Turkish Studies *Social Sciences*

Volume 14 Issue 5, 2019, p. 2097-2116
DOI: 10.29228/TurkishStudies.30274
ISSN: 2667-5617
Skopje/MACEDONIA-Ankara/TURKEY

INTERNATIONAL
BALKAN
UNIVERSITY

EXCELLENCE FOR THE FUTURE
IBU.EDU.MK

Research Article / Araştırma Makalesi

Article Info / Makale Bilgisi

✍ *Received/Geliş:* 20.08.2019

✓ *Accepted/Kabul:* 20.10.2019

✍ *Report Dates/Rapor Tarihleri:* Referee 1 (10.10.2019)-Referee 2 (15.10.2019)

This article was checked by iThenticate.

CALENDAR ANOMALIES IN CRYPTOCURRENCIES

*Ayşegül ÇİMEN**

ABSTRACT

According to Efficient Market Hypothesis, markets reflect all available information to the investors. For this reason, investors do not have the chance to get abnormal return on their investments. At this point, Efficient Market hypothesis contradicts with the calendar anomalies. One of the most important innovation and technological development in the financial markets is the introduction of Bitcoin. Bitcoin and blockchain sector was introduced in 2008 as a peer-to-peer cash system (Nakamoto, 2008). Since the introduction of first cryptocurrency, which is Bitcoin, number of cryptocurrencies in the financial markets has risen rapidly. Investors' awareness of cryptocurrencies has also increased and these instruments have a rising share in both the individual and institutional investors' portfolios. There are many studies regarding the calendar anomalies for different time periods and different equity markets. However, due to being a new financial instrument, the literature that analyses the calendar anomalies in the cryptocurrency market is limited. This study aims to fill the gap in literature with an empirical analysis that focuses on the turn of the month effect and day of the month effect in cryptocurrency market for a period of January 01, 2015 and May 31, 2019. Dummy variables are used to find out the turn of the month effect and day of the month effect throughout the month. Crypto currency index (CCI30) as well as the cryptocurrencies -Bitcoin and Litecoin are investigated for the empirical analysis. Findings of the empirical analysis prove the positive significance of turn of the month effect in Crypto Currencies Index (CCI 30) and Litecoin for 10 % level. Coefficient for the Bitcoin is also positive but not statistically significant. Although turn of the month effect is present for Crypto Currencies Index, day of the month effect is not present.

* Dr. Dokuz Eylül Üniversitesi, E-posta: aysegul.cimen@deu.edu.tr

STRUCTURED ABSTRACT

Traditional finance theories assume that all investors behave rationally and there is no chance to get excess return with the information given. Since all investors reach the same information, they could get the same return given the information. As researchers conduct empirical analysis, it is found that the findings contradict with rational asset pricing models. Findings of the studies prove that, traders and investors behave irrationally rather than behaving rationally.

With the light of these information, psychological aspects are assumed to have more impact on the traders' behaviour, especially in financial decision making. Behavioural finance gets the attention of researchers to explain the anomalies in the financial markets.

In this fast paced environment, the importance of technology is inevitable. Technological developments have positive impact on each industry whereas the drawbacks of technology are still a debate. Financial markets and financial instruments are also affected from these technological improvements.

One of the most important innovation and technological development in the financial markets is the introduction of Bitcoin. Bitcoin and blockchain sector was introduced in 2008 as a peer-to-peer cash system (Nakamoto, 2008). Since the introduction of first cryptocurrency, which is Bitcoin, number of cryptocurrencies in the financial markets has risen rapidly. Investors' awareness of cryptocurrencies has also increased and these instruments have a rising share in both the individual and institutional investors' portfolios.

Calendar anomalies are only one of the behavioural issue that the researchers focus on. Calendar anomalies mean that on specific periods of week, month or year, researchers obtain abnormal returns. For this reason, this chapter focus on the time dependent anomalies on Crypto Currencies Index (CCI 30), Bitcoin and Litecoin. Dataset covers period from January 1, 2015 to May 31, 2019.

There are many studies which are conducted on different equity markets for various time periods. Even though many researchers have investigated various calendar anomalies for a long time, there is not a consensus among them regarding the reasons behind these anomalies. Due to being a new introduced financial instrument in the financial markets, studies related to cryptocurrencies are limited.

For instance, Baur et al. (2019) studies the time of the day, day of the week and month of the year effects in terms of return and trading volume for Bitcoin. More than fifteen million intraday observations have analysed by using heatmaps. Findings prove that higher returns are found on Mondays and weekend effect is present in terms of trading volume.

Caporale and Plastun (2017) studies day of the month effect in Bitcoin, Litecoin, Ripple and Dash. Findings prove the presence of Monday effect in Bitcoin market. Efficiency of Bitcoin and Litecoin market is analysed by Latif and Azri (2017). Empirical findings show the speculative power of cryptocurrencies. Kurihara and Fukushima (2017) also investigates the efficiency of Bitcoin market from July 17, 2010 to December 29, 2016. Results show the inefficiency of Bitcoin market.

Eyüboğlu (2018) investigates the day of the week and month of the year effects in Bitcoin and Litecoin markets for a period from May 1, 2013 to December 21, 2017. In the empirical analysis in which GARCH (1, 1) is used, on Monday, Tuesday and Friday Bitcoin has significant positive returns whereas Litecoin has negative returns on Saturday. Regarding the month of the year effect, in the Bitcoin market it is found that in February, October and November there is significant and positive return while in Litecoin market, negative August effect is present.

The main aim of this chapter is to find out two main calendar anomalies in Crypto Currencies Index (CCI 30), Bitcoin and Litecoin. These two anomalies are turn of the month effect and day of the month effect. The cryptocurrencies are in terms of USD. The Crypto Currencies (CCI30) Index is introduced on January 1, 2015. The index is rule based and aims to measure short term and long term performances of cryptocurrencies. The index includes the 30 largest cryptocurrencies based on market capitalization. Index tries to attract individual investors whereas provides a benchmark for institutional investors and professionals.

Descriptive statistics show that the maximum and the minimum returns are Litecoin's returns. Litecoin has the highest standard deviation as well. Based on these information, it is possible to say that Litecoin has higher volatility compared to Bitcoin and the Crypto Currencies Index. Bitcoin has the minimum average return while Litecoin has the highest within the period analysed.

Regarding the turn of the month effect for Bitcoin, the coefficient of β_1 is positive but statistically not significant. Empirical analysis indicate that there is not a statistically significant abnormal return on turn of the month trading days for Bitcoin.

Findings illustrate the presence of turn of the month effect in Litecoin for the analysed period. Since the coefficient of β_1 is positive, it can be said that investors have the chance to get positive abnormal returns on turn of the month trading days. First three and last three days of the month is accepted as turn of the month trading days. On these days, dummy variable takes the value of one and on rest of the days, dummy variable takes the value of zero.

Keywords: Efficient Market Hypothesis, Cryptocurrency, Calendar Anomalies

KRİPTO PARALARDA TAKVİM ANOMALİLERİ

ÖZ

Etkin Piyasa Hipotezi'ne göre, piyasalar tüm mevcut bilgileri yatırımcılara yansıtmaktadır. Bu sebeple, yatırımcıların yatırımlarından anormal getiri elde etme şansları yoktur. Bu noktada, Etkin Piyasa Hipotezi, takvim anomalileriyle çelişmektedir. Finansal piyasalardaki en önemli yeniliklerden ve teknolojik gelişmelerden biri Bitcoin'in alım-satımının başlamasıdır. Bitcoin ve blockchain sektörü 2008 yılında tanıtıldı (Nakamoto, 2008). İlk kripto para birimi olan Bitcoin'in piyasaya sunulmasından bu yana finansal piyasalardaki kripto

paraların sayısı hızla artmıştır. Yatırımcıların kripto paralar konusundaki farkındalığı da artmış ve bu finansal araçların hem bireysel hem de kurumsal yatırımcı portföylerindeki payı artmaktadır. Takvim anomalileri ile ilgili farklı sermaye piyasalarında, farklı zaman dilimlerinde yapılan birçok çalışma bulunmaktadır. Fakat, yeni bir finansal araç olması nedeniyle kripto para piyasasında takvim anomalilerini analiz eden çalışma sayısı sınırlıdır. Bu çalışmanın amacı literatürdeki boşluğu, 1 Ocak 2015 ve 31 Mayıs 2019 dönemlerinde kripto para piyasasında ay dönüşü etkisi ve ayın günü etkisini ampirik olarak analiz ederek doldurmaktadır. Ay dönüşü etkisi ve ayın günü etkisi için kukla değişkenler kullanılmaktadır. Ampirik analiz için kripto para endeksi (CCI30) ve kripto paralardan Bitcoin ve Litecoin kullanılmıştır. Ampirik analizin bulguları, kripto para endeksinde (CCI 30) ve Litecoin’de ay dönüşü etkisinin % 10 anlamlılık düzeyinde pozitif olduğunu kanıtlamaktadır. Bitcoin için katsayı da pozitifdir ancak istatistiksel olarak anlamlı değildir. Her ne kadar Kripto Para Endeksi (CCI) için ay dönüşü etkisi mevcut olsa da ayın günü etkisi bulunmamaktadır.

Anahtar Kelimeler: Etkin Piyasa Hipotezi, Kripto Para, Takvim Anomalileri

Introduction

In this fast paced environment, the importance of technology is inevitable. Technological developments have positive impact on each industry whereas the drawbacks of technology are still a debate. Financial markets and financial instruments are also affected from these technological improvements.

One of the most important innovation and technological development in the financial markets is the introduction of Bitcoin. Bitcoin and blockchain sector was introduced in 2008 as a peer-to-peer cash system (Nakamoto, 2008). Since the introduction of first cryptocurrency, which is Bitcoin, number of cryptocurrencies in the financial markets has risen rapidly. Investors’ awareness of cryptocurrencies has also increased and these instruments have a rising share in both the individual and institutional investors’ portfolios.

As of June 24, 2019 there are 2278 cryptocurrencies with a market capitalization of \$329,167,839,358 (CoinMarketCap). Bitcoin is the first cryptocurrency introduced in the financial system. Bitcoin has dominated the market since being the first cryptocurrency in the market. As of June 24, 2019 Bitcoin has 59 % of total market capitalization while Ethereum and XRP are the second and the third cryptocurrency with 10 and 6 % market share respectively.

According to Baur et al. (2019), Bitcoin is a relatively new and unregulated financial instrument. Due to these characteristics, it attracts investors. Especially in some periods such as 2017, cryptocurrency market has higher volatility and abnormal return compared to the other financial instruments.

Cryptocurrencies are traded globally on a 24/7 basis. Being traded continuously, makes it interesting for researchers to focus on the calendar anomalies in the cryptocurrency market. This chapter aims to find out the presence of calendar anomalies in the cryptocurrency market in order to give an insight to investors to gain abnormal returns. The Crypto Currencies Index (CCI30 Index) as well as the Bitcoin and Litecoin are analysed for a period from Jan 1, 2015 to May 31, 2019. The study contributes to the cryptocurrency market literature empirically by analysing the presence of turn of the month effect and day of the month effect. To the best of author’s knowledge, calendar

anomalies have not been studied for Crypto Currencies Index (CCI 30) previously. From this perspective, this study contributes to the literature by analysing the calendar anomalies on Crypto Currencies Index as well as the Bitcoin and Litecoin.

Calendar anomalies are only one of the behavioural issue that the researchers focus on. Calendar anomalies mean that on specific periods of week, month or year, investors obtain abnormal returns. For the empirical analysis, turn of the month effect as well as the day of the month effect has been analysed by GARCH model. For the turn of the month effect, first three days of the month and last three days of the month is assumed to be turn of the month trading days. Dummy variables are used in order to find out the impact of turn of the trading days. Each analysis is conducted for Crypto Currencies Index (CCI 30), Bitcoin and Litecoin separately.

This paper is organized as follows. Section 2 describes the theoretical background and terminology used throughout this paper as well as the previous literature. Section 3 describes main focus of the chapter with an emphasis on data and research methodology used for empirical analysis. Section 4 indicates the findings of the analysis as well as the recommendations. Section 5 gives an insight for the future research directions and finally section 6 provides the conclusion of this paper.

Literature Review

In the finance literature, traditional theories assume that all investors are rational. Given the same information, investors make choice based on the trade-off between risk and return. Besides, Efficient Market Hypothesis investigates the securities' price movements. As Fama (1970) states, securities prices reflect all available information and based on this information, investors do not have chance to gain abnormal returns. However, some researchers have found abnormal returns of financial instruments in different financial markets.

According to Thaler (1987b), anomalies are extraordinary situations that can not be explained by theories. For an empirical finding to be anomaly, it should not be rationalized and based on unreasonable assumptions. These findings are inconsistent with the assumptions of Efficient Market Hypothesis.

Various anomalies have taken place over the centuries regarding the prices of financial products and commodities. The first of these is the Tulipmania that occurred in the 1630s. This anomaly is followed by the South Sea Bubble in 1719-1720 and the internet bubble reached its peak in the 2000s (Abreu and Brunnermeier, 2003)

Calendar anomalies occur on a specific day, period or month and have abnormal return on contrary to the other days, period or months. In the equity markets, calendar anomalies such as the turn of the month effect, holiday effect, weekend effect, January effect, day of the month effect have investigated empirically for a long time.

For instance, holiday effect (Ariel, 1990; Liano et al., 1992; Cadsby and Ratner, 1992; Liano and White, 1994; Kim and Park, 1994; Vergin and McGinnis, 1999; Meneu and Pardo, 2004; McGuinness, 2005; Chong et al. 2005; Sifeng, 2008; Marrett and Worthington, 2009; Dodd and Gakhovich, 2011; Gama and Vieira, 2013) is investigated by researchers for different equity markets and different time periods.

Some researchers focus on the weekend effect (French, 1980; Lakonishok and Levi, 1982; Keim and Stambaugh, 1984; Thaler, 1987; Connolly, 1989; Lakonishok and Maberly, 1990; Abraham and Ikenberry, 1994; Chow et al., 1997; Brusa et al., 2000; Steeley, 2001; Blau et al., 2009; Christophe et al., 2009; Caporale, 2016) whereas some focus on day of the week effect (Cross, 1973; Aggarwal and Rivoli, 1989; Rystrom and Benson, 1989; Solnik and Bousquet, 1990; Alexakis and Xanthakis, 1995; Dubois and Louvet, 1996; Poshakwale, 1996; Berument and Kiyamaz, 2001; Al-Loughani and Chappell, 2001; Demirel and Karan, 2002; Kohers et al., 2004; Ajayi et al., 2004;

Basher and Sadorsky, 2006; Berument and Dogan, 2012) in the financial markets. January effect is one of the most studied calendar anomalies in the finance literature (Thaler, 1987; Seyhun, 1988; Haugen and Jorion, 1996; Mehdiian and Perry, 2002; Chen and Singal, 2004; Haug and Hirschey, 2006; Moller and Zilca, 2008; Kang, 2010; Agnani and Aray, 2011).

Turn of the month effect, which is the main focus of this chapter, is also investigated by various researchers (Thaler, 1987; Jacobs and Levy, 1988; Ziemba, 1991; Martikainen et al., (1995); Booth et al., 2001; Kunkel et al., 2003; Li-Cheng, 2003; McConnell and Xu, 2008; Zwergel, 2010; Sharma and Narayan, 2014). The majority of the studies find that on the turn of the month trading days, there is chance for investors to gain abnormal return. Day of the month effect is the second point that this study focuses on. Day of the month effect states that on specific days of the month, traders may obtain abnormal return.

These studies are conducted on different equity markets for various time periods. Even though many researchers have investigated various calendar anomalies for a long time, there is not a consensus among them regarding the reasons behind these anomalies. Due to being a new introduced financial instrument in the financial markets, studies related to cryptocurrencies are limited. Bitcoin is the first cryptocurrency introduced in the financial system. For this reason, the first studies about the cryptocurrencies are about Bitcoin. Grinberg (2011) focuses on the cryptocurrency ecosystem, Bitcoin's sustainability as an alternative digital currency and the legal issues regarding the digital currencies. Barber et al. (2012) points out the structural problems and possible solutions as well as the theft and the loss of Bitcoin. By an emphasis on these issues, making the Bitcoin a long-lived stable currency is aimed.

Yermack (2013) describes what Bitcoin and peer to peer electronic cash system and tries to find out whether Bitcoin meets the typical characteristics of a currency. He concludes that Bitcoin seems to react as if it is a speculative investment rather than being a currency. Kristoufek (2013) analyses the relationship among search queries (Google Trends- weekly and Wikipedia- daily) and the price of Bitcoin. Findings reveal that digital currencies provide a basis for a bubble behavior as well as a speculative financial market. Böhme et al. (2015) gives detailed information about what Bitcoin is and how its relationship is with blockchain technology. Kroll et al. (2013) studies whether the Bitcoin protocol is stable and what happens if its value is destroyed by a malicious participant. Moore and Christin (2013) analyses the risk that Bitcoin holders face in case of exchange failures. For the analysis, 40 Bitcoin exchanges that are established over three years have used. Findings show that exchanges with lower popularity have more chance to fail.

Bouoiyour et al. (2014) investigates one of the most problematic phenomena in the cryptocurrency market which is Bitcoin price formation. Granger causality technique is used for two relationships which are Bitcoin price and transactions and the Bitcoin price and investors' attractiveness. Findings prove the speculative nature of Bitcoin. Ciaian et al. (2016) focus on the price formation of Bitcoin as well. Study takes into account traditional determinants of currency price in addition to the digital currencies specific factors. Dataset covers daily data for a five year period. Findings indicate that market forces and attractiveness of Bitcoin have a significant impact on Bitcoin price. Many studies have focused on price formation of Bitcoin from various perspectives. Different studies use different determinants to explain the price formation. For instance, Buchholz et al.(2012) uses supply of bitcoins in existence, total number of transactions per day, total value of bitcoin transactions each day and estimated price of Bitcoin to explain the price formation.

Bouoiyour and Selmi (2014) tries to explain Bitcoin prices by using investors' attractiveness, the exchange trade ratio, monetary Bitcoin velocity, estimated output volume, the Hash rate and the gold price for a period between 05/12/2010 and 14/06/2014. Findings of the ARDL test confirm that Bitcoin behaves like a speculative bubble. Van Wijk (2013) investigates the relationship Bitcoin closing prices and main market drivers such as closing value of the Dow Jones Index, the closing

value of the FTSE 100 Index, the closing value of the Nikkei 225 Index, the exchange rates between the U.S. dollar and the Euro and the Yen, the Brent oil price, the West Texas Intermediate oil price and the UBS Bloomberg Constant Maturity Commodity Index (CMCI). The Dow Jones Index is found to be the only statistically significant variable that has positive impact on Bitcoin closing prices.

As the Bitcoin becomes successful in the financial markets, alternative cryptocurrencies which are called altcoins have emerged. These altcoins such as Ethereum, Dash, Dogecoin, Litecoin, Peercoin, Ripple are based on very similar blockchain technology as Bitcoin. Every single altcoin has its own characteristic and aim. For instance, Litecoin is designed to save power needed for coin mining whereas Dash is designed to accelerate transactions and Ethereum maintains a basis for running smart contracts (Ciaian et al., 2018).

According to He et al. (2016) due to being a new, decentralised and having small market capitalization, cryptocurrencies and altcoins are more volatile than fiat currencies such as the United States Dollar, Euro. As Bitcoin is the first digital currency, majority of the studies focus on Bitcoin's price patterns and its relationship with other digital currencies. For instance, Ciaian (2018) investigates the relationship and interaction between Bitcoin and 16 digital currencies from 2013 to 2016. Results indicate that Bitcoin and altcoin markets are interdependent. Bitcoin-altcoin price relationship is found to be statistically significantly stronger in the short run, compared to the long run.

Regarding the relationship between Bitcoin and altcoins, Gandal and Halaburda (2016) use the seven cryptocurrencies that have been traded on BTC-e from May 2, 2013 to July 1, 2014 which are Bitcoin (BTC), Litecoin (LTC), Peercoin (PPC), Namecoin (NMC), Feathercoin (FTC), Novacoin (NVC) and Terracoin (TRC). In the study in which reinforcement effect and substitution effect is analysed, positive correlation among the cryptocurrencies have found.

Osterrieder et al. (2017) focus on the extreme value behaviour of cryptocurrencies, correlations among them, tail dependencies and their statistical properties. Data set covers from September 2013 to September 2016 and includes Bitcoin and the G10 currencies. Findings indicate that six virtual currencies in the analysis that have similar underlying technology behave similarly. Results show that Bitcoin returns are much volatile, riskier compared to the traditional currencies. Corbet et al. (2018) investigates the return and volatility transmission among three cryptocurrencies which are Bitcoin, Ripple and Litecoin as well as the gold, bond, equities and the global volatility index (VIX). Results reveal that the major cryptocurrencies Bitcoin, Ripple and Litecoin are interconnected while the cryptocurrencies are not connected with the other financial markets. It is found that Bitcoin prices have impact on Ripple and Litecoin. Besides, in the short term, since cryptocurrencies are not correlated with other markets, they provide diversification chance to the investors.

Studies that focus on the calendar anomalies in the cryptocurrencies are even fewer. For instance, Baur et al. (2019) studies the time of the day, day of the week and month of the year effects in terms of return and trading volume for Bitcoin. More than fifteen million intraday observations have analysed by using heatmaps. Findings prove that higher returns are found on Mondays and weekend effect is present in terms of trading volume.

Caporale and Plastun (2017) studies day of the month effect in Bitcoin, Litecoin, Ripple and Dash. Findings prove the presence of Monday effect in Bitcoin market. Efficiency of Bitcoin and Litecoin market is analysed by Latif and Azri (2017). Empirical findings show the speculative power of cryptocurrencies. Kurihara and Fukushima (2017) also investigates the efficiency of Bitcoin market from July 17, 2010 to December 29, 2016. Results show the inefficiency of Bitcoin market. Eyüboğlu (2018) investigates the day of the week and month of the year effects in Bitcoin and Litecoin markets for a period from May 1, 2013 to December 21, 2017. In the empirical analysis in which GARCH (1, 1) is used, on Monday, Tuesday and Friday Bitcoin has significant positive returns whereas Litecoin

has negative returns on Saturday. Regarding the month of the year effect, in the Bitcoin market it is found that in February, October and November there is significant and positive return while in Litecoin market, negative August effect is present.

Data And Methodology

The main aim of this chapter is to find out two main calendar anomalies in Crypto Currencies Index (CCI 30), Bitcoin and Litecoin. These two anomalies are turn of the month effect and day of the month effect. The cryptocurrencies are in terms of USD.

The Crypto Currencies (CCI30) Index is introduced on January 1, 2015. The index is rule based and aims to measure short term and long term performances of cryptocurrencies. The index includes the 30 largest cryptocurrencies based on market capitalization. Index tries to attract individual investors whereas provides a benchmark for institutional investors and professionals.

Being diversified, being replicable, being transparent, providing detailed information of the whole blockchain sector and presenting the best risk-adjusted performance values are the main characteristics of the CCI 30 Index in order to meet its aims.

Table 1: Constituents of the Crypto Currencies Index

Bitcoin	Bitcoin SV	Tezos
Ethereum	Monero	VeChain
XRP	IOTA	Ontology
EOS	Dash	Dogecoin
Litecoin	Maker	Bitcoin Gold
Bitcoin Cash	NEO	Qtum
Stellar	Ethereum Classic	OmiseGO
TRON	NEM	Basic Attention Token
Binance Coin	Zcash	Zilliqa
Cardano	Waves	0x

Source: (CCI 30 Index, 2019)

Table 1 shows the constituents of the Crypto Currencies Index. Cryptocurrencies in the index are listed based on their market capitalization. Bitcoin has the highest market capitalization whereas 0x is the cryptocurrency in the index with the lowest market capitalization. The number of constituents in the index is set at 30 because 30 is assumed to be the benchmark for being statistically significant.

Dataset covers the same period with the Crypto Currencies Index. This is the reason behind why Bitcoin and Litecoin is chosen for the analysis. As of January 1, 2015, the starting day of Crypto Currencies Index, Bitcoin and Litecoin has already been traded in the financial markets. For this reason, in addition to the Crypto Currencies Index, Bitcoin and Litecoin are included in the analysis.

Daily price data of the cryptocurrencies in the index are gathered from CoinMarketCap and <https://cci30.com>. The daily returns in the cryptocurrency market is calculated as follows. In Equation 1, $P_{i,t}$ is the closing price of Bitcoin, Litecoin and Crypto Currency Index on day t and $P_{i,t-1}$ is the closing price of Bitcoin, Litecoin and Crypto Currency Index on the previous day (t-1).

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \quad (1)$$

High daily return fluctuations are observed in Crypto Currencies Index, Bitcoin and Litecoin as seen from Figure 1, Figure 2 and Figure 3.

Figure 1: Daily returns of Crypto Currencies Index

Source: <https://cci30.com>, 2019

Figure 1 shows the daily returns of Crypto currency index (CCI30) from January 1, 2015 to May 31, 2019. In the second half of the 2017 and the beginning of 2018, index records the highest positive and negative returns.

Figure 2: Daily returns of Bitcoin

Source: : www.coinmarketcap.com, 2019

Figure 2 illustrates the daily returns of Bitcoin for the empirically analysed period which is from January 1, 2015 to May 31, 2019. In the beginning of 2015, the volatility is seen higher than the other periods. Besides, in the second half of the 2017 Bitcoin records the maximum daily returns

Figure 3: Daily returns of Litecoin

Source: : www.coinmarketcap.com, 2019

Figure 3 indicates the daily returns of Litecoin for a period from January 1, 2015 to May 31, 2019. In the April 2017, Litecoin recorded highest daily returns which is followed by the second highest return in late 2017s. The maximum return of Litecoin in this period is almost three times more than the maximum daily return of Bitcoin.

In order to find out the turn of the month effect, the following regression is used.

$$R_{it} = \alpha_i + \beta_i D_{it} + \varepsilon_{it} \quad (2)$$

Equation 2 indicates the return of cryptocurrency and the index based on the dummy variable, which is used as a proxy for turn of the month effect. D_{it} is the dummy variable that takes the value of one for turn of the month trading days, zero for non- turn of the month trading days. First three and last three days of the month are taken as turn of the month trading days which means that, on these days dummy variable takes the value of one. ε_{it} represents the error term.

Significance of the β_i suggests the presence of turn of the month effect for the variables. Significantly positive β_i represents the abnormal return on turn of the month days over non-turn of the month days however significantly negative β_i represents the abnormal return on turn of the month days below non-turn of the month days.

$$R_{it} = \alpha_i + \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \beta_6 D_{6t} + \beta_7 D_{7t} + \beta_8 D_{8t} + \beta_9 D_{9t} + \beta_{10} D_{10t} + \beta_{11} D_{11t} + \beta_{12} D_{12t} + \beta_{13} D_{13t} + \beta_{14} D_{14t} + \beta_{15} D_{15t} + \beta_{16} D_{16t} + \beta_{17} D_{17t} + \beta_{18} D_{18t} + \beta_{19} D_{19t} + \beta_{20} D_{20t} + \beta_{21} D_{21t} + \beta_{22} D_{22t} + \beta_{23} D_{23t} + \beta_{24} D_{24t} + \beta_{25} D_{25t} + \beta_{26} D_{26t} + \beta_{27} D_{27t} + \beta_{28} D_{28t} + \beta_{29} D_{29t} + \beta_{30} D_{30t} + \beta_{31} D_{31t} + \varepsilon_{it} \quad (3)$$

Day of the month effect for Crypto Currencies Index (CCi30 Index), Bitcoin and Litecoin are calculated by GARCH (1,1) model. Equation 3 shows the model that is used for the empirical analysis. Dummy variables are used for every single day to find out the presence of turn of the month effect. Dummy variable takes the value of one on the first day, otherwise zero, takes the value of one on the second day and otherwise zero and so on. For 31 days, dummy variable is used repeatedly.

Findings

This section of the chapter focus on the findings of the empirical analysis. The empirical analysis is divided into two sub groups. The first group represents the turn of the month effect while the second group represents the day of the month effect.

Table 2: Descriptive statistics of cryptocurrency returns and CCI 30 Index return

	CCI 30	Bitcoin	Litecoin
Mean	0.003148	0.002817	0.004250
Median	0.002695	0.002091	0.000000
Maximum	0.189370	0.272011	0.736111
Minimum	-0.231869	-0.254734	-0.439474
Std. Dev.	0.041100	0.039505	0.063339
Skewness	-0.276993	0.151555	2.296.099
Kurtosis	6.980.241	9.465.442	2.475.619
Jarque-Bera	1.083.343	2.810.377	33167.36
Probability	0.000000	0.000000	0.000000
Sum	5.068.880	4.535.265	6.842.874
Sum Sq. Dev.	2.717.883	2.511.064	6.454.954

Source: (www.coinmarketcap.com)

Table 2 indicates the descriptive statistics of Bitcoin, Litecoin and the Crypto Currencies Index returns. Table shows that the maximum and the minimum returns are Litecoin's returns. Litecoin has the highest standard deviation as well. Based on these information, it is possible to say that Litecoin has higher volatility compared to Bitcoin and the Crypto Currencies Index. Bitcoin has the minimum average return while Litecoin has the highest within the period analysed.

Table 3: Unit root test results

	ADF		PP	
	Intercept	Trend& Intercept	Intercept	Trend& Intercept
CCI 30	-40,350 *	-40,338*	-40,830 *	-40,820 *
Bitcoin	-41,032 *	-41,022 *	-41,023 *	-41,014 *
Litecoin	-39,760 *	-39,752 *	-39,900 *	-39,892 *

* denotes the significance at 1 % level.

Table 3 shows the Augmented Dickey Fuller and Philips Perron test results for the variables. Augmented Dickey Fuller test is the enhanced version of Dickey and Fuller (1979) test. Philips and Perron (1988) is the second test that is implemented for the returns of the CCI Index, Bitcoin and Litecoin.

The null hypothesis states that the variable has unit root or non-stationarity. Regardless of the method of unit root test, it is possible to reject the null hypothesis at level for both intercept and intercept & trend. Findings indicate that series are stationary at level.

Table 4: Turn of the month effect for CCI 30 Index- GARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
α	0.001645	0.000856	1.922.340	0.0546
β_i	0.003128	0.001778	1.759.655	0.0785

Table 4 indicates the turn of the month effect for Crypto Currencies Index from January 1, 2015 to May 31, 2019. In the equation where dummy variable is used for the turn of the month effect, probability of β_i proves the positive significance for 10 % level. Findings illustrate the presence of turn of the month effect in Crypto Currencies Index for the analysed period.

Table 5: Turn of the month effect for Bitcoin - GARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
α	0.001855	0.000940	1.972.257	0.0486
β_i	0.002292	0.001974	1.160.962	0.2457

Table 5 shows the turn of the month effect for Bitcoin from January 1, 2015 to May 31, 2019. The coefficient of β_i is positive but statistically not significant. Empirical analysis indicate that there is not a statistically significant abnormal return on turn of the month trading days for Bitcoin.

Table 6: Turn of the month effect for Litecoin - GARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
α	0.000363	0.001747	0.208029	0.8352
β_i	0.005702	0.003413	1.670.755	0.0948

Table 6 points out the turn of the month effect for Litecoin from January 1, 2015 to May 31, 2019. In the equation where dummy variable is used for the turn of the month effect, probability of β_i proves the positive significance for 10 % level. Findings illustrate the presence of turn of the month effect in Litecoin for the analysed period. Since the coefficient of β_i is positive, it can be said that investors have the chance to get positive abnormal returns on turn of the month trading days. First three and last three days of the month is accepted as turn of the month trading days. On these days, dummy variable takes the value of one and on rest of the days, dummy variable takes the value of zero.

Table 7: Day of the month effect for CCI 30 Index- GARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
α	-0.000944	0.008586	-0.109937	0.9125
β_1	0.001545	0.009191	0.168059	0.8665
β_2	0.009099	0.008607	1.057.206	0.2904
β_3	0.005144	0.009311	0.552422	0.5807
β_4	0.003953	0.010413	0.379575	0.7043
β_5	0.004990	0.009643	0.517552	0.6048
β_6	0.005576	0.009135	0.610427	0.5416
β_7	0.001718	0.009905	0.173434	0.8623
β_8	0.002745	0.009287	0.295572	0.7676
β_9	0.004548	0.009372	0.485276	0.6275
β_{10}	-0.006060	0.009719	-0.623538	0.5329
β_{11}	-0.006244	0.009170	-0.680925	0.4959
β_{12}	-0.001672	0.009270	-0.180357	0.8569
β_{13}	0.007265	0.009378	0.774679	0.4385
β_{14}	0.008872	0.010042	0.883579	0.3769
β_{15}	-0.006261	0.009099	-0.688046	0.4914
β_{16}	0.007744	0.009099	0.851049	0.3947
β_{17}	0.008797	0.010149	0.866790	0.3861
β_{18}	-0.001437	0.009295	-0.154628	0.8771
β_{19}	0.003492	0.010230	0.341392	0.7328
β_{20}	0.003858	0.010520	0.366705	0.7138
β_{21}	0.005978	0.010075	0.593315	0.5530
β_{22}	0.001834	0.009918	0.184893	0.8533
β_{23}	-8.32E-05	0.010379	-0.008013	0.9936
β_{24}	0.003629	0.009952	0.364667	0.7154
β_{25}	0.007048	0.009616	0.732934	0.4636
β_{26}	-0.003180	0.010897	-0.291809	0.7704
β_{27}	0.003433	0.009640	0.356181	0.7217
β_{28}	0.004843	0.009625	0.503135	0.6149
β_{29}	0.010691	0.009539	1.120.819	0.2624
β_{30}	0.004303	0.009288	0.463248	0.6432
β_{31}	-0.001322	0.007281	-0.181573	0.8559

Table 7 proves the presence of turn of the month effect for Crypto Currencies Index. In order to develop and find out the presence of calendar anomalies on every single day separately, dummy variables are used for 31 days. By doing so, day of the month effect is analysed. Table 7 shows the findings of the day of the month effect for Crypto Currencies Index. Although turn of the month effect

is present for Crypto Currencies Index, day of the month effect is not present, regarding the probabilities of the dummy variables.

Table 8: Day of the month effect for Bitcoin - GARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
α	-0.008602	0.010255	-0.838785	0.4016
β_1	0.008060	0.010653	0.756621	0.4493
β_2	0.022409	0.009779	2.291.624	0.0219
β_3	0.010814	0.010274	1.052.507	0.2926
β_4	0.015880	0.011663	1.361.529	0.1733
β_5	0.009048	0.011162	0.810563	0.4176
β_6	0.011038	0.010884	1.014.106	0.3105
β_7	0.010433	0.011188	0.932504	0.3511
β_8	0.011465	0.010597	1.081.883	0.2793
β_9	0.010282	0.011113	0.925186	0.3549
β_{10}	0.008422	0.011025	0.763903	0.4449
β_{11}	0.003014	0.010750	0.280323	0.7792
β_{12}	0.005956	0.010788	0.552086	0.5809
β_{13}	0.009776	0.010780	0.906892	0.3645
β_{14}	0.015105	0.011372	1.328.254	0.1841
β_{15}	0.007112	0.010689	0.665375	0.5058
β_{16}	0.014069	0.010959	1.283.724	0.1992
β_{17}	0.013664	0.011863	1.151.776	0.2494
β_{18}	0.010221	0.010686	0.956403	0.3389
β_{19}	0.008849	0.011485	0.770448	0.4410
β_{20}	0.008963	0.011399	0.786266	0.4317
β_{21}	0.016229	0.011142	1.456.567	0.1452
β_{22}	0.011498	0.011651	0.986843	0.3237
β_{23}	0.008281	0.011044	0.749828	0.4534
β_{24}	0.008701	0.010991	0.791644	0.4286
β_{25}	0.012009	0.010971	1.094.567	0.2737
β_{26}	0.006070	0.012065	0.503050	0.6149
β_{27}	0.011542	0.011261	1.024.878	0.3054
β_{28}	0.013748	0.010903	1.260.985	0.2073
β_{29}	0.007719	0.011864	0.650634	0.5153
β_{30}	0.012933	0.010492	1.232.628	0.2177
β_{31}	-0.001862	0.007889	-0.236049	0.8134

Table 8 illustrates the findings of day of the month effect for Bitcoin from January 1, 2015 to May 31, 2019. On contrary to the findings of Table 5, in which presence of turn of the month not found, day of the month effect is statistically significant in Table 8. For instance, on the second day of

the month for the analysed period, investors gain positive and statistically significant abnormal return with an amount of 0.022409. Only on the second day of the month, the probability of dummy variables is less than 5 % which indicates statistical significance of the variables.

Table 9: Day of the month effect for Litecoin - GARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
α	0.016247	0.022653	0.717238	0.4732
β_1	-0.016362	0.019455	-0.841040	0.4003
β_2	-0.005215	0.023608	-0.220883	0.8252
β_3	-0.012368	0.023837	-0.518869	0.6039
β_4	-0.007674	0.024783	-0.309637	0.7568
β_5	-0.014059	0.024351	-0.577349	0.5637
β_6	-0.012236	0.024144	-0.506767	0.6123
β_7	-0.021641	0.024705	-0.875994	0.3810
β_8	-0.016148	0.022618	-0.713926	0.4753
β_9	-0.015831	0.024179	-0.654760	0.5126
β_{10}	-0.017902	0.025023	-0.715424	0.4743
β_{11}	-0.031810	0.023647	-1.345.195	0.1786
β_{12}	-0.016850	0.024446	-0.689287	0.4906
β_{13}	-0.019178	0.023945	-0.800922	0.4232
β_{14}	-0.017519	0.023940	-0.731789	0.4643
β_{15}	-0.027016	0.023510	-1.149.150	0.2505
β_{16}	-0.006131	0.023975	-0.255730	0.7982
β_{17}	-0.013300	0.024630	-0.539978	0.5892
β_{18}	-0.017258	0.023379	-0.738192	0.4604
β_{19}	-0.014130	0.025888	-0.545811	0.5852
β_{20}	-0.015208	0.025234	-0.602692	0.5467
β_{21}	-0.008751	0.024358	-0.359239	0.7194
β_{22}	-0.015835	0.022829	-0.693610	0.4879
β_{23}	-0.026727	0.024060	-1.110.878	0.2666
β_{24}	-0.000437	0.023934	-0.018250	0.9854
β_{25}	-0.003891	0.023160	-0.167996	0.8666
β_{26}	-0.028095	0.023501	-1.195.492	0.2319
β_{27}	-0.016604	0.024946	-0.665591	0.5057
β_{28}	0.007683	0.024000	0.320110	0.7489
β_{29}	-0.023643	0.022425	-1.054.304	0.2917
β_{30}	-0.017860	0.023404	-0.763107	0.4454
β_{31}	0.000622	0.022513	0.027639	0.9779

Table 9 shows the day of the month effect for Litecoin for a period of January 1, 2015 and May 31, 2019. Since Table 6 proves the presence of turn of the month effect for Litecoin, it is

expected to have abnormal returns on the first and last days of the month separately. On contrary to the expectations, findings indicate statistically insignificant abnormal returns based on the day of the month.

Conclusion

Traditional finance theories assume that all investors behave rationally and there is no chance to get excess return with the information given. Since all investors reach the same information, they could get the same return given the information. As researchers conduct empirical analysis, it is found that the findings contradict with rational asset pricing models. Findings of the studies prove that, traders and investors behave irrationally rather than behaving rationally.

With the light of these information, psychological aspects are assumed to have more impact on the traders' behaviour, especially in financial decision making. Behavioural finance gets the attention of researchers to explain the anomalies in the financial markets.

Calendar anomalies are only one of the behavioural issue that the researchers focus on. Calendar anomalies mean that on specific periods of week, month or year, researchers obtain abnormal returns. For this reason, this chapter focus on the time dependent anomalies on Crypto Currencies Index (CCI 30), Bitcoin and Litecoin. Dataset covers period from January 1, 2015 to May 31, 2019.

For the empirical analysis, turn of the month effect as well as the day of the month effect has been analysed by GARCH model. For the turn of the month effect, first three days of the month and last three days of the month is assumed to be turn of the month trading days. Dummy variables are used in order to find out the impact of turn of the trading days. Each analysis is conducted for Crypto Currencies Index (CCI 30), Bitcoin and Litecoin separately.

For the day of the month effect, dummy variables are given to each day to observe the day specific abnormal return. The same analysis is repeated for Crypto Currencies Index (CCI 30), Bitcoin and Litecoin.

Findings of the empirical analysis prove the positive significance of turn of the month effect in Crypto Currencies Index (CCI 30) and Litecoin for 10 % level. Coefficient for the Bitcoin is also positive but not statistically significant.

Regarding the day of the month effect, although turn of the month effect is present for Crypto Currencies Index, day of the month effect is not present, regarding the probabilities of the dummy variables. For Bitcoin, on the second day of the month for the analysed period, investors gain positive and statistically significant abnormal return with an amount of 0.022409. For Litecoin, findings indicate statistically insignificant abnormal returns based on the day of the month.

REFERENCES

- Abraham, A., & Ikenberry, D. L. (1994). The individual investor and the weekend effect. *Journal of Financial and Quantitative Analysis*, 29(2), 263-277.
- Abreu, D., & Brunnermeier, M. K. (2003). Bubbles and crashes. *Econometrica*, 71(1), 173-204.
- Aggarwal, R., & Rivoli, P. (1989). Seasonal and day- of- the- week effects in four emerging stock markets. *Financial review*, 24(4), 541-550.
- Agnani, B., & Aray, H. (2011). The January effect across volatility regimes. *Quantitative Finance*, 11(6), 947-953.

- Ajayi, R. A., Mehdian, S., & Perry, M. J. (2004). The day-of-the-week effect in stock returns: further evidence from Eastern European emerging markets. *Emerging Markets Finance and Trade*, 40(4), 53-62.
- Al-Loughani, N., & Chappell, D. (2001). Modelling the day-of-the-week effect in the Kuwait Stock Exchange: a nonlinear GARCH representation. *Applied Financial Economics*, 11(4), 353-359.
- Alexakis, P., & Xanthakis, M. (1995). Day of the week effect on the Greek stock market. *Applied Financial Economics*, 5(1), 3-50.
- Ariel, R. A. (1990). High Stock Returns before Holidays: Existence and Evidence on Possible Causes. *The Journal of Finance*, 45(5), 1611-1626.
- Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, Technology, and Governance. *Journal of Economic Perspectives*, 29(2), 213-238.
- Barber, S., Boyen, X., Shi, E., & Uzun, E. (2012). Bitter to better — How to make bitcoin a better currency. *Financial Cryptography and Data Security* (pp. 399-414). Springer.
- Basher, S. A., & Sadorsky, P. (2006). Day-of-the-week effects in emerging stock markets. *Applied Economics Letters*, 13(10), 621-628.
- Baur, D. G., Cahill, D., Godfrey, K., & Liu, Z. (2019). Bitcoin time-of-the-day, day-of-week and month-of-year effects in returns and trading volume. *Finance Research Letters*, 78-92.
- Berument, H., & Kiyamaz, H. (2001). The day of the week effect on stock market volatility. 25(2), 181-193.
- Berument, M. H., & Dogan, N. (2012). Stock market return and volatility: day-of-the-week effect. *Journal of Economics and Finance*, 36(2), 282-302.
- Blau, B., Van Ness, B., & Van Ness, R. (2009). Short selling and the weekend effect for NYSE securities. *Financial Management*, 38(3), 603-630.
- Booth, G. G., Kallunki, J. P., & Martikainen, T. (2001). Liquidity and the turn-of-the-month effect: evidence from Finland. *Journal of International Financial Markets, Institutions and Money*, 11(2), 137-146.
- Bouiyou, J., Selmi, R., & Tiwari, A. (2014). Is Bitcoin business income or speculative bubble? Unconditional vs. conditional frequency domain analysis. *Munich Personal RePEc Archive*, 1-24.
- Bouiyou, J., & Selmi, R. (2014). What bitcoin looks like?
- Brusa, J., Liu, P., & Schulman, C. (2000). The weekend effect, 'reverse' weekend effect, and firm size. *Journal of Business Finance & Accounting*, 27(5-6), 555-574.
- Buchholz, M., Delaney, J., Warren, J., & Parker, J. (2012). Bits and Bets Information, Price Volatility, and Demand for Bitcoin. *Economics* (312).
- Cadsby, C. B., & Ratner, M. (1992). Turn-of-month and pre-holiday effects on stock returns: Some international evidence. *Journal of Banking & Finance*, 16(3), 497-509.
- Caporale, G. M., Gil-Alana, L., & Plastun, A. (2016). The weekend effect: an exploitable anomaly in the Ukrainian stock market? *Journal of Economic Studies*, 43(6), 954-965.
- Caporale, G. M., & Plastun, A. (2018). The day of the week effect in the cryptocurrency market. *Finance Research Letters*.
- Chen, H., & Singal, V. (2004). All things considered, taxes drive the January effect. *Journal of Financial Research*, 27(3), 351-372.

- Chong, R., Hudson, R., Keasey, K., & Littler, K. (2005). Pre-holiday effects: International evidence on the decline and reversal of a stock market anomaly. *Journal of International Money and Finance*, 24(8), 1226-1236.
- Chow, E., Hsiao, P., & Solt, M. E. (1997). Trading returns for the weekend effect using intraday data. *Journal of Business Finance & Accounting*, 24(3), 425-444.
- Christophe, S. E., Ferri, M. G., & Angel, J. J. (2009). Short selling and the weekend effect in Nasdaq stock returns. *Financial Review*, 44(1), 31-57.
- Ciaian, P., Rajcaniova, M., & Kancs, A. (2016). The economics of bitCoin price formation. *Applied Economics*, 48(19), 1799-1815.
- Ciaian, P., Rajcaniova, M., & Kancsa, d. (2018). Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, 52, 173-195.
- Connolly, R. A. (1989). An examination of the robustness of the weekend effect. *Journal of Financial and Quantitative Analysis*, 24(2), 133-169.
- Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 28-34 .
- Cross, F. (1973). The behavior of stock prices on fridays and mondays. *Financial Analysts Journal*, 67-69 .
- Demirer, R., & Karan, M. B. (2002). An investigation of the day-of-the-week effect on stock returns in Turkey. *Emerging Markets Finance & Trade*, 47-77.
- Dickey, D., & Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74, 427-431.
- Dodd, O., & Gakhovich, A. (2011). The holiday effect in Central and Eastern European financial markets. *Investment Management and Financial Innovations*, 8(4), 29-35.
- Dubois, M., & Louvet, P. (1996). The day-of-the-week effect: The international evidence. *Journal of Banking and Finance*, 20(9), 1463-1484.
- Eyüboğlu, K. (2018). Examining day of the week and month of the year effects in Bitcoin and Litecoin markets. *Çankırı Karatekin University Journal of Faculty of Economics and Administrative Sciences*, 8(1), 165-183.
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 383-417.
- French, K. (1980). Stock returns and the weekend effect. *Journal of financial economics*, 55-69.
- Gama, P. M., & Vieira, E. (2013). Another look at the holiday effect. *Applied Financial Economics*, 23(20), 1623-1633.
- Gandal, N., & Halaburda, H. (2016). Can we predict the winner in a market with network effects? Competition in cryptocurrency market. *Games*, 7(3), 7-16.
- Grinberg, R. (2011). Bitcoin: An Innovative Alternative Digital Currency. *Hastings Science and Technology Law Journal*, 160-208.
- Haug, M., & Hirschey, M. (2006). The january effect. *Financial Analysts Journal*, 62(5), 78-88.
- Haugen, R. A., & Jorion, P. (1996). The January effect: Still there after all these years. *Financial Analysts Journal*, 52(1), 27-31.

- He, D., Habermeier, K., Leckow, R., Haksar, V., Almeida, Y., Kashima, M., Verdugo-Yepes, V. (2016). *Virtual currencies and beyond: Initial considerations*. IMF.
- Jacobs, B. I., & Levy, K. N. (1988). Calendar anomalies: Abnormal returns at calendar turning points. *Financial Analysts Journal*, 28-39.
- Kang, M. (2010). Probability of information-based trading and the January effect. *Journal of Banking & Finance*, 34(12), 2985-2994.
- Keim, D. B., & Stambaugh, R. F. (1984). A further investigation of the weekend effect in stock returns. *The journal of finance*, 39(3), 819-835.
- Kim, C., & Park, J. (1994). Holiday Effects and Stock Returns: Further Evidence. *Journal of Financial and Quantitative Analysis*, 29(1), 145-157.
- Kohers, G., Kohers, N., Pandey, V., & Kohers, T. (2004). The disappearing day-of-the-week effect in the world's largest equity markets. *Applied Economics Letters*, 11(3), 167-171.
- Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific reports*, 3(3415).
- Kroll, J., Davey, I., & Felten, E. W. (2013). The economics of bitcoin mining or, bitcoin in the presence of adversaries. *Proceedings of WEIS*.
- Kunkel, R. A., Compton, W. S., & Beyer, S. (2003). The turn-of-the-month effect still lives: the international evidence. *International Review of Financial Analysis*, 12(2), 207-221.
- Kurihara, Y., & Fukushima, A. (2017). The market efficiency of Bitcoin: a weekly anomaly perspective. *Journal of Applied Finance and Banking*, 7(3), 57.
- Lakonishok, J., & Levi, M. (1982). Weekend effects on stock returns: A note. *The Journal of Finance*, 37(3), 883-889.
- Lakonishok, J., & Maberly, E. (1990). The weekend effect: Trading patterns of individual and institutional investors. *The Journal of Finance*, 45(1), 231-243.
- Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. 403–425.
- Latif, S. R. Mohd, M. A. (2017). Testing the weak form of efficient market in cryptocurrency. *Journal of Engineering and Applied Sciences*, 12(9), 2285-2288.
- Li-Cheng, F. E. N. G. (2003). "Month-of-the-Year Effect" and "Turn-of-the-Month Effect" in the Chinese Stock Markets [J]. *Policy-making Reference*, 1.
- Liano, K., Marchand, P. H., & Huang, G. (1992). The holiday effect in stock returns: evidence from the OTC market. *Review of Financial Economics*, 2(1), 45-54.
- Liano, K., & White, L. R. (1994). Business cycles and the pre-holiday effect in stock returns. *Applied Financial Economics*, 4(3), 171-174.
- Martikainen, T., Perttunen, J., & Puttonen, V. (1995). Finnish turn-of-the-month effects: Returns, volume, and implied volatility. *Journal of Futures Markets*, 15(6), 605-615.
- Marrett, G. J., & Worthington, A. C. (2009). An empirical note on the holiday effect in the Australian stock market, 1996–2006. *Applied Economics Letters*, 16(17), 1769-1772.
- McConnell, J. J., & Xu, W. (2008). Equity Returns at the Turn of the Month. *Financial Analysts Journal*, 64(2), 49-64.
- Mcguinness, P. B. (2005). A re-examination of the holiday effect in stock returns: the case of Hong Kong. *Applied Financial Economics*, 15(16), 1107-1123.

- Meneu, V., & Pardo, A. (2004). Pre-holiday effect, large trades and small investor behaviour. *Journal of Empirical Finance*, 11(2), 231-246 .
- Moller, N., & Zilca, S. (2008). The evolution of the January effect. *Journal of Banking & Finance*, 32(3), 447-457.
- Moore , T., & Christin, N. (2013). Beware the middleman: Empirical analysis of bitcoin-exchange risk. *Financial Cryptography and Data Security* (pp. 25-33). Springer.
- Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. <https://bitcoin.org/bitcoin.pdf>.
- Ogden, J. P. (1990). Turn- of- month evaluations of liquid profits and stock returns: A common explanation for the day of the month and January effects. *The Journal of Finance*, 45(4), 1259-1272.
- Osterrieder, J., Lorenz, J., & Strika, M. (2017). Bitcoin and Cryptocurrencies - Not for the Faint-Hearted. *International Finance and Banking*, 4(1), 56-94.
- Philips, P., & Perron , P. (1988). Testing for a unit root in time series regression. *Biometrika*, 335-346.
- Poshakwale, S. (1996). Evidence on weak form efficiency and day of the week effect in the Indian stock market. *Finance India*, 10(3), 605-616.
- Rystrom, D. S., & Benson, E. D. (1989). Investor psychology and the day-of-the-week effect. *Financial Analysts Journal*, 45(5), 75-78.
- Seyhun, H. N. (1988). The January effect and aggregate insider trading. *The Journal of Finance*, 43(1), 129-141.
- Sharma, S. S., & Narayan, P. K. (2014). New evidence on turn-of-the-month effects. *Journal of International Financial Markets, Institutions and Money*, 29, 92-108.
- Sifeng , L. L. (2008). Are There Holiday Effect in China's Stock Market? *Journal of Financial Research*, 2.
- Solnik, B., & Bousquet, L. (1990). Day-of-the-week effect on the Paris Bourse. *Journal of Banking and Finance*, 14(2-3), 461-468.
- Steeley, J. (2001). A note on information seasonality and the disappearance of the weekend effect in the UK stock market. *Journal of Banking and Finance*, 25(10), 1941-1956.
- Thaler, R. H. (1987). Anomalies: Weekend, holiday, turn of the month, and intraday effects. *Journal of Economic Perspectives*, 169-177.
- Thaler, R. H. (1987b). Anomalies the January Effect. *Economic Perspectives*, 1(1), pp. 197-201.
- Van Wijk, D. (2013). *What can be expected from the Bitcoin?* Rotterdam: Erasmus Universiteit Rotterdam.
- Vergin, R. C., & McGinnis, J. (1999). Revisiting the holiday effect: Is it on holiday? *Applied Financial Economics*, 9(5), 477-482 .
- Yermack, M. (2013). Is Bitcoin a Real Currency? *NBER Working Paper 19747*.
- Zwergel, B. (2010). On the exploitability of the turn-of-the-month effect—an international perspective. *Applied Financial Economics*, 20(11), 911-922.
- Ziemba, W. T. (1991). Japanese security market regularities: Day of the month, turn-of-the-month and year, holiday and golden week effects. *Japan and the world Economy*, 3(2), 119-146.