued that price volatility increases clustering. To observe this, they have plotted the frequency distribution of prices before and after the October 1987 stock market crash. It has been observed that the price clustering has increased in the stock exchange and dealer markets at all price levels after the collapse. It has been observed that all of the frequency differences between dates are largely statistically significant.

In the article, multivariate regression analysis has made to associate transaction frequency and firm size with clustering. Two dependent variables have determined. The first of these is the total difference between the even and odd eighth frequencies. This difference has chosen to measure which quarters were greater than odd eight. The second is the frequency of integers. This frequency has chosen as it is a more general measure of clustering. Three independent variables have determined in the study. The first of these is time series volatility, and it has been suggested that it should be associated with the reservation price distribution because it is stated that the information is not uniformly distributed and interpreted when cases change values rapidly. The second is firm size and it has been suggested that it should have an inverse relationship with the reservation price distribution. Because the amount of information about large companies in the market is more than the amount of information about small companies. The third is the transaction frequency, and it has been suggested that this should be inversely proportional to the reservation price distribution. Because it has been argued that trade brings together the information of different traders and reveals stock values. The price level has been determined as a regressor. A new indicator variable has been specified. If the primary market of this variable stock is the over-the-counter market, it takes the value 1 otherwise 0. The estimated regression equation is very similar to the previous one, only a new indicator variable named "dealer" has been added at the end. It has been observed that prices clustering is more in the dealer market.

The details of the economic model developed by the researchers for the stock price cluster are as follows. According to the model, market participants use price sets larger than 1/8 price change. The purpose of the model is to estimate the frequency of using odd-sixteens by market participants if exchanges allow the use of odd-sixteens. Since stocks have affected by size, volatility and frequency of transactions, these cross-sectional differences are shown in the model.

In the model, it has assumed that all price negotiations consist of two parts. And it has assumed that first the price limits of the traders are determined separately and then negotiations are made for a certain price from these price limits. While the model has exemplified in the article, the function of prices using a minimum 1/8 price set is determined as $\alpha 8$. And it is assumed that market participants are equally likely to trade on odd and even eight. In addition, likewise α_8, α_4 (quarter), α_2 (half) and α_1 (whole) price sets have assigned. The clustering distribution of this model has expressed as follows:

$$
f_i = \begin{cases} \alpha_8/8 + \alpha_4/4 + \alpha_2/2 + \alpha_1, & i=0, \\ \alpha_8/8 + \alpha_4/4 + \alpha_2/2, & i=4 \\ \alpha_8/8 + \alpha_4/4, & i=2,6 \\ \alpha_8/8, & i=1,3,5,7 \end{cases} \qquad (1)
$$

f_i denotes the ith eight frequency of prices. The researchers asked what would happen if there was no price differential regulation and assumed that market participants would use a separate set based on minimum price change. They named this relative minimum price change as "R" and determined a function called F (R). F (R) shows the cumulative distribution function of R over all positive coefficients. In order to express the minimum price change in terms of price, it has assumed that R is multiplied by P, ie the price level. Then the result has been rounded to the closest change in the "1, 1/2, 1/4, 1/8" price set in which the proximity has measured by geometric distance. These assumptions have made to obtain " d ". Here 'd' represents the discrete price set:

d= 1/8, if P x R≤ k_8,

1/4, if k_8 < P x R≤ k_4,

1/2, if k_4 < P x R≤ k_2,

1, if k_2 < P x R, (2)

where

$k_8 = \sqrt{(1/8\ x\ 1/4)}$

$k_4 = \sqrt{(1/4\ x\ 1/2)}$

$k_2 = \sqrt{(1/2\ x\ 1/1)}$ (3)

these implies the geometric midpoints. The rules for the α_8, α_4, α_2, and α_1 :

$\alpha_8 = F(k_8/P)$,

$\alpha_4 = F(k_4/P) - F(k_8/P)$,

$\alpha_2 = F(k_2/P) - F(k_4/P)$,

$\alpha_1 = 1 - F(k_2/P)$. (4)

The parameters of F (R), which is the distribution function, have determined as F(R; μ_i, v). Here μ_i has assumed as the location parameter of the stock and v is the common shape parameter. In addition, the location parameter has allowed to vary according to the stock;

$$\mu_i = \gamma_0 + \gamma_1 \text{ AvePrice} + \gamma_2 \text{ STDRet}_i + \gamma_3 \text{ LogMkVal}_i + \gamma_4 \text{ InvSQRTrans}_i \quad (5)$$

STDRet is determined as the five-day standard deviation of percentage returns. According to the results of the previous section, it has been suggested that "γ_2" and "γ_4" should give positive results and "γ_3" should give negative results. Since the required minimum price change in the equation has expressed as a fraction of the price, it has stated that γ_1 must be zero. It has stated that the model described above colud be used for a cross-sectional stock sample if the functional form of F is specified. The gamma distribution has used in the analysis. It has been argued that this distribution varies according to all positive coefficients and is easy to use.

In the model, paremetrization has determined to be the mean of the m distribution. The determined gamma distribution model is as follows:

$$F\,(R; \mu_i ,\lambda) = \int_0^R \frac{\lambda\,(\lambda r)^{\nu-1}\, e^{-\lambda r)}}{\Gamma\,(\nu)}\, dr, \qquad (6)$$

where $\lambda = \nu/\, \mu_i$

Full information and maximum likelihood estimation method have used in the model. The data of the model consists of stock sample frequency distributions. Calculation of the frequencies ia follows:

$\beta_1 = f_0^{\alpha}$ (wholes),

$\beta_2 = f_4^{\alpha}$ (halves),

$\beta_4 = f_2^{\alpha} + f_6^{\alpha}$ (odd quarters),

$\beta_8 = f_1^{\alpha} + f_3^{\alpha} + f_5^{\alpha} + f_7^{\alpha}$ (odd eights). (7)

Model implications for these frequencies are:

$\beta_1 = \alpha_8/8 + \alpha_4/4 + \alpha_2/2 + \alpha_1,$

$\beta_2 = \alpha_8/8 + \alpha_4/4 + \alpha_2/2\,,$

$\beta_4 = 2(\alpha_8/8 + \alpha_4/4)\,,$

$\beta_8 = 4\alpha_8/8,$ (8)

Where the α in this equation is same as the Equation (1). The logarithm of the stock data vector as fallows:

$$\text{Log}\, \mathcal{L} = T\,(\beta_1 \log \beta_1 + \beta_2 \log \beta_2 + \beta_4 \log \beta_4 + \beta_8 \log \beta_8) \qquad (9)$$

where T is the number of time series observations.

The model has applied for the CRSP and Fitch sample, and all of the coefficient estimates are as expected. It is stated that it is very important that the AvePrice estimate does not differ significantly from zero. Because it has been argued that this result provides sufficient arguments to explain the relationship between the model's structure and the price level in the sample and clustering. Due to the low return volatility and high market value of expensive stocks, it has been observed that the desired minimum price change decreases in direct proportion to the price level.

It has suggested that market participants use price sets as a mechanism to eliminate negotiation costs. The level of uncertainty increases in a crisis or heavy trade conditions. This leads market participants to use a less detailed price chart as they want to speed up trading and trade at the lowest cost. According to the hypothesis, it is suggested that this situation decreases the level.

2.1.3. Attraction Hypothesis

The Attraction Hypothesis (Curcio and Goodhart 1991) suggests that market participants tend to more interest in certain numbers than other numbers without rational reasons, and this causes clustering. According to the hypothesis, this tendency is natural and has no specific rational explanation. Researchers have worked on foreign exchanges spot prices. First, they obtained the values of the last digit of the low (bid) prices of the whole sample during five trading days, then plotted the percentage of each numerical value in the grand total.

As a result, they observed that the total percentage of the numbers 0 and 5, respectively, was higher than the other numbers. In addition, it has been observed that the frequency of 2,3,7 and 8 is generally close to each other, but 8 is more than 7 and 3 is more than 2 for low (bid) prices. Then, associated distribution for higher (ask) prices has examined. 3 groups have determined. These were selected as 0-5, 2,3,7,8 and 1,4,6,9 respectively. Here, the first group was again observed as 0 is more than 5, but others were observed as 7 is more than 8 and 2 is more than 3 for higher (ask) prices then they obtained average results where distribution has made for both bid and ask price. In this distribution, as expected, 0 is more than 5 and the results were very close and similar except for the 8, which was clearly higher for the others (2 = 3 = 7

= 8 and 1 = 4 = 6 = 3 = 9). By using the chi-square test, the equality of 5-0, 2-3-7-8 and 1-4-6-9 frequencies has tested independently for all data and then for each day.

The researchers also examined the size of the spreads to further clarify their findings. First of all, the observation percentage of all spreads in the data is reported. The researchers here aimed to examine a size clustering rather than the final digit clustering. In the report, it has been suggested that there may be different reasons for the spread size clustering between banks. It has mentioned that the difference may arise from factors such as transaction costs, information inequality, degree of competition, and different cost structures. The report contains sufficient information for each bank in the data set. The researchers chose banks that offer more than 100 quotes per week from the sample to detail this. While some of the banks have always offered the same spreads, some have offered different spreads. Therefore, banks are divided into subsets according to their spread numbers. These are as follows:

Number of Spreads:	1	2	3	4	5	6
Number of Banks:	26	18	8	2	1	1

As seen in the table, it is observed that 26 banks use only 1 spread, while the remaining 30 banks use at least 2 spreads.In the context of this result, the researchers commented that banks may change their spreads according to market conditions. However, there is no theory as to how this developed. In the most used spreads of 18 banks that using two spreads, it has been observed that 4, 6 and 9 are never adjacent. It has been observed that there are 5 and 10 in spreads. It is claimed that this presence of the clustering between spreads may have been caused by the attraction. Curcio assumed that price clustering between spreads of 10 would be greater than those containing the lower value of 5. The results for the 5,7 and 10 spreads are as follows:

Ferquencies of Final Digit

Spread	1	2	3	4	5	6	7	8	9	0	Observation
5	5,69	9,57	10,75	5,33	18,66	5,69	9,57	10,75	5,33	18,66	16754
7	3,32	12,47	10,2	5,18	17,24	2,27	15,23	10,05	4,01	20,03	5332
10	1,52	7,07	6,95	1,56	31,02	1,62	6,36	9,28	1,17	33,45	16630

For example, the spread of 5 has been observed 16754 times in the whole sample, and the ratio of the prices in the spread with the final digit ending with 1 is 5.69%. It has been observed that 64% of the prices have clustering at 0 and 5. As a result of this distribution, it has been found that the scope of the desired price resolution for those with larger bids (10) in the report is closer than ¼ to ½, and less than ¼ for narrower spreads (5 and 7). Finally, from the above conclusion, the researchers suggested that even those using the highest spreads want a price resolution of less than ½ and that there should be no clustering in the penultimate digits. This result is the opposite of clustering in the first sample, and indeed the most common number in the penultimate digit is a marginal number (1). In addition, they observed that the frequencies were not approximately equal.

In summary, it is suggested that market participants have a natural interest in the numbers 0, 5, 2, and 8, respectively and this situation leads to greater clustering on these numbers in trade. It has also suggested that the numbers of least interest are 1 and 9, because they are followed by 0. In addition, it has argued that the level of interest and clustering of 3 and 7, 4 and 6 are equal in the article. It has also suggested that market participants tend to cluster more to even numbers than odd numbers.

2.1.4. Collusion Hypothesis

The Collusion Hypothesis (Christie and Schultz 1994) suggests that there is a collusion between market participants at NASDAQ to protect their profits, and provides evidence of a deliberate cooperation between NASDAQ dealers to maintain their wide spreads. In the article, odd-eight quotes were not observed in 70 of the 100 securities traded in NASDAQ, including Apple and Lotus. This has led to the question of whether the traders at NASDAQ are doing this on purpose. Unlike previous studies in the literature, the study selected a detailed sample of inside bid and inside ask quotes for the 100 most active stocks traded on the NASDAQ in 1991 and examined the distribution of the dollar spread.

The researchers also examined NYSE and AMEX firms to compare this odd-eight deficiency in the NASDAQ and observed that all octal values were used here. They argued that this lack of odd-eights in the NASDAQ meant an internal spread of at least $ 0.25. The article suggested that this difference between NASDAQ and NYSE / AMEX is due to the structural differences of the two markets. The NASDAQ inspection mechanism is not as stringent and effective as NYSE / AMEX. It is stated that the main pillar of the NASDAQ system is that competition for order flow between dealers is based on generating narrow spreads. Unlike organized exchanges, NASDAQ limit orders are not open to the public, so the public cannot use limit orders directly to compete with NASDAQ Market players, in which case the inside quotes cannot reflect the existence of limit orders. The data of the study consists of the price, bid /ask and quotes for the 100 stocks of the most actively traded NASDAQ and 100 NYSE / AMEX stocks in 1991.

In the study, firstly, the distribution of closing prices and year-end equity capitalization for both samples has calculated. The mean, maximum, minimum and quartiles values of the distribution of average closing prices among stocks have obtained and this was named Panel A. Panel B is the distribution of year-end equity capitalization among stocks. After that, the dollar spread distribution for NASDAQ and NYSE / AMEX has plotted and compared. As a result of the comparison, it has observed that there is an unimodal amount of 0.25 USD per share in NYSE / AMEX shares. One-eight and three-eights spreads are equally common, with 5% of all quotations valued at $ 0.50. On the other hand, it has been observed that the spreads of NASDAQ stocks are 0.25 USD and its multiples. It has been observed that spreads of 0.25 and 0.5 USD are more common than spreads of 0.375 USD. Likewise, it has been observed that spreads of 0.5 and 0.75 USD are more common than spreads of 0.625 USD.

Later in the article, a distribution of price quotes that provide one-eight distribution among 100 NASDAQ and NYSE / AMEX firms has obtained. As a result of this distribution, one-eight spreads have observed in less than 4% of the quotes in most NASDAQ companies. After these two distributions, the researchers asked the question "Are NASDAQ and Listed Stocks Quoted Differently?"

They plotted the percentage of $ 0.125 internal spreads for 100 NASDAQ and NYSE / AMEX securities with similar price and year-end capitillations. Here, it has been observed that spreads of 0.25 USD and its multiples have used for NASDAQ, especially where odd-eight and even-eight price quotes should be used. In order to compare the frequency of odd-eight and even-eight quotes between the two markets, the percentage of all bid / ask in every eighth place has calculated. Percent represents the average of the frequencies in the quotes. As a result of the calculation, it has been observed that odd-eight quotes in the NYSE / AMEX market are less than the even-eight quotes. In this respect, the study has shown findings that support Harris (1991) study. On the other hand, odd-eights quotes have been observed very rarely in NASDAQ compared to NYSE / AMEX. Later in the article, to determine whether the underuse of odd-eights quotes for all NASDAQ stocks, the percentage of odd-eight quotes has computed for each firm, and it is observed that for some stocks this is much more significant than others.

To observe whether the odd-eight quotes model has changed, the cumulative monthly quotation percentage seen in odd-eigth for the five most actively traded firms during the year has plotted. It has been observed in the graph that the odd-eight quotation percentage, which started at 50% at the beginning of the year, dropped to 0% by the end of the year. The article has so far summarized the suspicion that odd-eight quotes have almost disappeared in a market where a large number of market participants are competing. In the continuation of the study, some analyzes have made in order to better understand and explain the reasons for this result.

In the article, it is tried to make sense whether the economic parameters could explain this lack of odd-eight in spreads. It has been stated that the cross-sectional differences in the use of odd-eight quotes between firms can be explained by economic factors that determine bid-ask spreads. It has been suggested that spreads may be inversely proportional to volume if higher volume indicates that dealers can handle risk faster. In addition, it has been suggested that high volatility could result in higher trade losses for dealers in terms of higher inventory risk and more compared to specialist traders.

In order to measure the effects of these variables on the use of odd-eights, companies have divided into groups according to whether they use odd-eigts or not. Then, the annual average of the daily closing price of each stock, the daily size (obtained by multiplying the stock price by the number of unpaid stocks), daily trading volume, daily market makers, and the standard deviation of the average of the daily returns have obtained. In addition, dummy variables have used to indicate whether the trades were conducted on a regional stock exchange and whether the listed options were in 1991.

Logistic regression has made using odd-eights to estimate the probability of quotation for firms. Three regressions have been constructed. The first regression includes the whole sample. The second and third regressions include the same July-December period. Only in the third regression, unlike the first two, the dummy variable "past" was used. Since the regressions have made for different periods, the monthly rate of odd-eights qoutes were averaged separately in both regressions. First, if odd-eight qoutes is at least 25% per month, stocks have classified as "odd-eight qoutes".

The dependent variable takes the value 1 for odd-eight qoutes. The independent variables are as follows: Volume (approximately 100,000 stocks per day), size (equity capitalization in multiples of 1 million USD), variance (daily return of the midpoint of the closing bid / ask spreads), price (bid / ask middle of all bids) point) and the number of dealers. "Listed options" has determined as the dummy variable that takes value 1 for the companies of the listed options in 1991. "Dual" has determined as the dummy variable that takes the value 1 for firms whose stocks are listed on regional stock exchanges. "Past" has determined as the dummy variable that takes the value 1 if the companies used odd-eight in January. Logistic regressions have predicted the probability that a stock will be quoted as odd-eight. The regressions has made with the determinants of price, size, volume, varriance, number of dealers, listed options, Dual listed and Past (past is just in 3rd regrression). includes classification accuracy. If the stocks contain odd-eight quotes (or not) and the probability of the stock to contain odd-eight quotes is assigned at least 0.5 in the model, it means that it is correctly classified.

The results of the first two regressions show that the price and variance coefficients are statistically significant at the 5% level. With this observation, it is stated that the probability of the stock to contain odd-eight quotes is inversely proportional to its price and return volume. The article has tried to control the ability of logistic regression to correctly classify stocks whether they are quoted in odd-eight or not. For this, first the sample has divided into parts. As a criterion, the probability of using odd-eights larger / smaller than 50% of the model has determined. Then, it has examined whether this criterion was correctly divided for companies using odd-eights in the sample and those that did not .Since the economic factors used in logistic regression could not explain the rare use of odd-eights, a third regression has made. In this regression, the "past" dummy variable mentioned above was used. It has observed that the use of the ‘Past’ dummy variable significantly affected the results. In summary, in the article, contrary to what has observed in NYSE / AMEX stocks, it has been observed that there are no spread quotes of 0.125 USD and quotations of 0.375 USD in NASDAQ.

It has been observed that in 70% of NASDAQ stocks, odd-eights quotes have virtually nonexistent, bringing costs to the traders. The researchers have suggested that as a possible explanation for these results, market participants have a tendency to secretly protect spreads of at least USD 0.25 by avoiding odd-eights quotations. However, the researchers also noted that their study have not directly provide evidence of a collusion between NASDAQ market participants. It has argued that by avoiding odd-eight quotes, dealers encourage non-competitive trading margins, thus this avoidance leads to a price clustering.

3.LITERATURE REVIEW

Osborne (1962) examined the internal properties of common stock prices. The data of the study consists of the closing prices of the stocks that have sold more than fifty lots in the New York Stock of Exchange. In the study, the distribution of stock prices is intended to be associated with Brownian Motion (R. Brown 1828). In this context; by using statistical distribution methods, price change and volume sequences are associated and the order of the prices behaves and how the volumes change have tried to be explained. The average of the initial price and median daily volume in round lots of the stocks of the companies in the data has been calculated. Cumulated sequential frequency distrubutions of daily volumes of individual stocks were plotted and analyzed by normal and lognormal distrubution method. Contingency table tests were applied to measure the effects of price change sequences. It has observed that 60.8% of the closing prices were at the odd-eights. Osborne was the first to identify this in the literature. As a result of the study, it was suggested that price distributions would not be uniform. It has been stated that stock prices tend to cluster in integers, halves, quarters and odd-eights. This study appears to be the first comprehensive study on price clustering in literature.

Niederhoffer (1965) tested the applicability of the Random Walk Hypothesis (Cootner 1964) to stock prices. In this context, the books of five specialists from New York Stock Exchange were examined and sample was selected. The sample consists of the closing prices of the first 128 stocks listed in the New York Stock Exchange on February 3, 1964 with a price above 50. End of the day values of stocks have been tested with the standard deviation. It is argued that clustering is due the tendency of, traders placing orders in numbers they are accustomed to, such as integers or round numbers, and repoted that such a structure and price pattern raises serious doubts about the assumption that share prices are random.

Niederhoffer and Osborne (1966) examined the rules of stock price fluctuation in the market. They tested the prices of six of the first seven stocks traded under Dow Jones Industrial Index (DJA) in their study. The data of the article consists of the full set prices of six the first seven stocks in the DJA on twenty two trading days of October 1964. This data set equals to 2,5% off all transactions traded on the same time line. They analyzed the connection between the recorded price movements and assumptions of the Random Walk Hypothesis (Cootner 1964), and they used joint frequency distribution, estimation of transaction matrix and chi-square test. Random Walk Hypothesis (Cootner 1964) is rejected by the analysis. It is reported that prices, unlike the random walk, were accumulated in some time periods and that prices formed in the past were not random.

Niedenhoffer (1966) found the ratio of transactions in the stock market at even eighth prices. Francis Emory Fitch Daily Stock Exchange Sales (Blue Pages) has selected as the source. The data consists of the full records of NYSE stocks for seven days that randomly selected in 1964. Prices in the study are classified into three groups. The first group consists of 1000 records where the price does not change compared to the previous trade. The second group consists of 12,800 records where the price changes by one eighth, and the third group consists of 11,000 records where the price changes more than one eighth. Variance and binomial distribution method were used in the study. As a result of this study, it has found that 58.5% of all transactions were in even eighth and this has mostly seen in the third group. It has been argued that this is due to the fact that traders place more limit and spot orders at the even eighths.

Ball, Torous and Tschoegl (1985) analyzed the frequency, qualifications and reasons of rounding in price in order to uderstand the rounding of asset prices under the optimal condition. For this reason; the gold market, which represents an important and efficient asset market, and especially London fixing prices have been chosen as the data source. The data set consists of the fixing prices of the London Gold Market from January 2, 1975 to April 30, 1981. Dummy variable reggression and multiple linear regression analysis methods are used in the article. As a result of the study, it has been argued that the clustering tendency of prices is directly proportional to the uncertainty of the market. In addition, price volatility is expected to affect the level of clustering, because volatility can be expressed as the uncertainty of the value of a security. In summary, the study indicates that price clustering is more likely in conditions where market information and quality are insufficient. Price Resolution Hypothsesis has been proposed in this article (Ball, Torous and Tschoegl 1985).

Harris (1991) analyzed the stock price clustering and its relationship to some observable traits and calculated the level of cluster as the percentage of daily prices closed by round increments. Data is consists of 25-year closing price of 2510 stocks reported by the CRSP between January 1963 and December 1987 to the CRSP Daily Stock Master on December 31, 1987, and the distribution of price clusters of four securities between March 22, 1854 and May 15, 1854 at the NYSE. Multivariate regression analysis has been used. It is claimed that traders tend to reduce their trading terms when the need to trading increases, and the price clustering will increase during abnormally heavy trading periods. In the study, it was found that the degree of clustering varies in direct proportion to the price and volatility level but inversely with firm size and trade frequency. In addition, it is reported that there is a positive relationship between clustering frequency and return volatility in this article. The Negotiation Hypothesis has been suggested in this article. According to this hypothesis, prices are accumulated to reduce the agreement time and costs during trading process.

Goodhart and Curcio (1991) analyzed the price clustering in foreign exchange markets. In the study; it is aimed to examine whether round numbers are attractive or other specific numbers are attractive. The data consists of spot foreign exchange transactions taken from Reuters' FXFX and FXFY screens between April 9 and July 3, 1989; and these foreign exchange transactions consist of the parity of the German Mark to the US dollar. The data were divided into 3 groups, and using the standard distribution and chi-square test, with chi-square test it was analyzed whether the distribution of the steps was uniform. It was tested how often certain numbers were repeated for all 3 groups compared to the others. Likewise, which numbers are less common has been tested. At the end of the study, it has been shown that the price resolution degree requested by the traders and Forex Spot Ask / Bid Prices are independent. It has been suggested that each round number has a basic attraction and the rounding of asset prices to these numbers reflects this suggestion. The findings of this article proposed the attraction hypothesis in the literature for the first time In the hypothesis, it is suggested that rounding of asset prices to integers is due to the attraction of round numbers. (Curcio and Goodhart 1991).

Christie and Schultz (1994) compared the daily price distribution of NASDAQ securities with the distributions in NYSE and AMEX markets. The data consists of all trading prices and bid/ask revisions for the 100 major stocks that were actively traded on NASDAQ, NYSE and AMEX in 1991 and it was taken from the Institute for The Study of Securities Markets (ISSM). Data includes both daily transaction prices and share amounts. It has compared the distrubition of average prices and the distribution of end-of-year equity capitiliztions of both NASDAQ and NYSE / AMEX stocks. The percentages of bid revisions that create a spread of $ 0.125 for each firm are calculated using all internal bids. To examine whether the infrequent use of odd-eight prices is shared by NASDAQ stocks, the percentage of bids for odd-eight is calculated for each firm, where the percentage is an average of the frequencies during bid and ask. Comparing the stocks in NASDAQ to the other two markets; it is noteworthy that even in large companies such as Aplple Computer and Lotus Development, it is almost never traded at odd-eigthts.

It has shown that the internal spread for stocks in the NASDAQ is at least $ 0.25 compared to other markets. With this study of Christie and Schultz; It was asked whether NASDAQ dealers collude to maintain wide spreads and profit from it, and "Collusion Hypothesis" has proposed for the first time in this article. As a result of this article, a billion-dollar investigation was initiated by the US Department of Justice (U.S. v. Alex Brown & Sons (NASDAQ Market Makers), 1996).

Aitken, Brown, Buckland, Izan and Walter (1996) examined the price clustering of stocks traded individually in the Australian Stock Market. The data of the study consists of the last digits of the hourly transactions of the stocks of companies that are traded at least 5 times a day and extracted from the ASX (Australian Stock Exchange) and SEATS (Stock Exchange Automated Trading System) database between 1990-1993. The lowest and highest price and volume of regular traders were extracted from data and additional variables were obtained. The final database consists of 2.610.400 observations. Ten variables are determined for the analysis. These are; Stock price, Market-wide volatility, Price clustering, Trade size, Resources versus non-resources, Indvidual stock volatility, Firm size, Liquidity, Optioned versus non-optioned stocks, Short-selling, and Buyer-initiated trades respectvely. Multivariate logistic regression was used in the study to explain clustering and define the combined ability of variables. With logistic regression, binary dependent variable (clustering / non-clustering) is predicted depending on the values of the explanatory variables. First, all potentially explanatory variables are regressed against the binary variable. Then; The parsimonious regression model is used for price volatility, firm size, frequency, and market-wide volatility.

At the end of the study, it has found that there was clustering in 0-5 and even numbers (2-4-6-8), respectively. In the article; It has emphasized that as the price level, trade size, market-wide volatility and individual stock volatility increased, the price clustering also increased. It was also determined that there is less clustering in option stocks and stocks with short sales. Similarly, it has stated that clustering is inversely proportional to the frequency of operation and directly proportional to uncertainty. In this article two important findings are stated. These; as firm size increases, clustering is detected more frequently and less clustering is observed in resource stocks compared to non-resource stocks.

Grossman, Miller, Cone, Fischel and Ross (1997) analyzed the price clustering for liquid assets. It is examined how the degree of clustering is affected by the market structure, and the relationship between spreads and transaction costs is discussed. London Stock Exchange, London Gold Market and London Foreign Exchange Market have been examined in the article in order to test the Collusion Hypothesis (Christie and Schultz 1994). The data consists of the above mentioned markets and the prices, spreads and internal quotations in the Automatic Quotation System of the Stock Exchange in 1990-1994. The last digits of the prices have been analyzed. The determinants of clustering, based on the literature, listed as uncertainty, liquidity and risk in the article.The standard is set as the range between the highest and lowest bid frequencies for comparison of different markets. The standard distribution of the last digits of the prices for each market was measured and the differences were compared cross-sectionally with the study of Christie and Schultz (1994).

As a result of the analysis, it was found that there is clustering in the assets that are valued and priced precisely in competitive markets to reduce costs. It has been argued that the offers are less valuable than prices, so they are more clustered. It has been emphasized that the degree of clustering will differ between securities and markets over time. Based on this evidence, it has been argued that the alleged Collusion Hypothesis (Christie and Schultz 1994) in NASDAQ is unreasonable.

Hameed and Terry (1998) aimed to measure the effect of tick size on price clustering and trade volume in Singapore Stock Market. The data used in the study were taken from the Stock Exchange of Singapore Main Board. Data consists of two different groups. The first group consists of the daily highest and lowest closing prices of 234 stocks traded between January 1980 and July 1994. The second group, on the other hand, consists of stocks which prices were above $ 25 and tick value reduced $ 0.10 within 90 days before and after 18 July 1994. Three variables were determined in both groups. These variables are listed as daily volume, daily volatility and closing price. The mean and medians of each variable in 5 different price ranges were measured. Percentage Frequency of the Final Digits of Daily Closing Price has been measured for 5 different price ranges. The goodness of the fit between the price ranges and the selected variables was tested and a regression analysis was performed in the price range between 1-3 USD. It has been observed that the price clustering increases with the stock price level, but on the contrary decreases with the trade volume. It has been argued that price volatility does not have a significant effect on the clustering. It has concluded that the tick size is inversely proportional to the level of clustering.

The article has provided limited evidence that the reduction in tick size increases the trading volume under actively trading conditions. It has been supported that Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) in that the study concludes the increasing in negotiation costs of stocks reduces the positive effect on transaction volume.

Gwilym, Clare and Thomas (1998) analyzed of price clustering in financial derivative instruments, which has not been studied in the literature before. In this context, the article was the first study to measure price clustering in derivatives in the literature. The data of the study consists of trading minute values and all quotations of FTSE100 stock futures contracts between 24 January 1992 and 30 June 1995. First, the frequency of even and odd ticks in the sample contracts were measured. Then, price clustering is measured on the fourth digit of the index value and the last digit of the option price for futures contracts. It was measured by calculating the percentages of the traded and quoted prices in the last digit of the price. Afterwards, the intraday distribution of odd and even-tick transactions in futures contracts was plotted. The relationship between the percentage of odd-tick transactions and transaction size, price, transaction frequency and volatility was examined.

It has stated that the average trade size is larger for odd-tick trades, meaning an expected positive coefficient here. In the analysis, it was suggested that the clustering is expected to increase in periods of high volatility and therefore the average absolute return coefficient should have a negative coefficient and regression analysis has made with this suggestion. In the article, it was reported that price clustering increased as volatility and transaction frequency increased, and decreased with trade size. In addition, it has been reported that as the buy and sell spreads expand, odd ticks decrease and even-ticks increase. For financial derivatives, this evidence of extreme clustering has been a first. It has supported that Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) in finding that the market's half index points do not require additional price elaboration. For futures contracts, it has supported that the Negotiation Hypothesis (Harris 1991) in terms of reporting the relationship between the percentage of individual transactions and the average trade size.

Brown, Chua and Mitchell (2002) analyzed the price clustering in Asia-Pacific Stock Exchanges and whether there is a cultural effect on this clustering. It has focused on analyzing the effect of Chinese culture on clustering. Six market has been studied. These are ; Australia, Hong Kong, Indonesia, the Philippines, Singapore and Taiwan. The data consists of the last two digits of the daily closing stock prices in each market between January 1, 1994 and December 31, 1998. The largest and smallest 160 companies traded on the markets were selected. First, for each market, the currency, price range, minimum tick size, clustering digit, volatility of index, daily avarage volume, daily avarage value, Transaction cost (%), Ethnic Chinese stock percentage and number of cases statistics has been measured and plotted. Chi-square test has used to test whether the distribution was uniform or not.

Trade clustering, determined as the dependent variable, has regressed to Chinese cultural variables (ominous numbers, festival periods) and firm variables (size, volatility) determined as independent variables. Binomial logit model has used to measure Attraction Hypothesis (Curcio and Goodhart 1991), Price Resolution Hypothesis (Ball, Torous and

Tschoegl 1985) and chinese culture effect for each market. In terms of its findings showing the clustering of prices in 0, 5 and even integers, the study has shown results that support the Attraction Hypothesis (Curcio and Goodhart 1991). Price Resolution Hypothesis (Ball, Torous ve Tschoegl 1985) has supported in terms of showing the result that the clustering increases with the price level of the stock and decreases with precision. Only in the Hong Kong market, a tendency to avoid 4, which is the ominous number in Chinese culture, has observed during the Chinese New Year and festival times. In this context, it has been argued that only for this market, Chinese culture affects the clustering.

Sopranzetti and Datar (2002) analyzed the measurement of the price clustering in the foreign exchange spot market in this study. The parity of the German mark, the Japanese yen, the UK pound, the French franc, the Italian lira and the Swedish krona to the US dollar has been observed. The data of the study was drawn from the Federal Reserve Bank of New York and consists of the daily exchange rate indicative quotes of the above five currencies between January 1, 1971 and December 31, 1993. A sample was chosen from the buying exchange rates in The Federal Reserve Bank of New York at noon for each day. The median of this sample has taken and recorded in a daily series. The sample consists of this daily median ratio series. The frequency distribution has been made for the two decimal places of each currency and it has been observed that the exchange rates ending in 0 and 5 are higher than the others. Probit analysis has used in the study to examine the factors affecting the clustering of exchange rates in even digits. A binary dependent variable has used where the last digit of the exchange rate is 9 or 5 when it is equal to 1 otherwise it is equal to 0. The aim is to measure whether trade volume and volatility are affecting the clustering. The natural logarithm of the annual transaction volume (LNVOL) for all currencies in Federal Reserve Bank of New York has been chosen as the volume proxy. If clustering increases with the volume, the LNVOL coefficient was expected to be positive. The absolute value of daily price changes (SIGMA) of the currencies in the sample was chosen as the proxy of volatility. It is observed that all coefficients on both indicators are positive and it is statistically significant at 5% level in all currencies except Swedish krona. Regarding these results, it is concluded that as volume and volatility increase, the tendency to cluster will also increase. The study has shown findings that support Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) in terms of this result.

Schwartz and Van Ness (2004) examined the price clustering in futures markets. The data of the study consists of tick by tick and daily trade prices of S&P 500 futures contracts between 1999 and 2000. All data was taken from the Chicago Mercantile Exchange. Since the minimum tick size in the S&P 500 is 0.10 cents, the number and percentage of the transactions occured at 10 cent intervals for the two steps after the decimal point in 1999 and 2000 were measured. First, the mean, the standard deviation, and the lowest and highest prices of the settlement price were measured in both years. Afterwards the number of the opening, closing and settlement prices at 10 cent intervals are measured and the clustering here is examined. In addition, the data were divided into four as front-month contract (8-99 days), back-month contract (greater than 99 days) between 1-7 days and Expiration Day. The number of prices and percentages in 10 cent intervals were measured.

Regression analysis has used in the study. The percentage of transactions at x.00 and x.50 were regressed to volume and volatility, and it has observed that volume and volatility significantly affected the futures price clustering. The clustering is argued to be a positive function of price volatility, and a negative function of volume and open interest. For the front-month / back-month analysis of the contract, the dummy variable equals 1 when the futures contract is designated as back-month, and 0 when designated as front-month. As a result, it has found that front-month and back-month trade also significantly affected the price clustering.

Ahn, Cai and Cheung (2005) analyzed the clustering in trade and quoted prices in electronic limit order books in Hong Kong Stock Exchange. The data of the study has taken from the Trade and Bid-Ask Records on the Main Board of the Hong Kong Stock Exchange (SEHK). The data of the study consists of the trade records of 698 common stocks listed in the SEHK for the period January-June 2020. For each stock listed, the trade record includes the transaction price, volume information, bid-ask record, bid-ask offer, queue length, number of orders, and bid-ask amount in the stock volume every 30 seconds.

The data has divided into eight different tick size groups. Number of stocks, price range, market capitilization, average stock price, avarege daily number of trades, avarage daily share volume, daily return standard deviation, bid-ask spread in Hong Kong dollars in percentage terms, average bid -ask size have obtained and recorded. The mean and median of these calculated. Regression analysis method was used in the study. Abnormal even and integer price frequencies have chosen as the dependent variable. The independent variables have selected as the natural logarithm of the average stock price, the natural logarithm of the daily stock volume, the natural logarithm of the market value and the inverse of the return standard deviation and they have regressed to the clustering ratio.

As a result of the study, an abnormally even and integer frequency has observed in bid and transaction prices for all tick size groups. It has been found that there is stronger clustering in deeper quotes. In addition, it is analyzed that fine tick size is a factor that limits the price resolution process. The study has shown findings that support Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) in terms of these results.

Ohta (2006) analyzed the price clustering in the Tokyo Stock Exchange (TSE). The data of the study consists of TSE's best bid-ask offers on tick basis, transaction prices and their volumes. It has included that common stocks data in TSE between September 2001 and February 2002 . All transactions and offers were drawn at minute intervals. Price clustering has been observed in five-minute, half-hour intervals, continuous and call auctions. Three variable clustering has presented to examine the price clustering. These are a dummy variable called DIGIT5 for each transaction where prices are five and their multiples equal to one otherwise zero, AVG5 which is the average of DIGIT5 for each observation, and CR5 which is the volume weighted average of DIGIT5. CR5 has chosen as the concentration ratio in transaction volume for prices ending in zero or five. The clustering of these values in five minutes, thirty minutes, continuous and call auctions was observed, respectively. The sample was tested in five different models. CR5 has chosen as the dependent variable of Model 1, AVG5 as the dependent variable of Model 2, and DIGIT5 as the dependent variable of Model 3-4-5. The logarithm of the daily market values, the logarithm of the number of transactions for the interval, the return volatility of the day, and the logarithm of the transaction volume were listed as independent variables. Model 1 and 2 have analyzed by using the random effect model and Model 3-4-5 by using probit model. The point where Model 3-4-5 differs from Models 1 and 2 is the threshold number of transactions. The threshold number of transactions in Model 1 and 2 was greater than 500 for CR5 and AVG5, greater than 500 for DIGIT5 in Model 3, less than / equal to 500 in Model 4, and threshold number of transactions has not observed in Model 5.

As a result of the study, it has found that the price clustering has at its highest level at the market opening, decreased dramatically in the first half hour and then reached a stable level. It has been observed that the price clustering degree does not increase again when the market closing time has coming. It has been argued that there is no serious difference between call auctions and continuous auctions. Before the market opens, the price tends to cluster because there is uncertainty in the market. The study has shown results that support the Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) in terms of this findings.

He and Wun (2006) analyzed whether cultural and economic reasons affect the clustering of bid/ask and quoting prices in the stock markets in China. Shanghai and Shenzhen Stock Exchanges have observed in the study. These two Stock Exchanges have preferred because they are the two largest stock exchanges in China. The data of the study consists of 771 stocks with a price of more than one Chinese Yuan in the period from January 1, 1998 to December 31, 2000. For each stock in the sample; daily volume, daily amount of money transacted, end-of-day closing price, market capitalization, last bid and ask prices of each trading day values have been obtained. The data has divided into 4 groups as a price range (All: 1-40¥, Low: 1-9¥, Middle: 10-19¥, High 20-40¥). The average price and number of stocks for each range have calculated. First, the non-path-adjusted and path-adjusted frequency in bid/ask and close prices of the stocks have obtained to determine the existence of a clustering at multiples of 5. Then, non-path-adjusted and path-adjusted frequency were obtained for all numbers to determine the presence of clustering in the last decimal.

It has been observed that the frequency at 10, 5 cents and 8 as the last decimal place has an effect of 10% on the buy and sell spreads. Eight parameters were determined for analysis. These; the frequency of close price with 10 cent rounding (F10), the frequency of close price with 5-cent rounding (F5), the frequency of close price with the last decimal point on 8 (F8), avarage close price, the volatility of daily price returns, daily number of shares transacted, daily number of shares transacted, daily amount of money transacted. The minimum, maximum values, mean, median, and standard deviation of these parameters have plotted. Price rounding frequency has regressed to the above parameters by using the regression analysis. Bid-ask spreads have also regressed to parameters and rounding frequencies.

At the end of the study, it has been suggested that there will be a rolling tendency in developing countries as well as in developed countries due to economic reasons, and it has been observed that traders tend to be prominent figures such as 0 and 5. In addition, the number 8, which is pronounced "Fa" in Cantonese language in Chinese culture, means having and attaining wealth. It has been argued that the clustering observed in the 8th of the last decimal number is culturally influenced by this phenomenon.

Booth and Yüksel (2006) tested price resolution in the emerging market. Istanbul Stock Exchange has been chosen as the market. The data of the study consists of the opening and closing prices, transaction numbers and volumes of the first 30 stocks traded in the Istanbul Stock Exchange between January 1998 and February 1999. First, the frequency of the two decimal digits of the stocks for each number has measured. Chi-square test has used to measure the presence of the clustering. It has been observed that there is a tendency to cluster in 0, 5 and even numbers. Then the data was divided into 3 groups. These are: all transactions, transactions that cause price change, and a series of consecutive transactions that take place at the same price, ie relative price stickness. Their weekly averages have calculated for even and odd series. The ratio of this, that is odd to even, has shown that the transactions tends to spend long time in even numbers than in odd numbers.

Regression has used to test the relationship between uncertainty and clustering and the magnitude of the spread and price change. The data has again divided into 3 groups as above. In addition, weekly price stickiness and weekly relative price stickiness groups have added. For each group, volatility, trade size, trade frequency, relative ticknes, have plotted. The dependent variable has chosen clustering measure for the first two groups, weekly price stickiness for the third and fourth groups, and relative price stickiness for the fifth group. It has regressed to the above independent variables. As a result of the study, it was observed that prices have been sticky in periods of medium and low uncertainty. In addition, it has been suggested that the level of clustering in the Istanbul Stock Exchange is less than in other emerging markets. It is concluded that the existing clusterign has due to the same price of the transactions consecutively. It has been concluded that the positive relationship observed in previous studies between uncertainty, price changes and clustering is also in this study, when there are multiple tick spreads, prices change frequently and uncertainty is high.

Alexander and Peterson (2007) tested the existence of a trade size clustering for NYSE and Nasdaq stocks and its economic consequences. The data of the study consists of six parts. The first sample consists of 144 randomly selected stocks traded between November 1990-January 1991 from the public database TORQ (Trades, Orders, Reports, and Quotes) for NYSE stocks. The second, third and fourth parts of the data consist of the trade and quotation of 200 stocks traded in 1995, 1998 and 2002, respectively. The fifth and sixth parts consist of the trade and quotation of 200 Nasdaq common stocks selected randomly from 1998 and 2002. The first group of the study has named TORQ data and the other groups TOQ data. For each group, mean, median, standard deviation, average price, average number of trades / orders per day are plotted. The dependency of the price and trade size clustering has tested by using the chi-square test. Because of this dependence, the bivariate probit model has used instead of the univariate probit model in the analysis. Dependent variables have determined as clustering and trade size. The independents have chosen as: demeaned standardized number of trades in previous fifteen minutes, inverse of the quote midpoint for the current trade, natural log of the market cap at the end of the previous year, dummy variable equal to one if trade size is greater than ten thousand shares otherwise zero, dummy variable equal to one if trade size is greater than depth otherwise zero, dummy variable equal to one if previous trade is rounded otherwise zero and the quoted spreads.

As a result of the study, it has argued that trade size clustering increased in three groups in NYSE and Nasdaq. These are multiples of 500, 1000 and 5000 stocks. It has observed that there is clustering in the rounded prices for the rounded size transactions. The study has supported the Negotiation Hypothesis (Harris 1991) in terms of suggests that trade size clustering is high during heavy trade periods when information is intense. In addition, it has been argued that size rounding occurs less in higher-priced stocks.

In 2001, stock markets in the U.S.A. have taken a smoother decimal format with a penny tick size. Ikenberry and Weston (2008) analyzed the effect of this change on price clustering. The data of the study consists of NYSE and NASDAQ stocks priced between 5-500 USD in the last six months of 1996 and 2002. First, the sample has divided into two groups, NYSE and NASDAQ shares. For the stocks listed in each group; market value, price, volume, number of trades, share turnover, return volatility, quoted spread, relative spread have plotted on the basis of mean, median and standard deviation. Then, clustering at the one and two-digit levels has measured, respectively. To compare the clustering in the eighth system in 1996 and the decimal system in 2002, the chi-square 'goodness of fit' test has made. Data has divided into four groups on the basis of price ranges separately for NYSE and NASDAQ. Clustering has tested for each number (0-9) in both eight and decimal systems. Regression has made to find the cross-sectional determinants of the clustering. Dependent variable has selected as the observed frequency of transaction prices that fall on either nickels or a dimes. Independent variables have determined as size and price average, standard deviation of daily returns, and buy-sell spread. At the end of the study, price clustering has observed with increases of five and ten cent. After the share splits and earnings announcements, no decrease has observed in the price clustering. In addition, it has been argued that the clustering has not varied between markets and at different levels of volatility.

It has been argued that the level of clustering after the arrangement has not differed from before the arrangement. In the study, It has suggested that the clustering tendency has consistent with the Negotiation (Harris 1991) and Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985), the level of clustering could not only be explained by transaction cost but also had other factors. In addittion, it has been argued that the Negotiation (Harris 1991) and Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) have generally explained the scope of the clustering, but it has suggeted that an alternative hypothesis which is the clustering may be the result of a psychological bias in terms of the results in the decimal system.

Aşçıoğlu, Comerton-Forde and Mclnish (2007) analyzed the price clustering in Tokyo Stock Exchange. Unlike other studies in the literature, clustering analysis has also made on the basis of limit-order depth in this study. The data of the study consists of intraday data of stocks traded in Tokyo Stock Exchange between January 2003 and October 2003. The data has divided into groups according to tick and lot sizes. Lot sizes have classified as 1-10-50-100-500-1000 and tick sizes as 1-5-50-100-1000 Japanese Yen. In the article, the first three digits after the comma of the stock prices have analyzed. In the study, the distribution of quote digits by tick size has plotted first. Then, using a sample of stocks with different tick sizes, the difference in depth between even and odd price quotes has tested. After, proportion of depth at even and odd quotes by side of the market and tick size has plotted. In order to test the clustering level of uncertainty, the data has divided into two groups. The period has classified as before and after the broker disclosure change on June 30, 2003. These two periods has been tested by t-test and the relationship between anonymity and clustering has tried to be analyzed. Again, the depth ratio of even and odd bid prices according to minimum lot size, risk and market value has analyzed by using a t-Test.

At the end of the study, it has observed that prices tend to cluster at 0 and 5, respectively. In this respect, the study has shown findings that support the Attraction Hypothesis (Curcio and Goodhart 1991). In the article, it has observed that the depth in even numbers is greater than the odd numbers and this clustering has independent of the minimum tick and lot size. It has also suggested in the study that clustering tendency is common in all risk groups and sizes but does not have a uniform relationship with uncertainty. In terms of this result, the study provides limited evidence to support Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985).

Brown and Mitchell (2008) analyzed the effect of China's cultural values on the price clustering of stocks. The places of 4, which is considered an ominous number in Chinese culture, and 8, which is considered a lucky number, on the clustering in the stock market have tested. Shanghai, Shenzhen, Hong Kong and London stock exchanges have analyzed in the study. The London stock exchange has included in the data for comparison. The data of the study consists of the last digit of the prices of stocks traded on Shanghai, Shenzhen, Hong Kong and London Stock Exchanges between December 19, 1990 and December 31, 2002. Daily opening, highest, lowest and closing prices have plotted.

First, the frequencies of the last digits of each market's closing price have obtained. Then the observed clustering has divided into 3 groups these are; 2 vs 8, 4 vs 6 and 4 vs 8. In terms of cultural impact, two should occur less than eight, four should occur less than six, four should occur less than eight. The predicted rate for each group was set at <1. Data is divided into 5 groups, which are Shanghai A shares, Shanghai B Shares, Shenzhen A Shares, Shenzhen B Shares, Hong Kong H shares, and London Stock Exchange shares. For each group, the average daily ratio, median daily ratio, number of days, propotion of daily ratios <1, days when ratio

<1 and days when ratio >1 have plotted. Using the biominal logit model, the relationship between 2v8, 4v6 and 4v8 has been analyzed for all Chinese markets. A binary dummy variable has chosen as the dependent variable. In this variable, the closing price is 1 if 4, and 0 if 8. The independent variables have determined as the log of the tradable market value of the relevant company shares on the day of the trade, price level natural logarithm, standard deviation of sixty-day returns (volatility), volume and five different Chinese festival periods.

At the end of the study, it has been suggested that Chinese cultural elements affect the stock price clustering. In general, clustering has observed more clustering at 8 on A stocks traded by the Chinese, and less clustering at 8 on B and H stocks, which have mostly traded by foreigners.The findings of the study have supported that cultural influences will diminish as markets mature. It has conflicted with the Attraction Hypothesis (Curcio and Goodhart 1991) in terms of the finding that the clustering in 8 is more than 4.

Narayan, Popp and D'Rosar (2011) tested the clustering of stocks in Mexico and the determinants of the clustering in their study. The Mexican stock market has discussed in the study. The study have differed from the studies analyzed in other emerging markets in terms of the economy of Mexico is significantly affected by terrorism, cultural factors and sports activities. The data of the study consists of daily price data of the stocks of 12 biggest companies in Mexico listed in Bloomberg between 2003-2008. First, the numerical frequencies, mean, median, standard deviation, maximum price and minimum prices of the two decimal digits of stock prices for each company have plotted.

It has observed that the absence of clustering in the 3 companies with the lowest stock prices. It has observed that the 2 companies with the highest stock prices tend to cluster more than the other 10 companies. In total, it has been observed that 49% of the prices tend to cluster at x,00 and x,05. The Standard Probit Model has used to analyze the determinants of the price clustering. The binary dummy variable which takes one if the price is clustered at x,00 and x,05 and othewise zero, has determined as the dependent variable. Two models have used for eight companies where price clustering has observed. In the first model, volume and price have regressed to clustering, and in the second model, volume and volatility have regressed to clustering.

At the end of the study, it has shown that the prices of stocks cluster at 0 and 5. The study has provided findings that support Negotiation Hypothesis (Harris 1991) and Price Resolution Hypothesis (Ball, Torous and Tschoegl 1985) in terms of arguing that volatility and volume are inversely proportional to price clustering. At the same time, the study has shown evidences that conflict these hypotheses in terms of the own price is inversely proportional to the clustering.

Narayan and Popp (2011) analyzed the price clustering in oil futures markets. The data of the study consists of futures contracts of five different oil types. These are the blend stock for crude oil (02 January 1985--30 April 2009), reformulated regular gasoline (28 January 1994--29 September 2006), regular gasoline blending reformulated gasoline oxygenate (03 October 2005--30 April 2009), No 2 Heating Oil (02 February 1994 - 30 April 2009) and propane in spray type burners or medium capacity commercial-industrial burner units for internal heating (08 February 1994 - 30 April 2009). All of the data has been obtained from the website of www.eia.doe.gov. First; the mean, median, standard deviation, minimum and maximum values of the futures contract prices of each oil type have calculated. Then, the numerical frequencies and t-values for the two decimal digits of the prices of futures contracts for each oil type have plotted.

At the end of the study, strong statistical evidence has observed that there is a price clustering in the oil futures market. In terms of this result, the study has presented findings that conflict with the Efficient Market Hypothesis (Fama 1969), which argues that future predictions cannot be made using information obtained from previous contracts. The study has shown findings that support the Attraction Hypothesis (Curcio and Goodhart 1991) in terms of clustering the prices at 0 and 5 levels. The study has conflicted with the Negotiation (Harris 1991) and Price Resoulution Hypothesis (Ball, Torous and Tschoegl 1985), which explains the clustering of prices in terms of transaction costs, and has argued that this tendency may be the result of people's psychological biases, suggesting that a new alternative hypothesis can be developed.

Blau and Griffith (2016) tested the relationship between price clustering and stock price stability in their study. It has aimed to identify the determinants of volatility with this study. The data of the study consists of the price, volume, stock exchange list, closing bid / ask prices of stocks traded in NASDAQ and NYSE between 1995-2012. The first four decimal places of prices have included in the analysis.The data has divided into three groups. Group A has contained all observations. Group B has covered the period in which prices are not decimalized before 2001, and group C has covered the period after they become decimal. For each group, the clustering percentage, the standard deviation of daily returns, the difference between the highest and lowest price in the month, market capitilization, closing price, monthly volume ratio, spread, illiquidity measure have plotted and the mean, median and standard devitation of them have obtained. Clustering ratio has determined as the proportion of closing prices that are divisible by round increments.

Regression analysis has used in the study. Dependent variables have determined as return and price volatility. Price volatility has calculated as the difference between monthly high and monthly low prices. The independent variables have determined as the ratio of the clustered daily closing prices to the number of days, the natural logarithm of the market capitilization, the natural logarithm of the closing prices, the monthly volume ratio, the spread, and illiquidity.

As a result of the reggression, a positive relationship has found between stock price volatility and price clustering. The findings of the study has shown that price clustering is a powerful factor in determining the level of volatility. At the end of the study, it has argued that prices with limited information caused by bias and the tendency to avoid negotiation have lead to the increase in the level of volatility and this have affected the price stability of stocks negatively.

Urquhart (2017) analyzed the price clustering in Bitcoin. The study has been the first study in the literature on bitcoin in terms of price clustering. The data of the study consists of the daily closing prices and volumes of the coins traded on Bitstamp between May 1, 2012 - April 30, 2017. Chi-square test has used in the study. First, the time series of daily prices and volume have plotted. The two digits after the comma have determined as the M-value and the frequencies of the M-values have plotted. The mean, median, maximum value and minimum value of the prices and returns have been obtained. Clustering has observed in at least 73, 34,37,83, 46 and at most 00, 50, 99, 75, 19, respectively. The numbers with the most and the least clustering have divided into two groups. In both groups; frequency, percentage of frequency and the factor, which have obtained by dividing the frequency by expected frequency, has calculated for each number on the basis of price and volume.

Regression has used in the study, first price and volume, then volume and price volatility have regressed into clustering. At the end of the study, it has argued that there is a tendency for bitcoin prices to cluster in integers. It has been observed that more than 10% of the prices are clustered at 00. In addition, it has been argued that the price clustering has significantly related to the volume. In this respect, the study has shown findings that support the Negotiation Hypothesis (Harris 1991).

Das and Kadapakkam (2018) tested the price clustering for exchange trade funds (ETF) and individual stocks in a period of high automatic trading. The study has focused on the period after decimalization. The data source of the study is Trade and Quotes Database (TAQ) in NYSE. The data of the study consists of the trade data of ETF and stocks traded in NYSE between 2001-2010. The first two decimal places for prices have included in the analysis. First, price clustering for ETFs has graphed in the study. The clustering has calculated as the ratio of the number of transactions ending in 0 or 5 to the total number of transactions. The clustering rate, total clustering, annual change, average trade size for each number of the last digit of ETF's prices per second have plotted. Then the price clustering in S&P 500 stocks has analyzed.

Companies have divided into three groups according to their size (small-medium-large) and average market capitalization, average price clustering, average trade size plotted by years for each group. In addition, the mean market cap, median market cap, average volume, mean clustering, median clustering, average trade size, average proportion of very small trades have obtained for each group. Independent variables consist of the logarithm of the firm's avarage closing price, the ratio of transaction volume to market capitilization, the logarithm of the year-end market capitilization and the standard deviation of daily returns. According to the December price S&P 500 stocks divided Decile 1 and Decile 5 tocks and regression analysis are done. T-Test has conducted to measure the effect of trade size on price clustering. Analysis has made in four panels. Panel A has represented the total dollar volume in each trade size group, Panel B has represented each group's share of the total volume, Panel C has represented the daily cluster average of transactions in each group, Panel D has represented the median time per second transactions for each group.

At the end of the study, it has been suggested that clustering tendency for ETFs have less observed than for individual stocks. It has been suggested that in the algorithmic trading period, price clustering has decreased for both ETFs and individual stocks. This decrease has been observed for all sizes of firms and stocks. In this respect, it has been argued that algorithmic trading is immune to psychological biases affecting clustering.

Hu, Jiang, McInish and Ning (2019) analyzed the impact of the Chinese Securities Regulatory Commission’s (CSRC) decision to suspend export price limitations on the price clustering of Chinese public offerings. The data of the study consists of the quotes and price data of public offerings and stocks between 1992 and 2014. It has divided into six groups according to the category of companies. These categories are; finance, utilities, properties, conglomerates, industrials and commerce. First, the distribution of the prices of public offerings according to the last digit has calculated. Then, based on the release date of the limitation decision, the time interval has divided into two periods as 1992-2000 and 2001-2014. After, the distribution of the last digit of prices as zero, non-zero, integer and fraction have plotted. In order to analyze the clustering according to the price level, the offer prices have divided into three groups as low (<10 ¥), medium (10-20 ¥) and high (> 20 ¥). Zero, non-zero, integer, fraction distribution in the last digit for each group has plotted.

T-test has made for price clustering and pricing uncertainty analysis. The time interval for gap is 60 in the first panel and 90 days in the second. For each panel, the last digit ending with zero, not ending with zero, integers, fractions, and its percentages have obtained. Logistic regression has used with the binary dummy dependent variables to measure the public offering price clustering and window guidance. Dependent variables have determined as zero-ending IPO and integer IPO (one if ending with zero and integer, zero otherwise). Independent variables have determined as intercept, window guidance, medium offer price, high offer price, gap, market volatility, stock volatility, Natural logarithm of the average daily CNY(¥) value of the number of shares traded, natural logarithm of the average market value of the firm in 1,000 CNY over the measurement interval and natural logarithm of the total proceeds from the IPO in 1,000 CNY. In order to measure the cultural impact, clustering analysis has made by using binomial tests for the numbers 8 and 4. The clustering of 8 and 4 has compared proportionally with other numbers.

At the end of the study, it has observed that 54.3% of the 2335 observations clustered at 0. It has been suggested that increased bid prices and uncertainty have increased the Chinese IPO price clustering. In this respect, the study has shown findings that support the Negotiation Hypothesis (Harris 1991). In addition, it has argued that there is a clustering at higher prices after the suspending of the quidence. In the cultural analysis of the price clustering, it has been observed that the 8 is more preferred than the 4.

Baig, Blau and Sabah (2019) analyzed the level of price clustering on Bitcoin in their study. In the study, the relationship between Bitcoin's high sensitivity and price clustering has tried to be tested. The data of the study has taken from https://bitcoincharts.com and consists of Bitcoin / USD data from 65 active and 23 inactive exchanges. Bitcoin data with a price higher than $5 withdrawn from the five most active exchanges of Bitcoin between 10 May 2010 and 31 October 2018 has selected as sample. These five active exchanges are; BTCE, Bitfinex, Bitstampt, Mtgox, Coinbase. Each transaction date, time, price, and volume has included in the sampling. For sensitivity tests, data on the downward and upward trend have obtained from Google Trends, Bloomberg and the American Association of Individual Investors for the word of "bitcoin". The first two digits after the comma in bitcoin prices have included in the analysis.

Ordinary Least Squares method has applied in the study. First, three different clusterings have determined. These are; round clustering(prices do not randomly walk and cluster in round numbers), strategic clustering (prices ending in .01 and .99 dollars) and total clustering. Then; mean, median, standard deviation, minimun value and maximum value for the total data including 2582 observations have plotted. Then, the above-mentioned three clustering groups (round, strategy, total) have determined as dependent variables. The independent variable has determined as the sensitivity that includes the downward and upward trends.

The results have suggested that different sentiment proxies have a positive relationship with the price clustering. It has been argued that as the investor sensitivity increases, the price clustering also increases in the study. In addition, it has been argued that when uncertainty and negotiation costs are high, the level of price clustering is also high. In this respect, the study has shown findings that support Negotiation Hypothesis (Harris 1991).

4.RESEARCH METHODOLOGY

4.1. Research Data

The data of the study consists of the closing prices and volumes of the stocks of 12 banks selected from Turkey and Europe. The selected banks from Europe are as follows. Deutsche Bank has selected from Germany. HSBC, Royal Bank of Scotland, Barclays have selected from England. Credit Agricole, Societe Generale and BNP Paribas have selected from France. Türkiye İş Bankası, GarantiBBVA, Akbank, Yapı Kredi and Vakıf Bank have selected from the Turkey. Although the original data covers the years 1999-2020, it has included 2005 and later in the analysis due to the removal of six zeros from the Turkish Lira. In addition, since Vakıfbank's data before 2007 could not be accessed, Vakıfbank's data covers the dates of 03.01.2007-14.10.2020. The date range for all remaining banks is 03.01.2005-14.10.2020. All data of the study has obtained from Bloomberg.

The analysis has based on the work of Urquart (2017). In this context, the data has been arranged for the analysis models to be applied to the data. The arrangement of the data has carried out as follows. Since the two decimal digits of the closing prices of the stocks will be analyzed, the two decimal digits of these prices have been created as a new data set. A variable has created that indicates whether the next digit in the comma is equal to 00. It has calculated how often the two digits after the comma occur in the data. The two digits after the comma have squared for each value. The closing price of the previous day is brought next to each day. Simple returns have been calculated $\{(P_t-P_{t-1})/P_{t-1}\}$. The natural logarithm of the daily trading volume has taken. Volatility has calculated by taking the standard deviation of the return values of the last twenty days for each day. The conditional effects used by Dowling, Cummins and Lucey (2016) to measure the trade effect of the analysis have examined. Four different dummy variables have created from the data regarding the increase or decrease in prices on the basis of the previous and next days. Table 2 provides a three-day cross-section of how the studys data have categorized:

Table 2: A Three-Day Cross-Section From The Data

date	px_last	last_digits	px_volume
17.9.20	6,69	69	65732298
16.9.20	6,71	71	57792234
15.9.20	6,76	76	72270340
is_whole_number	**frequency**	**last_digits_squared**	**px_volume_log**
0	24	.4761	18,00
0	31	.5041	17,87
0	49	.5776	18,10
px_last_lag1	**return**	**return_lag1**	**volatility**
6,71	0,00	-0,01	0,02
6,76	-0,01	0,00	0,02
6,78	0,00	0,00	0,02
is_falling_price_cluster	**is_rising_price_cluster**	**ADZ_lag1**	**BDZ_lag1**
0	0	0	0
0	0	0	0
0	0	0	0
AUZ_lag1	**BUZ_lag1**	**ADZ_lag2**	**BDZ_lag2**
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
AUZ_lag2	**BUZ_lag2**	**ADZ_lag3**	**BDZ_lag3**
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
AUZ_lag3	**BUZ_lag3**	**ADZ_lag5**	**BDZ_lag5**
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
AUZ_lag5	**BUZ_lag5**	**ADZ_lag10**	**BDZ_lag10**
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
AUZ_lag10	**BUZ_lag10**		

0	0
0	0
0	0
0	0

In Table 2, the "date" column indicates the traded date .

The "px_last" column indicates the closing price of the stock for that day.

The "last_digits" column indicates the two digits after the comma.

The "px_volume" column indicates the trading volume of that day.

The column "is_whole_number" is the dummy variable that takes value of 1 if the two digits after the comma are equal to 00, zero otherwise.

The "frequency" column indicates the frequency of the two digits after the comma.

The "last_digits_squared" column indicates the square of the digits after the comma.

The "px_volume_log" column indicates the natural logarithm of the volume.

The column "px_last_lag1" indicates the closing prices of the previous day.

The column "return" calculated as a simple return.

The column "return_lag1" the return value of the previous day.

The ‘’volatility" column indicates the standard deviation of the return values of the last 20 days for each day.

In cases where the two digits after the comma are equal to "00", BDZ, BUZ, ADZ, AUZ columns have created for the previous and next N days, respectively, depending on whether the previous day's closing price is lower or higher than that day's closing price.

4.2.Methodology

In this study, it is aimed to conduct research on the price clustering of bank stocks. In this context, stock prices and volumes have analyzed by using data similar to the data of many studies in the literature. The method of the study is similar to that of Urquhart (2017) and Dowling at al (2016). The model of the study has run with the statsmodels tool in the Python program.

The steps of the analysis as follows. First of all, to test the price clustering, linear regression analysis has made to estimate the frequency of the two digits after the comma, using the variable and the intersection point, which shows whether the first two digits after the comma are equal to 00.

For the price clustering kurtosis test, linear regression analysis has made to estimate the frequency of the two digits after the comma, using the square of the two digits after the comma and the intersection point.

For the price clustering trading-based conditional effect test, a linear regression analysis has made to estimate the return by using the previous day's return value, BDZ, BUZ, ADZ, AUZ and the intersection point.

In order to determine the determinants of price clustering, probit regression analysis has made in which the variable of price, volume and volatility and the variable showing whether the two digits after the comma are equal to zero or not. Two separate probit regression analyzes have made for volume and volatility.

In order to test the clustering in equities several models are constructed and results are given below. Model 1 test the clustering effect at the whole number. The equation is as follows:

$$f(M) = \alpha + \beta D^i + \epsilon \tag{1}$$

Where;

$f(M)$ is the absolute frequency of the last 2 digits after the decimal point

$D^i$is 1 if last 2 digits after the decimal point is 00, 0 otherwise.

While the β value is equal to zero in the null hypothesis, if there is clustering, the M values should have a higher frequency at the clustering point, so β will have a positive and significant result.

In addition clustering kurtosis test has also made to observe the frequency shape around whole numbers. The equation is as follows:

$$f(M) = \mu + \delta_1 M + \delta_2 M^2 + \epsilon \tag{2}$$

Where;

$f(M)$ is the absolute frequency of the last 2 digits after the decimal point

$M$is the last 2 digits after the decimal point,

$M^2$is the square of M.

According to the equation, δ_2 should be zero if there is a normal distribution. But if there is an abnormal distribution, the coefficient of δ_2 should be negative. According to the equation, the existence of price clustering is suggested with a positive and significant δ_2.

Since the trading effects of price clustering cannot be measured in the above models, Dowling at al.'s (2016) method has followed. In this context, four different dummy variables have created depending on the increase and decrease in the price. These variables are as follows:

BDZ_t^n is 1 for to n days before a whole price that occurred through falling prices, 0 otherwise.

BUZ_t^n is 1 for to n days before a whole price that occurred through rising prices, 0 otherwise.

ADZ_t^n is 1 for to n days after a whole price that occurred through falling prices, 0 otherwise.

AUZ_t^n is 1 for to n days after a whole price that occurred through rising prices, 0 otherwise.

The equation used to analyze the trading effects of price clustering on the basis of these variables is as follows:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDZ_t^n + \beta_3 BUZ_t^n + \beta_4 ADZ_t^n + \beta_5 AUZ_t^n + \epsilon \qquad (3)$$

Where;

$R_t$is return for period t

$R_{t-1}$is the return for period t-1.

Finally, the method of Narayan et al (2011). is used to analyze the determinants of price clustering. Here, probit regression analysis has performed to estimate the relationship between price clustering, volume and volatility. The equations are as follows:

$$P(Y = 1) = \sigma(\beta_0 + \beta_1 Price + \beta_2 log(Volume)) \qquad (4)$$

Where;

σ is the logistic function

Y is 1 if a whole price occurs, 0 otherwise

$Price$ is the price in given day

$log(Volume)$ is the natural logarithm of the trading volume in given day.

$$P(Y = 1) = \sigma(\beta_0 + \beta_1 Price\ + \beta_2 Volatility) \quad (5)$$

Where;

σ is the logistic function

Y is 1 if a whole price occurs, 0 otherwise

$Price$ is the price in given day

$Volatility$ is the 20 day rolling standard deviation of the price.

5.EMPIRICAL FINDINGS

5.1. Descriptive Statistics

In our study, first the mean, maximum value and minimum value have obtained for each stock. Afterwards, the kurtosis and skewnes values of these values have observed. Table 3 has shown the mean, maximum value, minimum value, kurtosis and skewness values for all stocks:

Table 3: Descriptive Statistics

RETURN								
Bank name	**Stock name**	**Mean(%)**	**SD**	**Max**	**Min**	**Kurt.**	**Skew.**	**n**
Deutsche Bank	DBK EUR	-0,05	0,03	0,23	-0,17	7,83	0,16	4018
HSBC	HSBA USD	-0,04	0,02	0,15	-0,23	16,55	-0,41	3687
Royal Bank of Scotland	NWG USD	-0,11	0,04	0,31	-1,11	210,87	-7,29	3844
BARCLAYS	BARC USD	-0,04	0,03	0,56	-0,28	34,35	0,80	3739
Credit Agricole	ACA EUR	-0,02	0,03	0,23	-0,18	7,43	0,06	4018
Societe Generale	GLE EUR	-0,04	0,03	0,21	-0,23	8,33	-0,29	4018
BNP Paribas	BNP EUR	-0,01	0,02	0,19	-0,19	9,25	0,05	4018
İş Bankası	ISCTR TRY	0,02	0,03	0,34	-0,14	10,41	0,48	3948
GarantiBBVA	GARAN TRY	0,04	0,03	0,16	-0,14	2,43	-0,05	3948
Akbank	AKBNK TRY	0,01	0,02	0,19	-0,12	2,60	0,17	3948
Yapı Kredi	YKBNK TRY	0,02	0,02	0,12	-0,16	2,70	-0,10	3946
Vakıf Bank	VAKBN TRY	0,01	0,03	0,17	-0,12	2,16	-0,11	3444

*** All return values are given as percentages.**

In Table 3, the first column has presented the bank name, the second column is the stock name, the third column is the mean value, the fourth column is the standard deviation value, the fifth column is the maximum value, the sixth column is the minimum value, the seventh column is the kurtosis value, the eighth column is the skewness value and the last column is the total observation.

5.2.Price Clustering Test

In our price clustering test, P-value in chi-squared test calculated by chi-squared statistics show how likely it is to see the observed frequencies for the given distribution. Thus getting a low p-value for the observed frequencies of digits compared to the uniform distribution where each digit's frequency is the same suggests that digits are not distributed uniformly. Table 4 shows the chi-square test results and these values for each stock:

Table 4: Price Clustering- Chi-squared Test

Stock name	Most common	Freq	%	Least common	Freq	%	Chi-squared:
DBK EUR	58	57	1,42%	74	28	0,70%	108,42
HSBA USD	82	60	1,50%	60	28	0,70%	100,28
NWG USD	29	56	1,40%	92	29	0,73%	116,97*
BARC USD	4	51	1,28%	83	29	0,73%	98,37
ACA EUR	10	60	1,49%	83	27	0,67%	146,68***
GLE EUR	0	72	1,78%	17	27	0,67%	200,10***
BNP EUR	0	84	2,08%	3	28	0,69%	199,70***
ISCTR TRY	0	61	1,54%	36	24	0,60%	231,91***
GARAN TRY	30	81	2,04%	93	17	0,43%	622,85***
AKBNK TRY	76	81	2,04%	33	23	0,58%	332,42***
YKBNK TRY	13	75	1,89%	69	20	0,50%	369,40***
VAKBN TRY	66	57	1,64%	67	21	0,61%	209,48***

*** significant at %10, ** significant at %5 and *** significant at %1**.

Table 4 has shown the chi-square test results of stocks. The first column represents the stock name, the second column represents which digitis are the most after the comma, the third column represents the frequency, and the fourth column represents the percentage. Likewise, the fifth column represents the least number of digits after the comma, the sixth column represents its frequency, and the seventh column represents the percentage. Finally, the eighth column shows the results of the chi-square test. In this context, Stocks of NWG USD, ACA EUR, GLE EUR, BNP EUR, ISCTR TRY, GARAN TRY, AKBNK TRY, YKBNK TRY and VAKBNK TRY have significantly non-uniform last 2 digit distributions. In addition, it has been observed that the two most repeated digits after the comma for GLE EUR, BNP EUR and ISCTR TRY are 00.

5.3. Model 1: Clustering Test

Linear regression analysis has made for the price clustering test. The equation used in the model is as follows:

$$f(M) = \alpha + \beta D^i + \epsilon \qquad (1)$$

Where;

$f(M)$ is the absolute frequency of the last 2 digits after the decimal point

$D^i$is 1 if last 2 digits after the decimal point is 00, 0 otherwise

The regression analysis for clustering test is designed in such a way that if β coefficient takes a significant positive value this indicates that whole numbered prices (00 digits after the decimal) have higher frequency than others. Table 5 presents the regression coefficient results.

Table 5: Regression Coefficient's for Model 1

Country	Bank Stock	Alpha	Beta	Adjusted R^2
Germany	DBK EUR	40,18***	0,81	-0,03
UK	HSBA USD	39,97***	-7,97	-0,01
	NWG USD	39,84***	5,15	-0,03
	BARC USD	39,94***	-4,94	-0,03
France	ACA EUR	40,27***	12,72*	0,01
	GLE EUR	40,08***	31,91***	0,14
	BNP EUR	39,95***	44,04***	0,31
Turkey	ISCTR TRY	39,48***	21,51**	0,06
	GARAN TRY	39,55***	14,44	-0,01

AKBNK TRY	39,87***	-17,87	0,02
YKBNK TRY	39,59***	8,4	-0,02
VAKBN TRY	34,83***	17,83**	0,04

*** significant at %10, ** significant at %5 and *** significant at %1**.

According to the Table 5; for most of the stock prices, we do not see significant positive values for the β coefficient which states that there is not clustering. However for stocks in France ACA EUR, GLE EUR, BNP EUR and in Turkey ISCTR TRY and VAKBN TRY have positive significant β coefficient that implies the clustering at whole number .

5.2. Model 2: Clustering Kurtosis Test

Linear regression analysis has made for the price clustering kurtosis test. The equation of the model is as follows:

$$f(M) = \mu + \delta_1 M + \delta_2 M^2 + \epsilon \quad (2)$$

Where;

$f(M)$ is the absolute frequency of the last 2 digits after the decimal point

M is the last 2 digits after the decimal point

M^2 is the square of M

The regression analysis for clustering test is designed in such a way that $\delta_2$takes a value of zero for normal distribution around whole numbers, negative value for abnormal shapes around whole numbers and positive value for price clustering around whole numbers. Table 6 presents the clustering kurtosis results.

Table 6: Clustering Kurtosis Results

Country	Bank Stock	μ	$\delta_1(\%)$	$\delta_2(\%)$	adjusted R^2
Germany	DBK EUR	37,936069	14,23	-0,14*	0,01
UK	HSBA USD	40,79***	-11,11	0,14*	0,02
	NWG USD	36,49***	31,04***	-0,36%***	0,19
	BARC USD	42,39***	-1,82	-0,04	0,08
France	ACA EUR	46,85***	-28,84***	0,23**	0,07
	GLE EUR	43,87***	-16,13***	0,13***	0,00
	BNP EUR	41,49***	-6,68	0,06	-0,02
Turkey	ISCTR TRY	47,69***	-43,69***	0,41***	0,09
	GARAN TRY	38,88***	0,06	0,02	-0,02
	AKBNK TRY	35,56***	1,73	0,09	0,07
	YKBNK TRY	44,26***	4,71	-0,21	0,15
	VAKBN TRY	33,05***	6,79	-0,05	-0,02

All δ_1 and $\delta_2$values are given as percentages.
*** significant at %10, ** significant at %5 and *** significant at %1.**

According to Table 6 six of the stocks in our dataset have insignificant values for δ_2. The coefficient of δ_2 implies distribution shapes. It has observed that HSBA USD, ACA EUR, GLE EUR & ISCTR TRY have positive significant values while DBK EUR, NWG USD have negative significant values. It has observed that results consistent with Table 5 for ACA EUR, GLE EUR and ISCTR TRY. On the other hand, it has been observed that DBK EUR and NWG USD have a negative significant value, HSBA USD have a positive significant value and VAKBN TRY and BNP EUR have a insignificant value which has differed from Table 5.

5.3. Model 3: Conditional Effects of Clustering

The analyzes made so far in the study have been insufficient to explain the trading effects of the clustering. For this reason, dummy variables have determined according to the increase or decrease in price before and after clustering, and linear regression analysis has made. The equation of the model is as follows:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDZ_t^n + \beta_3 BUZ_t^n + \beta_4 ADZ_t^n + \beta_5 AUZ_t^n + \epsilon \quad (3)$$

Where

R_t is the return for period t

R_{t-1} is the return for period t-1

BDZ_t^n is 1 for to n days before a whole price that occurred through falling prices, 0 otherwise

BUZ_t^n is 1 for to n days before a whole price that occurred through rising prices, 0 otherwise

ADZ_t^n is 1 for to n days after a whole price that occurred through falling prices, 0 otherwise

AUZ_t^n is 1 for to n days after a whole price that occurred through rising prices, 0 otherwise

Table 7 presents the results of the linear regression analysis:

Table 7: Conditional Effects of Round Numbers

DBK EUR	1	2	3	5	10
Constant	-0,05	-0,05	-0,06	-0,05	-0,04
r_t1	3,59**	3,52**	3,46**	3,45**	3,49**
BDZ	-0,73	-0,26	-0,25	-0,37	-0,18
BUZ	0,98*	0,75**	0,55*	0,37	0,21
ADZ	0,34	0,18	-0,01	-0,05	-0,11
AUZ	-0,46	-0,16	0,22	0,12	-0,05

HSBA USD	1	2	3	5	10
Constant	-0,04	-0,04	-0,04	-0,03	-0,03
r_t1	-1,26	-1,26	-1,32	-1,28	-1,40
BDZ	0,45	0,22	0,15	0,02	0,19
BUZ	-0,33	-0,17	-0,10	-0,34*	-0,29**
ADZ	0,09	-0,31	-0,25	-0,06	0,01
AUZ	0,13	-0,01	0,28	-0,21	-0,21
NWG USD	**1**	**2**	**3**	**5**	**10**
Constant	-0,10	-0,10	-0,10*	-0,11*	-0,07
r_t1	13,38***	13,29***	13,28***	13,27*	13,27***
BDZ	1,22	0,53	0,77	0,63	-0,26
BUZ	-0,70**	-0,54	-0,36	-0,25	-0,06
ADZ	0,33	-2,65	-0,06	0,02	-0,27
AUZ	-0,11	0,33	0,27	0,09	0,13
BARC USD	**1**	**2**	**3**	**5**	**10**
Constant	-0,04	-0,05	-0,05	-0,05	-0,04
r_t1	6,39	6,32*	6,34***	6,39***	6,39**
BDZ	1,57	0,77	0,65	0,43	0,19
BUZ	0,00	0,26	0,08	0,11	-0,11
ADZ	-0,58	-0,53	-0,36	0,00	0,14
AUZ	-0,49	0,02	0,00	-0,13	-0,14
ACA EUR	**1**	**2**	**3**	**5**	**10**
Constant	-0,02	-0,03	-0,03	-0,02	-0,03
r_t1	4,09***	3,93***	3,83**	3,80**	3,74**
BDZ	-0,24	0,00	-0,14	-0,18	-0,08
BUZ	-0,04	0,44	0,09	0,05	0,34
ADZ	0,30	0,23	0,07	-0,04	-0,09
AUZ	-0,87	0,04	0,44	0,29	0,12
GLE EUR	**1**	**2**	**3**	**5**	**10**
Constant	-0,05	-0,07	-0,06	-0,06	-0,06
r_t1	5,19***	5,28***	5,28***	5,31***	5,30***
BDZ	-0,35	0,06	0,20	0,41*	0,18

BUZ	0,90**	0,46	0,12	-0,06	-0,10
ADZ	0,20	0,53	0,41	0,33	0,31*
AUZ	0,88*	0,56	0,23	-0,05	-0,06
BNP EUR	**1**	**2**	**3**	**5**	**10**
Constant	-0,03	-0,03	-0,03	-0,01	-0,04
r_t1	1,14	0,98	1,07	1,13	1,04
BDZ	0,58	0,17	0,19	0,11	0,19
BUZ	0,43	-0,03	-0,01	-0,02	-0,04
ADZ	0,43	0,08	0,04	-0,15	-0,08
AUZ	0,73	0,52	0,33	0,10	0,22
ISCTR TRY	**1**	**2**	**3**	**5**	**10**
Constant	0,03	0,03	0,02	0,03	0,03
r_t1	-0,76	-0,74	-0,73	-0,60	-0,65
BDZ	-0,16	-0,10	-0,11	-0,17	-0,08
BUZ	-1,22*	-0,62	-0,43	-0,17	0,01
ADZ	0,19	0,07	0,19	0,23	0,12
AUZ	0,72	0,34	0,37	-0,19	-0,18
GARAN TRY	**1**	**2**	**3**	**5**	**10**
Constant	0,03	0,04	0,03	0,03	0,04
r_t1	-1,16	-1,26	-1,20	-1,11	-1,09
BDZ	0,70	0,11	0,52	0,28	-0,15
BUZ	-0,35	0,10	0,38	0,01	-0,02
ADZ	-0,20	-0,60	-0,41	-0,14	0,08
AUZ	0,55	0,26	-0,16	0,11	0,05
AKBNK TRY	**1**	**2**	**3**	**5**	**10**
Constant	0,01	0,0002	-0,003	-0,003	0,007
r_t1	1,28	1,20	1,15	1,22	1,27
BDZ	1,19	0,68	1,14	0,46	0,04
BUZ	0,67	0,88	0,71	0,60	0,14
ADZ	-0,02	0,68	0,68	0,33	-0,14

AUZ	-0,39	0,53	0,06	0,08	0,12
YKBNK TRY	**1**	**2**	**3**	**5**	**10**
Constant	0,01	0,01	0,01	0,01	0,01
r_t1	2,44	2,15	2,12	2,14	2,09
BDZ	-0,02	0,00	-0,02	0,00	-0,07
BUZ	0,00	-0,32	-0,17	-0,27	-0,02
ADZ	1,45**	0,50	0,30	0,28	-0,09
AUZ	-0,05	0,48	0,41	0,28	0,30
VAKBN TRY	**1**	**2**	**3**	**5**	**10**
Constant	0,004*	0,01	0,01	0,01	0,01
r_t1	3,78	3,79	3,81	3,75	3,74
BDZ	0,13	0,27	-0,10	0,24	-0,08
BUZ	-0,85	-0,45	-0,06	-0,27	0,00
ADZ	0,39	-0,17	-0,42	-0,26	-0,34
AUZ	1,25	0,48	0,06	0,30	0,11

All values are given as percentages.
*** significant at %10, ** significant at %5 and *** significant at %1**.

Table 7 represent that for the stocks of DBK EUR, NWG USD, ACA EUR and GLE EUR in our datasets previous day's returns (R_{t-1}) has a significant positive relationship with the day's return R_t which states that clustering have relationship with return. In addition β_3 coefficient for BUZ_t^n seldomly (for DBK EUR, NWG USD) takes significant values for days of 1, 2, 3, 5 & 10 which indicates a relationship between the days before price clustering and return. Furthermore β_4 coefficient of the ADZ_t^n also takes a significant value for , YKBNK TRY for day 1 which is states that a relationship between the days after price clustering and return.

5.4. Determinants of Clustering

This section presents the findings on the determinants of price clustering.

5.4.1.Model 4: Price and Volume

In order to observe the relationship of volume with price and its effects on price clustering, probit regression analysis has made by using the two decimal places of stock prices and the natural logarithm of the trading volume. The model is as follows:

$$P(Y=1)=\sigma(\beta_0+\beta_1 Price\ +\beta_2 log(Volume)) \tag{4}$$

Where

$\sigma$is the logistic function

Y is 1 if a whole price occurs, 0 otherwise

$Price$ is the price in given day

$log(Volume)$ is the natural logarithm of the trading volume in given day

Table 8 presents the findings regarding the relationship between stock prices and volume.

Table 8: Price and Volume

Country	Bank Stock	Price(%)	log(Volume)
Germany	DBK EUR	0,17***	-0,49***
UK	HSBA USD	7,19***	-0,19***
	NWG USD	-0,03	-0,14***
	BARC USD	4,39***	-0,15***
France	ACA EUR	-1,62**	-0,13**

	GLE EUR	-1,23***	-0,10***
	BNP EUR	-1,04***	-0,10***
Turkey	ISCTR TRY	-3,27	-0,12***
	GARAN TRY	6,39***	-0,15***
	AKBNK TRY	-0,27	-0,15***
	YKBNK TRY	-1,56	-0,13***
	VAKBN TRY	3,87	-0,16***

All price values are given as percentages.

*** significant at %10, ** significant at %5 and *** significant at %1**.

According to Table 8, For almost all of the stocks in our dataset β_2 coefficient of $log(Volume)$ is negative and statistically significant which is consistent with the negotiation hypothesis which states that stocks with high volume have less dispersion in traders' reservation price hence less clustering. β_1 coefficient of $Price$ on the other hand is negative and significant for some stocks but for most of the stocks (DBK EUR, HSBA USD, BARC USD, etc.) price takes significant positive value which is consistent with the negotiation hypothesis which states that high priced stocks have less clustering.

5.4.2. Model 5: Price and Volatility

In order to observe the relationship between volume and volatility and its effects on price clustering, volatility has first calculated by taking the standard deviation of the return values of the last 20 days for each day, and probit regression analysis has made by using the variable that shows whether the digit after the comma is equal to 00. The model is as follows:

$$P(Y = 1) = \sigma(\beta_0 + \beta_1 Price \ + \beta_2 Volatility) \qquad (5)$$

Where

$\sigma$is the logistic function

Y is 1 if a whole price occurs, 0 otherwise

$Price$ is the price in given day

$Volatility$ is the 20 day rolling standard deviation of the price

Table 9 presents the findings regarding the relationship between stock prices and volatility.

Table 9: Price and Volatility

Country	Bank Stock	Price(%)	Volatility
Germany	DBK EUR	-1,92***	-90,78***
UK	HSBA USD	-16,35***	-52,53***
	NWG USD	-1,33***	-79,58***
	BARC USD	-7,89***	-107,73***
France	ACA EUR	-11,43**	-36,91**
	GLE EUR	-3,78***	-26,34***
	BNP EUR	-3,18***	-20,16***
Turkey	ISCTR TRY	-26,90***	-39,79***
	GARAN TRY	-11,14***	-63,05***
	AKBNK TRY	-22,42***	-57,93***
	YKBNK TRY	-51,13***	-51,53***
	VAKBN TRY	-28,49***	-62,94***

All price values are given as percentages.

*** significant at %10, ** significant at %5 and *** significant at %1.**

According to Table 9, For all the stocks in our dataset β_2 coefficient $Volatility$ has significant negative values which is consistent with the negotiation hypothesis however β_1 coefficient of $Price$ also turns out to be significantly negative which creates an inconsistency with the negotiation hypothesis which states that as volatility will cause uncertainty, it will also increase price clustering.

6. CONCLUSION

Market anomalies have always been an interesting and studied area in financial markets. Price clustering, which is one of these anomalies, has been kept up-to-date since 1962 (Osborne 1962), when its first study has studied, and many studies have made on it. Different theories have been developed on price clustering, and these theories have been tested in different sectors and different instruments.

In this study, it has aimed to analyze the price clustering of the stocks of Turkish and European banks. Although price clustering has been measured in many different areas in the literature, this study differs from others because it is a study specific to the banking sector. In addition, there are studies have made in different geographical regions and in different markets in the literature. This study differs from the others in that it covers two neighboring regions such as Turkey and Europe. It offers a long-term observation in terms of covering a time period between 2005-2020.

In this study, the price clustering of the stocks of seven banks from Europe and five banks from Turkey has analyzed. These banks are Deutsche Bank, HSBC, Royal Bank of Scotland, Barclays, Credit Agricole, Societe Generale, BNP Paribas, Türkiye İş Bankası, GarantiBBVA, Akbank, Yapı Kredi and Vakıfbank, respectively. The stock prices and volumes of these twelve banks between 2005 and 2020 have obtained from Bloomberg and their price clusters and determinants have analyzed.

The data of the study consists of the end-of-day closing prices and volumes of the above-mentioned banks' stocks between 2005 and 2020. Price clustering and its determinants have analyzed using a method similar to that of Urquhat (2017) and Dowling at al (2016). In the study, chi-square and linear regression analysis has applied to test price clustering, and probit regression analysis has applied to test the determinants of price clustering.

As a result of the study, significant and positive values have observed for DBK EUR, GLE EUR, BNP EUR and ISCTR TRY stocks, suggesting price clustering for integers. As a result of the chi-square test, a significant non-uniform two-digit distribution has observed for NWG USD, ACA EUR, GLE EUR, BNP EUR stocks from Europe and all stocks from Turkey. This result is inconsistent with Random Walk Hypothesis (Cootner 1964). In the regression analysis made to measure the trading effects of the clustering, the relationship between the price clustering and the days before and after the return did not have a significant value for the majority of our data, but only for YKBNK TRY.

Probit regression analysis has made to test the determinants of price clustering. In most studies in the literature, price clustering has been associated with volume and volatility. In this context, analysis has made for volume and volatility in this study. For almost all of the stocks in our dataset consistent with the Negotiation Hypothesis (Harris 1991), which states that stocks with high volume have less dispersion in traders' reservation price hence less clustering. On the other hand, statistically significant results have observed for volatility in all stocks in our dataset. In this respect, it is consistent with the Negotiation Hypothesis (Harris 1991), which suggests that clustering will increase as volatility increases.

Our study can be a reference point for future studies in the literature for the banking sector in the Turkey-Europe region. Likewise, since there has never been a study specific to these two regions in the literature, future price clustering studies can be applied. As the next stage of this study, a different financial sector from the banking sector can be selected and studies in which these two sectors or these two geographical regions are compared can be carried out.

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APPENDIX

SUMMARY STATISTICS FOR STOCKS ANALYZED

Descriptive Statistics

DBK EUR	Mean	SD	Max	Min	Kurt	Skew	N
Price	32,16587	21,272786	91,47	4,8	-0,152754	0,880297	4019
Returns	-0,000469	0,025633	0,225235	-0,172695	7,82781	0,15665	4018

Price Clustering

	Freq.	%	Factor
Most Common			
58	57	1,42%	1,4183
35	56	1,39%	1,3934
40	56	1,39%	1,3934
18	56	1,39%	1,3934
45	55	1,37%	1,3685
Least Common			
74	28	0,70%	0,6967
19	27	0,67%	0,6718
44	26	0,65%	0,6469
91	25	0,62%	0,622
63	25	0,62%	0,622

Chi-squared: 108,4197562

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	40.181818***	0,818182	-0,03
p-value	0	0,91	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	37,936069	0,142321	-0.001459*	0,01
p-value	0	0,12	0,1	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	-0.000467(0.25)	-0.000515(0.21)	-0.000559(0.18)	-0.000507(0.24)	-0.000428(0.34)
r_t1	0.035893**(0.02)	0.035203**(0.03)	0.034612**(0.03)	0.034458**(0.03)	0.034871**(0.03)
BDZ	-0.007295(0.24)	-0.002647(0.55)	-0.002468(0.49)	-0.003692(0.19)	-0.001768(0.38)
BUZ	0.009771*(0.06)	0.007481**(0.04)	0.005533*(0.07)	0.00367(0.13)	0.002137(0.22)
ADZ	0.003449(0.58)	0.001752(0.69)	-0.000055(0.99)	-0.000506(0.86)	-0.001086(0.59)
AUZ	-0.004568(0.38)	-0.001621(0.66)	0.002209(0.47)	0.001182(0.62)	-0.000464(0.78)

Determinants of price clustering

Model 1

Price	log(Volume)
0.001694***(0.00)	-0.148588***(0.00)

Model 2

Price	Volatility
-0.019168***(0.00)	-90.77592***(0.00)

Descriptive Statistics

HSBA USD	Mean	SD	Max	Min	Kurt	Skew	N
Price	10,49974	2,989777	17,23	4,02	-0,655239	0,37092	3688
Returns	-0,000416	0,018196	0,153685	-0,22968	16,553819	-0,414383	3687

Price Clustering

	Freq.	%	Factor
Most Common			
82	60	1,50%	1,503759
66	52	1,30%	1,303258
78	51	1,28%	1,278195
65	51	1,28%	1,278195
38	50	1,25%	1,253133
Least Common			
60	28	0,70%	0,701754
89	28	0,70%	0,701754
28	26	0,65%	0,651629
71	25	0,63%	0,626566
31	23	0,58%	0,576441

Chi-squared: 100,2756892

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.979798***	-7,979798	-0,01
p-value	0	0,21	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	40.796704***	-0,111146	0.001402*	0,02
p-value	0	0,2	0,09	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	-0.000426(0.16)	-0.0004(0.18)	-0.000437(0.15)	-0.000291(0.34)	-0.000254(0.42)
r_t1	-0.012582(0.45)	-0.01263(0.45)	-0.013161(0.43)	-0.012754(0.44)	-0.014031(0.39)
BDZ	0.004487(0.44)	0.002234(0.58)	0.001538(0.64)	0.000209(0.93)	0.001929(0.27)
BUZ	-0.003346(0.45)	-0.001689(0.58)	-0.001044(0.68)	-0.003355*(0.09)	-0.00287**(0.04)
ADZ	0.000928(0.87)	-0.003093(0.45)	-0.002504(0.45)	-0.000633(0.8)	0.000092(0.96)
AUZ	0.0013(0.77)	-0.00005(0.99)	0.002759(0.28)	-0.002074(0.3)	-0.002147(0.14)

Determinants of price clustering

Model 1

Price	log(Volume)
0.071929***	-0.188228***

Model 2

Price	Volatility
-0.163521***	-52.528413***

SUMMARY STATISTICS FOR STOCKS ANALYZED

Descriptive Statistics

NWG USD	Mean	SD	Max	Min	Kurt	Skew	N
Price	24,171511	35,770196	116,85	1,24	0,166057	1,389809	3845
Returns	-0,001087	0,037548	0,31314	-1,108484	210,865013	-7,286809	3844

Price Clustering

	Freq.	%	Factor
Most Common			
29	56	1,40%	1,403509
25	55	1,38%	1,378446
35	54	1,35%	1,353383
31	53	1,33%	1,328321
69	53	1,33%	1,328321
Least Common			
92	29	0,73%	0,726817
91	28	0,70%	0,701754
3	25	0,63%	0,626566
98	25	0,63%	0,626566
81	23	0,58%	0,576441

Chi-squared: 116.967418546365*

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.848485***	5,151515	-0,03
p-value	0	0,46	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	36.495399***	0.310433***	-0.003643***	0,19
p-value	0	0	0	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	-0.000979(0.11)	-0.000952(0.12)	-0.001041*(0.09)	-0.001066*(0.09)	-0.000734(0.26)
r_t1	0.133803***(0.00)	0.132896***(0.00)	0.132817***(0.00)	0.132657*(0.00)	0.132662***(0.00)
BDZ	0.012193(0.15)	0.00534(0.37)	0.007722(0.11)	0.00629*(0.10)	-0.002551(0.36)
BUZ	-0.007033**(0.04)	-0.005439(0.34)	-0.003638(0.43)	-0.002524(0.49)	-0.000582(0.83)
ADZ	0.003331(0.60)	-0.002649(0.66)	-0.00058(0.91)	0.000194(0.96)	-0.002695(0.34)
AUZ	-0.001135(0.89)	0.003329(0.55)	0.002661(0.57)	0.000923(0.80)	0.001336(0.61)

Determinants of price clustering

Model 1

Price	log(Volume)
-0,00034	-0.139786***

Model 2

Price	Volatility
-0.013342***	-79.581936***

Descriptive Statistics

BARC USD	Mean	SD	Max	Min	Kurt	Skew	N
Price	4,89862	3,287495	13,96	0,65	0,157592	1,178812	3740
Returns	-0,000448	0,032734	0,561811	-0,284737	34,350866	0,800188	3739

Price Clustering

	Freq.	%	Factor
Most Common			
4	51	1,28%	1,278195
99	51	1,28%	1,278195
35	50	1,25%	1,253133
28	50	1,25%	1,253133
66	50	1,25%	1,253133
Least Common			
83	29	0,73%	0,726817
55	28	0,70%	0,701754
64	27	0,68%	0,676692
62	24	0,60%	0,601504
88	22	0,55%	0,551378

Chi-squared: 98,37092732

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.949495***	-4,949495	-0,03
p-value	0	0,44	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	42.394991***	-0,018233	-0,000485	0,08
p-value	0	0,83	0,55	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	-0.000426(0.43)	-0.000469(0.38)	-0.000464(0.39)	-0.000484(0.39)	-0.000387(0.51)
r_t1	0.063856(0.00)	0.063196*(0.00)	0.063361***(0.00)	0.063926***(0.00)	0.063876**(0.00)
BDZ	0.015681*(0.1)	0.007748(0.25)	0.006471(0.24)	0.004345(0.31)	0.001879(0.55)
BUZ	-0.000023(0.99)	0.002559(0.61)	0.000766(0.85)	0.001119(0.73)	-0.001052(0.65)
ADZ	-0.005773(0.54)	-0.005322(0.43)	-0.003557(0.52)	-0.000036(0.99)	0.001419(0.65)
AUZ	-0.004853(0.49)	0.000174(0.98)	-0.000025(0.99)	-0.001337(0.68)	-0.001368(0.56)

Determinants of price clustering

Model 1

Price	log(Volume)
0.043935***	-0.147821***

Model 2

Price	Volatility
-0.078907***	-107.727962***

SUMMARY STATISTICS FOR STOCKS ANALYZED

Descriptive Statistics

ACA EUR	Mean	SD	Max	Min	Kurt	Skew	N
Price	13,318467	6,668499	32,72	2,88	0,535807	1,132631	4019
Returns	-0,00022	0,026219	0,233615	-0,184906	7,434504	0,059101	4018

Price Clustering

	Freq.	%	Factor
Most Common			
10	60	1,49%	1,485149
98	57	1,41%	1,410891
20	55	1,36%	1,361386
40	54	1,34%	1,336634
75	54	1,34%	1,336634
Least Common			
83	27	0,67%	0,668317
48	27	0,67%	0,668317
54	26	0,64%	0,643564
42	25	0,62%	0,618812
77	23	0,57%	0,569307

Chi-squared: 146.683168316831***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	40.272727***	12.727273*	0,01
p-value	0	0,1	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	46.856808***	-0.288405***	0.002381**	0,07
p-value	0	0	0	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	-0.000173(0.68)	-0.000293(0.49)	-0.000268(0.53)	-0.000204(0.64)	-0.000293(0.53)
r_t1	0.040897***(0.01)	0.039325***(0.01)	0.03832**(0.02)	0.037981**(0.02)	0.037421**(0.02)
BDZ	-0.002388(0.61)	-0.000029(0.99)	-0.001449(0.59)	-0.00177(0.40)	-0.00076(0.62)
BUZ	-0.000435(0.94)	0.004396(0.30)	0.000876(0.80)	0.000507(0.85)	0.003442*(0.08)
ADZ	0.002996(0.52)	0.002311(0.48)	0.00067(0.80)	-0.000439(0.84)	-0.00091(0.55)
AUZ	-0.008741(0.15)	0.000398(0.92)	0.004412(0.21)	0.002875(0.29)	0.001207(0.54)

Determinants of price clustering

Model 1

Price	log(Volume)
-0.016161**	-0.127924**

Model 2

Price	Volatility
-0.114266**	-36.909215**

Descriptive Statistics

GLE EUR	Mean	SD	Max	Min	Kurt	Skew	N
Price	48,620722	27,750161	140,55	11,77	0,943422	1,329168	4019
Returns	-0,000406	0,027782	0,214255	-0,23034	8,327866	-0,287179	4018

Price Clustering

	Freq.	%	Factor
Most Common			
0	72	1,78%	1,782178
40	69	1,71%	1,707921
50	64	1,58%	1,584158
80	63	1,56%	1,559406
15	56	1,39%	1,386139
Least Common			
17	27	0,67%	0,668317
36	27	0,67%	0,668317
61	24	0,59%	0,594059
69	21	0,52%	0,519802
4	20	0,50%	0,49505

Chi-squared: 200.09900990099***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	40.080808***	31.919192***	0,14
p-value	0	0	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	43.873209***	-0.161347***	0.001375***	0,00
p-value	0	0	0	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	-0.000541(0.22)	-0.000674(0.13)	-0.000629(0.17)	-0.000635(0.18)	-0.00063(0.21)
r_t1	0.051905***(0.00)	0.052782***(0.00)	0.052793***(0.00)	0.053089***(0.00)	0.053016***(0.00)
BDZ	-0.003479(0.47)	0.000598(0.86)	0.002025(0.47)	0.004096*(0.06)	0.001804(0.26)
BUZ	0.009025**(0.05)	0.004623(0.15)	0.001151(0.66)	-0.000638(0.76)	-0.00101(0.52)
ADZ	0.002023(0.67)	0.005306(0.12)	0.004066(0.15)	0.003303(0.14)	0.003067*(0.06)
AUZ	0.008767*(0.05)	0.005593*(0.08)	0.002268(0.40)	-0.000458(0.83)	-0.000571(0.71)

Determinants of price clustering

Model 1

Price	log(Volume)
-0.012309***	-0.103682***

Model 2

Price	Volatility
-0.037837***	-26.340801***

SUMMARY STATISTICS FOR STOCKS ANALYZED

Descriptive Statistics

BNP EUR	Mean	SD	Max	Min	Kurt	Skew	N
Price	53,09798	13,418284	91,6	20,78	0,0203	0,288243	4019
Returns	-0,000096	0,024427	0,189768	-0,191166	9,247446	0,046727	4018

Price Clustering

	Freq.	%	Factor
Most Common			
0	84	2,08%	2,079208
30	64	1,58%	1,584158
85	60	1,49%	1,485149
50	59	1,46%	1,460396
45	56	1,39%	1,386139
Least Common			
3	28	0,69%	0,693069
83	28	0,69%	0,693069
13	27	0,67%	0,668317
73	27	0,67%	0,668317
44	26	0,64%	0,643564

Chi-squared: 199.702970297029***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.959596***	44.040404***	0,31
p-value	0	0	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	41.494479***	-0,066863	0,000675	-0,02
p-value	0	0,59	0,58	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	-0.000318(0.42)	-0.000254(0.52)	-0.000264(0.51)	-0.000121(0.77)	-0.000384(0.39)
r_t1	0.011449(0.47)	0.009833(0.54)	0.010731(0.50)	0.011295(0.47)	0.010352(0.51)
BDZ	0.005847(0.16)	0.001657(0.57)	0.001897(0.43)	0.001065(0.57)	0.001904(0.17)
BUZ	0.00425(0.24)	-0.000292(0.91)	-0.000127(0.95)	-0.000219(0.89)	-0.000435(0.72)
ADZ	0.004258(0.31)	0.000812(0.78)	0.000352(0.88)	-0.001549(0.42)	-0.000843(0.54)
AUZ	0.007275**(0.04)	0.005233**(0.04)	0.003296(0.11)	0.001015(0.53)	0.002191*(0.06)

Determinants of price clustering

Model 1

Price	log(Volume)
-0.010396***	-0.098086***

Model 2

Price	Volatility
-0.031758***	-20.16058***

Descriptive Statistics

ISCTR TRY	Mean	SD	Max	Min	Kurt	Skew	N
Price	4,727364	1,394272	8,22	1,76	-0,566051	-0,090491	3949
Returns	0,000233	0,025212	0,340531	-0,141746	10,41061	0,478941	3948

Price Clustering

	Freq.	%	Factor
Most Common			
0	61	1,54%	1,536524
2	59	1,49%	1,486146
28	58	1,46%	1,460957
86	57	1,44%	1,435768
20	56	1,41%	1,410579
Least Common			
36	24	0,60%	0,604534
63	24	0,60%	0,604534
73	24	0,60%	0,604534
27	24	0,60%	0,604534
79	23	0,58%	0,579345

Chi-squared: 231.914357682619***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.484848***	21.515152**	0,06
p-value	0	0,03	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	47.6906***	-0.436996***	0.004154***	0,09
p-value	0	0	0	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	0.00026(0.52)	0.00027(0.51)	0.000224(0.59)	0.000303(0.48)	0.000286(0.53)
r_t1	-0.007607(0.63)	-0.007434(0.64)	-0.007287(0.65)	-0.005971(0.71)	-0.006542(0.68)
BDZ	-0.001648(0.70)	-0.000982(0.75)	-0.001104(0.66)	-0.001715(0.39)	-0.00075(0.61)
BUZ	-0.012233**(0.03)	-0.006219(0.11)	-0.00432(0.18)	-0.001663(0.51)	0.000143(0.94)
ADZ	0.001858(0.67)	0.000713(0.82)	0.001945(0.45)	0.002311(0.25)	0.00116(0.43)
AUZ	0.007247(0.19)	0.003361(0.39)	0.003732(0.25)	-0.001852(0.46)	-0.001772(0.33)

Determinants of price clustering

Model 1

Price	log(Volume)
-0,032742	-0.116166***

Model 2

Price	Volatility
-0.268994***	-39.792507***

SUMMARY STATISTICS FOR STOCKS ANALYZED

Descriptive Statistics

GARAN TRY	Mean	SD	Max	Min	Kurt	Skew	N
Price	6,680215	2,578914	12,48	1,49	-0,778691	-0,392394	3949
Returns	0,000379	0,025453	0,159065	-0,141516	2,429696	-0,05412	3948

Price Clustering

	Freq.	%	Factor
Most Common			
30	81	0,020403	2,040302
60	80	0,020151	2,015113
90	77	0,019395	1,939547
10	73	0,018388	1,838791
80	66	0,016625	1,662469
Least Common			
93	17	0,004282	0,428212
49	17	0,004282	0,428212
59	15	0,003778	0,377834
41	14	0,003526	0,352645
67	13	0,003275	0,327456

Chi-squared: 622.846347607052***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.555556***	14,444444	-0,01
p-value	0	0,36	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	38.881607***	0,000659	0,000239	-0,02
p-value	0	1	0,91	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	0.000344(0.4)	0.000376(0.36)	0.000319(0.45)	0.000307(0.47)	0.000397(0.38)
r_t1	-0.011559(0.47)	-0.012624(0.43)	-0.011964(0.45)	-0.011132(0.48)	-0.010871(0.49)
BDZ	0.006967(0.23)	0.001148(0.78)	0.005156(0.13)	0.002758(0.30)	-0.001504(0.43)
BUZ	-0.003495(0.45)	0.000974(0.77)	0.003791(0.16)	0.000128(0.95)	-0.000187(0.90)
ADZ	-0.001999)0.73(	-0.006034(0.15)	-0.004109(0.23)	-0.001432(0.59)	0.000752(0.69)
AUZ	0.005467(0.24)	0.002627(0.43)	-0.001639(0.55)	0.001052(0.62)	0.000486(0.75)

Determinants of price clustering

Model 1

Price	log(Volume)
0.063942***	-0.150038***

Model 2

Price	Volatility
-0.111385***	-63.047609***

Descriptive Statistics

AKBNK TRY	Mean	SD	Max	Min	Kurt	Skew	N
Price	5,916022	1,556104	9,51	2,18	-0,382142	-0,365228	3949
Returns	0,000137	0,024937	0,189796	-0,120628	2,595799	0,165803	3948

Price Clustering

	Freq.	%	Factor
Most Common			
76	81	2,04%	2,040302
73	70	1,76%	1,763224
86	64	1,61%	1,612091
89	63	1,59%	1,586902
82	62	1,56%	1,561713
Least Common			
33	23	0,58%	0,579345
49	23	0,58%	0,579345
36	22	0,55%	0,554156
0	22	0,55%	0,554156
29	12	0,30%	0,302267

Chi-squared: 332.418136020151***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.878788***	-17,878788	0,02
p-value	0	0,12	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	35.56212***	0,017391	0,000998	0,07
p-value	0	0,91	0,5	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	0.000107(0.79)	0.000002(0.99)	-0.000031(0.94)	-0.000038(0.92)	0.000075(0.86)
r_t1	0.0128(0.42)	0.011964(0.45)	0.011458(0.47)	0.012167(0.44)	0.012727(0.42)
BDZ	0.011861(0.21)	0.006807(0.31)	0.011393**(0.04)	0.004587(0.28)	0.000425(0.89)
BUZ	0.006737(0.35)	0.00884*(0.08)	0.007104*(0.09)	0.006034*(0.06)	0.001383(0.55)
ADZ	-0.000159(0.99)	0.00678(0.31)	0.006841(0.21)	0.003328(0.43)	-0.001364(0.65)
AUZ	-0.003926(0.59)	0.005346(0.30)	0.000585(0.89)	0.000817(0.80)	0.001179(0.61)

Determinants of price clustering

Model 1

Price	log(Volume)
-0,002707	-0.151149***

Model 2

Price	Volatility
-0.224189***	-57.929257***

SUMMARY STATISTICS FOR STOCKS ANALYZED

Descriptive Statistics

YKBNK TRY	Mean	SD	Max	Min	Kurt	Skew	N
Price	2,260372	0,64089	4,02	0,92	-0,759511	-0,028561	3947
Returns	0,000196	0,024187	0,120628	-0,157186	2,699033	-0,096596	3946

Price Clustering

	Freq.	%	Factor
Most Common			
13	75	1,89%	1,890121
4	64	1,61%	1,612903
20	64	1,61%	1,612903
18	64	1,61%	1,612903
66	62	1,56%	1,5625
Least Common			
69	20	0,50%	0,504032
79	18	0,45%	0,453629
81	14	0,35%	0,352823
92	13	0,33%	0,327621
72	11	0,28%	0,277218

Chi-squared: 369.399193548387***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	39.59596***	8,40404	-0,02
p-value	0	0,49	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	44.266593***	0,047181	-0,002108	0,15
p-value	0	0,76	0,16	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	0.000137(0.72)	0.00013(0.74)	0.000109(0.78)	0.000138(0.73)	0.000078(0.85)
r_t1	0.024437(0.13)	0.02145(0.18)	0.021198(0.18)	0.021372(0.18)	0.020866(0.19)
BDZ	-0.000232(0.97)	-0.000042(0.99)	-0.000162(0.96)	0.000029(0.99)	-0.000706(0.73)
BUZ	0.000035(0.99)	-0.003205(0.33)	-0.001683(0.54)	-0.002737(0.21)	-0.000158(0.92)
ADZ	0.014497**(0.02)	0.004953(0.25)	0.00299(0.40)	0.002776(0.32)	-0.000937(0.64)
AUZ	-0.000512(0.91)	0.004769(0.15)	0.004125(0.13)	0.00275(0.21)	0.002995*(0.06)

Determinants of price clustering

Model 1

Price	log(Volume)
-0,015592	-0.127628***

Model 2

Price	Volatility
-0.511261***	-51.528819***

Descriptive Statistics

VAKBN TRY	Mean	SD	Max	Min	Kurt	Skew	N
Price	4,083393	1,242738	7,57	1	0,47947	0,078702	3445
Returns	0,000066	0,025591	0,166185	-0,115182	2,156427	-0,106554	3444

Price Clustering

	Freq.	%	Factor
Most Common			
66	57	1,64%	1,644547
7	54	1,56%	1,557992
53	52	1,50%	1,500289
9	50	1,44%	1,442585
55	50	1,44%	1,442585
Least Common			
67	21	0,61%	0,605886
48	20	0,58%	0,577034
81	19	0,55%	0,548182
0	17	0,49%	0,490479
83	13	0,38%	0,375072

Chi-squared: 209.476053087132***

Clustering test

	alpha	beta	adjusted r-squared
Coefficient	34.838384***	-17.838384**	0,04
p-value	0	0,04	

Clustering kurtosis test

	mu	delta1	delta2	adjusted r-squared
Coefficient	33.058765***	0,067914	-0,000536	-0,02
p-value	0	0,57	0,64	

Conditional effects of round numbers

Window	1	2	3	5	10
Constant	0.000042(0.92)	0.000057(0.90)	0.000099(0.82)	0.000062(0.89)	0.000137(0.76)
r_t1	0.037755**(0.03)	0.037922**(0.03)	0.038059**(0.02)	0.037528**(0.03)	0.037424**(0.03)
BDZ	0.001332(0.88)	0.00265(0.68)	-0.001014(0.85)	0.002424(0.55)	-0.000847(0.77)
BUZ	-0.00848(0.35)	-0.004473(0.48)	-0.000623(0.90)	-0.002705(0.51)	-0.000035(0.99)
ADZ	0.003862(0.66)	-0.00166(0.80)	-0.004158(0.43)	-0.002639(0.52)	-0.003357(0..25)
AUZ	0.012454(0.17)	0.004827(0.45)	0.00063(0.90)	0.00302(0.46)	0.001065(0.71)

Determinants of price clustering

Model 1

Price	log(Volume)
0,038738	-0.16089***

Model 2

Price	Volatility
-0.284873***	-62.944425***