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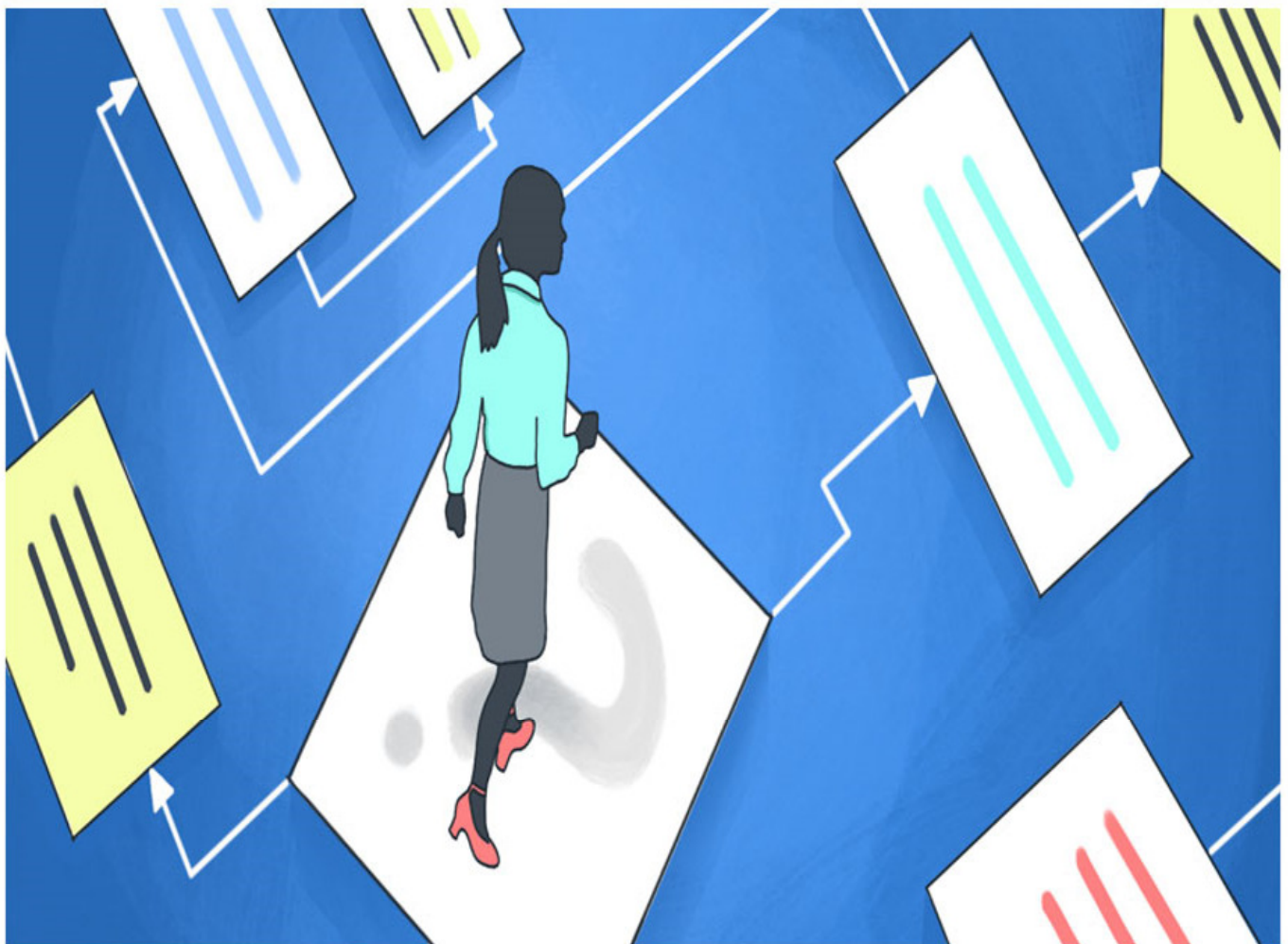
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A SPECIAL ISSUE ON
Performance, Risk and Decision Making (SIBRM4)



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EDITORIAL PREFACE

By Chief Guest Editor
Professor Selim AREN
(Yildiz Technical University, Turkey)

Two important variables in financial transactions are performance and risk. The investor determines the instruments at the risk level that he can accept among the investment instruments that will provide high performance. The next step is decision making. These three important variables of the investment process inspired this special issue of the **International Journal of Business Research and Management (IJBRM)**.

The performance of financial instruments is measured by its return. Since the return of the financial instruments to be invested cannot be known in advance, it must be estimated. This estimation process is done by modeling in financial markets. The risk is the deviation from the expected (Aren and Koten, 2019). This is most simply measured with the standard deviation. Decision-making is choosing the most appropriate one among the alternatives according to risk/return.

The most appropriate choice according to neoclassical finance; It is the purchase of financial instruments with the highest return at acceptable risk level or financial instruments with the lowest risk at acceptable return level. This approach relies on mathematical operations and assumes no emotions.

In contrast, behavioral finance and, more generally, post-classical finance consider emotions in the decision-making process. It is concerned with how the individual feels and how is perceiving, rather than the mathematical calculation of risk. Perception is a sensory experience (Romo and Rossi-Pool, 2020). Experience is shaped by how the individual perceives these events, as well as based on the objective events that the individual has experienced in the past. For this reason, it includes both cognitive evaluation and is affected by factors such as optimism, fear and regret (Loewenstein et. al., 2001). A financial instrument that did not provide a very high return in the past, but earned the amount that the individual urgently needs, contains positive emotions in the individual. If the amount earned corresponds to the hospital expenses of the newborn baby or the school installment of the child who has been accepted from a good university, the individual always remembers that investment with positive feelings. On the other hand, when a financial investment provides a return slightly below the expected return and the difference causes the house not to be purchased, it will be evaluated very negatively by the investor. For this reason, risk perception is the subjective feelings of individuals regarding various losses when buying assets (Li et. al., 2020). It is shaped not only by quantitative facts but also by qualitative features (Sachse et. al. 2012), and the same alternatives may lead to different preferences at different times (Aren and Akgüneş, 2018).

As a result, decision making is associated with performance and risk in both neoclassical and post-classical finance. In this special issue, there are three articles that contribute to the literature with different approaches.

The first article in this journal used the TOPSIS method, which is one of the multi-criteria decision making methods. It is extremely interesting in terms of investigating who tends to make the most rational decision out of the big five personality traits. Data were collected from over 600 subjects. In addition to personality traits, risk taking, risky investment intention, objective and subjective financial literacy variables were used. In addition, in the continuation of the study, loss aversion and pleasure seeking, two important concepts of neurofinance, were included in the study and the personality trait that was most successful in rational decision making was investigated.

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In the second article, the TOPSIS method, which is one of the multi-criteria decision-making methods, was used. Fifteen fund managers' performances were analyzed over a ten-year period. As predicted by the theory, empirical findings have been provided that the performance achievements of fund managers are completely coincidental.

The last study investigated whether bitcoin investments could be a hedging instrument for other financial instruments using the VAR model. It has been found that Bitcoin has a deterministic process and is not associated with other financial instruments.

REFERENCES

- [1] Aren, S., and Koten, A. B., (2019). "The Effects Of Emotions On Risk Aversion Behaviour", *Journal of Life Economics*, 6(4), pp. 421-436.
- [2] Romo, R. & Rossi-Pool, R. (2020). Turning Touch into Perception. *Neuron*, 105(1), 16-33
- [3] Li, Z., Sha, Y., Song, X., Yang, K., ZHao, K., Jiang, Z., & Zhang, Q. (2020). Impact of risk perception on customer purchase behavior: a meta-analysis. *Journal of Business & Industrial Marketing*, 35(1), 76-96. DOI:10.1108/jbim-12-2018-0381
- [4] Loewenstein, G.F., Weber, E.U., Hsee, C.K. & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, 127, 267-286.
- [5] Sachse K., Jungermann H. & Belting J.M. (2012). Investment risk The perspective of individual investors. *Journal of Economic Psychology*, 33, 437-447
- [6] Aren S., Akgünes A.O., (2018) Evaluation of the Effect of Emotions on Investment Decision Making with Structural Equation Model, *International Journal of Academic Value Studies*, 4(19), 363-371

Evaluation of Personality Traits and Rational Behavior Relationship with TOPSIS Method

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Abstract

In this study, it was aimed to determine which personality trait tends to behave most rational. In this context, the Big Five model was used while determining personality traits; and individuals' risky investment intentions, risk aversion, and objective and subjective financial literacy levels were also measured using the survey method. 649 questionnaires were collected with convenience sampling. First of all, factor analysis was performed by using SPSS Statistics program. Following the data collection and analysis process, the TOPSIS method was used to rank the tendency of personality traits to behave rationally. Calculations related to the TOPSIS method were done with Microsoft Excel. In the second stage of the study, the pleasure desire (reward system) and loss aversion, which are the main two motivations of neuro finance, were also included in the model separately and the ranking process was repeated. As a result, it was determined that individuals who tend to behave most rationally have an openness personality trait. However, it was found that when the reward system is included in the model the extroversion personality trait tends to behave most rationally, on the other hand, when the loss aversion is included, the agreeableness personality trait tends to behave most rationally.

Keywords: Big Five, Personality Trait, TOPSIS, Rationality.

1. INTRODUCTION

The concept of “economic rationality”, defined as providing the most benefit with the least cost among the economic decision units, has an important place in the literature of finance and economics. The classical and neoclassical view of finance has also accepted that individuals are rational when making decisions. However, with the spread of behavioral finance, researchers have revealed that individuals are not rational when making decisions, and have made researches to support these views by making use of disciplines such as psychology and sociology. Kahneman (2013) mentions dual-process theory in relation to decision making. Accordingly, individuals make decisions analytic or intuitive. Individuals are lazy in the context of thought (Kahneman, 2013) and make use of various short-cuts and heuristics to make quick decisions (Tversky and Kahneman, 1974; Kahneman and Lovallo, 1993). This decision-making behavior is common in both experienced and knowledgeable and inexperienced and uninformed individuals (Tversky and Kahneman, 1974).

As the behavioral finance view claims, individuals may tend to behave rationally, even if they are not entirely rational. The main purpose of the study is to determine the tendency of individuals to behave rationally. Within the scope of this purpose, the personality traits in the Big Five model were taken as a basis and it was determined which of the relevant personality traits behaved

most rationally. The Big Five Personality Traits model is one of the most widely used and successful models in the literature (Durand *et al.*, 2008). It has been stated that the model is suitable and sufficient for explaining the investment behaviors of individuals and measuring their risk perceptions (Nicholson *et al.*, 2005; Brown and Taylor, 2014; Pinjisakikool, 2017; Jalilvanda *et al.*, 2018). The environment of uncertainty and accompanying risks have an important place in the decision-making processes of individuals (Dal and Eroglu, 2015). For this reason, the risk factor is included very much in the studies.

Another factor associated with risk is financial literacy. However, many studies in the field of finance only measure objective financial literacy (Aren and Köten, 2019). Studies on subjective financial literacy have been on the agenda recently. When measuring the level of objective financial literacy, questions on various financial issues such as risk, interest calculation, and understanding inflation (Lusardi and Mitchell, 2014) are used; in subjective financial literacy, there are question/questions about the level at which individuals see their financial level of knowledge (Bellofatto *et al.*, 2018).

TOPSIS method, which is one of the multiple decision-making techniques, was used to determine which personality traits tend to behave more rationally. TOPSIS helps researchers to determine the best alternative among decision units or alternatives. TOPSIS has been preferred by researchers as a decision-making method in various sectors for many years (Dandage *et al.*, 2018). However, in the literature review, a study on personality traits and financial decision making was not encountered by using TOPSIS. In this context, we think it will contribute to the literature. The second important contribution of the study is related to the field of neuro-finance. In this framework, the reward system and loss aversion, which are the two main motivations of neuro finance, were included in the model separately, and personality traits were reevaluated.

In the second section of the study, a wide literature review was given. In the third section, there was information about the methods used and the data set. Then, in the fourth section, there were analyses. In the last section, the findings were discussed.

2. LITERATURE REVIEW

2.1 Personality Traits

In recent years, personality traits have been at the center of many studies that have been conducted and it has been pointed out that it is an important factor (Durand *et al.*, 2013; Brown and Taylor, 2014; Kourtidis *et al.*, 2016). In this context, the only research which investigate personality traits and risky investment and risk appetite separately belongs to (Aren and Hamamcı, 2020). Other studies have generally investigated the relationship between risk taking / avoidance and personality traits. Although the results indicate a general judgment, there is no dominant opinion in some personality traits. Neurotic individuals's risk preferences harbor affective characteristic (Wilt and Revelle, 2015) and are generally considered to avoid to risk (Nicholson *et al.*, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016). However, in this context, Aren and Hamamcı (2020), which is the only study that evaluates risk aversion and risky investment intention separately, did not find a meaningful relationship with risk aversion, but found a positive relationship with risky investment intention. It is accepted that there is a positive relationship between the extraversion personality trait and risk appetite (Nicholson *et al.*, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016). However, differently, Aren and Hamamcı (2020) and Aren *et al.* (2019) could not identify a relationship with risk taking. Regarding the Openness personality trait, Aren and Hamamcı (2020) found a positive relationship with risk aversion, and the general judgment regarding these people is that risk appetites are high (Kleine *et al.*, 2016; Aren *et al.*, 2019). It is accepted that there is a positive relationship between risk aversion and the other two personality traits that are agreeableness (Nicholson *et al.*, 2005; Soane and Chmiel, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016) and conscientiousness (Aren and Hamamcı, 2020).

Various models were developed to measure personality traits. Among these models, the Big Five Personality Model (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness) is one of the most preferred. It was determined that the Big Five model is suitable and sufficient to measure risk perception (Nicholson *et al.*, 2005; Pinjisakikool, 2017) and to understand and explain investment decisions (Brown and Taylor, 2014; Jalilvanda *et al.*, 2018).

Individuals with extraversion are social, energetic, sympathetic, cooperative, optimistic, seeking innovation, talkative and assertive (Durand *et al.*, 2008; Pinjisakikool, 2017; Tauni *et al.*, 2017a). Similar to other personality traits, extroversion is also associated with risk-taking, financial decision and investment decision (Durand *et al.*, 2008; Brown and Taylor, 2014; Pinjisakikool, 2017). Becker *et al.* (2012) and Pinjisakikool (2017) found that individuals with extraversion want more risks. On the contrary, Durand *et al.* (2008) and Durand *et al.* (2013) stated that they tend to trade less.

Individuals with conscientiousness are disciplined, goal-oriented, responsible, careful, capable, and who have organization skills (Durand *et al.*, 2008; Becker *et al.*, 2012; Tauni *et al.*, 2017a). Dohmen *et al.* (2010) and Akhtar and Batool (2012) stated that they would want more risks; on the contrary, Pinjisakikool (2017) found a negative relationship between risk appetite and related personality trait.

Individuals with agreeableness are benevolent, respectful to others' beliefs, harmonious, reliable, successful social relationships, friendly, sympathetic, and avoider from disagreement and dispute (Durand *et al.*, 2008; Kleine *et al.*, 2016; Pinjisakikool, 2017). Becker *et al.* (2012) could not find a relationship between agreeableness and investment preferences and financial decisions. In contrast, Dohmen *et al.* (2010) stated that individuals with agreeableness personality traits will have high-risk appetites.

Individuals with neuroticism personality trait are emotionally unstable, anxious, fragile, shy, anxiety, pessimistic, and have the potential to experience negative emotions such as fear and anger in a lack of self-confidence and self-control (Durand *et al.*, 2008; Pinjisakikool, 2017; Tauni *et al.*, 2017a; Tauni *et al.*, 2017b). Becker *et al.* (2012) stated that individuals with neuroticism trait would avoid more risks. In contrast, more researchers have emphasized that these individuals will want more risk (Durand *et al.*, 2008; Chitnis and Vaidya, 2016; Pinjisakikool, 2017).

Individuals with openness are highly imaginative, intellectual, open-minded, intelligent, creative and open to innovation and knowledge (Durand *et al.*, 2008; Becker *et al.*, 2012; Tauni *et al.*, 2017a). Durand *et al.* (2008) and Pinjisakikool (2017) found that individuals with this trait want more risk.

2.2 Personality and Rationality

People make conscious or unconscious decisions constantly. The finance theory regarding these decisions has two different perspectives. The first is the normative approach and deals with the logic that causes the decision and addresses how to make decisions. The other is descriptive, concerned with beliefs and preferences that lead to decisions (Kahneman and Tversky, 1984). It is generally accepted that the first approach represents standard finance and the second approach represents behavioral finance. Normative approach has some basic principles such as transitivity, dominance and immutability. If A is preferred to B and B is preferred to C, then A is preferred to C. This is called transitivity. If A is at least as good as B in all respects and better than B in at least one respect, then A should be preferred over B. This is dominance. The last one is immutability. Preference is independent of defining options. However, when the same option is framed or defined differently (loss / gain) this condition is generally not provided. For this reason, Kahneman and Tversky (1984) say that immutability is normatively essential, intuitively attractive, but psychologically impossible.

Kahneman (2013) stated that Expectation Theory, which is the basis of behavioral finance, was accepted by many researchers and the reason for this was considered as various contributions such as loss avoidance and reference point, rather than the accuracy of the theory. Kahneman and Tversky first mentioned this theory in their 1979 article. In this study, a new approach is presented with a critical view of the expected utility theory (Kahneman and Tversky, 1979). The focus of the new approach is human behaviors that is not consistent with rational theory. In this context, over time, both them and other behavioral finance researchers have shown that many bias and mental shortcuts distort the rationality in financial decisions. In fact, in many cases individuals make choices that are incompatible with the rational decision-making theory, but they do not even know that their choices are not rational (Kahneman and Tversky, 1979). This is because of the cognitive biases they have. Cognitive biases cause individuals to neglect basic rates, not paying attention to the abilities and skills of others as much as they trust their own beliefs, talents and abilities and neglect the role of luck in success (Kahneman, 2013).

Both individual and institutional investors can make irrational decisions (Aren and Dinç-Aydemir, 2015). Various psychological factors and personality have an effect on these irrational decisions (Aren and Aydemir, 2014; Kokkinos *et al.*, 2017). Personality is the characteristics that affect an individual's emotions, thoughts and behaviors (Wilt and Revelle, 2015; Nishita *et al.*, 2016; Isidore and Christie, 2017).

Mind Theory states that decision making has cognitive and affective characteristics (Abu-Akel *et al.*, 2012). Cognitive traits consist of information, beliefs, and intentions (Wilt and Revelle, 2015; Volkova and Rusalov, 2016; Bajwa *et al.*, 2017). It includes the individual to have awareness of information, to search for it, to analyze and interpret it. The focus is on information. However, various biased behaviors can be seen frequently in the steps related to the interaction of beliefs and intentions. On the other hand, affective traits refer to the effect of emotion, sentiment and mood in the decision-making process (Ahmad *et al.*, 2017). As Kahneman (2013) stated, decision making does not only occur with analytical processes, that is, cognitive processes. It is also often affected by affective processes. The mutual interaction and degree of these two forms personality (Peterson, 2007).

Personality is effective on risk preference (Aren and Zengin, 2016; Aydemir and Aren, 2017a; Aydemir and Aren, 2017b). Although the general attitude towards risk and the tendency to take financial risk are conceptually different, they are not very different in terms of behavior (Schoemaker, 1993). Although there are many different personality traits classifications, the Big Five Personality Trait is considered better than other approaches (Digman, 1990; Peterson, 2007). There are five dimensions in the Big Five Personality Model: neuroticism, extraversion, openness to experience, adaptability and responsibility (Benet-Martinez and John, 1998).

As the level of neuroticism rises, investors trade more Durand *et al.* (2013). Although their attitudes towards risk are inconsistent (Wilt and Revelle, 2015), they generally avoid risk (Nicholson *et al.*, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016). Individuals with the trait of extroversion have a high risk appetite (Nicholson *et al.*, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016). Individuals with openness personality traits trade more due to their self-confidence (Isidore and Christie, 2017) and therefore their risk acceptance (Kleine *et al.*, 2016) is also high (Nicholson *et al.*, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016). On the other hand, individuals with the agreeableness personality trait trade less (Kleine *et al.*, 2016). Herd behavior is typical characteristic of these individuals (Isidore and Christie, 2017) but they do not want to take risks (Nicholson *et al.*, 2005; Soane and Chmiel, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016). Individuals with conscientiousness personality trait have low risk appetite despite high trade (Nicholson *et al.*, 2005; Soane and Chmiel, 2005; Durand *et al.*, 2013; Lönnqvist *et al.*, 2015; Kleine *et al.*, 2016).

2.3 Risk-Taking and Risky Investment Intention

Financial risk perception is one of the factors affecting the decision of the individual investor to distribute his/her money among various investment instruments in an optimal portfolio in terms of risk and return (Dizdarlar and Şener, 2016). Risky investment intention is investors' willingness to invest in a risky market or asset. While it is expected to be largely related to risk-taking, it is not an inference that should be precisely true. Weber *et al.* (2002) and McCarty (2000) stated that taking risks may vary depending on the situation at risk. Pinjisakikool (2017) states that whether risk attitudes are specific to a particular area or general, is a controversial issue and, both opinions are found in the literature. After that Sanou *et al.* (2018) stated that area-specific measurement is easier and more convenient.

In many studies, significant relationships were found between financial literacy and risk-taking (Sjöberg and Engelberg, 2009; Guiso and Jappelli, 2012; Aren and Zengin, 2016) and investment preferences. Tauni *et al.* (2017a) investigated the effect of information about financial assets on stock trading according to different personality characteristics. While this information reduces the stock trading volume of individuals with neuroticism trait; it has the opposite effect on individuals with agreeableness, extraversion and conscientiousness traits. Durand *et al.* (2008) also found similar results that individuals with neuroticism trait trade less.

2.4 Financial Literacy

With the developments in the financial system, the number of financial products and services increases and financial decision-making processes such as borrowing, investment and savings become more complicated (Nicolini and Haupt, 2019). For this reason, the need of individuals for financial literacy also gains importance (Aren and Dinç-Aydemir, 2015). Financial literacy is defined as the ability of individuals to understand, analyze or manage their financial situation and also, it expresses the financial knowledge and skills required for individuals to overcome the difficulties they face in their daily lives and decision-making processes (Soane and Chmiel, 2005; Servon and Kaestner, 2008; Bellofatto *et al.*, 2018; Kalwij *et al.*, 2019). Grohmann (2018) also points out that financial literacy is associated with good diversification, choosing the right investment tools, and conscious use of credit cards. When the literature is analyzed, many studies are examining whether financial literacy is effective in financial decision making (Dhar and Zhu, 2006; Rooij *et al.*, 2007; Rooij *et al.*, 2011; Guiso and Jappelli, 2012).

Various objective and subjective scales are used to measure financial literacy (Aren and Canikli, 2018). Lusardi and Mitchell (2014) have created a set of questions based on three basic factors in measuring financial literacy; being able to calculate math and interest rates, and understand inflation and risk diversity. In subjective financial literacy, it is based on the question or questions that individuals assess their financial knowledge and expertise (Bellofatto *et al.*, 2018). With this type of subjective evaluation, psychological variables that affect the decision-making process are obtained (Bellofatto *et al.*, 2018). When the relationship between objective and subjective financial literacy is examined, different results were obtained. While some researchers find a positive and strong relationship (Dorn and Huberman, 2005; Rooij *et al.*, 2011); some found a weak relationship (Lusardi, 2011; Guiso and Jappelli, 2012; Bucher-Koenen *et al.*, 2012).

3. METHODOLOGY

3.1. Research Aim

The study aims to determine the personality trait that tends to behave most rationally within the framework of the Big Five personality model. For this purpose, risk aversion, risky investment intention and objective and subjective financial literacy levels of individuals were measured. The low level of difference between risk appetite and risky investment intention was accepted as the first indicator of rationality. On the other hand, questions were asked to measure the objective financial literacy of individuals and objective financial literacy levels were calculated from this point. Also, individuals were wanted to evaluate themselves in terms of financial literacy levels. This assessment was called as subjective financial literacy. The low level of difference between the two levels of financial literacy achieved in this way was also regarded as a second rationality

indicator. It was also aimed to contribute to a limited number of non-laboratory neuro finance studies by including the effect of two basic motivations (reward system and loss aversion) expressed by neuro finance as a second step in the investigation of this relationship.

3.2. Research Method and Data Set

In the study, individuals' risky investment intentions, risk appetite, and subjective and objective financial literacy were measured with a survey method in order to determine the rational tendency of personality traits. In this context, a total of 649 subjects were reached using online and face-to-face questionnaires with convenience sampling and voluntary participation. Then, it was preferred TOPSIS method, which is one of the multi-criteria decision-making methods, to determine which personality trait behaves most consistently. Related calculations were made with Microsoft Excel.

The variables and scales used in the research were shown in Table 1. Also, four demographic questions were asked: gender, age, educational status and marital status.

Variables	Number of Items	Scales
Risky Investment Intention	4	Putrevu et al. (1994) / Dodds et al. (1991) (Modified by Aydemir and Aren, 2017a)
Risk Aversion	7	Donthu and Gilliland (1996)/Burton et al. (1998) (Modified by Aydemir and Aren, 2017a)
Big Five Personality Traits	25	Benet-Martines and John (1998) (Modified by Kalabalık and Aren, 2018)
Subjective Financial Literacy	1	Aren and Canikli, 2018
Objective Financial Literacy	10	Kahneman and Tversky (1984)

TABLE 1: Variables and Scales.

When the demographic characteristics of the research participants were examined, 295 (45.5%) of the respondents were male and 354 (54.4%) female; 211 (32.5%) were married and 438 (67.5%) single. While 137 (50.4%) were undergraduate graduates and 162 (25%) were graduate/doctorate graduates, the remaining 160 (24.6%) had high school and less education. When evaluated according to age groups, there were 416 people (64.1%) between the ages of 20-30 and 166 people (25.6%) between the ages of 31-40. There were 67 people (10.3%) aged 41 and over. It was gender-balanced according to demographic characteristics; a single, educated and young sample was achieved.

3.2.1. TOPSIS Method

Multi-criteria decision-making methods have attracted perfect attention for many years by the researchers and practitioners in evaluating and ranking decision units or alternatives (Dandage *et al.*, 2018). Multi-criteria decision-making models perform their analysis by ranking alternatives according to the different characteristics of them and then choosing the best one. There are more than one multiple criteria decision-making methods, including TOPSIS (Dandage *et al.*, 2018).

The TOPSIS method was first developed by Hwang and Yoon in 1981 (Ayaydin *et al.*, 2018). TOPSIS is based on the principle of choosing the best alternative among decision units (Chitnis and Vaidya, 2016). There are two main qualities in the TOPSIS method: ideal distance and non-ideal (negative) distance (Chitnis and Vaidya, 2016; Bilbao-Terol *et al.*, 2019). According to these qualities, the relative proximity value (C^*) to the ideal solution is calculated. In this way, the method tries to choose the alternatives that are closest to the ideal solution and also the farthest from the non-ideal (negative ideal) solution (Hwang *et al.*, 1993; Chitnis and Vaidya, 2016; Ayaydin *et al.*, 2018; Bilbao-Terol *et al.*, 2019). For this reason, Bilbao-Terol *et al.* (2019) stated that the TOPSIS method is based on a compromise philosophy.

The main stages of the TOPSIS method were briefly described in Table 2.

Steps	Descriptions	Matrices and Formulas
Step 1	Creating the decision matrix	$K_{hi} = \begin{bmatrix} k_{11} & \dots & k_{1p} \\ \vdots & \ddots & \vdots \\ k_{m1} & \dots & k_{mp} \end{bmatrix}$
Step 2	Creating the "Normalized Matrix" by performing the normalization process	$N_{hi} = \frac{k_{hi}}{\sqrt{\sum_{i=1}^m k_{hi}^2}}$
Step 3	Creating a Weighted Normalized Matrix according to the determined weights	$V_{hi} = \begin{bmatrix} v_{11} & \dots & v_{1p} \\ \vdots & \ddots & \vdots \\ v_{m1} & \dots & v_{mp} \end{bmatrix}$
Step 4	Finding the ideal solution value and non-ideal solution value	$I^+ = \{ \max v_{ij} \}$ (2) $I^- = \{ \min v_{ij} \}$ (3)
Step 5	Calculation of ideal distance (S+) and non-ideal distance (S-) for each decision unit	$S^+ = \sqrt{\sum_{i=1}^n (v_{hi} - v_i^+)^2}$ $S^- = \sqrt{\sum_{i=1}^n (v_{hi} - v_i^-)^2}$ $C^* = \frac{S^-}{S^- + S^+}$
Step 6	Calculating the relative proximity to the ideal solution (C*)	$S^+ = \sqrt{\sum_{i=1}^n (v_{hi} - v_i^+)^2}$ $S^- = \sqrt{\sum_{i=1}^n (v_{hi} - v_i^-)^2}$ $C^* = \frac{S^-}{S^- + S^+}$
Step 7	Decision units are ranked from good to bad according to calculated C* value.	

TABLE 2: Stages of the TOPSIS.

4. ANALYSES AND RESULTS

4.1. Factor and Reliability Analysis Results

Firstly, factor analysis and reliability analysis were performed on the collected data using SPSS and the results reported in the table below.

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
	K11	K1	K21	I1	R1	K16	K7
	K12	K2	K22	I2	R2	K17	K8
	K13	K3	K24	I3	R4	K18	K9
	K14	K4	K25	I4	R5	K19	
	K15	K5			R7	K20	
Reliability	0,827	0,818	0,785	0,826	0,739	0,717	0,629
KMO Value	0,905						
Bartlett's Test of Sphericity	10724,543(0,000)						

TABLE 3: Factor and Reliability Analyses.

Considering the factor analysis results in Table 3, the KMO value was found to be 0,905, and according to this result, the selected sample size is suitable for factor analysis. Bartlett test statistics are also significant at the 0,000 error level, so it can be accepted there is consistency

between the questions. 37 items were spread over 7 different factors. Factor1, "conscientiousness personality trait"; Factor 2, "extraversion personality trait"; Factor 3, "openness personality trait"; Factor 4, "risky investment intention; Factor 5, "risk aversion"; Factor 6, "neuroticism personality trait"; and Factor 7 is called the "agreeableness personality trait". When the reliability values of the factors were analyzed, the reliability of the three factors was above 0.80 and the other three factors were above 0.70. The reliability of the agreeableness personality trait factor was calculated as 0.629. Although this value is not very high, it was expressed by Aren and Hamamcı (2020) as an acceptable value.

4.2. TOPSIS Results

After the factor and reliability analyzes were performed, the differences between the objective and subjective financial literacy and risk-taking and risky investment intention levels of the individuals were calculated using SPSS. With the help of the SPSS program, the responses of the participants to the specified variables were subtracted from each other (objective-subjective and risky investment intention-risk aversion) calculations were made. The lowness of these differences was accepted as a sign of rationality (consistency) and, the most rational one was determined according to personality characteristics with the TOPSIS method. The decision units and criteria to be used in the TOPSIS method were determined and shown in Table 4. The expectation is that the difference between the risk aversion and the risk investment intention value is "0". This situation was also accepted as a sign of rational behavior. The difference between objective and subjective literacy equal to "0" was accepted as the determinant of the fact that people evaluate themselves realistically regardless of their emotions.

		Abbreviations
Decision Units	Extraversion (Personal Trait)	
	Agreeableness (Personal Trait)	
	Conscientiousness (Personal Trait)	
	Neuroticism (Personal Trait)	
	Openness (Personal Trait)	
Criteria	The difference between Objective Financial Literacy and Subjective Financial Literacy	FLD
	The difference between Risky Investment Intention and Risk Aversion Behavior	ROD

TABLE 4: Decision Units and Criteria Used in the TOPSIS Method.

First of all, the weight values of the criteria needed in the 3rd step of the TOPSIS method were calculated by the Entropy Weighting Method, and then the ranking was made among decision units by switching to TOPSIS.

4.2.1. Weight Calculation with Entropy Weighting Method

Step 1: Creating the Decision Matrix

The values of each decision unit related to the relevant criteria were found and a decision matrix was created with these values.

Step 2: Creating the Normalized Decision Matrix

To obtain the normalized matrix, the sum of each column in the decision matrix was calculated separately. Then, normalization was performed by dividing each value in the columns into their column totals separately.

Step 3: Finding Entropy Value Related to Criteria

In this step, each normalized value was multiplied by its "ln" value. Then the total value of the columns was taken. The "k value" needed to calculate the entropy value was calculated as $k = 1 / \ln(5) = 0.621335$. Entropy values of the criteria were obtained by multiplying the total value of the

columns with the $(-k)$ value. (Note: Since the number of decision units in the study is 5, it was used as "ln (5)" in the calculation of k value.)

Step 4: Calculating the Degree of Differentiation of Information

The degree of differentiation (dj) of the information was calculated by subtracting the entropy values obtained in the previous step from 1.

Step 5: Weights of Criteria

Finally, the dj value of each criterion was divided by the total dj value and the weights of the criteria were calculated: *FLD: 0,0982570; ROD:0,90174297*

4.2.2 Calculations with TOPSIS

After determining the research criteria and decision units, the decision matrix for the TOPSIS method was created and shown Table 5. Then, normalization was performed by squaring each value in the decision matrix (Equation 1). In the 3rd step, the weighted normalized matrix was formed by multiplying the weight values of the criteria calculated by the entropy weighting method with the relevant values in the normalized matrix. In the 4th step, the ideal solution value and the non-ideal solution value were calculated according to the Equation 2 and 3. In the next step, the ideal distances (S +) and non-ideal distances (S-) for each decision unit using Equation 4 and 5 (in Table 2) were calculated. In the last step, using the Equation (6), the relative proximity value to the ideal solution (C*) was calculated and all of these values were shown in Table 5. Finally, the results were ranked from good to bad.

	S+	S-	C*	Ranking
Extraversion	0,011824	0,014844	0,556622	4
Agreeableness	0,004882	0,020899	0,810640	3
Conscientiousness	0,003623	0,022070	0,858988	2
Neuroticism	0,025687	0	0	5
Openness	0,001705	0,0252259	0,936701	1

TABLE 5: Ideal distance (S +), Non-Ideal Distance (S-) and Relative Proximity Value to the Ideal Solution (C*) Results and Ranking.

When the results in Table 5 are analyzed, it was obtained that individuals with Openness personality traits are more consistent in terms of financial literacy and risk-taking intentions with a value of 94%. Individuals with openness personality trait were followed by individuals with conscientiousness (85%) and agreeableness (81%) personality traits. However, this consistency was not found in individuals with prominent neurotic features.

At the second stage of the research, while determining the decision units, the attitudes of pleasure and loss aversion in individuals were also taken into consideration. In this context, individuals with different personality traits were grouped according to their high sense of pleasure or loss aversion. The decision units and criteria determined by these conditions were shown in Table 6.

		Abbreviations
Decision Units	Extraversion (High Pleasure)	EPT_1
	Extraversion (High Loss Aversion)	EPT_2
	Agreeableness (High Pleasure)	APT_1
	Agreeableness (High Loss Aversion)	APT_2
	Conscientiousness (High Pleasure)	CPT_1
	Conscientiousness (High Loss Aversion)	CPT_2

Criteria	Neuroticism (High Pleasure)	NPT_1
	Neuroticism (High Loss Aversion)	NPT_2
	Openness (High Pleasure)	OPT_1
	Openness (High Loss Aversion)	OPT_2
	The difference between Objective and Subjective Financial Literacy	FLD
	The difference between Risk Intention and Risk Aversion Behavior	ROD

TABLE 6: Decision Units and Criteria Used in the TOPSIS Method.

In this part of the research, the weights related to the criteria were also calculated with the Entropy Weighting Method. In the previous section, weight calculations made in detail were repeated. The weight values of criteria found after the calculations: *FLD:0,500460; ROD:0,499540*

Then, the weights found the above processes were used in the calculation step of the weighted matrix in the TOPSIS Method and the weighted normalized matrix was obtained. Next step, the ideal solution value (taking the maximum value of each column) and the non-ideal solution value (taking the minimum value of each column) were calculated. After this step, the ideal distances (S+) and non-ideal distances (S-) for each decision unit were calculated using Equation 4 and 5, and finally when looking at Table 7; using the Equation (6), the relative proximity value to the ideal solution (C*) was calculated and the results were ranked from good to bad.

	S+	S-	C*	General Ranking	Pleasure (High)	Loss Aversion (High)
EPT_1	0,0102	0,0334	0,7656	5	1	3
EPT_2	0,0037	0,0407	0,9177	3		
APT_1	0,0146	0,0295	0,6699	6	2	1
APT_2	0,0001	0,0435	0,9972	1		
CPT_1	0,0158	0,0286	0,6435	7	3	2
CPT_2	0,0034	0,0402	0,9219	2		
NPT_1	0,0422	0,0069	0,1410	10	5	5
NPT_2	0,0365	0,0073	0,1666	9		
OPT_1	0,0211	0,0239	0,5308	8	4	4
OPT_2	0,0070	0,0366	0,8401	4		

TABLE 7: Ideal distance (S+), Non-Ideal Distance (S-) and Relative Proximity Value to the Ideal Solution (C*) Results and Ranking.

When the results in Table 7 were analyzed, it was concluded that individuals with high agreeableness personality traits with loss aversion attitude were more consistent with a value of 99%, both in terms of objective and subjective financial literacy and risky investment intentions. Individuals with the conscientiousness personality trait (92%) with a high attitude of loss aversion were in the second rank, and individuals with extraversion (91%) with a high attitude of loss aversion were in the third rank. Individuals with high-pleasure neuroticism personality trait were in the last in the general ranking. This means that they are not very consistent in terms of both financial literacy (objective and subjective) and risky investment intentions.

At the same time, when each personality trait is evaluated in itself in terms of two motivational elements (loss avoidance and pleasure), it was found that individuals exhibit more consistent behaviors in the situation of high loss aversion compared to the situation of high pleasure emotion (EPT_2>EPT_1; APT_2 > APT_1; CPT_2 > CPT_1; NPT_2 > NPT_1; APT_2 > APT_1).

When we rank the personality traits according to the situation where the attitude of loss aversion is high, it was found that the individuals with agreeableness personality trait are the most consistent (rational). It can be said that individuals with conscientiousness trait follow these individuals, and on the contrary, individuals with neuroticism trait behave more inconsistently than others.

When it was rank the personality traits according to the situation in which the emotion of pleasure is high, it can be said that individuals with extraversion trait are more consistent (rational) but again, as before, individuals with neuroticism trait behave more inconsistent than others.

5. CONCLUSION

Despite the claim that neoclassical finance is rational for individuals, behavioral finance states that individuals are normal and systematically deviate from rationality. Many studies conducted within this framework have investigated psychological variables that may be related to investment preferences. In recent years, personality trait is also a subject that has been investigated in terms of its relationship with investment preference. On the other hand, studies on neuro finance try to establish a link between investment preferences and brain-activated regions by using various brain imaging techniques. In this context, two main phenomena are emphasized: pleasure and loss aversion. This study investigated the tendency to behave rationally according to both personality traits purely and personality traits under the phenomena of pleasure and loss aversion. As far as we know, this is the first study in the field because of this feature.

It was expected that individuals' risk-taking will be consistent with their risky investment intentions, and their objective and subjective financial literacy levels should be close or the same. Two features mentioned were accepted as rational behavior criteria in this study. In this way, the rational behavior relation according to personality traits was investigated with the TOPSIS method, which is one of the multiple decision-making methods. As a result of analyzes, a personality trait that behaves the most rational was determined as openness. Individuals with neuroticism trait are those who do not behave rationally at all. The characteristics that define the openness personality trait are intellectuality, open-mindedness, and demanding information. It is not surprising that they exhibit rational behavior because of these features. On the other hand, neuroticism is expressed as emotional instability. It is quite possible and expected that people with this feature will be reflected in the decisions of the tides experienced in their inner worlds. For this reason, people with this feature demand risk on the one hand, and do not prefer risky investments on the other. On the contrary, people with openness personality traits exhibit more consistent behavior.

In addition to these findings, the effect of pleasure and loss aversion on rational behavior was investigated based on personality traits. Each personality trait was divided into two groups, as high pleasure and high loss aversion. Neurotics were also identified as those that displayed the most irrational behavior in both cases.

When evaluated in general, our study provides some findings that are the first in the literature. The relationship between personality traits and rationality was frequently evaluated with risk appetite, especially in some studies in the field of finance. However, according to the difference between risk appetite and risky investment intention, the first assessment was made in this study to the best of our knowledge. As cited in the literature section, even the number of studies evaluating the relationship between risk appetite and risky investment intention in the context of personality traits is quite limited. In addition, especially pension fund consultants and investment consultants tend to advise according to their customers' risk perceptions. However, their basic acceptance here is that individuals' risk perceptions and risky investment intentions are in harmony. Behavioral finance studies frequently cite such irrational behavior of individuals. This study is noteworthy in terms of showing which personality trait individuals have a higher potential to have such inconsistent behaviors in terms of personality traits. For example, it is not wrong to pay attention to risk appetite while advising individuals with openness personality traits. However,

due to the inconsistency between risk appetites and risky investment intentions of individuals with neurotic personality traits, recommendations given solely according to their risk appetite may not make customers happy.

On the other hand, the examination of pleasure seeking and loss aversion tendencies, which stand out with neurofinance studies, in terms of personality traits is interesting for both the literature and the industry. In addition to personality traits, individuals have a tendency to avoid loss resulting from their genetic makeup and experiences or to seek pleasure. These two contrasting tendencies are also closely related to attitude towards risk and rationality. Individuals with openness personality trait found as the most rational personality trait in our study drift away from rationality as their feelings of seeking pleasure and avoiding loss increase. On the other hand, it is understood that individuals with agreeableness personality traits that tend to avoid high loss and extroverts who seek high pleasure can make more rational decisions. These findings show how individuals with different personality traits, whose different impulses are activated, deviate from rationality.

As a result, these findings are more useful for investors and investment consultants. From the perspective of the investor, it is important in terms of recognizing himself/herself and knowing which type of behavior s/he is more prone to. On the other hand, it is also noteworthy for investment consultants as it will help them get to know their customers and provide them with rational or emotional advice.

6. REFERENCES

Abu-Akel, A., Shamay-Tsoory, S., Poletti, M., Enrici, I. and Adenzato, M. (2012). Cognitive and affective theory of mind in neurodegenerative diases: Neuropsychological, neuronatomical and neurochemical levels. *Neuroscience and Biobehavioral Review*, 36(9), pp. 2147-2164.

Ahmad, Z., Ibrahim, H. and Tuyon, J. (2017). Institutional investor behavioral biases: syntheses of theory and evidence. *Management Research Review*, 40(5), pp. 578 – 603.

Akhtar, M.N and Batool, I. (2012). Psychological Factors, Information Asymmetry and Investment Decision Making. *Actual Problems of Economics*, 2(4), pp. 200 – 205.

Aren, S. and Aydemir, S.D. (2014). The Evaluation Of Psychological Factors Influencing The Criteria For Individual Investment Decisions. *2nd International Conference on Management, Finance and Entrepreneurship (ICMFE-2014)* Istanbul, Turkey on October 25–26, pp. 84 – 94.

Aren, S. and Dinç-Aydemir, S. (2015). The Moderation of Financial Literacy on the Relationship between Individual Factors and Risky Investment Intention. *International Business Research*, 8(6), pp. 17-28.

Aren, S. and Zengin, A.N. (2016). Influence of Financial Literacy and Risk Perception on Choice of Investment. *12th International Strategic Management Antalya, Turkey*, Oct 28–29 (instead of Podgorica, Montenegro, July 21–23), pp. 859 – 865.

Aren, S. and Canikli, S. (2018). Effect Of Financial Literacy And Risk Perception On Individual Investors' Investment Choices. *Conference of 14th International Strategic Management Conference (ISMC) and 8th International Conference on Leadership, Technology, Innovation and Business (ICLTIBM)*, Prague, 12 - 14 July, pp. 800-809.

Aren, S. and Köten A.B. (2019). The Effects Of Emotions On Risk Aversion Behaviour. *Journal of Life Economics*, 6(4), pp. 421-436.

Aren, S., Hamamcı, H.N. and Özcan, S. (2019). Personality and Effect of Emotions On Risk-Taking Behavior. *VI. Yıldız International Social Sciences Congress*, İstanbul, 12–13 December, pp. 2690–2700.

Aren, S. and Hamamcı, H.N. (2020). Relationship between risk aversion, risky investment intention, investment choices: Impact of personality traits and emotion. *Kybernetes*, 49(11), pp. 1251-1268. DOI: <http://doi.org/10.1108/K-07-2019-0455>.

Ayaydın, H., Çam, A.V., Pala, F. and Sarı, Ş. (2018). Türk Bankacılık Sektöründe Performans Değerlendirmesi: AHS ve TOPSİS Yöntemleri Uygulaması. *Global Journal of Economics and Business Studies*, 7(13), pp. 51-64.

Aydemir, S.D. and Aren, S. (2017a). Do the effects of individual factors on financial risk-taking behavior diversify with financial literacy?. *Kybernetes*, 46, pp. 1706-1734.

Aydemir, S.D and Aren, S. (2017b). An Empirical Study on Psychological Motives for Individuals' Risk Mitigating Strategies. *Journal of Finance Letters*, 105, pp. 75–92.

Bajwa,S., Ullah, S.K. and Aslam, H. (2017). Exploring Big Five personality traits and gender as predictors of entrepreneurs' cognitive adaptability. *Journal of Modelling in Management*, 12(1), pp. 143-161.

Becker, A., Deckers, T., Dohmen, T., Falk, A. and Kosse, F. (2012). The Relationship Between Economic Preferences and Psychological Personality Measures. *Annual Review of Economics*, 4, pp. 453-478.

Bellofatto, A., D'Hondt, C. and De Winne, R. (2018). Subjective financial literacy and retail investors' behavior. *Journal of Banking and Finance*, 92, pp. 168-181.

Benet-Martinez, V. and John, O.P. (1998). Los Cinco Grandes across cultures and ethnic groups: Multitrait-multimethod analyses of the Big Five in Spanish and English. *Journal of Personality and Social Psychology*, 75(3), pp. 729-750.

Bilbao-Terol, A., Arenas-Parra, M., Alveraz-Otera, S. and Canal-Fernandez, V. (2019). Integrating corporate social responsibility and financial performance. *Management Decision*, 57(2), pp. 324-348.

Brown, S. and Taylor, K. (2014). Household finances and the 'Big Five' personality traits. *Journal of Economic Psychology*, 45(Dec), pp. 197–212.

Bucher-Koenen, T., Lusardi, A., Alessie, R. and Van Rooij, M. (2012). How financial literate are women? Some new perspectives on the gender gap. Network for Studies on Pensions Aging and Retirement. *Panel Paper31*.

Chitnis, A. and Vaidya, O.S. (2016). Efficiency ranking method using DEA and TOPSIS (ERM-DT): case of an Indian bank. *Benchmarking: An International Journal*, 23(1), pp. 165-182.

Dandage, R., Mantha, S. and Rane, S. (2018). Ranking the risk categories in international projects using the TOPSIS method. *International Journal of Managing Projects in Business*, 11(2), pp.317-331.

Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5), pp. 726-740.

Digman, J.M. (1990). Personality structure: emergence of the five-factor model. *Annual Review of Psychology*, 41(1990), pp. 417-440.

Dizdarlar, H.I. and Şener, Ö. (2016). An implementation on risk – taking behavior of investors. *International Journal of Social Sciences and Education Research*, 2(3), pp. 801-814.

Dohmen, T., Falk, A., Huffman, D. and Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability?. *American Economic Review*, 100(3), pp.1238-1260.

Dorn, D. and Huberman, G. (2005). Talk and Action: what individual investors say and what they do. *Review Finance*, 9(4), pp. 437-481.

Durand, R.B., Newby, R. and Sanghani, J. (2008). An Intimate Portrait of the Individual Investor. *The Journal of Behavioral Finance*, 9(4), pp. 193-208.

Durand, R.B., Newby, R., Peggs, L. and Siekierka, M. (2013). Personality. *The Journal of Behavioral Finance*, 14(2), pp. 116–133.

Dal, V. and Eroğlu, A.H. (2015). Farklı Kişilik Özelliklerine Sahip Bireylerin Risk Algılarının Tüketici Davranışı Açısından İncelenmesi: Üniversite Öğrencileri Üzerine Bir Araştırma. *The Journal of Faculty of Economics Administrative Sciences*, 20(2), pp. 361-385.

Grohmann, A. (2018). Financial literacy and financial behaviour: Evidence from the emerging Asian middle class. *Pacific- Basin Finance Journal*, 48 (2018), pp. 129-143.

Guiso, L. and Jappelli, T. (2012). Financial Literacy and Financial Portfolio Diversification. European University Institute, *Working Paper*, ECO 2008/31, pp. 1-36.

Hwang, C., Lai, Y. and Liu, T. (1993). A new approach for multiple objective decision making. *Computers in Operations Research*, 20(8), pp. 889-899.

Isidore, R. and Christie, P. (2017). Review of the Influence of Investor Personality (The Big 5 Model) on Investor Behavior. *International Journal of Research in Finance and Marketing*, 7(7), pp.23-32.

Jalilvanda, A., Noroozabad, M.R. and Switzer, J. (2018). Informed and uninformed investors in Iran: Evidence from the Tehran Stock Exchange. *Journal of Economics and Business*, 95(Jan-Feb), pp. 47–58.

Kahneman, D. and Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2), pp. 263-292.

Kahneman, D. and Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, 39(4), pp. 341-350.

Kahneman, D. and Lovallo, D. (1993). Timid Choices and Bold Forecasts: A Cognitive Perspective on Risk Taking, Additional contact information. *Management Science*, 39(1), pp. 17–31.

Kahneman, D. (2013). *Thinking, Fast and Slow*, NY, USA: Farrar, Straus and Giroux. (Translated: Deniztekin O. Ç., Deniztekin F. N., 2015, İstanbul: Varlık Yayınları)

Kalabalık, Y. and Aren, S. (2018). The Effects Of Demographic Factors On The Relationship Between Personality Traits And Financial Risk Taking. *International Congress of Management, Economy and Policy*, Spring, İstanbul, Turkey, pp. 256-267.

Kalwij, A., Alessie, R., Dinkova, M., Schonewille, G., Schors, A. and Verf, M. (2019). The Effects of Financial Education on Financial Literacy and Savings Behavior: Evidence From a Controlled Field Experiment in Dutch Primary School. *The Journal of Consumer Affairs*, Fall, pp. 699-730.

Kleine, J., Wagner, N. and Weller, T. (2016). Openness Endangers Your Wealth: Noise Trading and the Big Five. *Finance Research Letters*, 16 (February), pp. 239-247.

Kokkinos, C.M., Karagianni, K. and Voulgaridou. (2017). Relational aggression, big five and hostile attribution bias in adolescents. *Journal of Applied and Developmental Psychology*, 52(September), pp. 101-113.

Kourtidis, D., Sevic, Z. and Chatzoglou, P. (2016). Mood and stock returns: evidence from Greece. *Journal of Economic Studies*, 43(2), pp. 242-258.

Lönqvist, J.E., Verkasalo, M., Walkowitz, G. and Wichardt, P.C. (2015). Measuring Individual Risk Attitudes in the Lab: Tas kor Risk? An Empirical Comparison. *Journal of Economic Behavior & Organization*, 119(November), pp. 254-266.

Lusardi, A. (2011). Americans' Financial Capability. *National Bureau of Economics Research*, NBER Working Paper, No: 17103.

Lusardi, A. and Mitchell, O.S. (2014). The Economic Importance of Financial Literacy: Theory and Evidence. *Journal of Economic Literature*, 52(1), pp. 5-44.

McCarty, B. (2000). Researching The Dynamics of Risk-Taking and Social Learning: An Exploratory Study of Irish Entrepreneurs. *Irish Marketing Review*, 13(1), pp. 46-60.

Nicholson, N., Soane, E., Fenton-O'Creev, M. and Willman, P. (2005). Personality and domain-specific risk taking. *Journal of Risk Research*, 8(2), pp. 157–176.

Nicolini, G. and Haupt, M. (2019). The Assessment of Financial Literacy: New Evidence from Europe. *International Journal of Financial Studies*, 7(54), pp. 1-20.

Nishita, T., Makiko, T., Rei, O., Fujiko, A. and Hiroshi, S. (2016). Personality and global cognitive decline in Japanese community-dwelling elderly people: A 10-year longitudinal study. *Journal of Psychosomatic Research*, 91(December), pp. 20-25.

Peterson, R.L. (2007). *Inside the Investor's Brain: The Power of Mind over Money*, John Wiley & Sons, Hoboken: New Jersey.

Pinjisakikool, T. (2017). The Influence of Personality Traits on Households' Financial Risk Tolerance and Financial Behaviour. *Journal of Interdisciplinary Economics*, 30(1), pp. 32–54.

Rooij, M.V., Kool, C.J.M. and Prast, H.M. (2007). Risk-return preferences in the pension domain: Are people able to choose?. *Journal of Public Economics*, 91, pp. 701-722.

Rooji, M.V., Lusardi, A. and Alessie, R. (2011). Financial Literacy and Stock Market Participation. *Journal of Financial Economics*, 101(2), pp. 449-472.

Sanou, A., Liverpool-Tasie, L. and Shupp, R. (2018). Eliciting Risk Attitudes in the Field: Surveys or Experimental Methods? An Empirical Comparison in Rural Niger. *Journal of Development Studies*, 54(8), pp. 1450-1470.

Schoemaker. P.J.H. (1993). Determinants of risk- taking: behavioral and economic views. *Journal of Risk and Uncertainty*, 6(1), pp. 49–73.

Servon, L.J. and Kaestner, R. (2008). Consumer financial literacy and the impact of online banking on the financial behavior of lower-income bank customers. *Journal of Consumer Affairs*, 42(2), pp. 271-305.

Sjöberg, L. and Engelberg, E. (2009). Attitudes to Economic Risk Taking, Sensation Seeking and Values of Business Students Specializing in Finance. *Journal of Behavioral Finance*, 10(1), pp. 33-43.

Soane, E. and Chmiel, N. (2005). Are Risk Preferences consistent? The Influence of Decision Domain and Personality. *Personality and Individual Differences*, 38(8), pp. 1781-1791.

Sohn, S.H., Hoo, S.H., Grable, J.E., Lee, S. and Kim, M. (2012). Adolescents' financial literacy: The role of financial socialization agents, financial experiences, and Money attitudes in shaping financial literacy among South Korean youth. *Journal of Adolescence*, 35(2012), pp. 969-980.

Tauni, M.Z., Rao, Z.R., Fang, H.X., Mirza, S.S., Memon, Z.A. and Jebran, K. (2017a). Do investor's Big Five personality traits influence the association between information acquisition and stock trading behavior?. *China Finance Review International*, 7(4), pp. 450-477.

Tauni, M.Z., Rao, Z.R., Fang, H.X. and Gao, M. (2017b). Does investor personality moderate the relationship between information sources and trading behavior? Evidence from Chinese stock market. *Managerial Finance*, 43(5), pp. 545-566.

Tversky, A. and Kahneman, D. (1974). Judgement under Uncertainty: Heuristics and Biases. *Science*, 185(4157), pp. 1124–1131.

Tversky, A. and Kahneman, D. (1973). Availability: A Heuristic for Judging Frequency and Probability. *Cognitive Psychology*, 5(2), pp. 207–232.

Tversky, A. and Kahneman, D. (1971). Belief in The Law of Small Numbers. *Psychological Bulletin*, 2, pp. 105–110.

Volkova, E.V. and Rusalov, V.M. (2016). Cognitive styles and personality. *Personality and Individual Differences*, 99 (September), pp. 266-270.

Weber, E.U., Blais, A. and Betz, E.N. (2002). A Domain-Specific Risk- Attitude Scale: Measuring Risk Perceptions and Risk Behaviors. *Journal of Behavioral Decision Making*, 15(4), pp. 263-290.

Wilt, J. and Revelle, W. (2015). Affect, behaviour, cognition and Desire in the Big Five: An Analysis of Item Content and Structure. *European Journal of Personality*, 29(4), pp. 478-497.

Measuring The Performance of Fund Managers with The Multiple Criteria Decision Making Method

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Abstract

The performance of the funds has always been important for investors and has affected their investment preferences. Different factors such as managers' characters or performances has come to the fore in evaluation of funds' performance with the developments of behavioral finance field. For this reason, the relationship between managers' characters or performances and funds' performance has become the focus of researchers besides the effect of other outputs. For this purpose, it was aimed to measure the performances of fund managers who worked as stock fund managers in every year between 2008-2017. In addition, it was aimed to look for the answer to the question of are the success of managers continue by the years. In this context, the return of manager (%), Sharpe ratio, downside capture ratio and upside capture ratio were preferred as performance indicators of fund managers. The determined indicators were calculated with the help of the Finnet Analysis Expert program. TOPSIS method, which is one of the multi-criteria decision-making methods, was used to rank the performance of fund managers using these indicators. Calculations related to the TOPSIS method were made with Microsoft Excel. As a result, 15 fund managers, who were worked as manager between the relevant years consistently, were identified with the help of Finnet Analysis Expert program. An empirical finding was provided to the statement that no fund manager can show high performance for all years expressed theoretically in the literature. In a word, it was found that the success of the fund managers is mostly accidental.

Keywords: Fund Manager Performance, Sharpe Ratio, Downside Capture Ratio, Upside Capture Ratio.

1. INTRODUCTION

With the gaining importance of the studies in behavioral finance, it has started to draw the attention of the researchers whether the success or failure of the companies is influenced not only by the company outputs but also by the character of the company managers. The same situation applies to the evaluation of fund performances. It is not enough to evaluate only by looking at the outputs or characteristics related to funds. At the same time, managers' performances or characteristics should be taken into account (Graham *et al.*, 2019; Andreu *et al.*, 2019).

In the literature, mostly variables such as the size of funds, age of funds, and fund fees were used to measure fund performances (Gottesman and Morey, 2006; Aggarwal and Boyson, 2016; Ferreira *et al.*, 2018; Dyakov and Verbeek, 2019). However, the effects of the characteristics and demographics of fund managers on fund performances cannot be ignored. With the effect of

behavioral finance gaining importance in recent years, studies which are in this direction have started to take place in the literature. Liu *et al.* (2019) mentioned the effects of the social networks of fund managers on the performance of the funds they manage and stated that there is a positive relationship between performance and social relations. Bai *et al.* (2019) found concrete evidence that the high self-confidence of fund managers will increase fund returns. They also stated that relatively older fund managers' performances are better because of the ages of fund managers constitute an element of trust on investors. At the same time, there are studies in the literature that performance is not differentiated by gender (Atkinson *et al.*, 2003; Niessen-Ruenzi and Ruenzi, 2015; Aggarwal and Boyson, 2016; Alda *et al.*, 2017).

It also has been investigated whether portfolio densities affect or not the performance of managers (Alda *et al.*, 2017; Hung *et al.*, 2020). Fund managers, who specialize in a single fund, can easily take more risks because they have more information about the fund, and therefore they gain high returns and increase their performance (Alda *et al.*, 2017)

In the study, it was aimed to evaluate fund manager performances. There are studies in the literature based on different asset classes and markets. In fact, most empirical studies focus on asset classes such as mutual funds, hedge funds, and real estate, and markets such as the UK and US (Chekenya and Sikomwe, 2020). Contrary to this, emerging market and stock fund managers were preferred in this study. In this context, Sharpe ratio, Upside Capture Ratio, Downside Capture Ratio and Return of Manager (%) were taken into consideration as performance indicators. Although there are many studies in the literature using the Sharpe ratio (Chuang *et al.*, 2008; Nelson, 2009; Zakamouline and Koekebakker, 2009; Marlo and Stark, 2016; Niessen-Ruenzi and Ruenzi, 2019; Graham *et al.*, 2019), upside or downside capture ratios (Nelson, 2009) were used in the few study. In this study, a more holistic evaluation was made by using all of these ratios together.

The performance of the fund managers was calculated with TOPSIS. TOPSIS ranks the decision units according to the criteria determined and helps researchers, investors or experts in deciding on the best alternative. Sharpe ratio, upside capture ratio, downside capture ratio and return of manager were determined as the criteria to be used in the TOPSIS method and these ratios were calculated with the help of the Finnet Analysis Expert program. As the decision units, managers who worked as the fund managers in every year between 2008 and 2017 were selected. In this way, performance evaluation was made based on fund managers. In addition, the answer to the question of " Does the success of the managers (fund managers) continue by years or are they successful by chance in some years which is one of the theoretical discussion subjects of behavioral finance (Osei, 2017), was found empirically and contributed to the literature.

The second part of the study includes a literature review; the third part is the methodology, and the last part is the result and evaluation.

2. LITERATURE REVIEW

The fund manager is the person who responsible for managing a fund's trading activities and implementing a fund's strategic asset allocation (Hung *et al.*, 2020). In addition, another of its most important tasks is to protect the investors' wealth (Hung *et al.*, 2020). For this reason, the performances of fund managers are important. There are several factors that affect the performance of managers such as demographic factors, personal characteristics, competition, social networks, portfolio densities, etc. Hoberg *et al.* (2018) stated that competition is a determinant of the managers' persistence of performance as it affects the future positions of existing funds. Also, testing the persistence of performance of fund managers is important for investors not only in terms of providing information about past performance but also in predicting future fund performance (Ferreira *et al.*, 2018). Several studies in the literature are also divided into performance persistence positive and negative categories. While positive performance persistence means that managers who performed well in the past will have good performance in the future, negative persistence means that the manager who performed poorly in the past will

have poor performance in the future (Hung *et al.*, 2020). In addition to these, Ferreira *et al.* (2019) stated that testing the persistence of fund managers is also important in determining whether their managers have sufficient skills.

In addition, with the increasing popularity of behavioral finance, the effect of the social relations of fund managers on fund performances has become the focus of the attention of researchers (Liu *et al.*, 2019). Through their social networks, fund managers influence each other's trading behavior and fund performance (Hong *et al.*, 2004; Cohen *et al.*, 2008; Bajo *et al.*, 2016). Because social networks include people from business and working environments, their relationships with graduates, and their geographic regions, and all of these factors affect the investment behavior of managers (Pool *et al.*, 2015; Shen *et al.*, 2016; Gerritzen *et al.*, 2018; Liu *et al.*, 2019). Liu *et al.* (2019) were found that the existence of social networks of fund managers had a positive and significant relationship on the sharing of fund information and the trading behavior of fund managers. On the contrary, Zhu (2016) stated that there is a negative relationship between social relationships and performances. Bai *et al.* (2019) indicated that the fund managers who are high self-confidence have high social relationship skills and more information related to funds. They emphasize that these features are the determinants of high fund return.

Wahal and Wang (2011) found that the performance of fund managers decreased as new investment funds entered the sector. Alda *et al.* (2017) also stated that fund managers perform better when they work on a single fund or mutual fund.

In terms of demographic factors; Niessen-Ruenzi and Ruenzi (2019) stated that if female fund managers perform poorly, investors associate the skills of managers with gender. Also, they found that there is a decrease in fund flows when man managers are replaced by female managers. At the same time, they were reported that mutual fund investors directed less money to funds controlled by female managers. In contrast, Atkinson *et al.* (2003) and Niessen-Ruenzi and Ruenzi (2015) did not find a significant difference between the performance of female and male fund managers in the management of mutual funds. Likewise, Aggarwal and Boyson (2016) stated that professional investors such as hedge fund managers do not show significant differences according to gender in terms of risk and performance. Alda *et al.* (2017) stated that the performances of the managers are affected by the level of expertise of the managers rather than the demographic features such as gender. Bai *et al.* (2019) found that relatively older mutual fund managers perform better. Similarly, Andreu *et al.* (2019) stated that experienced managers tend to achieve better performance when they maintain a stable risk level in the overall portfolio. They stated that the same situation was valid for the age of the managers. In other words, older managers perform better than younger managers at a stable risk level. Chuprinin and Sosyura (2018) found that mutual fund managers born in wealthy families performed worse. Gottesman and Morey (2006) found that between 2000 and 2003, there was a positive and significant relationship between the average GMAT scores of the MBA program which fund managers graduated and fund performances. In contrast, they could not find a relationship between the quality of undergraduate graduation (based on average SAT score) and fund performance. There were various studies in the literature on the term of tenure of managers (Graham, 2019). Porter and Trifts (2014) stated that the tenure of managers does not have a significant effect on performance.

Hung *et al.* (2020) have investigated how the skills of fund managers and portfolio density will affect fund performance in the long and short term and whether portfolio density will affect the continuity of fund performance. They found that the portfolio density is more closely related to the market selection abilities than the fund managers' stock collection capabilities.

3. METHODOLOGY

3.1. Research Aim

In this study, it was aimed to measure the performances of 15 fund managers who worked as stock fund managers in every year between 2008-2017. In addition, it was aimed to look for the answer to the question of are the success of managers continue by years.

3.2. Research Method

Finnet Analysis Expert program was preferred in determining the fund managers to be evaluated within the context of the research. Finnet Analysis Expert is a financial analysis program that enables using and reporting the detailed data sets which are related to Turkey capital market instruments in the Excel. The program works as an extension on Excel. It uses all of the special 1200 functions that handle the huge dataset and includes various modules such as Stock Expert, Fund Expert, Bond Expert, Warrant Expert, Macro Expert. Also, it provides instruments to professionals with the help of rates customized according to sectors, markets or different investment instruments, and helps to create time series, organize data sets and perform analysis quickly (www.finnet.com.tr).

Using the Finnet Analysis Expert Program, the number of people who worked as stock fund managers between 2008 and 2017 was determined. It was found that 15 of them worked as fund managers uninterruptedly in the relevant period. It was observed that 4 of the related managers are women and the remaining 11 are men. In order to evaluate the performance of these managers, four different indicator values that are frequently preferred in the literature (Chitra, 2018; Arora and Raman, 2020) are used: the return of manager (%), Sharpe ratio, upside capture ratio and downside capture ratio. Finnet Analysis Expert Program was used to calculate these ratios. TOPSIS, one of the multi-criteria decision-making methods, was used to rank among the fund managers' performances and calculations were made with Microsoft Office Excel. In addition, the weights needed in step 3 related to the creation of the weighted normalized matrix of TOPSIS were calculated using the Entropy Weight Method.

3.2.1. Sharpe Ratio

The Sharpe ratio developed by Sharpe (1966) is a rate that use to measure investment performances and measures the relationship between the average of the excess returns and the standard deviation (Agudo and Sarto Marzal, 2004; Chuang *et al.*, 2008; Auer and Schuhmacher, 2013). It can be considered as the first measurement tool that combines risk and return that are the two main characteristics of financial investment. Accordingly, Arora and Raman (2020) stated that the Sharpe ratio is a criterion used for calculating the risk-adjusted return. Unlike the Treynor and Jensen indexes, it can measure performance without the need to verify a previous model (Agudo and Sarto Marzal, 2004). However, Zakamouline and Koekebakker (2009) stated that it is meaningful to measure performance with Sharpe ratio when the risk can be measured sufficiently with standard deviation.

Sharpe ratio is calculated as follows;

$$\text{Sharpe Ratio} = \frac{R_p - R_r}{\sigma_r}$$

R_p : Return of portfolio

R_r : Risk-free return

σ_r : Standard deviation of portfolio's excess return

Graham *et al.* (2019) stated that funds with low management or other fees have more attractive Sharpe rates and higher returns. At the same time, it is recommended to investors that to prefer funds with higher Sharpe ratios as funds with high Sharpe ratios provide higher returns than others in the same risk environment (Auer and Schuhmacher, 2013). In contrast, Chuang *et al.*

(2008) stated that the traditional Sharpe ratio does not adequately capture the downside risk and therefore may lead to serious prejudices in times of financial crisis.

3.2.2. Upside and Downside Capture Ratios

Upside and Downside Capture ratios are rates that determine whether a particular fund performs better when the market is strong or weak and, if a fund is performing better, helps to determine what rate it is (Cox and Golf, 2013). These rates provide investors with information on fund performances during periods when markets are high or low. Also, Marlo and Stark (2016) found a strong relationship between mutual fund flows and upside and downside capture ratios. Nelson (2009) conducted a survey study on whether capture ratios are used by professional investors and as a result, reported that capture rates are widely accepted and used.

The upside capture ratio is calculated by proportioning annual fund returns in high market period (Bull Runs) to benchmark returns.

$$\text{Upside Capture Ratio} = \frac{\text{Fund returns during bull runs}}{\text{Benchmark returns}} \times 100$$

The downside capture ratio is a rate calculated by proportioning annual fund returns during the period when the market falls (Bear Runs) and benchmark returns. It is used in analyzing the performance of fund managers as in the rate of Upside Capture.

$$\text{Downside Capture Ratio} = \frac{\text{Fund returns during bear runs}}{\text{Benchmark returns}} \times 100$$

3.2.3. TOPSIS Method

TOPSIS method was developed by Hwang and Yoon in 1981 as one of the multi-criteria decision-making methods (Ayaydin *et al.*, 2018). TOPSIS is a method to determine the best alternative by sorting according to the criteria determined among the decision units. It is the most practical and useful method of ordering alternatives (Sharma and Sudhanshu, 2019). The TOPSIS method has also been used frequently to facilitate decision making in various sectors such as banking and health, as multi-criteria decision-making methods have attracted many years of interest (Dandage *et al.*, 2018). In other words, this method was preferred in this research because it is both a practical and useful method and a method that is frequently used in performance evaluation and decision-making processes.

In TOPSIS method, the aim is to calculate the relative proximity value to the ideal solution by using the two main characteristics, ideal distance and non-ideal distance values, and to determine the best decision unit according to this value. In this way, the alternative closest to the ideal solution is tried to be determined (Dumanoğlu and Ergül, 2010; Chitnis and Vaidya, 2016; Bilbao-Terol *et al.*, 2019). This alternative should be the closest to the ideal solution and the most distant from the non-ideal solution (Lai *et al.*, 1994; Sharma and Sudhanshu, 2019).

The steps of the TOPSIS method are as follows (Hwang and Yoon, 1981);

Step 1: Creating the Decision Matrix

In the first stage of the method, a decision matrix is created in such a way that the criteria are in columns, and the decision units are in lines according to the predetermined decision units and criteria.

$$K = [k_{11} \cdots k_{1n} \vdots \vdots \vdots k_{m1} \cdots k_{mn}]$$

Step 2: Creating the Normalized Decision Matrix

In the decision matrix, the criteria values corresponding to each decision unit are squared, and the column total is calculated for each. After the square roots of the column totals are taken, the normalization process is performed using the formula below and the N_{ij} matrix is obtained.

$$n_{ij} = \frac{k_{ij}}{\sqrt{\sum_{i=1}^m k_{ij}^2}}$$

$$N = [n_{11} \cdots n_{1n} \vdots \vdots n_{m1} \cdots n_{mn}]$$

Step 3: Creating the Weighted Normalized Matrix

The weighted (V) matrix is obtained by multiplying the n_{ij} values found after the normalization process and the w values.

$$\begin{aligned} V &= [w_1 v_{11} \cdots w_n v_{11} \vdots \vdots w_1 v_{m1} \cdots w_n v_{m1}] \\ &= [v_{11} \cdots v_{1n} \vdots \vdots v_{m1} \cdots v_{mn}] \end{aligned}$$

(Note: $\sum_{i=1}^n w_i = 1$)

Step 4: Calculation of Ideal Solution Value and Non-Ideal Solution Value

Ideal solution values are calculated by taking the maximum value of each column in the weighted normalized matrix. Likewise, the non-ideal solution values are also calculated by taking the minimum value of each column.

$$I^+ = \{ \max v_{ij} \}$$

$$I^- = \{ \min v_{ij} \}$$

Step 5: Calculation of Ideal Distance (S^+), Non-Ideal Distance (S^-) and Relative Proximity Value to Ideal Solution (C^)*

After finding ideal and non-ideal solution values, ideal distance (S^+), non-ideal distance (S^-) and relative proximity to the ideal solution (C^*) are calculated with the formulas given below.

$$\begin{aligned} S_i^+ &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} & S_i^- &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} & C_i^* &= \\ & & & & &= \frac{S^-}{S^- + S^+} \end{aligned}$$

3.2.4. The Entropy Weight Method

The weighting process, which shows the importance levels of the criteria in multiple decision making methods, can be determined both subjective and objectively (Shemshadi *et al.*, 2011). While the evaluations of the researcher are taken into account in subjective weighting, calculations are made using the quantitative data of alternatives in objective weighting (Bakır and Atalık, 2018). In this study, objective weighting was taken into consideration and the "Entropy Weighting Method" was chosen to calculate the importance weights of the criteria.

The entropy weight method is a method used in the application of multiple decision-making methods. The strength of this method allows the calculation of weight values independent of the subjective judgments and opinions of experts or researchers (Perçin and Sönmez, 2018; Bakır and Atalık, 2018). This method allows calculating the weight values objectively, that is, independent of the subjective judgments and thoughts of the researchers (Perçin and Sönmez, 2018; Bakır and Atalık, 2018). In addition, this method is used to measure the amount of information provided by the available data (Wu *et al.*, 2011).

The stages of the entropy weight method were explained below (Wu *et al.*, 2011; Li *et al.*, 2011; Karami and Johansson, 2014):

Step 1: Creating Decision Matrix

The values of each decision unit regarding the relevant criteria are calculated and a decision matrix is created with these values.

$$X = [x_{11} \cdots x_{1n} \cdots x_{m1} \cdots x_{mn}]$$

Step 2: Obtaining the Normalized Matrix

For the normalized matrix, first, the sum of each column in the decision matrix is calculated separately. Then, normalization is performed by dividing each value in the columns separately by its own column total. The formula for this process was shown in equation (8).

$$P = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$$

Step 3: Finding Entropy Value Regarding Criteria

In this step, each normalized value (p_{ij}) is multiplied by its "ln" value. Then the total value of the columns is taken. The entropy coefficient (k) needed to calculate the entropy value is calculated by the formula given in Equation (9). The entropy value (E_j) of the criteria is obtained by multiplying the -k value with the total value of the columns (Equation (10)).

$$k = \frac{1}{\ln(n)}$$

$$E_j = -k * [\sum p_{ij} \ln p_{ij}]$$

Step 4: Calculating the Degree of Differentiation of Information

The degree of differentiation of information (d_j) is calculated by subtracting the entropy values obtained in the previous step from 1 as shown in equation (11).

$$d_j = 1 - E_j$$

Step 5: Weights Regarding Criteria

Finally, as shown in equation (12), the d_j value of each criterion is divided by the total d_j value and the weights (W_j) of the criteria are calculated.

$$W_j = \frac{d_j}{\sum_{j=1}^n d_j}$$

In addition, the sum of the weight values for the criteria is always equal to 1 (Çatı et al., 2017).

4. ANALYSIS

The performances of the fund managers are calculated separately for each year using the TOPSIS method. In this context, the performance calculations of the fund managers for 2008 were made in detail and the same processes were repeated in other years. Then, the performance rankings of the fund managers of all years were presented in a summary Table 2.

Firstly, the criteria and decision units to be used in the TOPSIS were determined and shown in Table 1.

		Descriptions	Abbreviations
Decision Units	Fund Manager 1 (Male)	People who were fund managers for ten years between 2008 and 2017.	FM_1 (M)
	Fund Manager 2 (Female)		FM_2 (F)
	Fund Manager 3 (Male)		FM_3 (M)
	Fund Manager 4 (Female)		FM_4 (F)
	Fund Manager 5 (Male)		FM_5 (M)
	Fund Manager 6 (Male)		FM_6 (M)
	Fund Manager 7 (Male)		FM_7 (M)
	Fund Manager 8 (Male)		FM_8 (M)
	Fund Manager 9 (Male)		FM_9 (M)
	Fund Manager 10 (Male)		FM_10 (M)
	Fund Manager 11 (Male)		FM_11 (M)
	Fund Manager 12 (Female)		FM_12 (F)
	Fund Manager 13 (Male)		FM_13 (M)
	Fund Manager 14 (Male)		FM_14 (M)
	Fund Manager 15 (Female)		FM_15 (F)
Criteria	Return of Manager		RM
	Sharpe Ratio	A risk-free return is subtracted from the return of the portfolio, and then the ratio is calculated by proportioning the result to the standard deviation of the excess return of the portfolio.	SR
	Upside Capture Ratio	It is calculated by proportioning annual fund returns in high market period (Pull Runs) to benchmark returns and multiplying 100.	UCR
	Downside Capture Ratio	It is calculated by proportioning annual fund returns during the period when the market falls (Bear Runs) and benchmark returns multiplying 100.	DCR

TABLE 1: Decision Units and Criteria.

The performance calculations of the stock fund managers for 2008 were calculated using the TOPSIS method. First of all, after determining the research criteria and decision units, the decision matrix for the TOPSIS method was created. Then, normalization was performed by squaring each value in the decision matrix (Equation 1). In the 3rd step, the weighted normalized matrix was formed by multiplying the weight values of the criteria calculated by the entropy weighting method with the relevant values in the normalized matrix (Equation 2). In the 4th step, the ideal solution value and the non-ideal solution value were calculated according to the Equation 3 and 4. In the next step, the ideal distances (S^+) and non-ideal distances (S^-) for each decision unit using Equation 5 and 6 were calculated and shown Table 2. In the last step, using the Equation (7), the relative proximity value to the ideal solution (C^*) was calculated and all of these values were shown in Table 2. Finally, the results were ranked from good to bad.

Fund Managers	S^+	S^-	C^*	Ranking
FM_1 (M)	0,3836	0,2905	0,4310	15
FM_2 (F)	0,2906	0,3780	0,5654	6
FM_3 (M)	0,2456	0,3487	0,5867	1
FM_4 (F)	0,2859	0,3794	0,5703	4
FM_5 (M)	0,2881	0,3653	0,5591	10
FM_6 (M)	0,2741	0,3351	0,5501	13
FM_7 (M)	0,2437	0,3136	0,5628	8
FM_8 (M)	0,2206	0,3096	0,5839	3
FM_9 (M)	0,2806	0,3613	0,5629	7
FM_10 (M)	0,2749	0,3315	0,5467	14
FM_11 (M)	0,2478	0,3138	0,5587	11
FM_12 (F)	0,2813	0,3502	0,5546	12
FM_13 (M)	0,2809	0,3663	0,5659	5
FM_14 (M)	0,2436	0,3427	0,5845	2
FM_15 (F)	0,2792	0,3555	0,5601	9

(Note: M = Male F= Female)

TABLE 2: Results and Rankings for 2008.

When the performance of the fund managers for 2008 was examined, it was that the number 3 fund manager is in the first rank. However, when it was examined the C^* values, it is noteworthy that in 2008 there was not a big difference between the performances of all fund managers.

The calculations made for the performance of fund managers in 2008 were repeated in the same way in other years. The summary results were shown in Table 3.

Fund Managers	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
FM_1 (M)	15	1	1	15	1	1	1	1	1	15
FM_2 (F)	6	7	8	1	15	6	10	2	11	13
FM_3 (M)	1	4	3	13	6	13	3	8	3	2
FM_4 (F)	4	8	12	3	12	4	13	6	14	12
FM_5 (M)	10	11	15	2	13	8	15	7	15	14
FM_6 (M)	13	15	6	9	9	2	14	4	7	5
FM_7 (M)	8	6	7	14	4	10	6	13	8	7
FM_8 (M)	3	2	2	12	3	5	8	12	4	4
FM_9 (M)	7	12	11	4	10	15	5	10	5	3
FM_10 (M)	14	14	13	7	14	3	12	3	13	9
FM_11 (M)	11	5	4	11	2	7	2	5	2	1

FM_12 (F)	12	13	14	8	11	9	11	15	12	11
FM_13 (M)	5	9	10	6	7	12	7	11	9	8
FM_14 (M)	2	3	5	10	5	14	4	9	6	6
FM_15 (F)	9	10	9	5	8	11	9	14	10	10

(Note: M = Male F= Female)

TABLE 3: Performance Rankings of Fund Managers Between 2008-2017.

Table 3 shows the performance rankings of fund managers between 2008-2017. The performance rankings calculated with TOPSIS point attractive findings. In the ten years, although fund manager 1 ranked first in 7 years, he is in the last rank in the other three years. While fund manager 2 was in the first rank in 2011, she dropped to the last rank a year later. Similarly, the 2nd and 3rd fund managers were able to find themselves in the lower ranks before or after the successful year. These findings support the view that the success of fund managers, as frequently stated in the literature, is mostly accidental (Berk and van Binsbergen, 2015).

5. CONCLUSION

In this study, it was aimed to measure the performance of stock fund managers, who have been managing continuously between 2008-2017. In this context, the performances of 15 fund managers in related years that determined with the help of the Finnet Analysis Expert program were calculated with the TOPSIS method and the performance of managers was ranked.

According to the results of the analysis, it was found that Fund Manager 1 ranks first in seven years, but in the last rank in other years. There is a certain continuity for only this manager regarding the continuity of success. However, it is noteworthy that this manager is in the last rank in the remaining years. When other managers were examined, it was found that managers (such as Fund manager 8, Fund Manager 11 and Fund Manager 14) were in the top three for two consecutive years and then dropped to the last ranks in other years. Fund Manager 1 was put aside as an exception and when the performances of the managers were examined in general, it was seen that there was no continuity regarding their success, which means, they were in the top ranks in some years incidentally. This finding supports the opinion of the literature that the success of fund managers is accidental (Osei, 2017). Similarly, Clare (2017) also found that the high performance of managers who serving long-time deteriorated over time and there is little evidence that performance is persistent. In addition to these, Grinblatt (2020) found evidence of the persistent performance of only well-performing hedge fund managers. They stated that there is no persistence in the performance of fund managers other than this. Also, this finding is consistent with Warren Buffett's recommendation that individual investors who want to choose a fund company should choose those who demand the least commission (Osei, 2017).

In addition, when the gender of the managers included in the study was examined, it was seen that four managers were women and eleven managers were men. According to the general table with performance rankings for years, it can be said that male managers are in the top three more than female managers. However, this does not give us a chance to compare performance and gender. We can only say something about their place in the rankings. However, the relationship between gender and performance was examined in the literature and Andreu *et al.* (2019) found that male managers exhibit a statistically significant and positive performance, especially in the bear market. On contrary, Atkinson *et al.* (2003) and Niessen-Ruenzi and Ruenzi (2019) did not find a significant difference between the performance of female and male fund managers in the management of mutual funds.

The results that are shown by the TOPSIS method indicate a point that needs further investigation. Managers who make different choices from the market will either be stars or scapegoats. Therefore, for future research, determining and comparing fund preferences by the following researchers will also provide more useful information. Also, in case of the fund managers' premium gains are achieved, comparing the premiums earned by the managers who

follow the herd with the premiums earned by the managers who became stars one year and ranked lower in the next year may provide significant findings for the fund managers to determine the right investment strategies in terms of their gains. In addition to these, the specific features of the fund that should reflect the management style of the manager / managers can be looked at further. The relative size of the funds, the underlying assets and focal points (asset class such as stocks, bonds, commodities or markets such as EU, US, developing) can be examined and specific connections can be discussed in line with these dimensions.

6. REFERENCES

Aggarwal, R. and Boyson, N.M. (2016). The performance of female hedge fund managers. *Review of Financial Economics*, 29, pp. 23-26.

Agudo, L.F. and Sarto Marzal, J.L. (2004). An analysis of Spain investment fund performance: some considerations concerning Sharpe's ratio. *The International Journal of Management Science*, 32, pp. 273-284.

Alda, M., Andreu, L. and Sarto, J.L. (2017). Learning about individual managers' performance in UK pension funds: The importance of specialization. *North American Journal of Economics and Finance*, 42, pp. 654-667.

Andreu, L., Sarto, J.L. and Serrano, M. (2019). Risk shifting consequences depending on manager characteristics. *International Review of Economics and Finance*, 62, pp. 131-152.

Arora, R. and Raman, T.V. (2020). A study on performance evaluation of equity mutual funds schemes in India. *International Journal of Financial Engineering*, 7(2), pp. 205-217. DOI: 10.1142/S2424786320500176

Atkinson, S.M., Baird, S.B. and Frye, M.B. (2003). Do female mutual fund managers manage differently?. *Journal of Financial Research*, 26, pp. 1-18.

Auer, B.R. and Schuhmacher, F. (2013). Performance hypothesis testing with the Sharpe ratio: The case of hedge funds. *Finance Research Letters*, 10, pp. 196-208.

Ayaydın, H., Çam, A.V., Pala, F. and Sarı, Ş. (2018). Türk Bankacılık Sektöründe Performans Değerlendirmesi: AHS ve TOPSİS Yöntemleri Uygulaması. *Global Journal of Economics and Business Studies*, 7(13), pp. 51-54.

Bai, J., Ma, L., Mullally, K.A. and Solomon, D.H. (2019). What a difference a (birth) month makes: The relative age effect and fund manager performance. *Journal of Financial Economics*, 132, pp. 200-221.

Bajo, E., Chemmanur, T.J., Simonyan, K. and Tehranian, H. (2016). Underwriter Networks, Investor Attention, and Initial Public Offerings. *Journal of Financial Economics*, 122(2), pp. 376-408.

Bakır, M. and Atalık, Ö. (2018). Entropi ve Aras Yöntemleriyle Havayolu İşletmelerinde Hizmet Kalitesinin Değerlendirilmesi. *İşletme Araştırmaları Dergisi*. 10(1), pp. 617- 638.

Berk, J. and van Binsbergen, J. (2015). Measuring managerial skill in the mutual fund industry. *Journal of Financial Economics*, 118, pp. 1-20.

Bilbao-Terol, A., Arenas-Parra, M., Alveraz-Otera, S. and Canal-Fernandez, V. (2019). Integrating corporate social responsibility and financial performance. *Management Decision*, 57(2), pp. 324-348.

Chekenya, N.S. and Sikomwe, S. (2020). Skin color and investment performance in South Africa's mutual funds industry. *Review of Behavioral Finance*, Vol. ahead of print.

Chitnis, A. and Vaidya, O.S. (2016). Efficiency ranking method using DEA and TOPSIS (ERM-DT): case of an Indian bank. *Benchmarking: An International Journal*, 23(1), pp. 165-182.

Chitra, V. (2018). Risk and return analysis of performance of mutual fund schemes in India. *International Journal of Applied Research*, 4(1), pp. 279–283.

Chuang, I.Y., Chiu, Y.C. and Wang, C.E. (2008). The performance of Asian airlines in the recent financial turmoil based on VaR and modified Sharpe ratio. *Journal of Transport Management*, 14, pp. 257-262.

Chuprinin, O. and Sosyura, D. (2018). Family decent as a signal of managerial quality: evidence from mutual funds. *Review Financial Studies*, 31, pp. 3756–3820.

Clare, A. (2017). The performance of long-serving fund managers. *International Review of Financial Analysis*, 52, pp. 152-159.

Cohen, L., Frazzini, A. and Malloy, C. (2008). The Small World of Investing: Board Connections and Mutual Fund Returns. *Journal of Political Economy*, 116(5), pp. 951–979.

Cox, D.R. and Golf, D.C. (2013). Capture Ratios: A popular Method of Measuring Portfolio Performance in Practice. *Journal of Economics and Finance Education*, 2(Winter), pp. 50-55.

Çatı, K., Es, A. and Özevin, O. (2017). Futbol Takımlarının Finansal ve Sportif Etkinliklerinin Entropi ve TOPSIS Yöntemiyle Analiz Edilmesi: Avrupa'nın 5 Büyük Ligi ve Süper Lig Üzerine Bir Uygulama. *International Journal of Management Economics & Business*, 13(1), pp. 199-222.

Dandage, R., Mantha, S. and Rane, S. (2018). Ranking the risk categories in international projects using the TOPSIS method. *International Journal of Managing Projects in Business*, 11(2), pp. 317-331.

Dumanoğlu, S. and Ergül, N. (2010). IMKB'de İşlem Gören Teknoloji Şirketlerinin Mali Performans Ölçümü. *Mufad Journal*, 48, pp. 101-111.

Dyakov, T. and Verbeek, M. (2019). Can Mutual Fund Investors Distinguish Good from Bad Managers?. *International Review of Finance*, 19(3), pp. 505-540.

Ferreira, M., Massa, M. and Matos, P. (2018). Investor stock decoupling in mutual funds. *Management Science*, 64, pp. 1975–2471.

Ferreira, M., Keswani, A. and Miguel, A.F. (2019). What determines fund performance persistence? International evidence. *The Financial Review*, 54(4), pp. 679-708.

Finnet Store. <https://www.finnet.com.tr/FinnetStore/Tr/Urun/AnalizExpert> [Accessed at: 15.02.2021].

Gerritzen, M., Jackwerth, J.C. and Plazzi, A. (2018). Birds of a Feather—Do Hedge Fund Managers Flock Together?. *Swiss Finance Institute Research Paper* (pp. 16–10).

Gottesman, A.A. and Morey, M.R. (2006). Manager education and mutual fund performance. *Journal of Empirical Finance*, 13(2006), pp. 145-182.

Graham, J.E., Lassala, J. and Riberio-Navarrete, B. (2019). A fuzzy-set analysis of conditions influencing mutual fund performance. *International Review of Economics and Finance*, 61, pp. 324-336.

Grinblatt, M., Jostova, G., Petrasek, L. and Philipov, A. (2020). Style and Skill: Hedge Funds, Mutual Funds and Momentum. *Management Science*, Vol. Articles in Advance, pp. 1–27.

Hoberg, G., Kumar, N. and Prabhala, N. (2018). Mutual fund competition, managerial skill, and alpha persistence. *Review of Financial Studies*, 31, pp. 1896–1929.

Hong, H., Kubik, J.D. and Stein, J.C. (2004). Social Interaction and Stockmarket Participation. *The Journal of Finance*, 59(1), pp. 137–163.

Hung, P., Lien, D. and Chien, Y. (2020). Portfolio concentration and fund manager performance. *Review Financial Economics*, 38(3), pp. 423-451.

Hwang, C.L. and Yoon, K. (1981). Methods for multiple attribute desicion-making. In Multiple Attribute Desicion Making. Lecture Notes in Economics and Mathematical Systems, *Springer*, 186, pp. 158-191.

Karami, A. and Johansson, R. (2014). Utilization of multi attribute decision making techniques to integrate automatic and manual ranking of options. *Journal of Information Science and Engineering*, 30, pp. 519-534.

Lai, Y.J., Liu, T.Y. and Hwang, C.L. (1994). Topsis for MODM. *European Journal of Operational Research*, 76(3), pp. 486-500.

Li, X., Wang, K., Liu, L., Xin, J., Yang, H. and Gao, C. (2011). Application of the entropy weight and TOPSIS method in safety evaluation of coal mines. *Procedia Engineering*, 26, pp. 2085-2091.

Liu, H., Liu, K., Li, D. and Li, Y. (2019). Fund Managers' Association Networks, Information Sharing and Fund Performance. *Applied Economics Letters*. DOI:10.1080/13504851.2019.1646400.

Marlo, T. and Stark, R.J. (2016). Ability to Capture Up Market Gains and Avoid Down Market Losses: The Upside and Downside Capture Ratios. Available at SSRN: <https://ssrn.com/abstract=2836451> or <http://dx.doi.org/10.2139/ssrn.2836451>. [Accessed at: 23.08.2020].

Nelson, C. (2009). How Planners Screen Investments. *Journal of Financial Planning* (3rd Quarter), pp. 8-9.

Niessen-Ruenzi, A. and Ruenzi, S. (2015). Sex matters: gender bias in the mutual fund industry. *University of Mannheim Working Paper*.

Niessen-Ruenzi, A. and Ruenzi, S. (2019). Sex Matters: Gender Bias in the Mutual Fund Industry. *Management Science*, 65(7), pp. 3001-3025.

Osei, D. (2017). *Active and passive fund management. A look at fund management performance against the Ghana stock exchange (GSE) composite index*, Grin Verlag Publisher.

Perçin, S. and Sönmez, Ö. (2018). Bütünleşik Entropi Ağırlık ve Topsis Yöntemleri Kullanılarak Türk Sigorta Şirketlerinin Performansının Ölçülmesi. *Uluslararası İktisadi ve İdari İncelemeler Dergisi*, 18(Special Issue), pp. 565-582.

Pool, V.K., Stoffman, N. and Yonker, S.E. (2015). The People in Your Neighborhood: Social Interactions and Mutual Fund Portfolios. *The Journal of Finance*, 70(6), pp. 2679–2732.

Porter, G.E. and Trifts, J.W. (2014). The career paths of mutual fund managers: the role of merit. *Financial Analysts Journal*, 70(4), pp. 55–71.

Sharma, M. and Sudhanshu, J. (2019). Brand Sustainability Among Young Consumers: An AHP-TOPSIS Approach. *Young Consumers*, 20(4), pp. 314-337.

Shemshadi, A., Shirazi, H., Toreihi, M. and Tarokh, M.J. (2011). A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting. *Expert Systems with Applications*, 38(10), pp. 12160-12167.

Shen, Y., Zhao, J. and He, X. (2016). Alumni Networks, Funds' Performance and Small World Effect. *China Economic Quarterly*, 1, pp. 10-17.

Wahal, S. and Wang, A. (2011). Competition among mutual funds. *Journal of Financial Economics*, 99, pp. 40–59.

Wu, J., Sun, J., Liang, L. and Zha, Y. (2011). Determination of weights for ultimate cross efficiency using Shannon ENTROPY. *Expert Systems With Applications*, 38(5), pp. 5162-5165.

Zakamouline, V. and Koekebakker, S. (2009). Portfolio performance evolution with generalized Sharpe ratios: Beyond the mean and variance. *Journal of Banking and Finance*, 33, pp. 1242-1254.

Zhu, A. (2016). Social Connections and Information Production: Evidence from Mutual Fund Portfolios and Performance. *SSRN Electronic Journal*. Available at SSRN 2831746 [Accessed at: 13.09.2020].

The Relationship Between BITCOIN and Other Financial Instruments: An Examination With VAR Models¹

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Abstract

Bitcoin has become one of the most popular financial assets in the world because it has an unregulated nature and does not require any central authority. However, there has been an ongoing debate about Bitcoin classification. Whatever classification Bitcoin is subject to, it has become a significant component of investors' portfolios. Accordingly, the returns of this instrument are an important matter of concern for both practitioners and academicians. In this study, we aim to analyze the effect of other financial assets on Bitcoin returns to figure out whether there is a hedging opportunity or not. In this manner, we used Vector Autoregression (VAR) model to test whether the associated variables; namely, gold, euro, and S&P 500 influence Bitcoin returns. The results of the study revealed that Bitcoin returns had no relationship with other financial assets in the long term. In other words, it was determined that financial assets did not affect Bitcoin prices. It was also found that Bitcoin had a deterministic process rather than a stochastic one. Hence, it is thought that Bitcoin should be examined by using VAR models instead of financial models such as ARMA, ARCH, and GARCH.

Keywords: Cryptocurrencies, Vector Autoregression, Bitcoin Returns, Bitcoin Volatility.

1. INTRODUCTION

Bitcoin is one of the most important financial innovations that has marked the last decade. The distinguishing feature of bitcoin is that it is part of a completely private monetary system, not depending on trust in any central bank but relying on trust in the community or the network of bitcoin that confirms transactions (Dowd and Hutchinson, 2015). Because of its unregulated nature, it has been very popular (Blau, 2018). In fact, there are more than two thousand cryptocurrencies and the number of these currencies is supposed to increase, but none of them has reached the popularity, volume, and market capitalization of bitcoin. In addition, almost all digital currency values are dependent on bitcoin prices.

After Bitcoin gaining popularity, it was started to be seen as a new kind of investment (Corbet et al., 2018). However, there is no consensus both in the literature and among finance professionals

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about the classification of Bitcoin. Some previous studies claim that it has some common feature with currencies (Dyhrberg, 2016; Polasik et al., 2015), while others put forward that it is a speculative asset and has some unique features that differentiate it from other financial instruments (Baur et al., 2018; Glaser et al., 2014; Klein et al., 2018). Also, the hedging capacity of Bitcoin has questioned by scholars in recent years. Similar to debates about the investment category of Bitcoin, previous studies also find different results for using Bitcoin as a hedging tool. Some studies conclude that involving Bitcoin in financial portfolios can help to mitigate risks (Demir et al., 2018; Guesmi et al., 2019; Katsiampa, 2017). On the other hand, it is also thought that market shocks affect all financial instruments as well as Bitcoin (Klein et al., 2018)

Although number of studies in the literature related to Bitcoin investment has significantly increased in the last decade, we think that there are still research areas which is not sufficiently discussed or shed light upon. In this manner, we contribute to the literature from various aspects. First, our paper is different from previous studies in terms of methodological approach. We employ Vector Autoregressive (VAR) and variance decomposition models to reveal the presence of causality between variables. Second, we include three common financial instruments which are S&P 500 index, gold, and Euro which represent equities, commodities and currencies, respectively in the model. Besides, we analyze our variables in a weekly basis to be able to diminish the effects of temporary and instant shocks. Also weekly analysis provides a benchmark since Bitcoin is traded in all day including weekends despite the fact that other financial instruments are not traded in weekends.

The research question of this study is: Does Bitcoin returns have a causal relationship with other financial assets? In this regard, both the effect of other financial assets on Bitcoin returns and the effect of Bitcoin returns on other financial assets are investigated in the study. In other words, the relationship between the returns of Bitcoin and other financial assets are analyzed to find out if there is a causality between Bitcoin and other financial instruments included in the study.

The structure of the paper is as follows. In the second section, a comprehensive literature review has been conducted. In this manner, the concept and history of Bitcoin has been explained. Additionally, some debates about the characteristics of Bitcoin have been mentioned. The last part of the section focuses on the previous studies investigating the relationship between Bitcoin and other financial assets. In the third section, information about the data and methodology utilized has been provided. Also, the results of the empirical analysis have been assessed. In the last section, the results are discussed and compared with previous studies. Also, the limitations of the study have been mentioned and some suggestions about future studies have been given.

2. THEORETICAL BACKGROUND

2.1 The Concept and History of Bitcoin

Bitcoin is the first and most popular digital currency in the world. Nakamoto (2008) has firstly used the concept of 'Bitcoin' in his paper entitled as 'Bitcoin: A Peer-to-Peer Electronic Cash System'. Nakamoto (2008) describes the system and provides technical information about how it can be created or utilized in monetary transactions. He also criticizes the current system in terms of having high transaction costs due to the large number of intermediaries involved in the process. With Bitcoin or any other cryptocurrency, it is aimed to allow members of a network to send or receive money directly between each other without any need for third parties like central banks (Raskin and Yermack, 2018). As opposed to the traditional system, in which there is a trust in financial intermediaries, this system is based on networks and cryptography (Cretarola et al., 2020). Furthermore, Bitcoin has an exchange rate varying according to supply and demand conditions (European Central Bank, 2012).

Bitcoin transactions have started in January 2009. The first bitcoin transaction has been carried out by Hal Finney, who downloaded the Bitcoin Client and received 10 Bitcoins from Nakamoto (Chohan, 2017). Since 2010, Bitcoin has also been used to buy products. Laszlo Hanyecz, the first person to use bitcoin as a medium of exchange has purchased two pizzas by paying 10,000

Bitcoins (Polasik et al., 2015). However, today there are more than ten thousand venues accepting bitcoin for payments. According to a website named cryptoglobe.com, more than half of these venues are general shopping stores, ATMs, and lodging services. In fact, virtual currencies have been issued on online game platforms since the late 1980s (Raskin and Yermack, 2018). However, Bitcoin differs from these currencies in terms of its use on various platforms and products.

Another unique feature of Bitcoin is that it has a futures market which makes it different from other cryptocurrencies. Bitcoin futures have started to be traded in The Chicago Mercantile Exchange (CME) since December 2017. Also, CBOE Futures Exchange (CFE) began trading CBOE bitcoin futures on 10th December 2017 under the ticker symbol "XBT". However, CFE stopped to offer new Bitcoin futures contracts in the March 2019. On the other hand, Bitcoin futures was launched by CME, the world's largest futures exchange on 17th December 2017 under the ticker symbol "BTC" which equals to 5 Bitcoins.

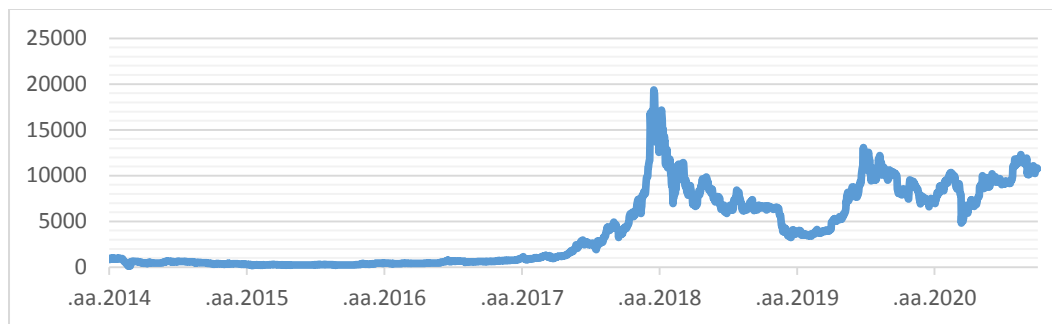


FIGURE 1: The Price of Bitcoin.

Figure 1 shows the data with respect to the historical prices of bitcoin between January 2014 and September 2020. The value of bitcoin has started to increase sharply since March 2017 until December 2017 from \$1,200 to \$19,350. Although, the price of bitcoin has been decreasing rapidly for 2018, it is observed that it has started to rise again in the first half of 2019. With the second half of 2019, the price of Bitcoin started to follow a fluctuating course. As of September 30, bitcoin is traded at about \$10,700.

2.2 Is Bitcoin an Asset or a Commodity?

Regulators and researchers want to define bitcoin in an economic manner because of its advantages (Dyhrberg, 2016). Bitcoin has similarities with fiat currencies because its value is not dependent on any commodity or valuable metal (Polasik et al., 2015). Thus, some studies claim that bitcoin is a currency, while others think it is a commodity or a speculative investment. Baur et al. (2018), claim that Bitcoin is used for investment purposes rather than commercial transactions. Due to the volatility of the cryptocurrencies, some researchers may question the notion of Bitcoin as a currency (Blau, 2018). According to Brière et al. (2015), the Bitcoin rate of return shows that it is significantly different from those of other commodities such as gold and oil, or assets like hedge funds. Klein et al. (2018) also state that Bitcoin is completely different from gold. Consistent with previous studies, Baur et al. (2018) finds that Bitcoin differs from both gold and traditional currencies as its risk-return characteristics and volatility process are not similar to any other financial instrument.

There are also some studies examining how bitcoin investors use Bitcoin. Glaser et al. (2014) state that new users think that bitcoin is an asset rather than a currency. In addition, Yermack (2015) claims that Bitcoin should be more stable to become reliable, be recognized as a currency, and be used as a store of value and a unit of account in markets.

Although Bitcoin is very popular in finance literature, few studies have concentrated on the volatility of Bitcoin. However, to examine Bitcoin volatility is very important because Bitcoin has become one of the most important investment tools in recent years (Katsiampa, 2017). According to the author, Bitcoin is different from any other asset and including it as part of a portfolio can be beneficial for risk management. The study of Guesmi et al. (2019), another research investigating hedging opportunities of Bitcoin, finds that portfolio risk is reduced if Bitcoin is included in a portfolio made up with gold, oil, and emerging stocks. Demir et al. (2018) also state that Bitcoin can be used as a hedging tool against uncertainty since it has a negative relationship with Economic Policy Uncertainty (EPU) index. However, the empirical findings of the study of Klein et al. (2018) show that Bitcoin cannot be used for hedging against equity investments as Bitcoin prices decrease together with market shocks.

According to Bouri et al. (2017), Bitcoin had a safe-haven property before the price crash in 2013, but this situation changed after the crash. It is also stated that adding Bitcoin to US Equity portfolios is effective in reducing risk. Findings of Dyhrberg (2016) show that Bitcoin reactions are significant to federal funds rate which makes it a currency; but it has some mutual features with gold as both of them react symmetrically after good or bad news. Hence, Bitcoin is an investment tool with characteristics that range between those of currencies and commodities.

2.3 The Relationship between Bitcoin and Other Financial Assets

Various studies compare Bitcoin and other financial assets such as currencies, stock indices, fund rates, commodities, and so on. The results of studies generally demonstrate that Bitcoin is not affected from traditional assets. However, few studies claim that there is a relationship between these assets. Ji et al. (2018) find that there is a weak relation between Bitcoin and some investment tools such as equities, gold, and dollar. They also state that the price movements of Bitcoin are relatively independent. Similarly, Zeng et al. (2020) conclude that the relationship between Bitcoin and other assets is weak. However, their findings show that the influence of negative returns on Bitcoin is relatively high. Evidence in the study of Corbet et al. (2018) indicates that Bitcoin and other cryptocurrencies are strongly connected to each other but they are isolated from conventional assets. Kurihara and Fukushima (2018) examine Bitcoin volatility by separating short-term and long-term volatility and find that its volatility is dependent on the length of the period. The authors also conclude that Bitcoin prices are not influenced by stock prices or exchange rates. On the contrary to the literature, Park et al. (2021) reveal that there are interactions between Bitcoin and other financial instruments. In particular, it is concluded that the impact of exchange rates on Bitcoin is stronger when compared to other financial assets. Similarly Bouri et al. (2018) point out that Bitcoin is not independent from other asset classes and especially commodities influence Bitcoin. Erdas and Caglar (2018) find a unidirectional relationship between Bitcoin and S&P 500 index. On the other hand, their results show that oil, gold, dollar, and BIST 100 index have no relationship with Bitcoin.

Most of the studies also examine Bitcoin volatility to figure out whether Bitcoin can be a diversifier for diminishing portfolio risks. According to Bouri et al. (2017), Bitcoin is an effective instrument for portfolio diversification although it has a hedging capacity and a safe haven feature. Kokkinaki et al. (2018) examine the relationship between bitcoin volatility and various exchange rates and it has been determined that raw annualized volatility of Bitcoin is higher than common currency volatilities. However, when the trade volume of Bitcoin is considered, the Bitcoin volatility is found to be significantly stabilized.

3. DATA AND METHODOLOGY

3.1 Data

We obtained weekly price data of all variables examined in the study from investing.com. The reason of choosing weekly data rather than daily is that Bitcoin is traded on all days of the week while other financial assets are traded only on week days. Accordingly, since we attempt to provide a simple benchmark to determine the effects of financial assets on Bitcoin returns, weekly

data is utilized. Our sample period was between March 1st, 2016 and April 24th, 2019. Our data consisted of 169 observations for each asset.

Variables in the study were selected according to the literature examining Bitcoin volatility and returns. As a currency, Euro is one of the mostly analyzed variables to determine Bitcoin hedging opportunities and to find out the effect of Bitcoin in diminishing portfolio risk (Eom et al., 2019; Guesmi et al., 2019; Kokkinaki et al., 2018). In addition, commodities are also included in studies about Bitcoin volatility or the hedging possibility of Bitcoin. Baur et al. (2018) have used both the spot and future price of Gold to determine the relationship with Bitcoin and to classify Bitcoin as a financial asset. Klein et al. (2018) have also used Gold price as a variable to evaluate the performance of a portfolio, which includes Bitcoin. The studies related to Bitcoin volatilities analyze not only currencies or commodities but also equity indices such as FTSE 100, MSCI indexes, and S&P 500 index (Baur et al., 2018; Klein et al., 2018). In line with literature, we selected Euro as a proxy of currencies, spot price of Gold as a commodity, and S&P 500 index to analyze the relationship with equities.

3.2 Methodology

The complexity of the relationships examined in econometric studies has necessitated the use of simultaneous equations. Since the macroeconomic variables can interact, it is difficult to separate the data as being only endogenous or exogenous. For this reason, Vector Autoregressive (VAR) Model is frequently used in practice (Tari and Bozkurt, 2006). It has advantages because of its potential to display the dynamic characteristics of the economy and its feature of not bringing any restrictions from a specific structural model (Keating, 1990). Since the autoregressive formulation is flexible, a large number of real data sets can be described statistically and many economic hypotheses can be embedded in a general statistical framework. Especially, the concept of integration, cointegration, and common trends can be defined through VAR formulation (Johansen, 1995).

Since all variables are considered to be endogenous and the effect of each variable on other variables is estimated simultaneously, a variable can increase the predictability of the model by its own impact on both the dependent variable and other predictor variables. Thus, variables contribute directly and indirectly via the system of estimated equations (Kumar et al., 1995). VAR models are a linear function of both variables' own and other variables' lagged values in the system. In VAR modeling, series are preferred to be stationary.

VAR Model

The VAR model developed by Sims (1980) is based on the Granger causality test model. If there are two endogenous variables in the model, these variables are associated with both their own and lagged values until a certain period (Ertek, 2000). The general representation of the standard VAR model with two variables is given in equations 3.1 and 3.2.

$$X_t = \alpha + \sum_{j=1}^m \beta_j X_{t-j} + \sum_{j=1}^m \delta_j Y_{t-j} + \varepsilon_{1t} \quad (t = 1, 2, \dots, T) \quad (3.1)$$

$$Y_t = \alpha + \sum_{j=1}^m \theta_j Y_{t-j} + \sum_{j=1}^m \gamma_j X_{t-j} + \varepsilon_{2t} \quad (3.2)$$

The lagged values of Y impact X variable; and the lagged values of X impact Y variable. In this model, since only the lagged variables are present on the right side of the equations, the values to be found by the least squares method will be consistent. The first-order structural VAR (1) model for the two variables is provided in equations 3.3 and 3.4.

$$X_t = \alpha_0 + \beta_1 X_{t-1} + \delta_0 Y_t + \delta_1 Y_{t-1} + \varepsilon_{1t} \quad (3.3)$$

$$Y_t = \alpha_1 + \theta_1 Y_{t-1} + \gamma_0 X_t + \gamma_1 X_{t-1} + \varepsilon_{2t} \quad (3.4)$$

In the equations given above, it is assumed that the variables X_t and Y_t are weakly stationary, and ε_{1t} and ε_{2t} are not correlated with each other, which is shown below:

$$\Sigma = \begin{bmatrix} \text{var}(\varepsilon_{1t}) & \text{cov}(\varepsilon_{1t}, \varepsilon_{2t}) \\ \text{cov}(\varepsilon_{1t}, \varepsilon_{2t}) & \text{var}(\varepsilon_{2t}) \end{bmatrix} \quad (3.5)$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \quad (3.6)$$

These structural VAR equations can be converted to the standard VAR equation using matrices. Matrix illustrations of equations 3.3 and 3.4 are given below.

$$\begin{bmatrix} 1 & \delta_0 \\ \gamma_0 & 1 \end{bmatrix} \begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} + \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (3.7)$$

The closed form expression is as follows:

$$Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \varepsilon_t \quad (3.8)$$

$$B = \begin{bmatrix} 1 & \delta_0 \\ \gamma_0 & 1 \end{bmatrix}, \quad x_t = \begin{bmatrix} X_t \\ Y_t \end{bmatrix}, \quad \Gamma_0 = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix}, \quad \Gamma_1 = \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix}, \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (3.9)$$

In Equation 3.9, standard VAR equations are obtained by multiplying both sides of the equation by B^{-1} (Enders, 1995). The closed form is shown below:

$$x_t = A_0 + A_1 x_{t-1} + e_t \quad (3.10)$$

In the standard VAR model, Akaike (AIC), Schwarz (SC), Hannan-Quinn (HQ), Final Prediction Error (FPE) and Likelihood Ratio (LR) are used to determine the optimal lag length. The correct determination of the lag length in VAR models is crucial because there may be degree of freedom loss in cases of excessive lag length and inconsistency problems in cases of low lag length. It is possible to use different lag lengths in the equations established for each variable. In practice, however, it is preferred to use the same lag length in order not to disturb the symmetry of the equation and to use the least squares technique effectively. Thus, the least squares estimators are ensured to be consistent and asymptotically effective. However, because of the fact that unreliable t-statistics are obtained due to multiple linear connections, the econometric significance of the parameters in VAR models is not clear. Therefore, impulse-response functions and moving average equations are used in the interpretation of the predicted VAR model. Both methods are considered to be useful tools for examining the relationship between economic variables (Enders, 1995).

Variance Decomposition

Coefficients are interpreted by making variance decomposition regarding error terms with moving averages method, in which the change in any of the endogenous variables within the system is divided into separate shocks that affect all endogenous variables. Thus, information can be obtained about the dynamic structure of the system. The main purpose of the variance decomposition analysis is to determine the effect that will occur in the forecast error variance due to each random shock (Kutlar, 2000).

In the methods used to determine the indirect and direct effect between the variables in the system, the reasons of the shocks that are seen in all variables are indicated as percentages. If all of the changes in any variable are caused by the shock in itself, this indicates that the related

variable acts endogenously. On the other hand, if it is caused by other variables within the system, it means that the related variable acts endogenously (Lütkepohl, 2005).

Impulse Response Function

Another method used in the assessment of the coefficients obtained in the VAR model estimation is impulse-response analysis. The responses of the variables in the system are measured through this method. The impulse-response functions provide information about the effects on the present and future values of the variables for a standard deviation of shock in any of the error terms. In addition, the direction and extent of these effects are examined with tables and graphs. After determining the most effective variable on a macroeconomic magnitude by using variance decomposition technique, the usability of this variable as a policy tool is determined by the effect-response functions (Tari, 2010).

Based on the matrix form representation of Equation 3.10, how the effect-response functions are obtained is represented as follows [36].

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} + \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (3.11)$$

A vector of errors is obtained by adding differences from the mean to the given matrix form.

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \bar{X} \\ \bar{Y} \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t-j} \\ \varepsilon_{2t-j} \end{bmatrix} \quad (3.12)$$

$$\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = [1/(1 - b_{12}b_{21})] + \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} + \begin{bmatrix} \varepsilon_{xt} \\ \varepsilon_{yt} \end{bmatrix} \quad (3.13)$$

The revised form of the matrix equation 3.12 with the moving average, in which the vector of errors is obtained, is shown below.

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \bar{X} \\ \bar{Y} \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \phi_{11}(j) & \phi_{12}(j) \\ \phi_{21}(j) & \phi_{22}(j) \end{bmatrix} + \begin{bmatrix} \varepsilon_{xt-j} \\ \varepsilon_{yt-j} \end{bmatrix} \quad (3.14)$$

In the method, the effects of ϕ coefficients and ε_{xt} and ε_{zt} shocks on X_t and Y_t series are revealed. These coefficients represent the impulse-response functions. Graphs which show how series react to different shocks are obtained by functions.

4. FINDINGS

The characteristics of the time series that were utilized in the analyses were examined through Eviews. The series, whose characteristics were determined, and the analyses that were applied are provided below.

Figure 2 displays the logarithmic levels of the series that are being investigated. In order to deal with the non-stationarity problem of the variances, logarithmic transformation was applied.

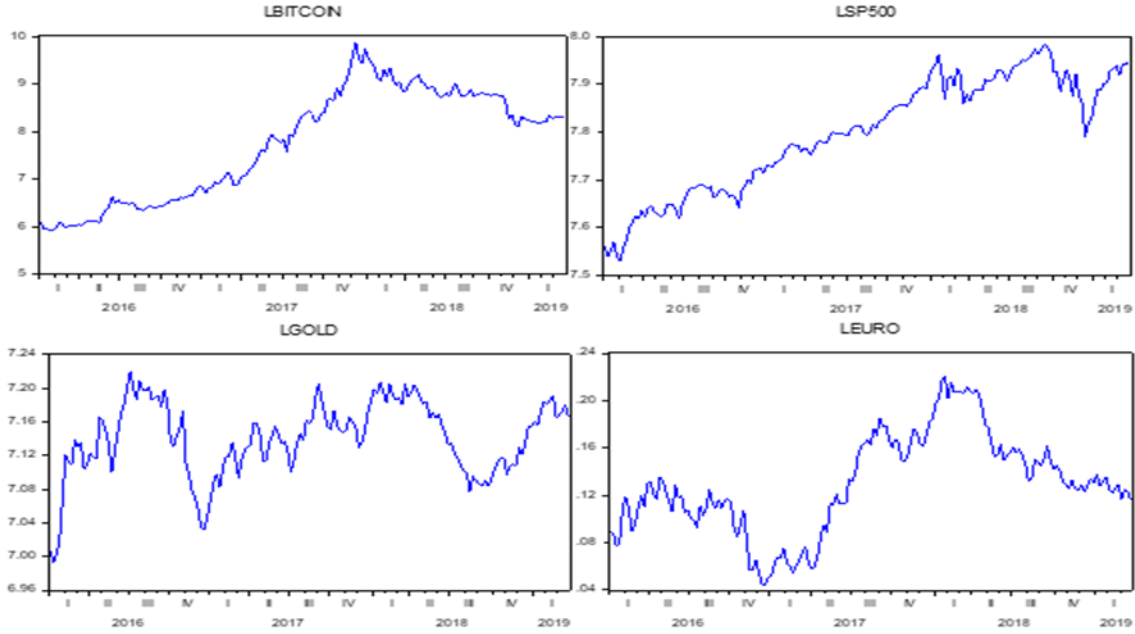


FIGURE 2: Level- Time Graphs of Series.

When the graphs shown in Figure 1 are examined, it can be seen that the means of the series is changing over time, in other words it is not distributed around a fixed average. By examining the graphs of the series, it is possible to state that they are not stationary on a level basis. However, as utilizing only the graphical analysis can give misleading results, Augmented Dickey-Fuller (ADF) unit root test developed by Dickey and Fuller (1979) was applied. The results are shown in Table 1.

Variables	LM Test	Table Critical Value (5 %) & Hypothesis	ADF	Table Critical Value (5 %) & Hypothesis	Result
LBITCOIN	11.16	$\chi^2_{12}=21.02$ $H_0: \rho_1 = \dots = \rho_{12}$	8.85 (0)	$\Phi_3=6.49$ $H_0: \beta = \rho = 0$ (DSP) $H_a: \beta \neq 0, \rho < 0$ (TSP)	H_0 is rejected
LGOLD	14.76		5.83 (0)		H_0 cannot be rejected.
LEURO	14.72		1.32 (0)		H_0 cannot be rejected.
LSP500	9.89		3.94 (0)		H_0 cannot be rejected.
<i>Note: As a testing method, a constant term and trend were used for all variables at level value.</i>					

TABLE 1: Results of Augmented Dickey –Fuller Test (1981).

As can be seen in Table 1, data generation processes of the time series differ. The processes for gold, Euro, and SP500 series were determined to be stochastic, whereas the Bitcoin series were found to be deterministic. In this case, the non-stationary series should be made stationary by differencing. After removing the bitcoin series from deterministic features, the same test was applied for error terms. The results are provided in Table 2.

Variables	DF	Table Critical Value (%5)	Hypothesis & Decision	Result	
$\hat{\varepsilon}_t$	-4.24	$\tau = -1.95$	$H_0: \rho = 0$ $H_a: \rho < 0$	H_0 is rejected.	$\hat{\varepsilon}_t \sim I(0)$
LGOLD	-11.55	$\tau_\mu = -2.89$		H_0 cannot be rejected.	$\Delta LGOLD \sim I(0)$
LEURO	-12.93	$\tau_\mu = -2.89$		H_0 cannot be rejected.	$\Delta LEURO \sim I(0)$
LSP500	-14.62	$\tau_\mu = -2.89$		H_0 cannot be rejected.	$\Delta LSP500 \sim I(0)$

TABLE 2: Dickey-Fuller (1979) Test Results for the First Difference Series.

According to Table 2, when the first differences of the variables were tested, H_0 hypothesis was rejected at 5% significance level and it was decided that the series was stationary at the level of $I(1)$ by accepting the alternative hypothesis that there was no unit root. In addition, since the data generation process of the Bitcoin series was deterministic and the error terms examined were stationary, they were used instead of the logarithmic Bitcoin series. Due to the different processes of the series, stationary VAR analysis was applied. First, we attempted to find the appropriate lag length in VAR model. The results are given in Table 3.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1401.905	NA	1.94e-13	-17.92186	-17.84365	-17.89009
1	1497.393	184.8565*	6.99e-14*	-18.94094*	-18.54994*	-18.78213*
2	1501.710	8.135576	8.12e-14	-18.79116	-18.08735	-18.50530
3	1508.852	13.09380	9.10e-14	-18.67759	-17.66098	-18.26469
4	1521.995	23.42011	9.46e-14	-18.64096	-17.31153	-18.10100
5	1531.131	15.81254	1.04e-13	-18.55296	-16.91073	-17.88596
6	1540.372	15.52111	1.14e-13	-18.46631	-16.51128	-17.67226

*: *Appropriate Lag Length*

TABLE 3: Determining the Appropriate Lag Length for VAR Analysis.

Table 3 represents that 1 lag is appropriate according to all information criteria. Therefore, the VAR (1) model was estimated and the results of the econometric assumption tests of the model are given in Table 4 below.

Lag Length	LM Test Statistics	Probability
1	10.84463	0.8190
2	11.30343	0.7904
3	12.36734	0.7183
4	20.34441	0.2051
5	18.80922	0.2787
6	15.72440	0.4724
7	12.18802	0.7309
8	15.45588	0.4915
9	14.71440	0.5456
10	9.780250	0.8778
11	13.42451	0.6415
12	16.75553	0.4016

TABLE 4: LM Autocorrelation Test Results.

The presence of autocorrelation problem in the model residuals was investigated with LM autocorrelation test and the analysis that was performed for 12 lags shows that there was no autocorrelation problem in the residuals. The White Heteroskedasticity test for VAR (1) model was used to determine whether there is heteroskedasticity. According to the test results given in Table 5, it was observed that there was no heteroskedasticity problem in the model.

Chi-Square Test Statistic	Degree of Freedom	Probability
119.9268	100	0.0851

TABLE 5: White Heteroskedasticity Test Results.

The characteristic roots of the estimated VAR model are given in Figure 2. All of the characteristic roots of the system remain within the unit circle which satisfies stability condition for the VAR (1) model. This confirms that the series are stationary and an appropriate mathematical form has been used in this study.

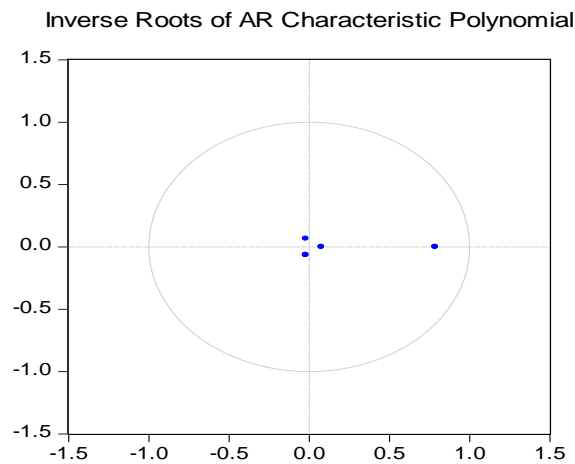


FIGURE 3: Inverse roots of AR characteristic polynomial of the estimated VAR (1) model.

Since the econometric assumptions of the VAR (1) model are satisfied, it is accepted to be the appropriate one and the model is provided as below. In line with the aim of the study, Bitcoin is selected as the dependent variable. Thus, the remaining variables are modelled as independent. Accordingly, the final model is;

$$\hat{\varepsilon}_t = -0.001262 + 0.824931\hat{\varepsilon}_{t-1} + 0.242337\Delta LGOLD_{t-1} - 1.623645\Delta LEURO_{t-1} - 1.171278\Delta LSP500_{t-1}$$

where;

LGOLD is the weekly returns of spot price of gold per ounce. LEURO is the weekly return of Euro in USD. LSP500 is the weekly return of S&P 500 index in USD.

However, the predicted coefficients in VAR models do not provide much information in terms of econometric interpretation. The important information is provided by the impulse-response functions obtained by the moving average equations. Variance Decomposition and Impulse-Response Function were examined in order to see the dynamic response of the variables to shocks.

The results of the variance decomposition for the Bitcoin series in the VAR (1) model are given in Table 6 and can be summarized as follows;

When the return of Bitcoin is considered as the dependent variable, it is seen that 99.48% of the change in the first period is determined by the Bitcoin return itself. In the second period, 99.07% of the change is explained by itself while 0.04%, 0.65%, 0.23% of the change are explained by Gold, Euro and S&P500, respectively. In the following periods, it is observed that the rate of explaining the change in Bitcoin by the other series is increasing, but this increase is very limited. Other periods can be evaluated in a similar manner.

According to Table 6, it is also seen that Bitcoin return does not influence other financial assets. As can be seen, in the first period Bitcoin does not determine Euro returns. In the last period only 0.024 % of Euro returns are determined by Bitcoin. Similarly, the impact of Bitcoin returns on S&P index is quite limited. The explanatory levels of Bitcoin returns in the first and last period are 0 % and 0.26 %, respectively. Gold returns are also determined by Bitcoin returns in very low percentage. However, the explanatory level is relatively higher when compared with the effect of Bitcoin returns on other financial assets. To sum up, the explanatory level of Bitcoin returns on financial assets is very minimal. Also, other financial assets explain Bitcoin returns restrictively. However, it is seen that Bitcoin is influenced more by the selected variables in the last periods. Similarly, Bitcoin returns affected the financial assets included in the study more in the last periods when compared to former periods.

BITCOIN Variance Decomposition						EURO Variance Decomposition				
Term	Standard Error	GOLD	EURO	SP500	BITCOIN	Standard Error	GOLD	EURO	SP500	BITCOIN
1	0.109907	0.056386	0.113252	0.346841	99.48352	0.009841	25.22790	74.77210	0.000000	0.000000
2	0.142774	0.041178	0.654507	0.233909	99.07041	0.009879	25.38961	74.40824	0.201181	0.000967
3	0.161359	0.044634	0.789098	0.191371	98.97490	0.009882	25.38466	74.39402	0.212979	0.008342
4	0.172856	0.047415	0.843314	0.172776	98.93650	0.009882	25.38324	74.38987	0.212971	0.013923
5	0.180255	0.048912	0.872859	0.162644	98.91558	0.009882	25.38227	74.38706	0.212964	0.017704
6	0.185117	0.049798	0.890384	0.156637	98.90318	0.009882	25.38161	74.38516	0.212960	0.020273
7	0.188352	0.050350	0.901298	0.152896	98.89546	0.009883	25.38116	74.38386	0.212957	0.022020
8	0.190520	0.050704	0.908304	0.150494	98.89050	0.009883	25.38086	74.38298	0.212955	0.023208
9	0.191980	0.050936	0.912890	0.148922	98.88725	0.009883	25.38065	74.38238	0.212954	0.024016
10	0.192967	0.051090	0.915930	0.147881	98.88510	0.009883	25.38051	74.38198	0.212953	0.024565
GOLD Variance Decomposition						SP500 Variance Decomposition				
Term	Standard Error	GOLD	EURO	SP500	BITCOIN	Standard Error	GOLD	EURO	SP500	BITCOIN
1	0.016541	100.0000	0.000000	0.000000	0.000000	0.017525	4.079182	0.346021	95.57480	0.000000
2	0.016794	97.94268	1.697244	0.113129	0.246947	0.017786	4.370968	1.536283	94.01354	0.079213
3	0.016816	97.69232	1.716759	0.117774	0.473149	0.017792	4.370720	1.535757	93.95375	0.139779
4	0.016829	97.53863	1.715761	0.117681	0.627924	0.017796	4.368959	1.535581	93.91527	0.180187
5	0.016838	97.43441	1.715201	0.117607	0.732779	0.017798	4.367760	1.535488	93.88912	0.207629
6	0.016844	97.36367	1.714834	0.117556	0.803943	0.017800	4.366946	1.535427	93.87135	0.226281
7	0.016848	97.31562	1.714585	0.117521	0.852274	0.017801	4.366392	1.535385	93.85926	0.238960
8	0.016851	97.28298	1.714416	0.117497	0.885110	0.017802	4.366015	1.535357	93.85105	0.247579
9	0.016853	97.26079	1.714301	0.117481	0.907425	0.017803	4.365759	1.535338	93.84546	0.253439
10	0.016854	97.24571	1.714223	0.117470	0.922592	0.017803	4.365585	1.535325	93.84167	0.257423

TABLE 6: Variance Decomposition Results.

Impulse-response analysis is used to examine the response of other variables to a shock occurring in one of the variables in the system. Figure 3 displays the responses of each variable to a one standard deviation shock in Bitcoin, Gold, Euro and SP500, respectively.

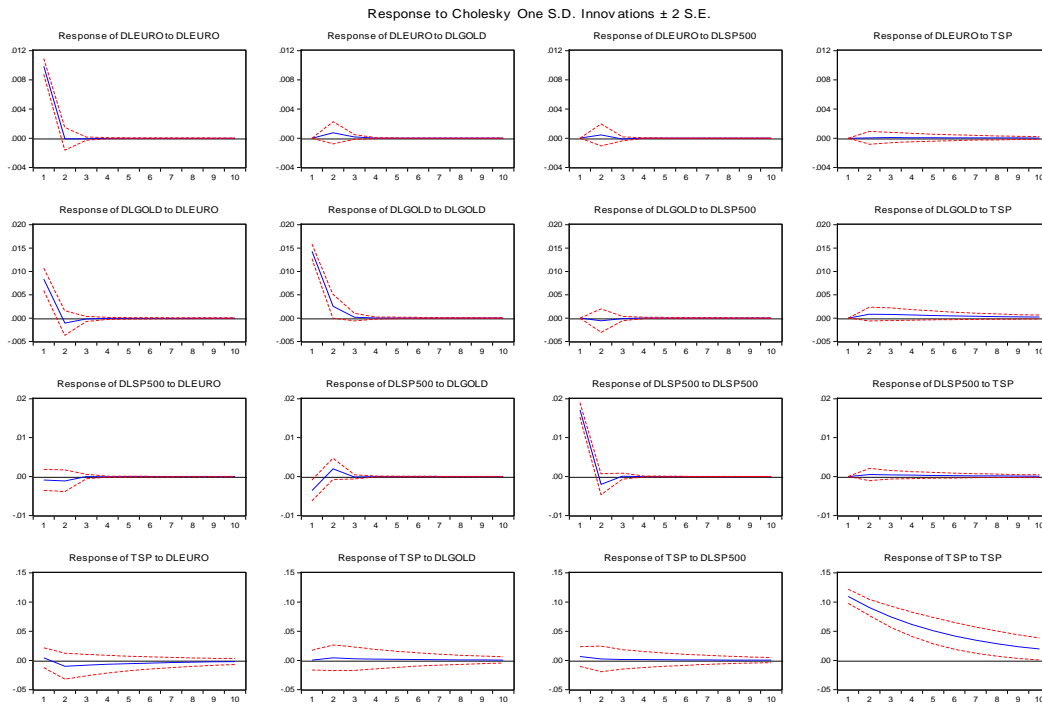


FIGURE 4: Impulse-Response Graphs of Variables Included in Analysis.

The graphs in the fourth line show the responses of the Bitcoin series to other variables. In the gold series, the Bitcoin series reacted positively in the 1st period to a standard deviation shock, while in the subsequent periods it reacted negatively. In the 10th period, it was below the previous level. In the Euro series, the Bitcoin series reacted positively in the 1st period against a standard deviation shock, while in the subsequent periods it reacted negatively. As can be seen, it was below the previous level in the 10th period. In the SP500 series, the Bitcoin series gave a positive response to a standard deviation shock in the 1st period. It also reacted positively in the following periods. In the 10th period it converged to its former balance.

4.1 Johansen Cointegration Test

The Johansen approach utilizes the maximum likelihood estimation to estimate the number of cointegration relationships and the parameters of these relationships, and is made up of VAR estimations which includes the differences and the levels of the non-stationary series and is a function of all endogenous variables' lagged values. Furthermore, this approach reveals the cointegrated relationships between the variables.

According to Trace and Maximum Eigenvalue test statistics below, it is seen that there is no long-term relationship between the examined variables. Thus, it is possible to say that Bitcoin differs from all other financial assets and no evidence has been obtained about the characteristic of Bitcoin having a relationship with other financial instruments.

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. Of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.114735	33.91156	40.17493	0.1850
At most 1	0.053227	13.55963	24.27596	0.5742
At most 2	0.025688	4.425409	12.32090	0.6493

At most 3	0.000476	0.079469	4.129906	0.8170
Trace test indicates no cointegration at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
** MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
			0.05	
Hypothesized		Max-Eigen	Critical	
No. Of CE(s)	Eigenvalue	Statistic	Value	Prob.**
None	0.114735	20.35193	24.15921	0.1510
At most 1	0.053227	9.134224	17.79730	0.5794
At most 2	0.025688	4.345940	11.22480	0.5741
At most 3	0.000476	0.079469	4.129906	0.8170

TABLE 7: Johansen Cointegration Test.

In order to test the forecast accuracy of the estimated VAR model given above, the model was re-estimated for the 16th July 2017 and 06th August 2017 period. The criteria based on the deviation between the estimated and actual values of the model were obtained and the results are given in Table 8.

Variables	RMSE	MAPE
$\hat{\varepsilon}_t$	0.006641	0.005454
$\Delta LGOLD$	0.014232	0.011903
$\Delta LEURO$	0.011104	0.010162
$\Delta LSP500$	0.086846	0.082443
$r = 0.9321$		

TABLE 8: Forecast Results for Estimated Model.

The criteria given in Table 8 are expected to be small and the correlation coefficient is expected to be close to 1 (Guttormsen, 1999). In addition, the finding that the MAPE (Mean Absolute Percentage Error) criterion is below 10% indicates that the estimation is good when evaluating the estimation accuracy of a single model (Temuçin and Temiz, 2016). In this respect, it can be said that the relationship between the predicted and actual values of the model is positive and high. Additionally, it is possible to say that the estimation accuracy within the period of the model is very high when evaluated according to the estimation criteria.

5. CONCLUSION

Digital currencies have become a part of the global financial system. The number of cryptocurrencies is more than two thousand and it has been increasing day by day. However, none of them is as popular as Bitcoin.

Bitcoin is firstly seen in Nakamoto's (2008) paper entitled as 'Bitcoin: A Peer-to-Peer Electronic Cash System'. The author explains how the blockchain system works and gives technical information about Bitcoin mining and trade in money transaction after the mining process. According to Raskin and Yermack (2018), investors or traders transfer money directly without any central bank.

The innovative notion of Bitcoin has attracted investors to use it as a financial instrument. Nevertheless, studies about Bitcoin or any other cryptocurrency have questioned how Bitcoin should be classified and where it can be placed in the financial system. The results are

complicated since some studies state that Bitcoin carries the characteristics of both a currency and a commodity (Dyhrberg, 2016; Polasik et al., 2015) whereas some claim that it is a speculative asset as it differs from some currencies and commodities and has high volatility (Baur et al., 2018; Briere et al., 2015). In addition, some studies have examined whether Bitcoin is a hedging tool or not and investigated its diversification capacity for diminishing portfolio risk. The results of these studies are also mixed. On one hand, findings of some studies reveal that Bitcoin can be used as an instrument to reduce portfolio risk and for hedging (Baur et al., 2018; Guesmi et al., 2019; Katsiampa, 2017). On the other hand, Bitcoin cannot be a good diversification tool in terms of decreasing risk in the portfolios according to some other studies (Klein et al., 2018).

The study differs from previous studies in terms of including data generation process in the analysis. In the literature, financial models such as ARCH and GARCH are mostly preferred and the series are generally accepted as stochastic. However, we have used the traditional time series model, in which determining the data creation process may provide more accurate results. Therefore, it is determined that Bitcoin series is deterministic after this process is examined. However, it should not be neglected that the process of the series may change if a different period is chosen or data frequency is changed.

Results in the study reveal that Bitcoin has no relationship with other financial assets in the long term. In other words, Bitcoin returns cannot be affected by other financial instruments. According to variance decomposition results, returns of Bitcoin are mostly explained by itself. The impact of other financial instruments on Bitcoin returns are very limited. Similarly, Bitcoin returns has no effect on Euro, Gold, and S&P 500 returns. Thus, it can be concluded that Bitcoin is a highly speculative asset and its returns cannot be explained with the returns of other financial instruments. In other words, we found that investors should consider Bitcoin's price movements rather than other financial instruments for their investment decisions since Bitcoin returns are mostly explained itself and not influenced by other assets. It is seen that these results obtained in the study support the studies finding Bitcoin is isolated from traditional assets in the related literature (Corbet et al., 2018; Ji et al., 2018; Kurihara and Fukushima 2018; Zeng et al., 2020).

But the study has time and variable limitations. So, examining the relationship with addition of different financial assets such as other indices, other currencies and other commodities may give different results. Additionally, the last three years were investigated in this study. To extend the period for analyses may provide different results. Also, we focused only on the relationship between Bitcoin and other financial assets. Future studies may extend the analysis by examining Bitcoin based on portfolio theories to figure out the impact of Bitcoin investing on the risk and returns of portfolios. Furthermore, investigating Bitcoin returns on daily or monthly basis may contribute to the literature related to Bitcoin and other cryptocurrencies.

6. REFERENCES

- Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar—A replication and extension. *Finance research letters*, 25, 103-110.
- Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets?. *Journal of International Financial Markets, Institutions and Money*, 54, 177-189.
- Blau, B. M. (2018). Price dynamics and speculative trading in Bitcoin. *Research in International Business and Finance*, 43, 15-21.
- Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics: The Open-Access, Open-Assessment E-Journal*, 11(1), 1-16.
- Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, 50(55), 5935-5949.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, 20, 192-198.

Bozkurt, P., & Tari, R. (2006). Türkiye'de İstikrarsız Büyümenin Var Modelleri İle Analizi (1991.1-2004.3). *Istanbul University Econometrics and Statistics e-Journal*, 4(1), 1-16.

Briere, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, 16(6), 365-373.

Chohan, U. W., (2017). A History of Bitcoin. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3047875

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28-34.

Cretarola, A., Figà-Talamanca, G., & Patacca, M. (2020). Market attention and Bitcoin price modeling: Theory, estimation and option pricing. *Decisions in Economics and Finance*, 43(1), 187-228.

Demir, E., Gozgor, G., Lau, C. K. M., & Vigne, S. A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters*, 26, 145-149.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a), 427-431.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society*, 49(4), 1057-1072.

Dowd, K., & Hutchinson, M. (2015). Bitcoin will bite the dust. *Cato Journal*, 35(2), 357-382.

Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold?. *Finance Research Letters*, 16, 139-144.

Enders, W. (1995). *Applied Econometric Time Series*. New York: Iowa State University. John Wiley & Sons.

Eom, C., Kaizoji, T., Kang, S. H., & Pichl, L. (2019). Bitcoin and investor sentiment: statistical characteristics and predictability. *Physica A: Statistical Mechanics and its Applications*, 514, 511-521.

Erdas, M. L., & Caglar, A. E. (2018). Analysis of the relationships between Bitcoin and exchange rate, commodities and global indexes by asymmetric causality test. *Eastern Journal of European Studies*, 9(2), 27-45.

Ertek, T. (2000). *Ekonometriye Giriş*, (Second Edition). Beta Publication.

European Central Bank (2012). Virtual Currency Schemes. <https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemes201210en.pdf>

Glaser, F., Zimmarmann, K., Haferhorn, M., Weber, M.C., & Siering, M., (2014). Bitcoin Asset or currency? Revealing users' hidden intentions. In: Twenty Second European Conference on Information Systems, ECIS 2014, Tel Aviv, pp. 1-14. Available at SSRN: <https://ssrn.com/abstract=2425247>

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, 63, 431-437.

Guttormsen, A. G. (1999). Forecasting weekly salmon prices: risk management in fish farming. *Aquaculture Economics & Management*, 3(2), 159-166.

Ji, Q., Bouri, E., Gupta, R., & Roubaud, D. (2018). Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance*, 70, 203-213.

Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press on Demand.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, 3-6.

Keating, J. W. (1990). Identifying VAR models under rational expectations. *Journal of Monetary Economics*, 25(3), 453-476.

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold—A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, 59, 105-116.

Kokkinaki, A., Sapuric, S., & Georgiou, I. (2018, October). The relationship between bitcoin trading volume, volatility, and returns: A study of four seasons. In *European, Mediterranean, and Middle Eastern Conference on Information Systems* (pp. 3-15). Springer, Cham.

Kumar, V., Leone, R. P., & Gaskins, J. N. (1995). Aggregate and disaggregate sector forecasting using consumer confidence measures. *International Journal of Forecasting*, 11(3), 361-377.

Kurihara, Y., & Fukushima, A. (2018). How does price of Bitcoin volatility change?. *International Research in Economics and Finance*, 2(1), 8-14.

Kutlar, A. (2000). *Ekonometrik zaman serileri*. Gazi Publication.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Unpublished manuscript, retrieved from <https://Bitcoin.org/Bitcoin.pdf>.

Park, S., Jang, K., & Yang, J. S. (2021). Information flow between bitcoin and other financial assets. *Physica A: Statistical Mechanics and its Applications*, 566, 1-13.

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price fluctuations and the use of bitcoin: An empirical inquiry. *International Journal of Electronic Commerce*, 20(1), 9-49.

Raskin, M., & Yermack, D. (2018). Digital currencies, decentralized ledgers and the future of central banking. In P. Conti-Brown, & M.L. Rosa (Eds.), *Research handbook on central banking*. (pp. 474-486). Edward Elgar Publishing.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 48(1), 1-48.

Tarı, R. (2010). *Ekonometri*, (Extended 6th Edition). Umuttepe Publications.

Temuin, T., & Temiz, İ. (2016). Trkiye Dış Ticaret İhracat Hacminin Projeksiyonu: Holt-Winters ve Box-Jenkins Modellerinin Bir Kıyaslaması. *Suleyman Demirel University The Journal of Faculty of Economics and Administrative Sciences*, 21(3), 937-960.

Yermack, D. (2015). Is Bitcoin a real currency? An economic appraisal. In D. L. K. Chuen (Ed) *Handbook of digital currency* (1st pp. 31-43). Academic Press.

Zeng, T., Yang, M., & Shen, Y. (2020). Fancy Bitcoin and conventional financial assets: Measuring market integration based on connectedness networks. *Economic Modelling*, 90, 209-220.

INSTRUCTIONS TO CONTRIBUTORS

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