INVESTORS’ ATTITUDE TOWARDS RISK: A COMPARISON BETWEEN THE CRYPTOCURRENCY MARKET AND THE TRADITIONAL ASSET MARKET

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ETHICAL DECLARATION

I hereby declare that I am the sole author of this thesis and that I have conducted my work in accordance with academic rules and ethical behaviour at every stage from the planning of the thesis to its defence. I confirm that I have cited all ideas, information and findings that are not specific to my study, as required by the code of ethical behaviour, and that all statements not cited are my own.

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Date: 01.08.2023

Signature:

ABSTRACT

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The existing studies indicate an influence of the investors risk attitude on their investment decision-making process. While previous research has explored this relationship in the traditional asset market, limited studies focused on cryptocurrencies. This study explores the similarities and differences as well as the dependence of the risk preference, risk perception and risk behavior in both markets. A survey was conducted and statistical analysis techniques were employed to analyze the data. Surprisingly, few correlations were observed between risk attitude and demographic factors, and risk preference did not significantly influence risk behavior. Furthermore, risk perception was found to be significantly higher in the cryptocurrency market compared to the traditional asset market. Additionally, despite the different markets, risk perception was found to influence risk behavior in a similar magnitude. The findings have implications for investors, institutions and policymakers, shedding light in the complex interrelationship in the risk attitude in emerging markets.

Keywords: Behavioral finance, Cryptocurrency, Risk attitude, Blockchain

ÖZET

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Baz, Lâle

İşletme Yüksek Lisans Programı

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Mevcut çalışmalar, yatırımcıların risk tutumunun yatırım karar verme süreçleri üzerinde bir etkisi olduğunu göstermektedir. Önceki araştırmalar bu ilişkiyi geleneksel varlık piyasasında incelemiş olsa da, kripto para birimleri üzerine sınırlı sayıda çalışma yapılmıştır. Bu çalışma, risk tercihi, risk algısı ve risk davranışının her iki piyasada da ortaklıklarını ve farklılıklarını, bağımlılıklarını incelemektedir. Bir anket yapılmış ve verileri analiz etmek için istatistiksel analiz teknikleri kullanılmıştır. Şaşırtıcı bir şekilde, risk tutumu ile demografik faktörler arasında sınırlı sayıda ilişki gözlemlenmiş ve risk tercihinin risk davranışını önemli ölçüde etkilemediği görülmüştür. Ayrıca, risk algısının geleneksel varlık piyasasına kıyasla kripto para piyasasında önemli ölçüde daha yüksek olduğu bulunmuştur. Ek olarak, farklı piyasalar olmasına rağmen, risk algısının benzer bir etkiye sahip olduğu görülmüştür. Bu bulgular, yatırımcılar, kurumlar ve politika yapıcılar için önemli sonuçlar sunarak, gelişmekte olan piyasalarda risk tutumu konusundaki karmaşık ilişkilere ışık tutmaktadır.

Anahtar Kelimeler: Risk algisi, Kripto Paralar, Blockchain

DEDICATION

I dedicate this thesis to those who have accompanied me on my way, always had an open ear for me, showed perseverance and supported me unconditionally.

To Prof. Dr. Heiko Jacobs, who ignited my passion for the field of finance. Your enthusiasm and ability to convey complex concepts in a serene and clear inspired me to delve into this field. Without your influence, I may not have embarked on this journey that has not only enriched my academic development but also shaped my professional career. I am grateful for the impact you have had on my academic growth.

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The process of writing this thesis demanded a lot of endeavor but it has been a significant milestone in my academic journey, and the knowledge and growth I have gained throughout the research have been invaluable.

First and foremost, I would like to express my sincere thanks to my supervisor, Professor Dr. Gulin Vardar. Her guidance, expertise, support and constructive feedback have been instrumental in shaping the direction of this thesis. I am deeply grateful for the time and effort she invested in mentoring me and pushing me to adopt new perspectives to achieve the best outcome.

I would also like to express my appreciation to my friends, whose encouragement and support have made me persevere and sustained me along this journey. Their presence has made the difficult moments more bearable and the success more meaningful.

Last but not least, I am immensely grateful to my family for their irrevocable love, inspiration and understanding throughout my academic journey. Their belief in my abilities and their endless and unconditional support made it possible for me to achieve my academic achievement.

Thank you all for being a part of this incredible journey.

PREFACE

This thesis represents the original work of Lâle Baz, an international master’s student at the Izmir University of Economics in Izmir, Turkey. Lâle completed her Bachelor´s degree in Business Administration with Finance as a major subject at the University of Duisburg-Essen in Germany. During her undergraduate studies, she discovered her passion for the field of finance due to the mandatory subjects offered at the university. This realization gave her the impetus to delve deeper into finance and wrote her Bachelor´s thesis focused on this subject area.

With the support of her professor, she developed a keen interest in behavioral finance, which explores the connection between psychology and finance. This fascination led her to pursue further research in this field during her master´s studies. Pr. Dr. Gulin Vardar gave her the opportunity to continue her research in the field of behavioral finance and to write her thesis. Given Professor Dr. Vardar´s expertise and focus on cryptocurrencies, it was a natural decision to combine those topics of behavioral finance and cryptocurrencies in Lâle´s research.

After the initial research in this topic was done, it quickly became apparent that there were limited academic papers exploring the intersection of cryptocurrencies and behavioral finance, with a majority of them primarily focusing on Bitcoin. This realization served as additional motivation for her to undertake this thesis and contribute to one of the first researches combining behavioral finance and cryptocurrencies.

The process of writing the thesis presented its own challenges, especially due to the Covid 19 pandemic, which necessitated distance learning and limited opportunities for direct interactions with fellow students. Nevertheless, with the guidance of her professor and the mental support of her friends and family, Lâle successfully completed her thesis.

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SOEP: Socio-economic panel

CAPM: Capital Asset Pricing Model

MPT: Modern Portfolio Theory

P2P: Peer-to-Peer

CHAPTER 1: INTRODUCTION

The investment landscape has experienced a significant paradigm shift with the emergence and rapid growth of the cryptocurrency market. Cryptocurrencies such as Bitcoin, Ethereum and many others, a new de-centered medium of exchange based on the blockchain system, gained worldwide attention as an alternative investment due to their high volatility and thus higher possible returns, anonymity, easy accessibility, increasing merchant acceptance and many more advantages that cryptocurrency brings with it. Meanwhile, the number of available cryptocurrencies is constantly increasing almost up to 22,932 alternatives in 2023 (Hicks, 2023).

For cryptocurrencies, as well as for all investment opportunities, decision making under risk is a crucial task for every investor whether as a professional or private investor. Therefore, it becomes imperative to understand the risk attitudes of investors in both the traditional asset market and the cryptocurrency market.

Although the instruments developed from capital market theory, such as Capital Asset Pricing Model (CAPM), Modern Portfolio Theory (MPT) or Efficient Market Hypothesis (EMH) have proven their worth in predicting and describing the securities and the flow of supply and demand in the market over the past years, prices still show hardly comprehensible fluctuations. After the view of the traditional capital market theory, financial markets are efficient, the investors are rational people and stock prices are dependent only on available information since the news spread rapidly (Yildirim, 2017). However, the classic capital market theories fall short in describing the stock prices in order to understand the price paths. Consequently, behavioral economics is used to explain market anomalies in the stock market because its assumption contradicts capital market theories that investors are irrational, and their cognitive biases affect the financial market.

Behavioral finance was first invented by Kahneman and Tversky (1979) and combines economic a psychology. According to Barberis and Thaler (2003), asset prices cannot be modeled without considering human psychology and behavior, which in turn influence the market.

In scholarly research, the investigation of investors' behavior and its correlation with their risk attitude has conventionally been confined to well- established and regulated traditional asset markets, including bonds, and other conventional financial instruments.

Although this area is well researched in traditional equity market trading, there are still unresolved questions regarding the factors that contribute to individual differences in risk attitude. Factors such as domain, gender, age, height, personal experiences and parental background have been identified as significant factors that shape individuals' willingness to engage in economic risk taking.
As cryptocurrencies complement the traditional investment landscape, the need to apply theories and models of behavioral economics to this emerging market becomes increasingly apparent. They have distinct characteristics such as high volatility, low to no regulation and complex technologies underpinning which means unique challenges and opportunities for investors. In this context, it is critical to examine the manifesting structures of risk attitudes to understand the dynamics of decision-making and develop effective strategies in this rapidly evolving market.
While previous research primarily focused on Bitcoin, predictive models or on the mining side of the Bitcoins, there remains a significant gap in the literature when it comes to understanding the investor behavior and their risk attitudes from the behavioral finance perspective. This thesis aims to address this gap by investigating the decision-making process of investors in the cryptocurrency market. By examining the psychological determinants of risk attitudes, this study seeks to provide valuable insights into the factors risk perception, risk preference and risk behavior in the cryptocurrency market compared to the traditional asset market. That is how the first research question of this thesis evolves: **Does the risk attitude differ between the cryptocurrency market and the traditional asset market?**
Moreover, it is also particularly important to explore how individual factors, such as risk preference and risk perception, individually influence risk behavior. This leads us directly to the second research question: **Do risk perception and risk preference exert risk behavior in the cryptocurrency market compared to the traditional asset market differently?** Additionally, the present study aims to explore the link between demographic factors and risk attitude, thereby offering a more comprehensive

understanding and providing a more holistic overview of the subject matter. Hence, this brings us to the third research question: **Do demographic factors have a different impact on the risk attitude in the cryptocurrency market and traditional asset market?** Other factors will not be included as they would exceed the scope of this thesis.

This thesis involves six sections. It begins with the introduction, which encompasses the classification and delimitation of the research topic, along with outlining the aim of the study. The second section elucidates the literature review, presenting an extensive examination of the relevant research in this field. Subsequently, the third section includes the methodology and the survey design, providing the applied research approach. The fourth part represents the empirical data and analysis of the survey followed by the discussion of the empirical data results. Finally, the thesis concludes with a comprehensive summary and the main findings and offering an outlook for further research.

Risk-taking behavior exhibit variations across different domains, such as an investment in the financial domain or in the health domain. Consequently, there is a high likelihood that decision making processes in the traditional asset market and the cryptocurrency market differ despite identical general conditions. The discrepancies in behavior across domains can primarily be attributed to differences in risk perception. The absence of prior studies addressing this comparison coupled with the growing popularity of cryptocurrencies and their increasing integration into our daily lives further emphasizes the significance of conducting such as study. Especially, noteworthy is the heightened awareness of investment opportunities during the recent years marked by the COVID-19 pandemic as evidenced by the increasing number of new investors in both the traditional asset market and the cryptocurrency market.

The contribution of the study to the literature is to fill the gap by providing insights into the differences in the risk attitude between the traditional asset market and the cryptocurrency market. It highlights the importance of considering demographic factors and risk preference in understanding investors risk behavior in these markets. By examining and comparing these factors, this thesis adds to the understanding of how the two markets and individual traits can influence risk behavior. This contribution helps to enhance the knowledge and comprehension of behavioral finance of the two markets.

CHAPTER 2: LITERATURE REVIEW

2.1.Cryptocurrency Literature

Following the global financial crisis in 2008, public trust in conventional banking systems was severely undermined, particularly after the declaration of bankruptcy by Lehman Brothers in September 2008 in the USA. This triggered a worldwide spread of crises. Due to the bursting of the financial bubble and the subsequent increase in interest rates, individuals gradually found themselves unable to repay their loans or obtain new ones, leading to the implementation of austerity measures. The resulting decrease in consumption and low investment levels exerted a detrimental impact on the economy, causing a decline in productivity and a rise in unemployment. This created a self-perpetuating cycle of adverse effects. The crisis of confidence emerged during this period as faith in the banking system diminished. This discontent culminated in movements like Occupy Wall Street, where protesters initially occupied Zuccotti Park in Manhattan's financial district and later expanded to other public spaces as a means of expressing their grievances.

Furthermore, a significant breakdown in trust occurred among banks. It was a common practice in the interbank business to lease money from bank to bank for some hours or just some days. This business relies heavily on trust without collateralization (Rejeb et al., 2021).

Unexpectedly, more banks and a substantial number of small loans were implicated, leaving them exposed to the uncovered volume of these small loans. Customers were not provided with transparency regarding these important transactions. And it became evident that banks were unable to repay each other, institutions began withdrawing from interbank transactions, further exacerbating the crises (Rejeb et al., 2021).

In the aftermath of the 2008 global financial crisis on October 31st, an anonymous entity group or organization using the pseudonym "Satoshi Nakamoto" published a white paper titled "Bitcoin: A Peer-to-Peer Electronic Cash System." This seminal paper introduced the concept of a decentralized currency utilizing Blockchain technology, which was subsequently implemented in the year 2009. The Bitcoin system allowed for direct transactions between buyers and sellers, bypassing the need for intermediaries. This development was driven by a response to financial institutions that frequently privatized profits while externalizing losses onto society (Lerer and McGarrigle, 2018). Bitcoin emerged as a solution to meet the demand for swift and cost-effective transactions without the involvement of traditional institutions or intermediaries.

Though, the idea of cryptocurrency was first introduced already by Dai in the year 1998. He was mentioning the word `B-Money` and described the concept of digital currency. In the same year Nick Szabo attempted to introduce Bit Gold which evolved to reduce the amount of trust needed to sending money. However, both ideas never were executed into reality and served as the basis for the creation of Bitcoin, an encrypted digital currency that uses the cryptography technique (Soni, 2020).

Since the launch of Bitcoin, more than 1600 cryptocurrencies have entered this market. Nowadays, cryptocurrencies are also useable as a payment in the real world to buy real goods and services (Dostov and Shoust, 2014; Guadamuz and Marsden, 2015). The general public has become familiar with digital payment methods, which have now become an integral part of everyday life, facilitating the acceptance of cryptocurrencies. The range of payment options is constantly expanding and new payment providers like PayPal are gaining popularity due to their user-friendly nature, simplifying the daily lives of numerous individuals. These providers eliminate the need to interact with traditional banking institutions and their smartphone applications offer clear and intuitive interfaces, enhancing accessibility for all users. Consequently, it is also understandable that so many new cryptocurrencies come on the market because the opening of a securities account with countless applications, contributions and confirmations from his bank, provided you have chosen a bank, make this all obsolete. Cryptocurrencies, especially Bitcoin, are new financial instruments and offer an alternative investment with diversification benefits even with even a small portion and can enhance the risk-return trade-off of a well-constructed investment portfolio (Brière et al., 2013). Moreover, many cryptocurrencies serve as mediums of exchange for daily transactions and exhibit similarities to precious metals, such as limited supply and being subject to speculative investments (Omane-Adjepong et al., 2018).

The cryptocurrencies market witnessed continuous growth in recent years, reaching its peak by the end of the year 2021. However, during this period, the market experienced a significant decline in market capitalization, experiencing its first serious downturn. Nonetheless, the market recovered quickly in the subsequent year. As of the present time, the global market capitalization stands at 890 billion dollars, whereof 329 billion dollars value belongs to Bitcoin.

Currently, there are 19.228.575 (Statista, 2023) Bitcoins in circulation, which accounts for approximately 91.565% of the total 21 million that will ever be available. The limited supply of Bitcoins is designed to prevent high price fluctuations. Participants of the cryptocurrency financial market have two main avenues for profit: engaging in particular transactions with other users or/and participating in the mining process. The miner or rather the computer takes the part of the validation process of transactions by evaluation blocks of data called hash. The blocks of data (nodes) travel through a reasonable number of systems until the information is encoded. After this step, the miner is responsible to be sure whether his solutions are exact. Once the nodes are confirmed, a new block can be added to the blockchain, providing proof of work and completing the transaction successfully. As a reward for their efforts, the miner receives a certain number of Bitcoins, which serves as motivation to continue solving the puzzle and bear the high costs associated with equipment and other incidental costs (Nakamoto, 2009). The Proof of work concept serves as a security measure to prevent hackers from verifying invalid transactions. It ensures the integrity of the cryptocurrency system. It is worth noting that Ethereum, for instance, utilizes a different approach known as proof of stake (Rejeb et al., 2021)

The task of the miner can be compared to a bank clerk along with many other clerks. From all over the world miners try to find the right code for the information and be the first one. In average it takes 10 minutes to find the correct solution (Ankalkoti and Santhosh, 2017).

2.1.1. Blockchain

Cryptocurrencies use cryptography to secure the transactions and protect user anonymity. Cryptography is a method of securing information and communication through inaccessible codes so that only those for whom the information is intended can read and process it. Most of the cryptocurrencies using blockchain technology on decentralized networks in a public-accessible distributed ledger with zero involvement of any governmental authority. In the illustrated life cycle of a transaction, it begins with the initiation of a transaction. The transaction is then transmitted to a peer-to-peer (P2P) network, which consists of nodes distributed globally. These nodes within the network perform a consensus protocol to determine the validity of a transaction. When the validity of the transaction is confirmed, the nodes are merged with other recently approved nodes to form a new transaction block. This block is then added to the ledger, which contains the whole history of all transactions. At the end the transaction is complete, and the data can be transferred to the device (Ghiro et al., 2021; Hassani et al., 2018; Soni, 2020). The use of cryptography within this process plays a crucial role in ensuring the robustness and security of the system. The cryptographic techniques employed make the transactions and data within the blockchain virtually impossible to tamper with or hack, enhancing the trust and reliability of the cryptocurrency system.

Currently, the Bitcoin Blockchain can validate up to 10 transactions in less than one second. This operational efficiency sheds light on the substantial power consumption associated with the system particularly when compared to a developed country like Ireland (Meneghello et al., 2019). The other side of the coin is that the process of validation requires a tremendous amount of storage space and consumes an incredible amount of energy (Vranken, 2017) and, accordingly, computer power. The amount of required energy demand is approximately the same such as Ireland (de Vries, 2018).

The use of Blockchain technology is not only limited to the cryptocurrency and bank sector (Cocco et al., 2017; Guo and Liang, 2016) but also attracted the attention of other subjects such as in the supply Chain Management (Miller, 2018; Montecchi et al., 2019; Tian, 2016; Tse et al., 2017), Healthcare (Dwivedi et al., 2019; Mettler, 2016; Xu et al., 2019; Yue et al., 2016), E-Voting (Ayed, 2017; Bistarelli et al., 2017; Kshetri and Voas, 2018; Noizat, 2015; Qi et al., 2017; Qu et al., 2020; Hardwick et al., 2018; Wang et al., 2018), digital identity (Pilkington, 2016), insurance (Gatteschi et al., 2018) and Internet of things (Lin and Liao, 2017; Reyna et al., 2018; Viriyasitavat et al., 2019; Wu et al., 2019; Zheng et al., 2018). This broad adoption of Blockchain technology and the capability to empower a wide range of IoT applications conceals a great potential. Moreover, this phenomenon contributes to the extension of the Big Data analytics network (Hassani et al., 2018), as blockchain enables secure and efficient storage, sharing and analysis of vast volumes of data across industries and domains.

2.1.2. The fields of investigation

Bitcoin and other cryptocurrencies have gained an increasing interest from various domains and scientist in the recent years (Voskobojnikov et al., 2020). The study of Yermack (2015) stands as one of the initial academic works to direct scholarly focus towards to the field of cryptocurrency. Most existing research in this domain is rooted in traditional asset markets. However, the research related to end-user risk-taking behavior in cryptocurrencies is almost non-existent. While some literature touches upon risk behavior, it often assumes a supportive role rather than being the central focus.

The papers dealing with the cryptocurrency market focus on the most popular cryptocurrency, Bitcoin. Yli-Huumo et al. (2016) note that approximately 80.5% of the literature is on Bitcoin, leaving only 19.5% to explore alternative applications of blockchain technology. It is noteworthy, however, that this market encompasses nearly 22,931 (Hicks, 2023) alternative cryptocurrencies.

The significance and acceptance of cryptocurrencies within society are closely linked to the perceived risks associated with technologies such as Bitcoin, e-service, and government as highlighted by previous studies (Abramova and Böhme, 2016; Belanger and Carter, 2008; Featherman and Pavlou, 2003). This observation clarifies that research conducted between 2011 and 2016 mostly focused on the examination of technological aspects.

A several numbers of research have focused on individual risk perception in relation to cryptocurrency transactions (Chen and Farkas, 2019), specifically examining the factors that influence risk perception rather than solely focusing on investor-related aspects. Some relevant studies explore characteristics such as trust, initial costs, security, privacy, among others, which in turn affect the adoption to the cryptocurrency (Auinger and Riedl, 2018; Bag et al., 2021; Lacity, 2018). Nevertheless, the adoption of cryptocurrency payments is experiencing rapid growth. This is evident through the acceptance of Bitcoin as a payment method by major companies such as Microsoft, Paypal, EBay, Dell, and Expedia (Javier Iglesias de Ussel et al., 2015).

Many studies formulated models to forecast the performance of cryptocurrencies. For instance, Liu and Tsyvinski (2018) developed a model, which predicts cryptocurrency market returns by using the momentum effect and utilizing proxies that capture investor attention towards cryptocurrencies. Similar approaches have been explored in other papers (Huberman et al., 2017; Neuhierl and Weber, 2018).

Another cluster of papers concentrates on examining the production aspect of cryptocurrencies, specifically addressing the challenges faced by miners. The miners' problem has been explored in studies such as by Cong et al. (2018). These works demonstrate the connection between the evolution of cryptocurrency prices and the marginal cost of production. Liu and Tsyvinski, (2018) have further contributed to this area of research by investigating the relationship between cryptocurrency prices and production costs.

2.1.3. Cryptocurrencies and Behavioral Finance

Cryptocurrencies exhibit high price volatility due to the influence of investor decisions, which in turn is influenced by psychological factors. It is important to consider that individuals may not always make rational decisions when it comes to cryptocurrency investments as emotions, biases and various other factors come into play. Given the fact that cryptocurrencies have only been around for a short time compared to other investment opportunities, there is a very limited number of researchers who have studied behavioral finance in relation to cryptocurrencies. Nonetheless, over the last few years, a growing number of researchers have recognized the significance of studying behavioral finance in the context of cryptocurrencies, leading to an increasing number of academic papers that explore the connections between these two domains.

One of the newest papers regarding cryptocurrencies and behavioral finance was published by Huang, 2022. Departing from traditional economic theories that posit limited influence of investor behavior on asset prices, he contributes to the literature with insights that support the presence of irrational behavior in the cryptocurrency market by summarizing incisive event facts with a particular focus on Bitcoin, Ethereum, Litecoin, and Dogecoin from the perspective of behavioral economics. Huang (2002) investigates the occurrence of the speculative bubbles in the cryptocurrency market, highlighting the role of noise traders'[1] behavior as an amplifier of cryptocurrency volatility. Conversely, Kumar (2020) argues that herding behavior becomes more pronounced during periods characterized by heightened market volatility.

However, the case of Dogecoin presents a different perspective. The endorsement of Dogecoin by the CEO of Tesla and his declaration that it is his favorite cryptocurrency, commonly referred to as "the people´s crypto," along with the announcement of support from his company had a profound impact. Consequently, the price of Dogecoin experienced a significant surge, especially on August 16th, 2021, when Elon Musk reinforced Cuban´s endorsement by asserting that Dogecoin is the most powerful medium of exchange and could be used for everyday transactions like purchasing bread. The most ironic part of this event is that Dogecoin was initially established to make jokes of all cryptocurrencies. This example serves as evidence that inexperienced noise traders are obviously influenceable by the expectations and behaviors of others. They tend to make decisions based on heuristics rather than sound, fundamentally justified rationales (Hamrick et al., 2018; Jalal et al., 2020).

Overconfidence among cryptocurrencies (Kim et al., 2022; Tran et al., n.d.), momentum effects (Caporale and Plastun, 2020), overreaction (Caporale and Plastun, 2020), contagion effect (Bazán-Palomino, 2022) are just a few examples of a huge pool of behavioral finance factors that have been observed in the cryptocurrency market, similar to their occurrence in the traditional asset market (Huang, 2022).

[1] Noise traders are investors who make decisions without the support of professional advice or technical analysis or careful assessment.

Generally speaking, it is a major task for researchers in the field of behavioral finance to conduct and analyze data, as the nature of modern financial instruments differs substantially from the traditional asset market. The way this market works, and the "architecture" of cryptocurrencies exhibit distinct characteristics that set them apart from traditional investment markets. Therefore, there exists a level of uncertainty regarding the tangible value or “anchor” of cryptocurrencies. This technical aspect of cryptocurrencies makes it challenging to pinpoint the factors and characteristics that define these modern assets (Ballis and Verousis, 2021). Not to be ignored, however, is the other side that this market brings. For instance, the vast amounts of data and increased transparency has the potential to shed light on long-standing debates among researchers, providing valuable insights and enhancing our understanding of financial phenomena.

2.2. Risk Attitude Literature

A considerable body of qualitative literature has examined the link between risk perception, risk behavior and risk preferences, revealing divergent opinions and empirical findings within this domain. Among the various models proposed, prospect theory (Kahneman and Tversky, 1979) has gained significant recognition and acceptance. According to prospect theory, investors exhibit a preference to take greater risks when faced with potential losses compared to potential gains. This implies that individuals display risk aversion following a loss, or conversely, a willingness to take on more risk after a gain as posited by the theory.

Risk is a fundamental concept in financial behaviour and the field of behavioural finance. Individuals encounter risks in various aspects of their lives, including loans, gambling, financial market trading, project investments, product purchases, job transitions and more. Central to these situations is the presence of uncertainty characterized by a lack of knowledge regarding the potential outcomes and their associated probabilities. This uncertainty can lead to positive or negative effects, with varying degrees of impact on personal or professional aspects of individuals’ lives. An often risk and uncertainty are mistakenly used interchangeably, uncertainty is component of risk rather than an equivalent term. Risk pertains to situations involving potential gains or losses where the probabilities are unknown. Risk behaviour is the key to understand the actions of individuals and their subsequent macroeconomic outcomes. Risk behaviour has tangible real-world consequences in areas such as labour markets, investment decisions, innovations, health outcomes and various other domains (Barsky, Juster, Kimball, and Shapiro 1997; Hong, Kubik, and Stein 2004; Bonin, Dohmen, Falk, Huffman and Sunde 2007; Anderson and Mellor 2008; Kimball, Sahm and Shapiro 2008; Jaeger, Dohmen, Falk, Huffan, Sunde, and Bonin 2010; Dohmen and Falk 2011; Becker, Deckers, Dohmen, Falk, and Kosse 2012; Dawson and Henley 2015; Hsieh, Parker, and van Praag 2017).

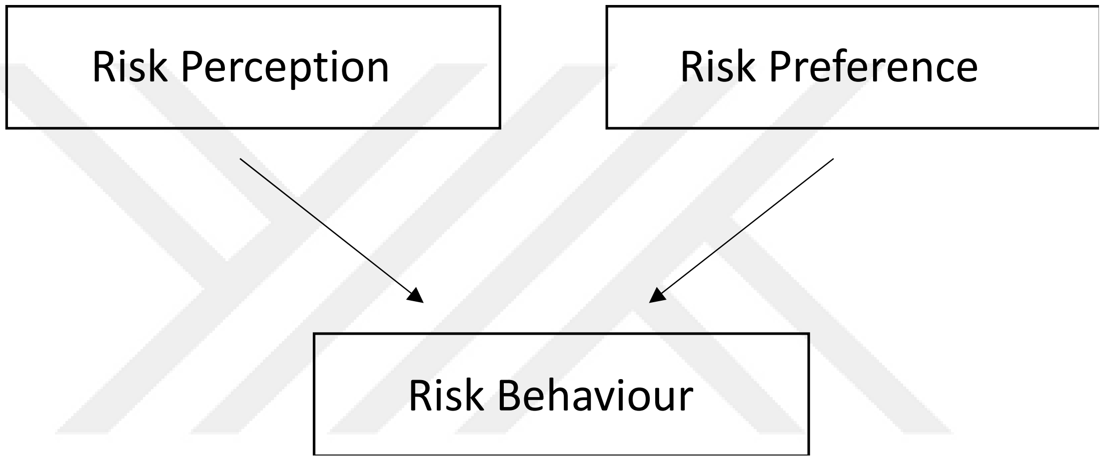

Figure 1. The interplay of risk perception, risk preference and risk behavior

2.2.1 Risk preference

Risk preference refers to an individual's inclination towards being risk averse, risk neutral or risk seeking when faced with decision-making involving uncertain outcomes. The concept of risk preference was initially introduced by mathematician Bernoulli in 1786. Bernoulli's investigation of decision making under risk aimed to address and provide an explanation for the St. Petersburg paradox, which revolves around decision-making in lotteries. The paradox examines individuals' reluctance to participate in fair games where the chances of winning and losing are equal. Bernoulli's work sought to understand the underlying reasons behind this phenomenon.

In the field of economics, that risk preference is commonly assumed to be stable across different contexts, affecting decision making under risk. However, in psychology, risk preference is commonly defined as the propensity to engage in behaviours or activities that are rewarding but have nevertheless a probability of loss (Steinberg, 2013). In psychology, risk preference is defined as the propensity to engage in behaviours that are rewarding but still involve a probability of loss. This is also the reason why some papers call the risk preference the risk propensity (MacCrimmon and Wehrung, 1990; Sitkin and Weingart, 1995). In economics, on the other hand, risk preference typically refers to the tendency to engage in behaviours associated with higher variability in returns, regardless of whether they involve gains or losses. These economic studies often focus on monetary payoffs (Harrison and Elisabet Rutström, 2008).

This conceptualized trait of an individual can change over time whereas the traditional concept of risk preference assumes to be stable (MacCrimmon and Wehrung, 1990; Schoemaker, 1990).

2.2.1 Risk preference and sociodemographic

According to the existing literature, there is a strong linkage between sociodemographic factors and risk preference. It is widely accepted that women are more risk averse than men, as supported by the study such as Croson and Gneezy (2009).

Moreover, individuals who are older, married, or have children demonstrate higher levels of risk aversion, as evidenced by research conducted using German micro data from the Socio-Economic Panel (SOEP) by Dohmen et al. (2011). Furthermore, individuals with a high school diploma or higher income tend to exhibit a greater inclination towards risk-taking. However, regarding the connection of income and education the investigations in the literature are still controversial (Hartog et al., 2002).

An interesting finding has emerged concerning the job selection, particularly in the financial sector. It has been observed that financial professionals exhibit distinct risk preferences compare to individuals in other professions. They tend to show a higher degree of analytical behaviour, rendering them less susceptible to behavioural biases when compared to the general population. This observation has been supported by studies such as Kaustia et al. (2008). Usually, students are employed as subjects in experiments to investigate risk preferences. However, the authors come to different conclusions about the accuracy and reliability of the data. The appropriateness of using students to gain insights into how investors make decisions under risk remains a subject of debate. Abdellaoui et al. (2013) conducted a study examining the value function parameters of professional investors. The findings indicated that, to a limited extent, professional investors exhibit less loss aversion compared to students participating in experimental settings. These findings were attributed to the experience factor because professional investors experience losses on a frequent basis, leading to a potential desensitization effect in comparison to the student participants.

Others believe that a small adjustment needs to be made to the results to make more precise and accurate statements and to generalize where losses are included. Decisions in the gain domain, on the other hand, do not need this kind of caution when it comes to transfer the findings of students to professional investors. However, it should be noted that there is limited research available on this specific topic.

The phenomenon of risk preference differentiation in employment choices can be attributed to occupational sorting. Individuals who exhibit a greater willingness to take risks tend to sort themselves into occupations that offer higher income variability (Fuchs-Schündeln and Schündeln, 2005; Grund and Sliwka, 2010) and in some cases, occupations with higher mortality risks. In particular, leadership positions within the finance sector usually involve working with incentive schemes that offer substantial rewards, which may attract individuals who are risk-seeking or have a higher risk tolerance (Dohmen and Falk, 2011).

These findings contribute to the forecast of the risk preference by using the so-called stereotyping based on known characteristics or attributes. Eckel and Grossman (2008) conducted an experimental study specifically focusing on gender stereotyping in relation to risk aversion. The results of the study confirmed the prevailing assumptions regarding the risk-taking behaviour of genders. Moreover, the study revealed that stereotyping, which involves extending assumptions to a group rather than to the individual, holds true for women in terms of risk aversion, whereas an overestimation of risk tolerance was observed for men. These findings underscore the influence of knowledge and beliefs regarding stereotypical characteristics preference predictions. (Judd and Park, 1993). Regarding cultural stereotypes, it is commonly perceived that Chinese individuals are more risk averse compared to Americans. Contrary to these expectations, experimental data indicates the opposite to be true (Hsee and Weber, 1999).

Furthermore, individuals with a low risk tolerance are less self-employed and are less inclined to invest in stocks, as substantiated by research studies (Falk et al., 2018). Furthermore, the empirical evidence demonstrates that individuals tend to become more risk averse as they age. This means for aging societies less self-employment and a lower level of the factor productivity, more savings, conservative investments and voting behavior. Germany serves as an exemplar of these phenomena persisting over an extended period. All these factors have enormous impact and meaning for the macroeconomic performance and political situation.

2.2.1.2. Risk preference and Stability

2.2.1.2.1 Stability in economics

Based on traditional economic literature, preferences, including the risk preferences, are assumed to be stable and unaffected by experience over time. This assumption is considered a fundamental principle in economics (Stigler and Becker, 1977). Changes in the individual's behaviour were attributed to changes in incentives or constrains rather than shifts in preferences. The stability of risk preferences in economics is typically defined as the consistency of an individual's level of risk aversion over time rather than the stability of the distribution of preferences in a given population. When measuring an individual's risk preference repeatedly over time, the observed willingness to take risks is expected to remain the same. Any deviation from this expectation, if incentives and constraints have remained unchanged, is considered a measurement error in the standard approach of economics. Therefore, the prevailing perspective in economics emphasizes the stability of individual risk preferences and dismisses the notion of preferences changing over time due to experience.

In the economic literature, risk preferences are often represented by a single parameter that characterizes an individual´s attitude towards risk. This parameter can range from risk-seeking and risk-neutral to risk-averse, with risk aversion being the most common preference among individuals (Dohmen et al., 2011). In a more general setting, Rothschild and Stiglitz (1970) defined risk aversion by relating it to mean-preserving spreads based on the expected utility function (Eeckhoudt et al., 2005). In the concept of the expected utility framework, originally introduced by Bernouili (1738), represents different risk preferences through the curvature of utility functions While the framework captures the varying levels and characteristics of risk preference and the additional utility generated per unit of compensation, it does not assume changes in risk preference over time. For instance, for being a risk averse individual's utility curve would be concave, with the curve initially steep and flattening as utility increases. It is important to note that only one of the three characteristics is assumed here, like the concepts of the mean-preserving spreads and the risk apportionment, where an individual is considered risk-averse when choosing a particular lottery over the mean-preserving spread of that lottery.

An amount, the concept of utility premium, which quantifies the intensity of risk preferences by measuring added risk in monetary terms, was originally defined by Arrow (1996) and Pratt (1964). However, this concept has been largely overlooked in the literature and has regained attention in this context again.

All these approaches share the common assumption that, in absence of measurement error, repeated testing should yield consistent estimates of individual's risk preferences. The issue of stability in risk preferences has been explored in several studies.

Kahneman and Tversky (1979) has significantly influenced the field of decision-making under risk. The prospect theory is one of the most widely accepted theories in behavioural finance and is considered a milestone among scientists. It is considered as one of the key papers in the behavioral finance and is used not only in the field of finance but also in other domains wherever a decision under risk is necessary. The theory challenges the traditional assumption of profit maximization and highlights the fact that individuals exhibit different behaviours in different domains of profit. Accordingly, this suggests that risk preferences are not constant and may change across different risk domains. Such findings undermine the notion of individuals as perfectly rational being "homo economicus" and instead reveal the presence of irrational behavior Kahneman and Tversky (1979).

2.2.1.2.2 Stability in Psychology

In contrast to the economic risk preference in psychology personality trait is used to define an enduring, consistent, and relative stable over time internal characteristic that vary from person to person (Roberts et al., 2006). Both personality traits and economic preferences are in common in sense of being characteristics, which are crucial for the prediction of an individual's decision making. However, the divergence arises in the definition of stability. In psychology, stability refers to the rank order preferences of individuals in terms of the intensity of a particular trait as measured through repeated assessments, rather than assuming a constant trait value throughout one's life. This concept of stability allows for systematic changes over time. In comparison to mean-level stability, the rank-order stability is an aspect of a trait. Mean-level stability refers to the consistency in the average level of a trait over time. It is important to stress out that concept of the "average level" or central tendency is not an exact specific parameter value and is thus a weaker definition of stability compared to the economic perspective. However, personality psychology acknowledges the existence of changes in traits within individuals over time, which might occur due to factors such as aging, new experiences, or traumatic events.

Roberts and DelVecchio (2000) conducted a meta-analysis to examine the stability of personality traits over a period of 6.5 years. They reported a high test-retest correlation coefficient for adult age of about 0.6-0.75. Furthermore, the results of the analysis showed the increasing trait consistency of 0.31 in childhood to 0.54 during the teenage years, reaching 0.64 at age 30 and stagnating between ages 50 to 70 at around 0.7. Thereupon Elkins et al (2017) examined the stability of personality over eight-year period during adolescence and young adulthood using panel data from Australia. The panel data of Australia showed just small changes in the unconditional mean-level. Therefore, Sahm (2012) and have adjusted the birth cohort and period effect from the age effect so that one could correctly conclude that the risk aversion increases with the lifecycle. These studies represent rare long-term investigations of personal traits.

Fleeson (2001) argues that personality traits should be conceived of as density distributions to account for within-person variation, the substantial amount of variability present.

Research on the stability of risk preference in economics is relatively new compared to the attention it has received in psychology. However, there are still big question-marks and areas for improvement in terms of definitions and measurements in both fields. Further refinement of these aspects is necessary to enhance the accuracy and applicability of predictions related to decision making. There is a need for overarching an overall theoretical framework that addresses changes in preferences over time.

Although risk preferences are considered a fundamental aspect of decision making for simplicity and feasibility, we imply that risk preferences remain stable in our study. This assumption does not affect the hypothesis testing, because our focus is on exploring the interaction between risk preference, and risk perception in different domains.

2.2.2 Risk perception

Perception is the process and result of subjective information acquisition and processing of stimuli from the environment and the personal intrinsic thought process through the senses such as seeing, hearing, and feeling. The end product is a subjective overall picture (Felisberti, 2018). Risk perception specifically pertains to how individuals interpret and assess risks which can vary among individuals and may not necessarily align with objective reality. It is defined as a person's estimate of how risky a situation is based on the perceived probability of the safety of the situation, the controllability of that uncertainty, and confidence in particular those estimates (Baird and Thomas, 1985; Bettman, 1973; Sitkin and Weingart, 1995).

For decades, the decision-making literature incorrectly assumed that individuals would perceive comparable levels of risk in identical decision-making scenarios (Nutt, 1986). This assumes that individuals are fully rational, seeking to maximize profit-and possess complete awareness of all relevant information. However, this perspective has been challenged by various researchers. Research in the field of behavioural decision making have indicated that individuals have limited cognitive capacities, which do not permit a comprehensive search for information or its precise interpretation, so that a large number of factors cannot be taken into account (Bohnenblust and Slovic, 1998; Cooper et al., 1995; March 1958).

Risk perception is influenced by cognitive biases, which refers to the use of mental heuristics or shortcuts in the formation of judgments. These cognitive biases have a significant impact on the processing of the information, such that individuals with a greater prevalence of biases in their behaviour tend to exhibit lower levels of risk perception. Consequently, these biases play a crucial role in shaping individuals' decision-making process (Simon et al., 2000).

Risk perception plays a major role in the decision-making process, especially in uncertain circumstances and accordingly also in financial decisions (Antonides and van der Sar, 1990; Forlani and Mullins, 2000; Hoffmann et al., 2013; Nguyen et al., 2016; Siebenmorgen et al., 2000). Meanwhile, the exact relationship between risk perception and decision making not clear (Keil et al., 2000). In the literature, there are many different opinions on how risk perception affects decision making. For example, it is argued that individuals with a high level of risk perception tend to avoid high-risk investments and instead favor low-risk investment options. Comparatively, investors with a low-risk perception tend to invest in riskier assets (Aren and Zengin, 2016; Keller and Siegrist, 2006). Differences in risk-taking over distinctive domains can be mainly explained through different risk perceptions (Baucells and Rata, 2006; E. Weber et al., 2002). However, the extensive literature on the framing effect suggests the opposite. Risk-seeking behaviour under negative problem framing is a well-known and accepted observation (Mcneil et al., 1982; Tversky and Kahneman, 1986). Whereby there is still an inconsistency across the investigations regarding risky behaviour.

The relationship between risk perception and decision making under risk is indeed complex. Sitkin and Pablo (1992) proposed a theoretical model that reconceptualizes the determinants of decision making under risk. In this model, exogenous factors, including framing, which were previously held responsible to have a direct influence on risk behaviour such as, are now directly connected by two mechanisms: risk perception and risk propensity. This suggests that risk perception and risk propensity play crucial intermediary roles in the relationship between exogenous factors and decision making under risk.

Risk perception is a subjective phenomenon influenced by various factors such as the assessment, availability, and reliability of information (van Raaij, 2016). This notion holds significant importance in modern decision theory as demonstrated by Neumann and Morgenstern's (1953) proposal that individual´s behaviour in games can be used to deduct their "utility function" – an objective measure of their preferences that is independent of specific content. By understanding the subjective value and the probability associated with each possible outcome in a given situation, it becomes possible to predict how the individual will likely to behave.

2.3. Conceptual Framework and Hypothesis development

The conceptual framework of this research is aligned with the goals of the research questions outlined in the introduction. The figure 1 below represents the conceptual framework that guiding this research.

The primary objective of this study is to compare the risk attitude of investors in two different markets, as formulated in the first research question. These two markets are represented by the two large orange squares in the figure. To accomplish this comparison, the study examines the relationship between risk preference, risk perception, and the risk behavior as these factors exert significant influence on an individual's risk behavior. By analyzing the association between risk preference and risk perception on one hand and risk behavior on the other hand, as indicated by the arrows in the figure, the second research question is addressed.

Furthermore, it is important to acknowledge the impact of demographic factors in shaping an investor's risk attitude, as suggested by the existing literature. However, there is no consensus on the extent to which they have an influence as it varies depending on the specific circumstances. Consequently, it is imperative to incorporate demographic factors into this study. Thus, the inclusion of demographic factors gives rise to the third research question, which aims to examine their influence on risk attitudes.

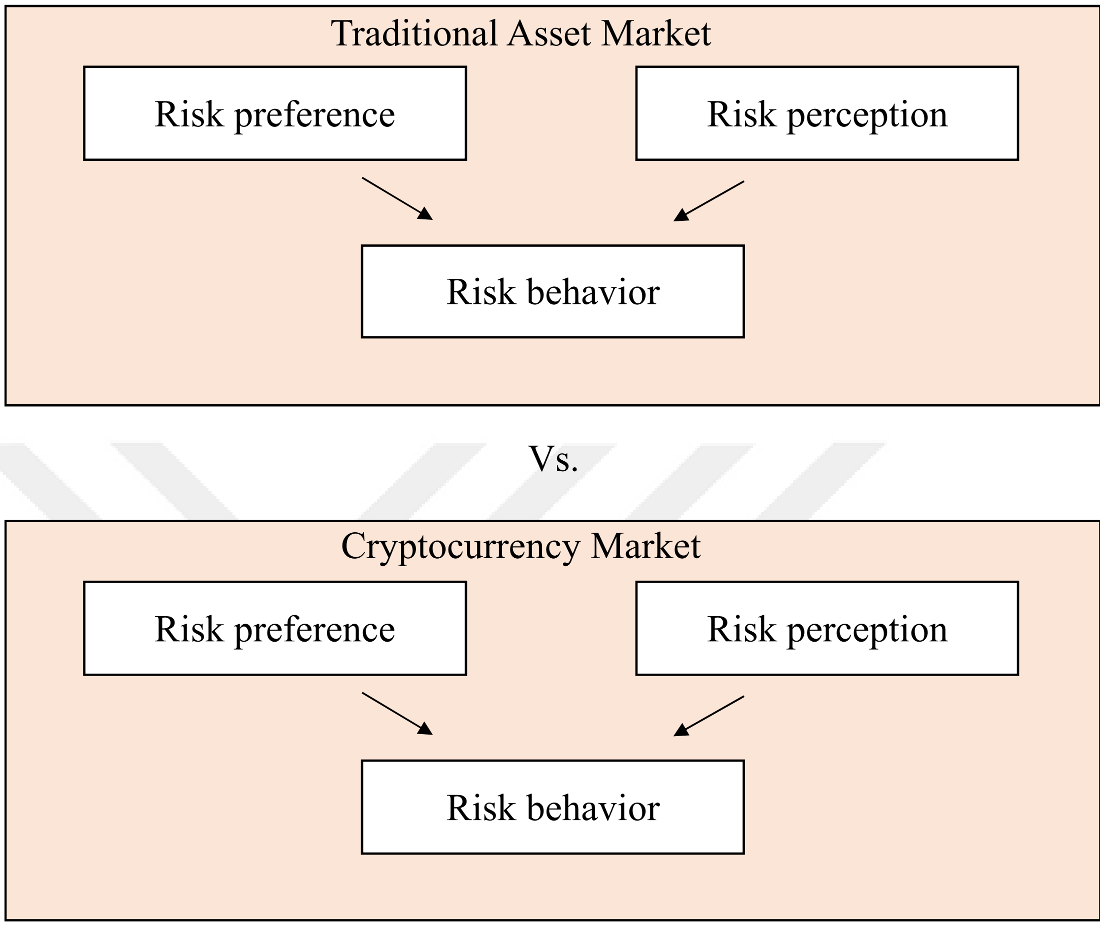

Figure 2. Conceptual Framework

RQ1: Does the risk attitude differ between the cryptocurrency market and the traditional asset market?

RQ2: Do risk perception and risk preference exert the risk behavior in the cryptocurrency market compared to the traditional asset market differently?

RQ3: Do the demographic factors have a different impact on the risk attitude in the cryptocurrency market and traditional asset market?

Based on these research questions, the hypotheses are listed as follows:

H1: There is a statistically significant relationship between demographic factors and personal risk preference.

H2: There is a statistically significant relationship between demographic factors and the risk perception in the traditional asset market.

H3: There is a statistically significant relationship between demographic factors and the risk perception in the cryptocurrency market.

H4: There is a statistically significant relationship between demographic factors and the risk behavior in the traditional asset market.

H5: There is a statistically significant relationship between demographic factors and the risk behavior in the cryptocurrency market.

H6: The risk behavior in the traditional asset market differs from the risk behavior in the cryptocurrency market.

H7: The risk perception in the traditional asset market differs from the risk perception in the cryptocurrency market.

H8: The risk perception and risk behavior in the traditional asset market are significantly dependent on each other.

H9: The risk perception and risk behavior in the cryptocurrency market are significantly dependent on each other.

H10: The risk preference and risk perception are not significantly correlated in the traditional asset market and cryptocurrency market.

H11: The risk preference and risk behavior are significantly dependent on each other in the traditional asset market and cryptocurrency market.

The hypotheses formulated in this study are derived from the research questions mentioned in the introduction part, with the objective of addressing these inquiries. By investigating the relationships of the demographic factors, risk preference, risk perception and risk behavior, this study seeks to deepen our understanding of the individual´s risk attitudes in both traditional asset and cryptocurrency market and to fill the existing gap in the literature on this topic. Furthermore, the findings of this study not only contribute to the existing literature but also enhance our understanding of the decision-making under risk, which holds significance relevance for investors and their investments.

In previous studies, the domain effect has been proven, highlighting the influence of different investment domains on individual´s decision making process under risk. Given this phenomenon, the findings of this study have the potential to yield significant advantages not only for individual investors but also for other institutions, including banks and political entities. These findings can inform the development of improved investment offerings and enhance the accuracy of forecasts, thereby benefiting a wide range of stakeholders.

Furthermore, the field of behavioral finance has shed light on many irrational behaviors observed in the decision-making process, including the disposition effect, whereby investors tend to hold onto loosing stocks for too long and sell winning stocks to soon, resulting in decreased returns. By identifying and understanding these biases through research, these countervailing actions can be taken. This knowledge can lead to improve the decision-making process, enhance the risk management strategies and create forecasts to provide better financial outcomes for individuals and society as a whole.

CHAPTER 3: METHODOLOGY

Previous studies have proven that risk-taking behavior does not differ between students, MBA students and executives, nor whether the consequences are monetary or not (Baucells and Rata, 2006).

In the main part of the questionnaire, the investor must decide between how much he would split of his wealth in a risk free and risky asset. In financial markets, it is customary to make decisions that involve a trade-off between risk and return. Typically, financial institutes show the investor a history price path of eligible assets to let them decide. By showing the investor a historical price history, numerous factors come into play in the decision-making process, such as the altitude, if it has recently gains or losses, the sequence of gains and losses, volatility, the length of the timeframe, the peak and the lowest point. However, the main goal of this study is to compare risk behaviour in the two domains, so the logical conclusion is not to show participants a price path and simply let them decide by giving them a situation.

In behavioral science, it is common to equate a decision with a gamble. Based on this perspective, many studies have been conducted in which participants find themselves in a situation where decisions and evaluations are made in connection with a monetary value, as in a casino. Lopes (1983) draws a comparison between significance of games in decision making research and the emergence of the fruit fly in genetics (Lopes, 1983). Like the assumption of Neumann and Morgernstern (1953) who believe that the behavior of people in games can be used to derive the utility function of each person. If the subjective value and probability of each outcome is known in a decision situation, it becomes possible to make predictions about the person's future course of action. According to these studies it should make no difference in which domain decisions were made for example in a health domain or financial one. This is contradicted by psychologists who believe that the situation and environment have a fundamental impact on decisions (Goldstein and Weber, 1995). If the decision is based solely on the problem content, its probabilities and personal decision strategies, these would exclusively determine the personal preference. Thus, they would have to be determinable for each individual, which is not the case (Rettinger and Hastie, 2001).

In the real world, it is often not feasible to determine all possible outcomes and their associated probabilities of occurrence, nor is it possible to fully ascertain the subjective preference that an individual holds with them. Based on the results, it is easy to see that the domain plays one of the larger factors in the decision-making process. In both domains, the same prerequisites are given, the probability of occurrence and its outcomes are determined. The questions are identical except for the wording, which is the domain.

In order to use the formulated research questions, different analysis procedures were used. Among others, one-way ANOVA test, V-contingency coefficient, Tukey-Kramer post-hoc test, Leven's test for equality, t-test, effect size such as the Eta squared and the mean. As the analysis tool the software IBM SPSS Statistics version 29.0.0.0 (241) was used. Each individual procedure is discussed in the analysis part.

3.1.Questionnaire Design

This questionnaire survey was designed to answer the research questions and the hypothesizes in a clear way. The survey was conducted online via the Surveymonkey platform and can be found in the Appendix. This is a popular platform for students or scientists for creating surveys for scientific work. The advantage is that the survey can be easily created on the platform and distributed through social media, web links, email and many other ways, which is very important if you want to conduct a quantitative study, as in this case. The participants in this study constitute a convenience sample, a non-probability sample method. The survey link was predominantly distributed among students from Izmir Economy University, as well as among family members and acquaintances. Furthermore, the participants come from diverse backgrounds, with individual hailing from various countries such as Turkey, Germany, and Latvia, among others. This international representation brings in a mix of perspectives and experiences, enriching the study´s findings.

The survey is divided into 5 parts. First, a small information text was displayed to inform the participants that this is a scientific survey conducted by the university. At the same time, it was mentioned in the text that the survey is related to finance and that the survey is completely anonymous. This information prepares the participant for the type of questions that await him/her and there is no fear of answering a question incorrectly, as this is an anonymous survey. For the participant to know how much time he or she has to take for the survey and for motivation, an estimated time for answering the questions was given.

The second part of the survey is for determining risk preference. The third and fourth part collects the risk perception and risk behavior data. The final part of the survey is to collect demographics of the individual to have a better overall understanding of the participants.

3.1.1. Risk preference

This section of the survey is like a small card game. To measure the risk preference is partially adapted by the procedure of (Filiz et al., 2018). The gamble deals with the decision between two lotteries. The participants can see two illustrated card piles, pile A and pile B. Both piles include four cards with numbers on it. The pile A have two cards with a profit of +6$ and two cards with +4$ on it. In pile B there are two cards with 10+$ and two cards with 0+-$ outcome. Furthermore, the participants are informed that the expected value in both piles is the same with +5$ and that the best and the worst possible event have a probability of 50%. In the original suggested survey, Filiz et al., (2018) put additionally two test questions to make sure that everyone has read and understood the task correctly.

Considering the fact that mostly students, which are used to solve intertwined assignments, fill out this survey and individuals with a higher education status these two control questions could irritate the participants due to the wholesome given written down information about this gamble. Students felt taken for a ride on the easy test questions or got confused and thought they misunderstood the question and tried to find the mistake because the control questions were too absurdly easy. This led to an increase in the total time for the survey. The longer the survey is, the higher the probability that it will be terminated prematurely. Which is why the control questions were not asked in the final survey.

The participant is told that he must choose between the two decks of cards. The participant has three possible answers. Only one answer is possible to click on, the internet platform takes care of that. If an attempt is made to click on two possible answers, the option clicked on first is visibly logged out. It can be decided to take a card from the deck A or a card from the deck B or the participant is undecided and for him it does not matter from which deck the card is drawn. In this way, a clear distinction can be made as to which risk preference is being followed (risk-seeking, risk-averse, risk-neutral). Risk-seeking persons would decide to take a card from pile A, a risk-avoiding subject would prefer pile B and a risk neutral are indifferent about the decision whether to choose from pile A or pile B.

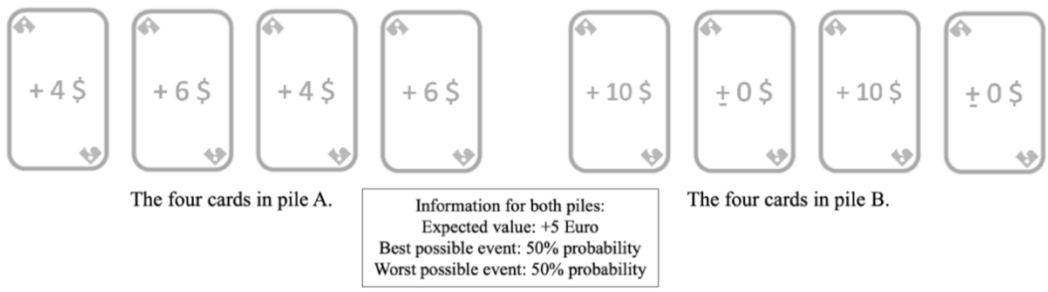

Figure 3. Survey Card piles

This method of measuring risk preference is simple and clear in its division into the three risk categories. There are many other approaches to measuring risk preference, but these procedures are complicated and so sophisticated that individuals respond spontaneously and unconsciously without any real reason or thought. Usually, they need further support of the interviewer to explain the desired task to make sure it is correctly understood when you consider that there a big table of numbers which describe for example numerous lotteries including standard deviation, expected value of the payoff, payoff of the coincidental event etc. (Eckel and Grossman, 2008; Holt and Laury, 2002). In an online survey, this could lead to the questionnaire being abandoned or to a high level of confusion, which could lead to a different answer being chosen when understanding the question or the lottery, which could ultimately lead to invalid data.

In this case further information or real-life support is unnecessary because of the familiarity of card games and the easy way of conceivability.
Moreover, the other approaches cannot clearly assign the responses to the three categories of risk preferences as, for example, in the method of Crosetto and Filippin, 2013. In the approach, participants are confronted with a decision-making scenario: Of a total of 100 boxes including one of them contains a "bomb" the participants have to decide how many of them they would collect whereas they receive 0. Euro per collected box. After they decided how many boxes they would like to collect (static version) a number between 1 and 100 is drawn from an urn. If the number is smaller or the same the "bomb" will explode, and the money of the subject is gone. If the randomly drawn number exceeds the predetermined number of collected boxes, the participant will receive a payout.

From the expected return viewpoint, it is constantly rising from the first to the 50^{th} box where the risk also increases. Individuals which choose 0 to 50 boxes are interpreted as risk averse. From the 50^{th} to the 75^{th} boxes the expected return is decreasing, and the risk is rising. Risk seeking individuals will choose this range. The highest expected return is when one is choosing exact 50 boxes. Therefore, a risk neutral one would choose exact 50 boxes. Every decision to pick more than 75 boxes is inefficient, the expected return is decreasing, and the risk is extremely high. Although this is a logical way of interpretating the outcome of the experiment it also has some weaknesses. Someone who collects exactly 50 boxes could also be slightly risk loving or risk avoiding. The range of the category risk neutral is very small in contrast to the risk loving or seeking. Moreover, the subjects have to do a considerable amount of calculation to know that the highest possibility of the expected return can be found at exactly 50 boxes. Another problem is the way how the ones who collected more than 75 boxes should be characterized. These number of boxes is insufficient which means that the participant is unaware of the shape of possibilities. It could also be the case that the one is extreme risk loving and calls the bluff and just the one who picked 100 boxes had not understood the task correctly (Filiz et al., 2020). However, this approach there are just three possible ways to answer to assign the individuals without a doubt to one of the three defined risk preference characters.

3.1.2. Risk perception

A lottery was presented to the participants to measure risk perception. They have the possibility to invest their initial wealth of 10.000 Dollar in stocks. The subject´s wealth can increase to 12000 dollars or decrease to 9 000 dollars both with the probability of 50%. The participants were asked to reflect their risk assessment of the lottery in a Likert-scale from 0-10. Zero means that the participant doesn't perceive any risk and 10 that the participant perceives a very high risk. Using a Likert-scale, measurement of personal setting, to evaluate the risk perception of the individuals is a common procedure in the literature (Pennings and Wansink, 2004; Weber and Hsee, 1998). The measure procedure of the risk perception is adapted by Nosic and Weber (2010).

The same question is asked in part three of the questionnaire with the difference that the subject do not have a lottery with possible stock investment but with a cryptocurrency investment. Since this is a cryptocurrency, the possible payout could be 15000 Dollars or 5000 Dollars again with the probability of occurrence of 50%. Cryptocurrencies are usually on average more volatile than stocks, so here the average volatility of last year was taken and shown here in the lottery, so that it comes as close as possible to the real cryptocurrencies. As in the previous task, the individuals were again able to mark their risk perception on a Likert-scale of 0-10.

Both questionnaire parts have a short information box with a description of a stock and cryptocurrency to make sure every individual, also the ones who are not usually investing their money and therefore not that much familiar with these terms, could set in picture.

In the literature, there are many other ways to measure the risk preference of subjects, such as Huber et al. (2019). There, participants were shown ten different price paths from a one-year horizon in the form of histograms with different skews in a randomized sequence. Subsequently, however, the subjects were again asked to rate their risk perception using a Likert-scale. This method of measuring risk perception takes a very long time and has the risk that the participant does not pay attention to the task or does not understand parts of the histograms. Since we are trying to measure all three risk attitudes of an investor in the asset market and the crypto market in this case, the questionnaire would be far too long and only a few participants would have filled it out to the end. Therefore, a short version was preferred here. Moreover, the problem arises in the cryptocurrency space. How could one have mapped the histograms in such a way that they depict the average cryptocurrencies reliably if all possibilities of the slopes are to be represented in the histograms. In addition, it is known that the price path can cause many distortions when presented to investors. The number of lows and highs, as well as the number of ups and downs that are inevitable with stocks, the order of the up and downs, are just a few examples of how the investor might be influenced (Grosshans and Zeisberger, 2018). In this structure of the study, there would be too many factors that could contaminate the result, making it impossible to make a specific derivation and comparison.

3.1.3. Risk behavior

To measure the individuals' risk behavior, they were asked how they would invest the \$10.00. The details are the same as in the task of risk perception with the only addition that they also have the option to invest the money in a risk-free alternative with a safe return of 3%. The participants can choose in a table from 0 to 100 how much of it they would invest in the stocks. 0 indicate that the entire 10.000 dollars will be invested in the risk-free investment with the safe 3% return, 100 means that 100% of the initial wealth will be invested in the said stock. In any way, the \$10.00 will be invested in full. There is no possibility to invest only a part of the assets. For example, if 30% is given by the participants, it means that 30% or 3.00 dollars will be invested in the stock and 70% or 7.00 in the risk-free alternative. Wärneryd (1996) proofed that hypothetical risky choice questions are meaningful answered by respondents so that the elicited risk responses are connected with the actual real life.

The same question was also be asked in the fourth cryptocurrency framed part so that a comparison between the two domains can be made.

In addition to the aforementioned question, the respondents were also asked to assess their willingness to take risks when making financial choices in both the traditional asset market and the cryptocurrency market. They had the opportunity to mark their answers on a five-point Likert-scale from 0 (Very low willingness) to 5 (Very high willingness).

CHAPTER 4: EMPIRICAL RESEARCH

4.1.Descriptive Statistics

This part of the thesis illustrates the descriptive statistics of the demographic factors of the survey.

The figure 4 presents the age distribution of participants in the study. Participants were grouped into six distinct age categories for analysis, ranging from “under 18” to “above 55” as in the x-axis represented. The y-axis shows the total number of participants.

An examination of the data reveals that there were no participants below the age of 18 or above of 55 in this study. The most represented age group is 18-25 with a total of 205 individuals falling within this range. Following the age group of 26-35 with 26 participants, signifying a relatively smaller representation.

In contrast, the older age groups demonstrate even lower numbers of participants. The 36-45 age category comprises only 10 individuals, while the 46-55 age group consists of a mere 5 participants.

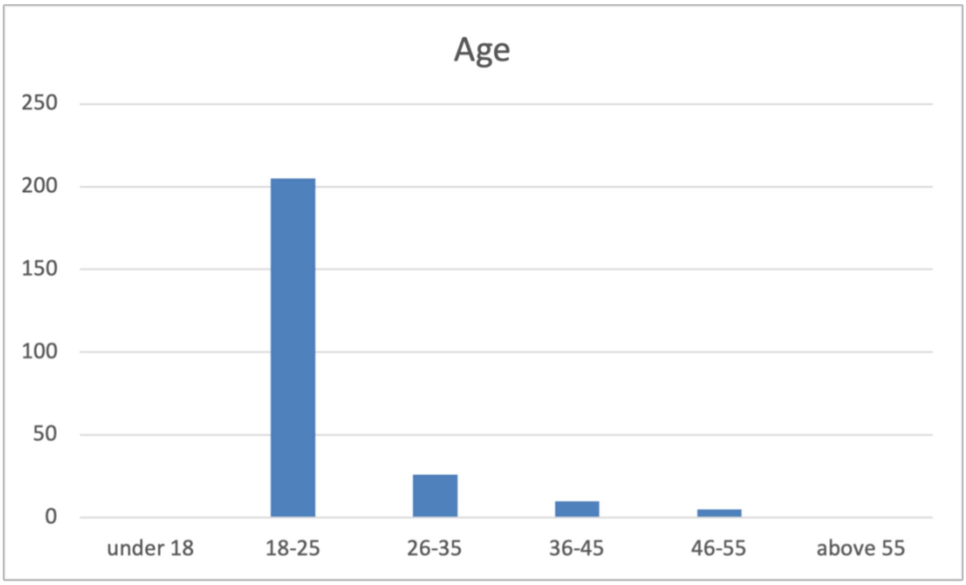

Figure 4. Age Distribution of Participants

The figure 5 presents the gender distribution of participants in the study, shedding light on the representation of different genders within the survey. Participants were categorized into three distinct gender groups: “Male”, “Female” and “Other”. The x-axis accords to a specific gender category, while the y-axis indicates the number of participants falling within that gender.

The data reveals that the majority of participants identify as male with a total of 138 individuals within this category. Following this the female category comprises 106 participants, representing a substantial proportion of the sample.

In contrast, the “Other” gender category is relatively underrepresented, consisting of only two participants.

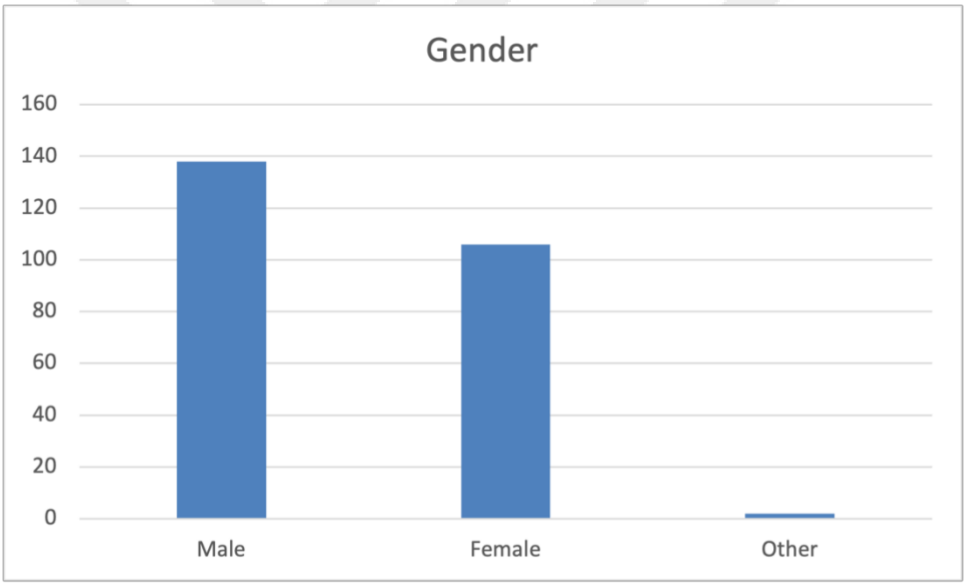

Figure 5. Gender Distribution of Participants

The figure 6 provides an overview of the salary distribution of participants in the study, offering valuable insights into the income levels within the sample. The salaries are categorized into different ranges, both in Turkish Lira (TL) and Euro (€). The x-axis corresponds to a specific salary category, while the y-axis indicates the number of participants falling within that particular income range.

Upon analysis of the data, it becomes apparent that the majority of participants fall into the “Less than 420 TL or less than 1,550 €” salary category, with a total of 132 individuals. Following this, the "4,251-6,000 TL; 1,551-3,000€" category comprises 47 participants, indicating a notable representation.

The "6,001-10,000 TL; 3001-5000 €" salary range encompasses 26 participants, suggesting a relatively smaller proportion within this income bracket. Similarly, the "10,001-15,000 TL; 5,001-7,000 €" category contains 15 participants, while the "above 15,001 TL or 7,001 €" group consists of 26 participants.

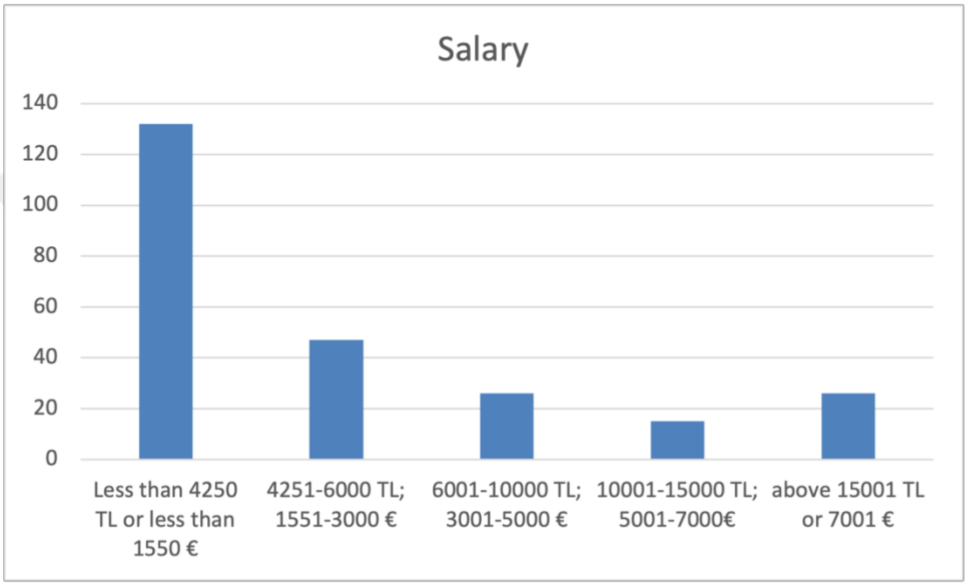

Figure 6. Salary Distribution of Participants

The table 7 presents data on the presence of children among the study participants, offering insights into the proportion of individuals with and without children. The data is categorized into two distinct groups: "Yes" for participants who have a child and "No" for participants without children. The x-axis represents the specific categories, while the y-axis indicated the number of participants falling within each group.

Upon the analyzing the data, it is evident that a minority of participants have children, as indicated by the "Yes" category, which comprises 17 individuals. In contrast, the majority of participants do not have children, represented by the "No" category, which encompasses 229 individuals.

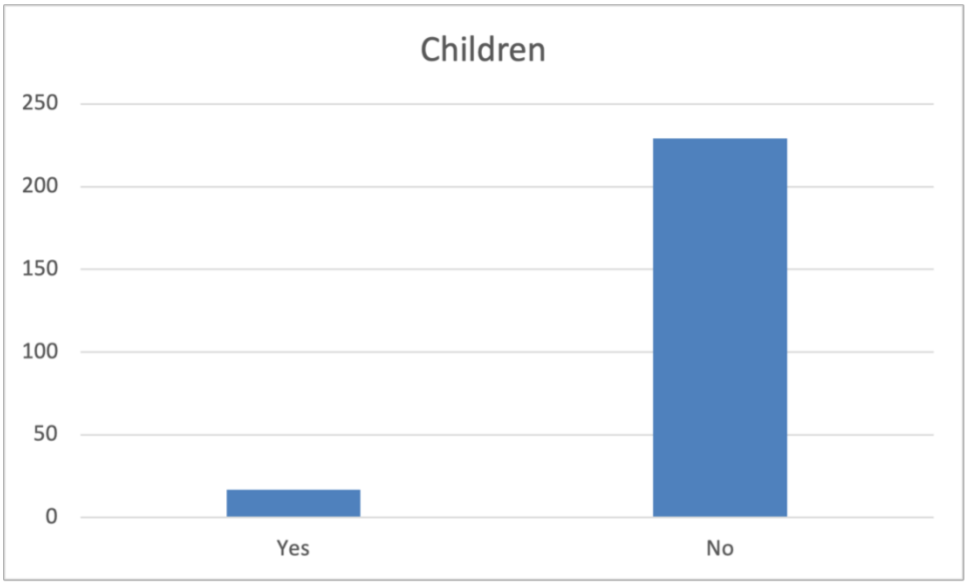

Figure 7. Presence of Children among Participants

The table 8 presents the distribution of relationship statuses among the study participants, offering valuable insights into the martial and relationship dynamics within the survey. Participants´ relationship statuses are categorized into five distinct groups: “Single”, “Married”, “Relationship”, “Widowed” an “Divorced”. The x-axis represents the categories of the relationship status, while the y-axis indicated the number of participants falling within each category.

An analysis of the data reveals that the largest proportion of participants identified as “Single”, with a total of 145 individuals falling within this category. In contrast, the “Married” category contains 18 participants, indicating a smaller representation of married individuals within the sample.

The “Relationship” category encompasses 83 participants, signifying a notable presence of individuals in committed relationships. On the other hand, there were no participants identified as “Widowed” or “Divorced” in the study.

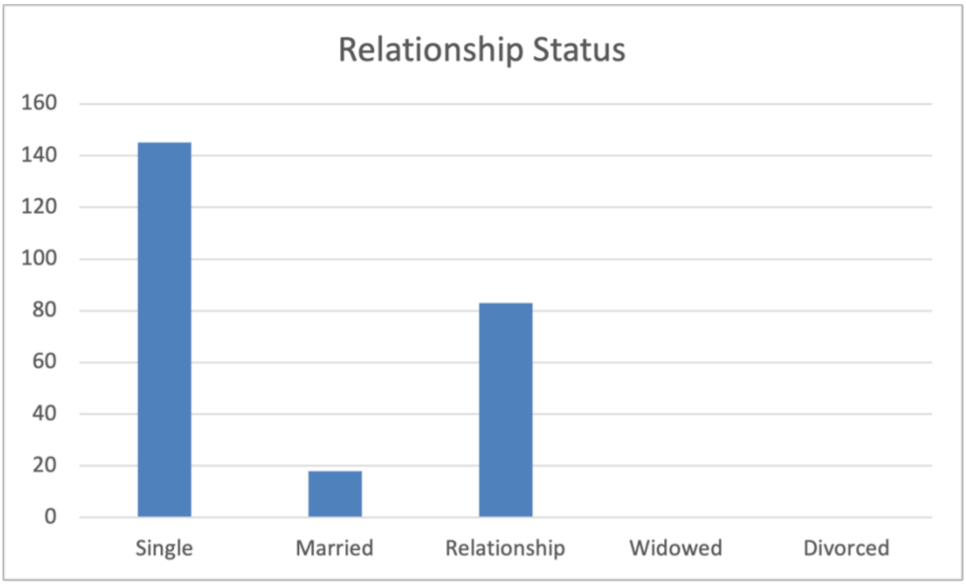

Figure 8. Relationship Status Distribution of Participants

The table 9 presents the distribution of employee statuses among the study participants, offering valuable insights into their occupational profiles. Participants' employee statuses are categorized into six distinct groups: "Student," "Employed," "Unemployed," "Self-employed," "Retired," and "Other." The x-axis corresponds to a specific employee status, while the y-axis indicates the number of participants falling within each category.

An analysis of the data reveals that the majority of participants are "Students," with a total of 173 individuals falling within this category. The "Employed" category comprises 56 participants, indicating a substantial representation of individuals currently working.

Among the participants, there are two individuals who identify as "Unemployed" and 13 individuals who are "Self-employed." However, there were no participants who reported being "Retired."

Additionally, there are two participants categorized as "Other," signifying a small group with unique employment circumstances that do not fit within the other predefined categories.

Figure 9. Employee Status Distribution among Participants

The table 10 presents the distribution of asset ownership among the study participants, providing insights into their possession of various assets. Participants' asset ownership is categorized into two distinct groups: "Yes" for those who own assets and "No" for those who do not. The x-axis corresponds to a specific asset ownership category, while the y-axis indicated the number of participants falling within each group.

An examination of the data reveals that a majority of participants, represented by 162 individuals, reported owning assets ("Yes"). On the other hand, 84 participants indicated that they do not own any assets ("No").

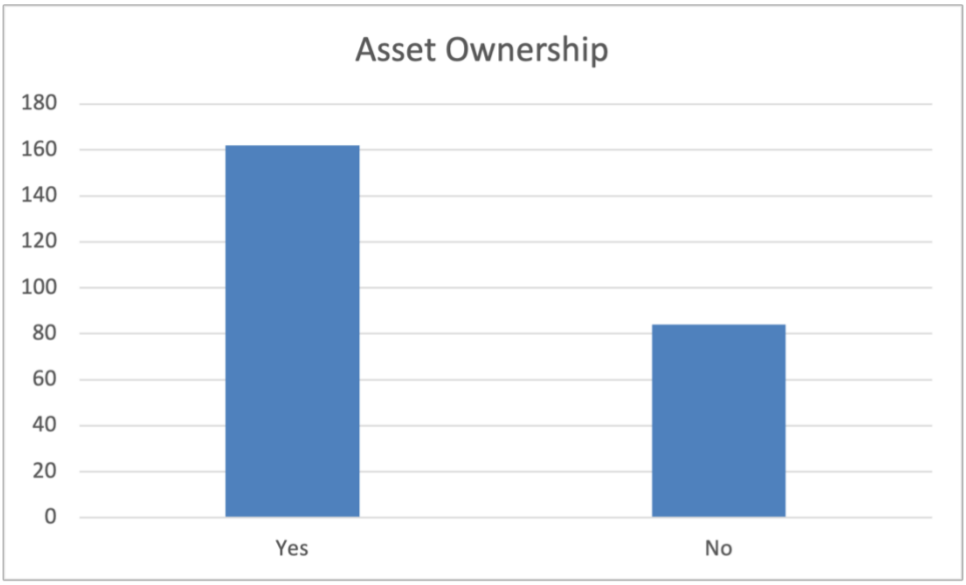

Figure 10. Asset Ownership Distribution among Participants

The table 11 presents the distribution of the number of assets held by study participants, offering insights into the variety of assets owned. Participants' asset holding numbers are categorized into four distinct groups: "0," "1-5," "6-10," and "More than 10." The x-axis corresponds to a specific asset holding number category, while the y-axis indicated the number of participants falling within each group.

Upon analyzing the data, it becomes evident that a significant number of participants, represented by 90 individuals, reported not owning any assets ("0"). The "1-5" asset holding category includes 111 participants, suggesting a substantial portion of the sample owns a relatively small number of assets.

Additionally, the "6-10" asset holding category encompasses 20 participants, indicating a smaller representation of individuals who own a moderate number of assets. Furthermore, 25 participants reported owning "More than 10" assets, signifying a smaller yet notable group with a considerable number of assets.

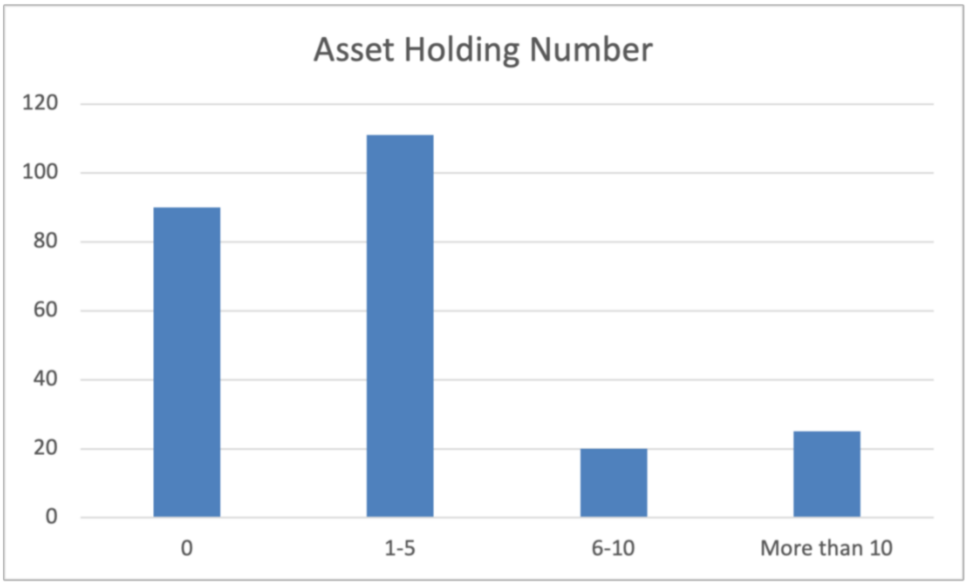

Figure 11. Asset Holding Number Histogram

The table 10 presents the distribution of cryptocurrency ownership among the study participants, providing insights into their involvement in the world of digital currencies. Participants' cryptocurrency ownership is categorized into two distinct groups: "Yes" for those who own cryptocurrencies and "No" for those who do not. The x-axis corresponds to a specific cryptocurrency ownership category, while the y-axis indicated the number of participants falling within each group.

An examination of the data reveals that a portion of participants, represented by 112 individuals, reported owning cryptocurrencies ("Yes"). On the other hand, 134 participants indicated that they do not own any cryptocurrencies ("No").

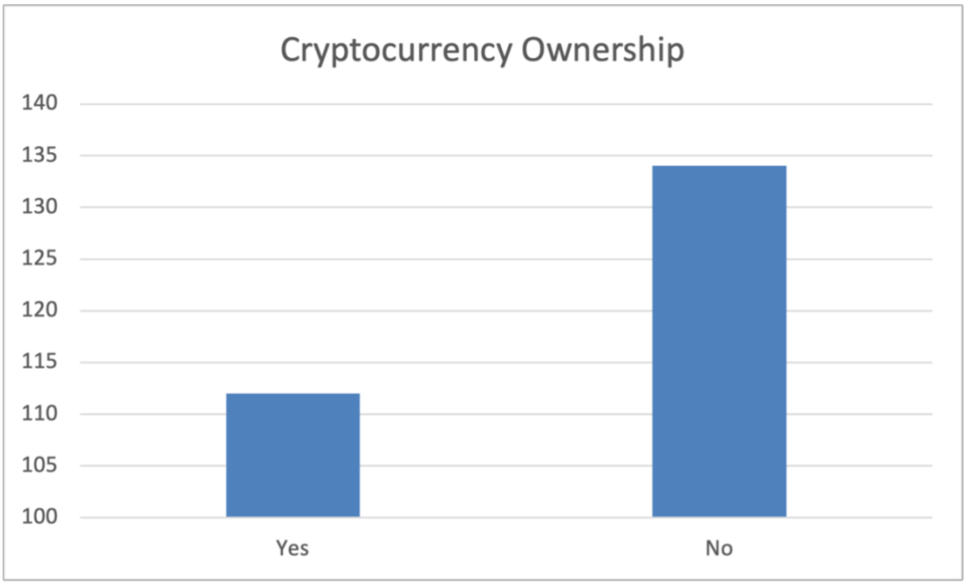

Figure 12. Cryptocurrency Onwership Distribution among Participants

The table 13 presents the distribution of the number of cryptocurrencies held by study participants, offering insights into the extent of their involvement in the cryptocurrency market. Participants' cryptocurrency holding numbers are categorized into four distinct groups: "0," "1-5," "6-10," and "More than 10." The x-axis corresponds to a specific cryptocurrency holding number category, while the y-axis indicated the number of participants falling within each group.

An analysis of the data shows that a majority of participants, represented by 134 individuals, reported not holding any cryptocurrencies ("0"). The "1-5" cryptocurrency holding category includes 77 participants, indicating a substantial portion of the sample owns a relatively small number of cryptocurrencies.

Additionally, the "6-10" cryptocurrency holding category encompasses 16 participants, signifying a smaller representation of individuals who hold a moderate number of cryptocurrencies. Furthermore, 19 participants reported holding "More than 10" cryptocurrencies, suggesting a smaller yet notable group of individuals with a considerable number of digital assets.

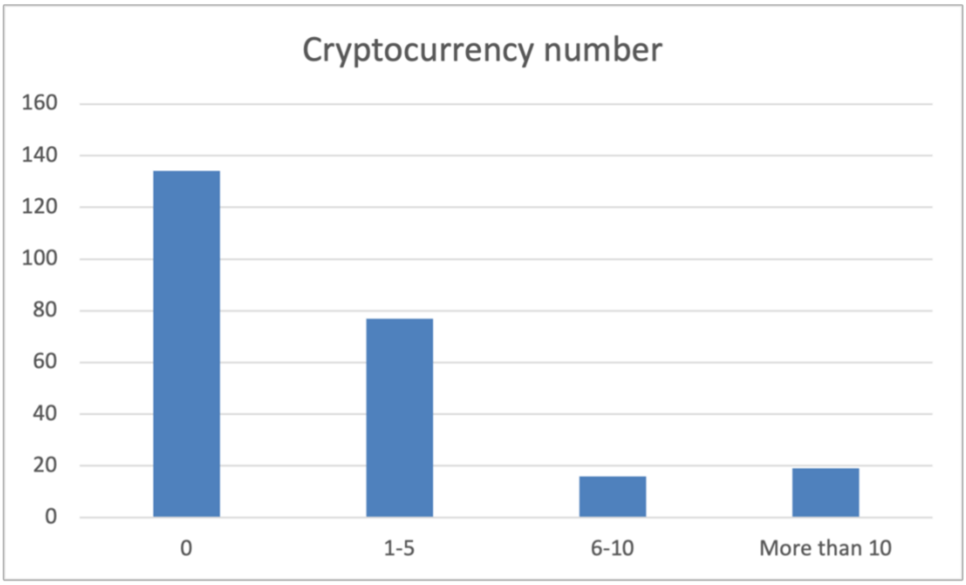

Figure 13. Cryptocurrency Holding Number Distribution among Participants

The table 14 presents the distribution of education levels among the study participants, providing valuable insights into their educational backgrounds. Participants' education levels are categorized into seven distinct groups: "Less than a high school diploma," "High school degree or equivalent," "Apprenticeship," "Bachelor's degree," "Master's degree," "Doctorate," and "Other". The x-axis corresponds to a specific education level category, while the y-axis indicated the number of participants falling within each group.

Upon analyzing the data, it becomes evident that the majority of participants, represented by 124 individuals, possess a "High school degree or equivalent." The "Bachelor's degree" category includes 87 participants, suggesting a substantial portion of the sample has completed undergraduate studies.

Moreover, there are 18 participants with a "Master's degree," and three participants hold a "Doctorate," indicating a smaller but notable group of individuals with advanced academic qualifications.

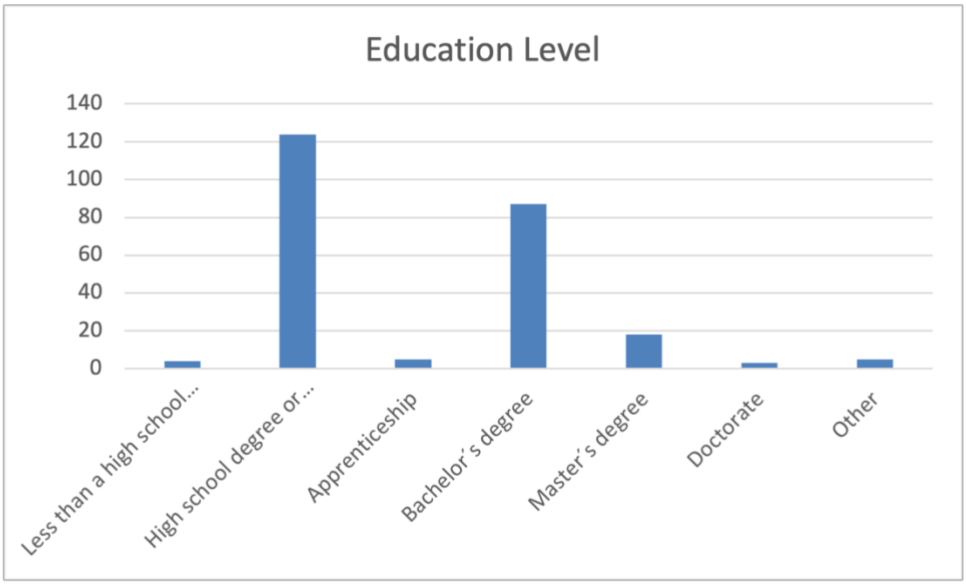

Figure 14. Education Level Distribution among Participants

4.2.Analysis

This part of the thesis deals with the analysis of the gathered information through the survey. With this analysis the previously formulated hypotheses can be rejected or confirmed.

H1: There is a statistically significant relationship between demographic factors and personal risk preference.

Table 1. Contingency Coefficient Analysis

Nominal by Nominal	Contingency Coefficient Value	Approximate Significance
Risk preference * Education	.189	.543
Risk preference * Gender	.133	.353
Risk preference * Age	.151	.457
Risk preference * Children	.134	.097
Risk preference * Relationship Status	.094	.698
Risk preference * Asset Owner	.172	.023*
Risk preference * Cryptocurrency Owner	.097	.308
Risk preference * Salary	.181	.402

The table 1 represents the results of the analysis to examine the relationship between the risk preference and the various demographic factors. For the analysis the V contingency coefficient, a statistical measure used to evaluate the strength of association between two nominal scaled variables based on the chi^2 test, is used.

In terms of risk preference and education a contingency coefficient value of 0.189 indicates a moderate positive association between the two variables. The contingency coefficient can reach values between 0 (no correlation) and close to 1 (strong correlation). However, the significant value must also be considered. It should be below 0.05 for the rejection of the null hypothesis (= no correlation). The approximate significance level of 0.543 is above 0.05, leading to the rejection of H_1 and implying that there is no significant correlation between risk preference and education level.

The situation is similar for the other demographic factors. The significance value of relationship status, having children, salary, gender, age and cryptocurrency ownership is above 0.05, which indicates that these demographic factors do not have a significant relationship with risk preference. This implies that the variations in risk preference cannot be attributed to these specific demographic variables.

In contrast to the other demographic factors, the factor of asset ownership shows a significance value of 0.0023, which indicates that the association is statistically significant. The contingency coefficient of 0.172 suggest a moderate positive relationship. Therefore, the there is evidence to suggest that being an asset owner is related to risk preference.

The Hypothesis (H1) cannot be rejected. There is one demographic factor which is significantly correlated with the risk preference.

H2: There is a statistically significant relationship between demographic factors and the risk perception in the traditional asset market.

Table 2. Statistics of the One-Way ANOVA Test for Demographic Factors on Risk perception in the traditional Asset market

Demographic Factors	Sum of Squares	df	Mean Square	F	Sig.
Education	27.248	5	5.450	1.142	0.339
Employee Status	50.623	4	12.656	2.711	0.031*
Relationship Status	36.318	2	18.159	3.872	0.022*
Salary	29.035	4	7.459	1.525	0.195
Sex	11.425	2	5.712	1.192	0.305
Age	24.341	3	8.114	1.705	0.167

Table 2 presents the results of the ANOVA test, analyzing the association between demographic factors and the risk perception in the traditional asset market. ANOVA test evaluates whether there is a statistically significant correlation between the demographic factors and the risk perception in the traditional asset market. The significance value of the test is shown in the right column, where values less than 0.05. indicate a significant correlation between the demographic factor and the risk perception. Based on the results, education, salary, sex and age have values greater than 0.05, suggesting that there is no significant correlation between demographic factors and risk perception in the traditional asset market

The null hypothesis (H_0) of the ANOVA test posits that there is no significant relationship between the two variables. Therefore, we can accept H_0 for the aforementioned demographic factors and reject the alternative hypothesis (H_1), which assumes a significant correlation between these factors.

The results of the ANOVA Test provided in the table 2 reveals that there is a statistically significant relationship between the risk perception and the variables of relationship status, employee status and having children. This inference is drawn from the significance value, which exceeds the predetermined threshold of 0.05 for all three demographic factors. Therefore, the alternative hypothesis (H_1) is accepted, while the null hypothesis (H_0) is rejected.

The questionnaire included a binary item concerning whether the participant has children or not., thereby precluding the use of ANOVA testing. Instead, a t-test is applied, which is displayed in Table 15 alongside the Levene´s Test for equality. The two-tailed p-value is calculated as 0.034, which falls below 0.05 threshold for statistical significance. This shows that the demographic factor having a children has a discernible impact on risk perception in the traditional asset market. The validity of the t-test is confirmed by the fact that the significance value for Levene´s test exceeds 0.05.

Table 3. Levene´s Test for Equality of Variances and t-test

		F	Sig.	df	Two- Sided p
Risk Perception Asset Market	Equal variances assumed	.459	.499	244	.034

Table 4. Test of Homogeneity of Variances

	Demographic factors		Levene Statistic	df1	df2	Sig.
Risk Perception Asset Market	Employee Status	Based on Median	.056	4	241	.994
	Relationship Status	Based on Median	.347	2	243	.707
	Education	Based on Median	.123	5	235	.987
	Age	Based on Median	.218	3	242	.884
	Salary	Based on Median	1.234	4	241	.297
	Sex	Based on Median	.725	2	243	.485

In order to perform a valid ANOVA test, it is necessary for the variances to be homogeneous. Table 4 displays the test of homogeneity of the variances for all the demographic factors except for the one regarding the children, as this variable meets the requirements of the t-test. The results of the homogeneity test, also designated as the F-test or Levene´s test, of the variances in Table 3, report significant values above the p-value of 0.05 for all demographic factors. This indicates that the homogeneity of the variances is confirmed and the assumption, sharing the same level of variance within the particular groups, is not violated. Hence, presumably the requirements for conducting an ANOVA test are presumed to be satisfied. Since all F-tests exceed the p-value, an ad hoc test can be performed for the three significant demographic factors that display significant differences It is unnecessary to carry out further testing for demographic factors as they are not significant.

Table 5. Tukey-Kramer ad-hoc test

(I) Employee Status	(J) Employee Status	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Self employed	Student	-1.076	.621	.417	-2.78	.63
	Employed	-.521	.665	.935	-2.35	1.31
	Unemployed	-4.538*	1.641	.048	-9.05	-.03
	Other	-.538	1.641	.997	-5.05	3.97

Table 5 presents the outcomes of an ad hoc test performed on the demographic factor of employee status. The Tukey-Kramer test is employed as the selected ad-hoc test, which compares all possible combination of groups and identifies the differences between them. Participants, as expected, do not have equal number of groups distributed on each category of employee status, therefore, the Tukey-Kramer post-hoc test is utilized. It is used as a follow up measure to determine which pairs contributed the overall significant difference in the comparison of the means that was observed in the ANOVA test.

In the Table 4 is the "Mean Difference (I-J)" column displayed, which shows the difference between the self-employed and unemployed groups. The value of -4.538 implies, on average, that the self-employed group perceive risk 4.538 points less than the unemployed group. The study adopts a significance level of 5%, which implies that a p-value of less than 0.05 is significant. In this case, the p-value of 0.048 for the self-employed and unemployed groups is significant.

Table 6. Tukey-Kramer ad-hoc test

(I) Relationship Status	(J) Relationship Status	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Single	Married	1.447*	.541	.022	.17	2.72
	Relationship	.385	.298	.401	-.32	1.09

Table 6 presents the results of the same test conducted in Table 16, with the only difference being the demographic factor tested, which is relationship status. A significance difference is observed between the single and married groups, with a significance value is 0.022, which is clearly lower than 0.05. The mean difference (I-J) of 1.447 suggests that the group of the single participant perceive the risk in the traditional asset market 1.447 points higher than the group of married participants.

Table 7. Effect Size

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Employee Status	Eta-squared	.043	.000	.089
Relationship Status	Eta-squared	.031	.000	.080
Children	Cohen´s d	.535	1.033	.043

Table 7 presents the effect sizes of the significant demographic factors. The effect sizes a measure of the strength or magnitude of the relationship between variables or differences among the groups. For the demographic factor of having children, a t-test is conducted, which allows the use the Cohen´s d value as an effect size. The value of 0.535 in the first third column is considered to be a medium effect size.

Unlike the demographic factor of children, the employee status and relationship status, the Eta-squared is preferred as an effect size. For the employee status, the Eta- squared value is 0.043 (4%), indicating that 4.3% of the variance in risk perception is explained by the employee status. Similarly, the Eta-squared value of the relationship status demographic factor is 0.031, meaning that the relationship status explains 3.1% of the variance in risk perception. These values provide a quantified representation of the percentage of variance that can be attributed to each demographic factor.

The Hypothesis (H2) can be accepted. The results suggest that some demographic factors are significantly correlated with the risk perception in the traditional asset market.

H3: There is a statistically significant relationship between demographic factors and the risk perception in the cryptocurrency market.

Table 8. One-Way ANOVA Test

Demographic Factors	Sum of Squares	df	Mean Square	F	Sig.
Education	11.534	5	2.307	0.486	0.787
Employee Status	49.915	4	12.479	2.745	0.029*
Relationship Status	4.452	2	2.226	0.474	0.623
Salary	16.456	4	4.114	0.878	0.478
Sex	15.676	2	7.838	1.686	0.187
Age	17.676	3	5.854	1.256	0.290
Asset number	5.864	3	1.955	.415	.742
Cryptocurrency number	15.469	3	5.156	1.104	.348

Table 8 shows the outcomes of the One-Way analysis of variance (ANOVA) test conducted to assess the association between demographic factors (education, employee status, relationship status, salary, gender, age, asset number, cryptocurrency number), and the risk perception in the cryptocurrency market. The table provides details on the tested demographic factors, including their sum of squares, degrees of freedom, mean square, F-value, and significance level.

The findings indicate that among the demographic factors examined, only employee status significantly influences that has a risk perception in the cryptocurrency market, as evidenced by the significance value of 0.029 with the F-value of 2.745. In this case, significance is indicated by the p-value being smaller than 0.05 while the F-value suggests that the variation in means across different levels of the employee status (self-employed, unemployed, employed, student, other) is statistically significant compared to the variability within the groups.

On the other hand, the remaining demographic factors do not exhibit a statistically significant impact on risk perception in the cryptocurrency market, as their significance levels exceed 0,05. Consequently, the null hypothesis, stating that there is no substantial correlation between the enumerated demographic factors and risk perception in the cryptocurrency market, is accepted.

Table 9. Test of Homogeneity

	Demographic factors	Levene Statistic	df1	df2	Sig.
Risk Perception Asset Market	Education Level	.123	5	235	.987
	Employee Status	.056	4	241	.994
	Relationship	.347	2	243	.707
	Salary	1.234	4	241	.297
	Sex	.725	2	243	.485
	Age	.218	3	242	.884
	Asset number	2.420	3	242	.067
	Cryptocurrency number	2.236	3	242	.085

Table 9 displays the results of the test of homogeneity, which is used to check if the variances of the groups being compared in the ANOVA test are equal or not. The table consists of six rows, each row corresponding to a demographic factor, and four columns: Levene Statistic, degrees of freedom and significance value.

For each demographic factor, the table shows the results of the Levene´s test based on the median. The results suggest that for all demographic factors, there is no statistically significant variances between the groups being compared, as being greater than 0.05. Overall, these results prove that the assumption of homogeneity of variances for the ANOVA test is met for all demographic factors.

Table 10. Post-hoc Test

(I) Employee Status	(J) Employee Status	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Employed	Student	.863*	.328	.009	.22	1.51
	Unemlpoyed	3.446*	1.534	.026	.42	6.47
	Self employed	1.062	.656	.107	-.23	2.35
	Other	-.054	1.534	.972	-3.08	2.97

Table 11. Anova Effect Sizes

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Risk Peception Crypto	Eta-squared	.044	.000	.090

Table 10 presents the outcomes of an ad hoc test conducted on the demographic factor of employee status. The test aims to explore the relationship of risk perception among participants based on their employee status.

The findings indicate that employed participants have a significantly higher mean difference compared to the groups of students and unemployed. The significance value for students and unemployed individuals are 0.009 and 0.026, respectively, which are both below 0.05. This suggests that the relationship between employee status and risk perception is statistically significant in respect to the mentioned groups.

Specifically, the results suggest that employed individuals have a higher degree of risk- seeking behavior compared to students and unemployed individuals.

Furthermore, the effect size represented in the Table 11, as given by the eta square point estimate of 0.044, suggests that the factor of employee status describes approximately 4.4% of the variability in risk perception. This effect size is relatively small, but still provides some insight of the relationship of employee status on risk perception.

Table 12. Levene´s Test for Equality of Variances and t-test

		F	Sig.	t	df	Significance	
						One-Sided p	Two-Sided p
Asset Owner	Equal variances assumed	.411	.522	.529	244	.299	.598
Children	Equal variances assumed	2.975	.086	-.680	244	.249	.497
Crypto Owner	No Equal variances assumed	3.570	.060	1.623	244	.053	.106

Due to the binary nature of the demographic factor concerning children, the use of ANOVA test is not applicable. Instead, a t-test is performed to examine the potential association between the demographic factor and risk perception within the cryptocurrency market. Table 12 provides the results of the Levene´s test for equality of variances and t-test. The table includes the F-value, significance level (Sig.), degrees of freedom (df), and two-sided p-value.

Regarding the comparison between the two groups, namely individuals with and without children, no significant distinction is observed in terms of variances. This is indicated by the F-value of 2.975, suggesting that there is no substantial variation, along with a significance level (Sig.) of 0.086, which denotes a lack of statistical significance. Consequently, the assumption of homogeneity of variances across the groups is satisfied, thereby validating the reliability of the t-test outcomes.

Furthermore, the two-sided p-value of 0.497 reveals that there is no statistically significant distinction in risk perception within the cryptocurrency market between the aforementioned groups, based on the demographic factor of children, at the specified alpha level of 0.05. This means that the risk perception in the cryptocurrency market remains consistent irrespective of whether individuals have children or not.

Similar results have the factors asset number and crypto number also. No significant distinction is observed in terms of variances. The two-sided p-value of 0.589 for the factor the holding number of assets and 0.106 for the holding number of cryptocurrencies indicates no statistically significant distinction in risk perception within the cryptocurrency market between the mentioned groups. These p-values of the groups were compared to the alpha level of 0.05. These findings suggest that the holding number of assets and cryptocurrencies as the factor of children does not affect the risk perception within the cryptocurrency market.

Given the results of the analysis the hypothesis (H3) can be accepted. There is a statistically significant relationship between demographic factors and the risk perception in the cryptocurrency market.

H4: There is a statistically significant relationship between demographic factors and the risk behavior in the traditional asset market.

Table 13. One-Way ANOVA Test

Demographic Factors	Sum of Squares	df	Mean Square	F	Sig.
Education	4,143.159	5	828.632	1.429	.215
Employee Status	2,562.336	4	640.584	1.11	.352
Relationship Status	947.326	2	473.663	.818	.442
Salary	5,195.336	4	1,298.834	2.114	.147
Sex	8,919.228	2	4,459.614	8.167	<.001
Age	1,846.73	3	615.524	1.066	.364
Asset Number	10887.68	3	3629.189	6.719	<.001
Crypto. Number	10410.78	3	3470.326	6.401	<.001

Table 13 provides a comprehensive overview of the outcomes obtained from a One-Way ANOVA test conducted to investigate the impact of various demographic factors on risk behavior within the traditional asset market. In total, nine distinct factors are considered, including education, employment status, relationship status, salary, gender, age, ownership and number of holding assets, as well as ownership and number of holding cryptocurrencies.

The presented table displays essential statistical measures such as Sum of Square, degrees of freedom, Mean Square, F-value, and significance level for each respective factor. The findings show that the holding number of assets, number of cryptocurrencies, and gender exhibit statistically significant effects on the respective variable of the risk behavior in the asset market. Specifically, the number of holding cryptocurrencies ($F=6.401$, $p<.001$), the number of holding assets ($F=6.719$, $p<.001$) and gender ($F=8.167$, $p<.001$) emerge as significant predictors of the risk behavior because the p-values are considerably smaller than the specified alpha level of 0.05.

On the other hand, the analysis reveals that education, employment status, relationship status, salary, and age do not exert a significant influence on risk behavior within the traditional asset market. This implies that these factors may not serve as important predictors for the dependent variable under examination.

Since the survey questions regarding asset ownership, crypto ownership and having children yield only two possible responses, a t-test is conducted to assess the relationship between these factors and risk behavior. The corresponding outcomes are presented in Table 14.

Table 14. Levene´s Test for Equality of Variances and t-test

		F	Sig.	t	df	Significance: One-Sided p	Significance: Two-Sided p	Mean Difference	95% Confidence Interval of the Difference: Lower	95% Confidence Interval of the Difference: Upper
Asset Owner	Equal variances assumed	.988	.321	3.524	244	<.001	<.001	11.133	4.910	17.357
Children	Equal variances assumed	.305	.581	1.454	244	.074	.147	8.767	-3.110	20.644
Crypto Owner	No Equal variances assumed	4.862	.028	3.079	243.750	.001	.002	9.150	3.296	15.003

The results pertaining to asset ownership indicate a statistically significant two-sided p-value (<0.001). The group of individuals who own assets exhibits a significantly higher risk behavior score compared to the non-Asset owner group, with a mean difference of 11.133.

Regarding the factor of having children, there is no significant discrepancy in risk behavior score between individuals with children and those without, as indicated by a two-sided p-value of 0.147. In the case of crypto ownership, a significant difference is observed in risk behavior score, with a mean difference of 9.150 and a two-sided p-value of 0.002. However, the assumption of equal variances is violated by the significance level in the Levene´s test of 0.028.

Table 15. Test of Homogeneity

	Demographic factors	Levene Statistic	df1	df2	Sig.
Risk Behavior Asset Market	Education Level	1.312	5	235	.259
	Employee Status	.672	4	241	.612
	Relationship	2.256	2	243	.107
	Salary	1,625	4	241	.169
	Sex	.749	2	243	.474
	Age	.486	3	242	.693
	Asset Number	1.308	3	242	.376
	Crypto. Number	2.072	3	242	.105

The results of the test examining the homogeneity, based on median, of the listed demographic factors are presented in Table 15. of. This table includes the Levene statistic, degrees of freedom (df1 and df2), and significance level (Sig.) associated with each factor. The significance level, represented by the p-value, plays a crucial role in determining whether the assumption of equal variances holds true. When the p-value exceeds 0.05, it suggests that the groups can be considered homogenous, which is a prerequisite for conducting ANOVA and t-tests. In the current study, all the demographic factors exhibit p-values above 0.05. This implies that the groups formed based on these factors demonstrate homogeneity, thereby validating the appropriateness of applying ANOVA and t-tests.

Table 16. Post hoc test risk behavior asset market and gender

Dependent Variable: Risk Behavior Asset Market

	(I) Sex	(J) Sex	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	male	female	11.260*	3.018	<.001	4.14	18.38
		other	-20.891	16.642	.422	-60.14	18.35

Table 17. Post hoc test risk behavior asset market and holding number of assets

Dependent Variable: Risk Behavior Asset Market

	(I) Asset Number	(J) Asset Number	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	0	1-5	-8.697*	3.297	.044	-17.23	-.17
		5-10	-18.372*	5.745	.008	-33.24	-3.51
		More than 10	-19.002*	5.254	.002	-32.59	-5.41

Table 18. Post hoc test risk behavior asset market and holding number of cryptocurrency

Dependent Variable: Risk Behavior Asset Market

	(I) Crypto number	(J) Crypto number	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Tukey HSD	0	1-5	-8.345	3.330	.061	-16.96	.27
		6-10	-21.959*	6.159	.002	-37.89	-6.03
		More than 10	-14.183	5.708	.065	-28.95	.58

Subsequent to the significant ANOVA test, post hoc analyses are conducted to examine the relationship between risk behavior in the assets market for the demographic factors of gender, holding number of assets, and holding number of cryptocurrencies. The results of these post hoc tests are shown in Tables 16, 17 and 18.

Table 16 indicates a significant disparity in the mean risk behavior score between male and female participants ($p<0.001$). Specifically, male participants exhibit a higher mean risk behavior score of 11.60 points in comparison to their female counterparts. No significant differences in risk behavior score are observed among other gender combinations.

In Table 17, a notable distinction difference in the mean risk behavior score is observed between the group of participants who do not hold any assets and the groups who hold assets. Participants who do not possess any assets display a significantly lower mean risk behavior score when compared to those who hold 1-5 assets (-8.697), 5-10 assets (-18.372) and more than 10 assets (-19.002).

Table 18 presents the post hoc test results for the number of holding assets in the traditional market, indicating significant differences among fewer groups.

Specifically, only participants who do not hold any cryptocurrencies exhibit a significantly lower mean risk behavior score when compared to those who hold 6-10 cryptocurrencies (-21.959).

In summary, the post hoc tests reveal significant differences in mean risk behavior based on gender, number of assets held, and number of cryptocurrencies held. Male participants have higher risk behavior scores compared to female participants. Moreover, participants who do not hold any assets demonstrate lower risk behavior scores compared to other groups with varying investment portfolios. Similarly, participants who do not possess cryptocurrencies exhibit lower risk behavior scores when compared to the group holding 6-10 cryptocurrencies.

Table 19. Effect Size

			95% Confidence Interval	
		Point Estimate	Lower	Upper
Asset Number	Eta-squared	.077	.019	.139
Crypto Number	Eta-squared	.074	.017	.135
Gender	Eta-squared	.063	.014	.125
Asset Owner	Cohen´s d	.474	.206	.738
Crypto Owner	Cohen´s d	.387	.133	.640

The effect sizes of the significant demographic factors are displayed in Table 19, utilizing Eta-squared and Cohen´s d as measures. Higher values of the estimated points indicate a stronger effect. For the factor asset number, the point estimate is 0.077, suggesting that approximately 7.7% of the variance in risk behavior within the assets market can be explained by differences in the number of assets held. Similarly, the factor of number of cryptocurrencies exhibits a comparable eta-square value of 0.074, suggesting that approximately 7.4% of the variability in risk behavior within the assets market can be attributed to variations in the number of cryptocurrencies held. Furthermore, the demographic factor of gender also demonstrates a discernible influence on risk behavior in the asset market, with an estimated effect size of 0.063, which corresponds to approximately 6.3% of the variance.

The last two rows of the table present the effect sizes for the asset owners and cryptocurrency owners, measured by Cohen´s d, yielding values of 0.474 and 0.387. These estimates indicate a small to medium effect size, meaning that individuals who own assets or cryptocurrencies exhibit a modest to moderate difference in their risk behavior in the asset market compared to non-owners.

The hypothesis (H4) can be accepted. There is a statistically significant relationship between demographic factors and the risk behavior in the cryptocurrency market.

H5: There is a statistically significant relationship between demographic factors and the risk behavior in the cryptocurrency market.

Table 20. One-Way ANOVA Test risk behavior cryptocurrency market and demographic factors

Demographic Factors	Sum of Squares	df	Mean Square	F	Sig.
Education	5,420.670	5	1,084.134	1.633	.152
Employee Status	5,173.925	4	1,293.481	1.909	.110
Relationship Status	2,161.116	2	1,080.558	1.579	.208
Salary	1,521.374	4	380.344	0.549	.700
Sex	1,362.951	2	681.476	0.991	.373
Age	3,270.447	3	1,090.149	1.597	.191
Asset Number	4,219,779	3	1,406,593	2,072	,105
Crypto. Number	14,964.51	3	4,988.017	7.862	<.001

Table 20 shows the results of the ANOVA test conducted to examine the relationship between demographic factors and risk behavior in the cryptocurrency market. The table displays the Sum of Square, degrees of freedom, Mean Square, F-value, and significance level for each respective factor.

Upon analysis, it is observed that the demographic factor of the number of holding cryptocurrency exhibits a p-value below 0.05, indicating statistical significance.

Specifically, the factor has p-values less than 0.001. On the other hand, the demographic factors of education, employee status, relationship status, salary, holding number of assets, sex, and age do not demonstrate statistically significant p-values, as all of them exceed 0.05. Consequently, based on these results, it can be concluded that there exists a correlation between these demographic factors and the risk behavior in the cryptocurrency market.

Table 21. T-test and Levene´s Test for Equality of Variances

						Significance			95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Lower	Upper
Asset Owner	Equal variances assumed	1.024	.313	2.449	244	.008	.015	8.548	1.672	15.424
Crypto Owner	Equal variances assumed	.084	.772	4.137	244	<.001	<.001	13.455	7.049	19.861
Children	Equal variances assumed	.763	.383	-1.11	244	.135	.269	-7.294	-20.27	5.686

Table 21 presents the results of the t-tests and Levene tests conducted for three distinct demographic factors: Asset Owners, Cryptocurrency Owners and Children. These factors possess only two response options in the survey, rendering the application of ANOVA test inappropriate. However, these statistical tests are employed to determine significant differences between the means of the two groups being compared and to assess whether the variances of the two groups are equal.

All the p-values obtained from the Levene´s test for all three factors (reported in the fourth column) are greater than 0.05, leading to the assumption of equal variances between the groups. Nevertheless, this assumption does not hold for the t-tests. A two-sided p-value less than or equal to 0.05 indicates a significant difference between the means of two groups.

In the case of Asset Owners, the t-test shows a significant result ($p=0.015$), indicating that the means of the groups are significantly different. The mean difference is 8.548, and the 95% confidence interval for the mean difference ranges from 1.672 to 15.424. Similarly, for Crypto Owners, the t-test also produces highly significant results ($p<0.001$), indicating a significant difference between means of the two groups. The mean difference is 13.455, and the 95% confidence interval for the mean difference falls between 7.049 and 19.810. Conversely, for Children, the t-test does not yield a significant result, with a two-sided p-value of 0.269. Hence, there is no noticeable distinction observed in the means of the two groups.

Table 22. Test of Homogeneity

	Demographic factors	Levene Statistic	df1	df2	Sig.
Risk Behavior Cryptocurrency Market	Education Level	1.363	5	235	.239
	Employee Status	.549	4	241	.700
	Relationship	2.772	2	243	.064
	Salary	.296	4	241	.880
	Sex	2.868	2	243	.059
	Age	.493	3	242	.687
	Asset Number	.562	3	242	.626
	Crypto. Number	2.138	3	242	.076

Table 22 presents the outcomes of the homogeneity test, a prerequisite for performing an ANOVA test. The test is important to ensure the assumption of equal variances across groups, which is necessary for the validity and reliability of the ANOVA test results. The table displays the results of the test for various demographic factors, including education level, employee status, relationship status, salary, gender, age, asset holding number, and cryptocurrency holding number. For each factor, the Levene Statistic, degrees of freedom (df1 and df2), and significance value are presented. The significance value for all factors is greater than 0.05, indicating that the assumption of homogeneity of the variances across the groups is met. Therefore, the results obtained from the previously performed ANOVA analysis can be deemed reliable.

Table 23. Post-Hoc test risk behavior in the cryptocurrency market and holding number of Cryptocurrencies

(I) Crypto number	(J) Crypto number	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
0	1-5	-13.425*	3.602	.001	-22.74	-4.11
	6-10	-18.297*	6.662	.033	-35.53	-1.06
	More than 10	-19.935*	6.175	.008	-35.91	-3.96

Table 23 represents the results of the Tukey post-hoc test conducted to explore the relationship between participants' risk behavior in the cryptocurrency market and the number of cryptocurrencies they hold.

The results reveal a significant difference between the groups that do not hold any cryptocurrencies and those that do, regardless of the specific number. Specifically, the group holding 1-5 cryptocurrencies exhibits a substantially higher average risk - seeking behavior by 13.425 points compared to the group that does not hold any cryptocurrencies. This difference is statistically significant, with a significance value of 0.001.

Furthermore, while the mean difference between the groups holding 1-5 cryptocurrencies and the group that does not hold any cryptocurrencies is -13.425, the mean difference to the group holding 6-10 cryptocurrencies is -18.297 and to the group holding more than 10 cryptocurrencies is -19.935. Both differences are statistically significant, with p-values below 0.05.

In conclusion, the findings strongly indicate a clear relationship between holding cryptocurrencies and risk behavior in the cryptocurrency market. Furthermore, the results suggest that individuals holding a greater number of cryptocurrencies exhibit even greater levels of risk-seeking behavior.

Table 24. Effect Size of Risk Behavior in the Cryptocurrency Market

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Crypto Number	Eta-squared	.089	.026	.154
Asset Owner	Cohen´s d	.329	.064	.594
Crypto Owner	Cohen´s d	.530	.274	.784

Table 24 reports the effect sizes of the significant factors influencing risk behavior in the cryptocurrency market, measured through two indicators: Eta-squared and Cohen´s d.

Eta-squared quantifies the proportion of variance in the dependent variable (risk behavior in the cryptocurrency market) that can be explained by the independent variable (number of cryptocurrencies held). With an estimated Eta-squared value of 0.089, the number of cryptocurrencies held has a moderate effect size on risk behavior in the cryptocurrency market. Approximately 9% of the variability in risk behavior can be accounted for by the variation in the number of cryptocurrencies held by the participants.

Regarding Cohen's d, which measures the standardized mean difference between groups, the estimate for crypto owners compared to non-owners is 0.53 and a 95% confidence interval ranging from 0.274 to 0.784. This suggests a moderate to large difference in risk behavior between crypto owners and non-owners. On the other hand, the Cohens´d estimate for asset owners compared to non-owners is 0.530, with a 95% confidence interval ranging from 0.064 to 0.594, indicating a small to moderate difference in risk behavior.

The Hypothesis (H5) can be accepted. The results indicate a significant relationship between demographic factors and risk behavior in the cryptocurrency market.

H6: The risk behavior in the traditional asset market differs from the risk behavior in the cryptocurrency market.

Table 25. Bivariate Correlation Analysis

		Risk Behavior Crypto	Risk Behavior Asset Market
Risk Behavior Crypto	Pearson Correlation	1	.298**
	Sig. (2-tailed)		<.001
	N	246	246
Risk Behavior Asset Market	Pearson Correlation	.298**	1
	Sig. (2-tailed)	<.001	
	N	246	246

Table 25 presents the results of a bivariate correlation analysis using Pearson's correlation coefficient to examine the relationship between risk behavior in the traditional asset market and the cryptocurrency market. Both variables are measured on a metric scale, making the Pearson correlation coefficient the best measure for assessing their correlation. The Pearson correlation coefficient between risk behavior in the cryptocurrency market and the traditional asset market is 0.298, indicating a moderate positive correlation between these two groups. This suggests that as risk behavior increases in the cryptocurrency market, it tends to also increase in the traditional asset market, and vice versa. The correlation is statistically significant, as indicated by the two-tailed significance level of <0.001, meaning that the observed correlation is unlikely to have occurred by chance. Thus, the hypothesis (H6) is rejected because the results suggest a relationship between the two market and, accordingly, are not different.

Table 26. *Statistics*

	N	Minimum	Maximum	Mean	Std. Deviation
Risk Behavior Asset Market	246	0	100	59.43	24.041
Risk Behavior Crypto	246	0	100	43.26	26.225
Valid N (listwise)	246				

Table 26 presents the mean and the standard deviation of the risk behavior in the traditional asset market and cryptocurrency market. The results of the study show that the mean differs by 16.17 points.

The Hypothesis (H6) can be accepted. Although there is a correlation of risk behavior between the two markets, the mean is significantly different.

H7: The risk perception in the traditional asset market differs from the risk perception in the cryptocurrency market.

Table 27. Bivariate Correlation Analysis

		Risk Perception Asset Market	Risk Peception Crypto
Risk Perception Asset Market	Pearson Correlation	1	.074
	Sig. (2-tailed)		.249
	N	246	246
Risk Perception Crypto	Pearson Correlation	.074	1
	Sig. (2-tailed)	.249	
	N	246	246

Table 27 displays the results of a bivariate correlation analysis utilizing Pearson's correlation coefficient to investigate the relationship between risk perception in the asset market and risk perception in the crypto market. The Pearson correlation coefficient between these two variables is determined to be 0.074, indicating a very small positive correlation. However, the associated p-value of 0.249 indicates that this correlation is not statistically significant at the conventional significance level of 0.05. In other words, while there is a slight tendency for risk perception in the asset market to be positively associated with risk perception in the crypto market, the observed correlation is not strong enough to conclude that this relationship is statistically significant. Therefore, we do not have sufficient evidence to suggest a meaningful and reliable correlation between risk perception in the asset market and risk perception in the cryptocurrency market based on the analyzed data.

Table 28. Descriptive Statistics

	N	Mean	Std. Deviation
Risk Perception Asset Market	246	5.38	2.191
Risk Perception Crypto	246	7.76	2.162
Valid N (listwise)	246		

In Table 28, the standard deviation can be seen in the last column. Here we can see that although this is very similar, the mean differs by 2.38 points.

The hypothesis (H7) can be accepted. The results of the bivariate correlation analysis indicate that between the cryptocurrency market and the traditional asset market is no significant relationship and the mean is significantly different thus the risk perception differs.

H8: The risk perception and risk behavior in the traditional asset market are significantly dependent on each other.

Table 29. Bivariate Correlation Analysis

		Risk Perception Asset Market	Risk Behavior Asset Market
Risk Perception Asset Market	Pearson Correlation	1	-.128*
	Sig. (2-tailed)		.044
	N	246	246
Risk Behavior Asset Market	Pearson Correlation	-.128*	1
	Sig. (2-tailed)	.044	
	N	246	246

To analyze the relationship between risk perception and risk behavior in the traditional asset market, a bivariate correlation analysis using Pearson's correlation coefficient is conducted. The results are presented in Table 29. The Pearson correlation coefficient is -0.128, indicating a weak negative correlation between the two variables. This means that when the individual's risk perception in the asset market increases, their risk-taking behavior in the same market slightly decreases. This makes sense if one considers that if an investment is associated with high risk for oneself, one does not reinvest very much in this investment opportunity because of the fear of losing the investment. This correlation is statistically significant with a p-value of 0.044, which is very close to the threshold of 0.05.

To enhance the understanding of the relationship between risk perception and risk behavior in the traditional asset market, a regression analysis is run. The results, represented in Tables 30-32, confirm that the predictor variable, risk perception in the asset market, has a significant negative effect on the dependent variable, risk behavior in the asset market. The R-squared value of 0.016 indicates that only 1.6% of the variance in risk behavior can be explained by risk perception in the asset market.

Although this is a small effect size, it is still statistically significant, as indicated by the significance value of 0.044 in the ANOVA table (Table 31).

Based on the coefficient for the predictor variable in Table 32, the estimated average effect of a one-unit increase in risk perception is accompanied by -1.409 points in risk behavior in the asset market decreases.

The Hypothesis (H8) can be accepted. The ANOVA test indicate a significant relationship between risk perception and risk behavior in the traditional asset market.

Table 30. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.128[a]	.016	.012	23.891

Table 31. ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2,334.191	1	2,334.191	4.089	.044[b]
	Residual	139,269.992	244	570.779		
	Total	141,604.183	245			

Table 32. Coefficients

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	67.004	4.045		16.566	<.001
	Risk Perception Asset Market	-1.409	.697	-.128	-2.022	.044

a. Dependent Variable: Risk Behavior Asset Market

H9: The risk perception and risk behavior in the cryptocurrency market are significantly dependet.

Table 33. Bivariate Correlation Analysis

		Risk Peception Crypto	Risk Behavior Crypto
Risk Perception Crypto	Pearson Correlation	1	-.128*
	Sig. (2-tailed)		.045
	N	246	246
Risk Behavior Crypto	Pearson Correlation	-.128*	1
	Sig. (2-tailed)	.045	
	N	246	246

Table 33 represents the bivariate analysis examining the correlation between risk perception and risk behavior in the cryptocurrency market. The p-value in the fourth column is reported as 0.045, which is below the predetermined alpha level of 0.05. Therefore, the relationship between risk perception and risk behavior is significant in the cryptocurrency market.

Moreover, the Pearson correlation coefficient is -0.128, which designates a weak negative correlation between the two variables. This suggests that as risk perception increases, risk behavior tends to decrease, and vice versa.

To further explore the relation between risk perception and risk behavior in the cryptocurrency market, a regression analysis is conducted. The dependent variable is risk behavior, while risk perception serves as the independent variable (predictor).

The R-squared value, shown in Table 34, is 0.016, implying that approximately 1.6% of the variance in risk behavior can be explained by risk perception. Accordingly, it is important to note that other factors may also contribute to the individual´s risk behavior in the cryptocurrency market, in addition to risk perception. Apart from the amount the risk perception is predicting the risk behavior, the relationship is significant, which is demonstrated in Table 35, with a p-value is 0.045 and thus below the alpha level of 0,05. The regression coefficient of -1.549 suggests that for every unit increase in risk perception, risk behavior decreases by 0.128 units (Table 36).

The Hypothesis (H9) can be accepted. The results of the analysis suggest a relationship between risk preference and risk behavior in the cryptocurrency market.

Table 34. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.128[a]	.016	.012	26.063

Table 35. ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2,748.869	1	2,748.869	4.047	.045[b]
	Residual	165,750.481	244	679.305		
	Total	168,499.350	245			

Table 36. Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	55.276	6.200		8.915	<.001
	Risk Perception Crypto	-1.549	.770	-.128	-2.012	.045

a. Dependent Variable: Risk Behavior Crypto

H10: The risk preference and risk perception are not significantly correlated in the traditional asset market and cryptocurrency market.

Table 37. ANOVA test risk preference and risk perception in the asset market

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.008	2	1.504	.312	.733
Within Groups	1,172.834	243	4.826		
Total	1,175.841	245			

Table 38. ANOVA test risk preference and risk perception in the cryptocurrency market

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.673	2	1.337	.284	.753
Within Groups	1,142.693	243	4.702		
Total	1,145.366	245			

Table 37 and 38 display an ANOVA test regarding the risk preference and risk perception in both markets. Both significance values are above 0.5 and thus not statistically significant. In the traditional asset market is the significance value 0.33 and in the cryptocurrency market 0.53. The results suggest that between the risk perception and the risk preference present is no significance correlation, in both markets.

According to these results, Hypothesis 10 can be accepted, the risk preference and perception are not significantly correlated in the traditional asset market and cryptocurrency market.

H11: The risk preference and risk behavior are significantly dependent on each other in the traditional asset market and cryptocurrency market.

Table 39. ANOVA Test regarding risk preference and risk behavior in the asset market

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2,584.807	2	1,292.404	2.259	.107
Within Groups	139,019.376	243	572.096		
Total	141604.183	245			

Table 40. ANOVA test risk behavior and risk perception in the cryptocurrency market

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1,198.918	2	599.459	.871	.420
Within Groups	167,300.432	243	688.479		
Total	168,499.350	245			

Given the fact that risk preference is a nominal value and the risk behavior we want to compare is a metric value, only the ANOVA test is suitable for this case. In the Tables 39 and 40 the results of the ANOVA test are represented. In the traditional asset market, the significance value is 0.07 and, in the cryptocurrency, market is it 0.20. Both significance values are above 0.05, which implies no significant relationship between the risk behavior and risk preference. An alpha level below or equal to 0.05

would have indicated a significant relationship. Conclusively the H11 is rejected. The results imply that between the risk behavior and the risk perception is no relevant significance.

CHAPTER 5: DISCUSSION

This section of the thesis aims to present and interpret the findings obtained from the analysis section conducted to answer the research questions in this study.

One of them is whether the demographic factors have a different impact on the risk attitude in the cryptocurrency market and the traditional asset market. To answer this question, hypotheses 1-5 were formulated. The results obtained are remarkable and diverge from existing literature in this domain. Although correlations were identified between risk attitudes and demographic factors, they were observed at a significantly lower magnitude than anticipated.

Specifically, the analysis revealed that asset ownership has a correlation with risk preference. Moreover, employee status and relationship status were found to be associated with risk perception in the traditional asset market, while solely employee status demonstrated a correlation with risk perception in the cryptocurrency market. The patterns were distinct when examining demographic factors in relation to risk behavior. Here, significantly more correlations were found. Within the traditional asset market, risk behavior was found to be linked to the ownership of assets and cryptocurrencies and their number of holding these, as well as to gender. In the crypto market, in turn, only crypto ownership and their number of holdings as well as asset ownership demonstrated correlations.

Interestingly, a correlation was revealed with gender in relation to risk-taking behavior in the traditional asset market, while no such correlation was observed in the cryptocurrency market. Consistent with prevailing opinions in the literature on in risk preference, risk perception and risk behavior, men show significantly higher level of risk-taking behavior in the asset market (Croson and Gneezy, 2009; Eckel and Grossman, 2008; Lopes, 1983). However, the results of this study challenge the consensus in the domain of risk preference and risk perception.

The observed disparities in the results can be attributed to the generational composition of the study participants, which primarily consist of students, who are actively engaged in gender equality issues. It is plausible that this particular generation displays an even risk attitude between men and woman because of their touchpoint with this topic and awareness compared to previous generations. This generation´s behavior may be also influenced by increased internet use, and, for example, transformation of language could have triggered the effect that this generation does not behave as risk averse as the Generation X (Reisenwitz and Iyer, 2009). Given the comparatively younger age structure of the cryptocurrency market in comparison to the traditional asset market, it is plausible that the gender difference in risk attitudes resulting from the generation gap could diminish or disappear, which could be the reason that the results showed no relationship regarding the risk attitude and gender.

In support results in this thesis, Filippin and Crosetto (2016) conducted an extensive analysis challenging the widely held belief that females are more risk averse than males. They conducted the largest Holt and Laury risk elicitation method (Holt and Laury, 2002) replication analysis to this date. They analyze a comparable dataset of 54 publications, which involved over 7000 subjects and account for more than half of all Holt and Laury replications. Their findings expose in less than 10% gender differences were found. Filippin and Crosetto (2016) attribute such differences in gender outcomes to task-specific factors and assume that females and males may respond differently to various tasks (Filippin and Crosetto, 2016).

Another notable distinction between the two markets is evident in terms of risk behavior. In the traditional stock market, there is a clear association observed between risk behavior and factors such as asset ownership, crypto ownership, the number of crypto holdings and number of asset holdings. Conversely, in the cryptocurrency market, only a connection to the risk behavior with crypto owners and their number of holding cryptocurrencies can be identified. Notably, the direction of the relationship goes in the same direction, as participants who do not own cryptocurrencies display a significantly higher level of risk aversion compared to those who do. This pattern holds true for both markets.

However, it is interesting to highlight that this difference is absent in the cryptocurrency market concerning participants who own assets. No discernible connection between asset ownership and risk behavior is apparent as between holding number of assets and risk behavior. This implies that the ownership and number of assets held do not strongly influence risk behavior in the context of the cryptocurrency market.

In comparing the outcomes of risk perception between the traditional asset market and cryptocurrency marker, several differences were observed. Firstly, in the traditional asset market, a correlation was found between employee status and relationship status. In the crypto market, on the other hand, this was only the case with employee status. Additionally, the results for employee status differed between the two markets. In the traditional asset market, the self-employed individuals showed a lower risk perception compared to the unemployed, whereas in the crypto market, the results suggest that employed individuals have a higher risk perception than students and unemployed individuals.

Unfortunately, risk tolerance and risk perception are often not clearly distinguished in the literature, so that risk tolerance has typically been studied (Nguyen et al., 2019). Risk tolerance refers to the extent to which an investor is willing to tolerate or endure risk in order to achieve his or her financial goal (Victor Ricciardi and Douglas Rice, 2014). On the contrary, the risk perception is the subjective decision-making process through which the investor evaluates the uncertainty and risk of a possible investment (Victor Ricciardi and Douglas Rice, 2014). While they may be interrelated, these are not interchangeable and should be treated separately during analysis and when drawing conclusions.

Furthermore, the relationship between employee status and risk perception has received limited research attention. However, a study by Brown et al. (2006) explored the association between risk-preference and employment status, suggesting that self-employed individuals tend to prefer riskier investment options. This could be attributed to the lower risk perception observed among self-employed individuals compared to the unemployed individuals, as the results of this study showed in the traditional asset market. However, this observation does not hold true in the crypto market.

Regarding risk perception in the traditional asset market, it was found that single individuals had a higher risk perception than married individuals. This finding contrasts with a study by Browne et al. (2022). They investigated the impact of family composition on the inclination to embrace risks and reached the conclusion that married individuals exhibit a higher propensity for risk aversion and these characteristics remain consistent an extended period. Previous research, such as the studies by Cooper and Faseruk, (2012) and Sahul Hamid et al. (2013), has demonstrated that risk behavior is strongly influenced by risk perception.

It is important to acknowledge that the results of this study may not align with broader literature on interrelation between demographic factors and risk attitudes. Existing literature indicates that demographic factors, such as education level, income, age and relationship status can have an impact on investors risk perception, risk preferences and risk behavior (Bashir et al., 2014; Slovic, 1997). However, the analysis conducted in this study could not observe significant relationships between income, age and risk attitude.

For example, education may influence an individual's risk perception, as those with higher level of education may have a better understanding of financial concepts and can better assess potential outcomes of their decisions compared to those with lower education levels. The analysis conducted in this study could not establish a serious relationship between education level and risk perception.

One possible explanation for these findings is the specific characteristics of the participants. The study includes a total of 241 participants, the majority of whom are finance students. These students have a better understanding of financial concepts and are likely more resistant against making uninformed investments or being vulnerable to financial scams as they are exposed to financial education and discussions on risk in their everyday university routine. This contributes to their ability to assess the risks associated with potential investments. Therefore, the lack of significant correlation between education level and risk attitude in this study could be a reason why in this study no relationship occurred.

According to a study by Statista in 2020, the median household income for individuals aged 15 to 24 year old is at 51.645 U.S. Dollars, which is the second lowest lifetime earnings in the study. The study group age in 9-year intervals, starting from age 15 to 75 years and above. The highest household income is reported among individuals aged 45 to 54, with a median income of $97.89 Dollars. This suggests that income tends to increase with age. Furthermore, individuals with a higher income can have better access to financial resources and advice, allowing them to make more informed decisions and better manage financial risks. That in turn gives individuals the opportunity to gain experience in making decisions and how to perceive risks.

According to previous research by Reisenwitz and Iyer, (2009), which focused on psychology, found that age individuals become more risk sensitive towards economic risk as they age. Similar results were observed in the study of Yao, Sharpe and Wang, (2011). The researchers arrived at this conclusion after analyzing the 1998 to 2007 survey of consumer finances cross-sectional datasets. Younger people may be more willing to attend on risky activities such as trying out some extreme sports or experimenting with drugs, while older people may perceive these activities as more dangerous and therefore riskier, because their tolerance for risk decreases with age. As people age, they may prefer to safe monetary gains over risky payoffs. Additionally, each year of life shortens the time horizon for recompensate potential losses.

From a psychological perspective, this increase in risk aversion may contribute to the overall development of risk aversion, as it suggests that individuals follow a different trajectory in economic risk taking than in other domains (Reisenwitz and Iyer, 2009).

The missing links in this study have not been found for the factor education level and similar reasons could apply to the factors age and income. Students with relatively low income and younger age may have access to the same knowledge and resources, which can improve their decision-making and risk-perception abilities. This could potentially explain why the results of this analysis do not support a significant relationship between risk attitude and income or age, either positively or negatively, in both markets the traditional asset market and the cryptocurrency market. Regarding risk preference, no distinction can be made between the two markets, but the reasons for the absence of relationship can be the same as mentioned.

The analysis of the relationship between risk preference and demographic factors supports the proposition that college students may be a suitable population to draw inferences about the risk preference of financial professionals. This is because the absence of any correlation between the risk preference and any demographic variables indicates that a financial professional significant work experience and familial responsibilities can exhibit the same degree of risk preference as a student with lower income and no dependents.

To address research question 1, hypotheses 6 and 7 were formulated to compare risk behavior and risk perception. The analysis indicated that there is a slight positive relationship between the risk behavior in the two markets, which suggests that individuals who display risk-taking behavior in one market are also likely to display it in the other market.

However, it was also observed that the risk perception differs between the two markets, indicating that individuals may perceive the risks associated with each market differently. Despite both markets offering similar potential outcomes in the survey, in terms of positive investment returns, the risk perceptions of individuals vary considerably between the two domains. It is possible that this lack of correlation may be attributed to the distinct characteristics of these two markets, which are reflected in the task instructions and the possible outcomes emphasized.

The analysis part provides an overview of the mean and the standard deviation of the risk perception in both markets. Notably, even though the standard deviations of the two groups are nearly identical (asset market: 2.191; cryptocurrency market: 2.162), there is a substantial mean difference of 2.38 points between them. Given that the Likert-scale ranges from 0 to 10, this disparity in means is considerable and supports the argument that the market domain is the driver of the difference in risk perception. Similar results were obtained when comparing the mean values of risk behavior. Here, there is a difference of 16.17 points, whereby the individuals in the crypto market were observed to be significantly more risk averse.

These findings are consistent with Rettinger and Hastie (2001), Weber, Blais and Betz (2002), Baucells and Rata (2006), which highlight domain-specific differences in risk taking, attributing them to variations in risk perception. That may be the case here as mean of the risk behavior in the cryptocurrency market was significantly lower than in the traditional asset market. This could be attributed to risk perception, as it is higher in the cryptocurrency market than in the traditional asset market.
However, it is important to note that these results are based on a single measure of risk perception and do not consider other factors that may be influencing individual´s perceptions of risk in these markets.

To address research question 3, hypothesis 8-11 were formulated to explore the interrelationships between risk perception, risk preference and risk behavior. These hypotheses aim to examine how these factors are interconnected and how they influence each other in which magnitude.

In the part of the conceptual framework demonstrate that the risk preference and risk perception have an impact on the risk behavior. To support this conceptual framework the hypothesis 10 is formulated as they indicate that the risk perception and risk preference do not significantly correlate with each other and have a direct impact on risk behavior. Thus, a clear demarcation can be made.

However, the analysis regarding risk behavior indicated a slight positive correlation. This means that risk behavior in the two markets slightly influences each other positive, which is an interesting finding.

Remarkably, the risk behavior in both the traditional asset market and cryptocurrency market demonstrates a similar dependence with risk perception, although the risk preference differs in a notable way. Specifically, the risk perception influences the risk behavior negatively.

This finding is similar to the literature in the traditional asset market. A study conducted by Broihanne, Merli and Roger (2014) surveyed 64 high-level professionals and showed that the risk behavior is strongly and negatively impacted by risk perception. In contrast to their findings, this study implies a slightly negative relationship, indicating a weaker association.

Unfortunately, due to the lack of comparable literature of comparing risk attitudes in the traditional asset market and cryptocurrency market, the result of this study hampers the ability to fully contextualized and put into perspective.

Additionally, the analysis revealed no significant correlation between risk preference and risk behavior. This aligns with real-life examples, such as the aftermath of the 9/11 terror attack in New York, where a large population of people avoided to take the plane and instead choose to travel by car, despite that fact that statistically flying is much safer than driving. Their intention was to minimize their risk and not to increase the risk. These irrational decisions illustrate the complexity of the decision-making process under risk and the limitations of how much the risk preference should be used as a predictor of individual´s risk behavior.

CHAPTER 6: CONCLUSION

This thesis endeavours to conduct a comparative analysis of risk attitudes within the traditional stock market and the cryptocurrency market. Additionally, it aims to explore the association between these attitudes and demographic factors, while also investigating the intricate interplay between risk preference, risk perception, and risk behavior. Through this examination, the study sheds light on the intricate and multifaceted nature of individuals' risk behavior, highlighting the multitude of factors that contribute to this phenomenon.

Compared to previous research of demographic factors indicated much fewer connections and were accordingly surprising. Nevertheless, the results induce that demographic factors do not play an insignificant role in decision making under risk and may vary between the two markets.

At the same time, the findings indicate that risk behavior and risk perception are different in the two markets. The study found a significantly more risk-averse attitude in terms of risk behavior and a significantly higher risk perception in the cryptocurrency market compared to the traditional equity market.
Furthermore, the risk perception is influencing the risk behavior in a similar magnitude in both traditional asset market and cryptocurrency market whereas the risk perception showed no relation to the risk behavior.

The observations made in this thesis also have their limitations. The findings and conclusions are based on a specific sample of participant´s. Most of the participants are students, which may not fully represent the broader population of investors in the cryptocurrency market although the participants were from different countries and other studies in this field have usually the same sample size, the generalizability of the results could be limited and should be cautioned when applying the findings to a larger population. Furthermore, the data is collected online, maybe participants responses maybe differently if the survey would have made under other circumstances, for example, a face-to-face interview. Moreover, the study´s design allows to identify associations and correlation but may not allow for definitive conclusions about causality. Lastly, the data collection was within a specific timeframe after the COVID-19 pandemic. The results may not capture the full range of potential variations in risk attitude or under different market conditions.

Nevertheless, this thesis aims to contribute to fill the gap in the field of behavioral finance literature by focusing specifically on the cryptocurrency market. Unlike previous studies that primarily concentrated on mining, forecasts or solely Bitcoin, this study places emphasis on the investors themselves. The study also aims to contribute to the understanding of investor behavior within the cryptocurrency market. Previous research in behavioral finance has identified various effects that have adverse effects on investment returns. For instance, the disposition effect, where investors tend to hold assets that have decreased in value and are reluctant to sell assets that have generated gains. Another notable effect is the prospect the prospect theory, for which Daniel Kahnemann received a Nobel Prize, as it revealed that investors exhibit a preference for certain gains over uncertain higher gains. Furthermore, during negative events, investors tend to display significantly higher risk-taking behavior. These findings indicate that investors evaluate their decisions in terms of expected utility relative to a reference point. Overall, this research aims to contribute to the understanding of investor behavior by exploring these effects within the context of the cryptocurrency market.

Based on the findings of this study, interested parties can focus on the factors that influence the risk perception in order to improve the accuracy of risk behavior forecasts. This, in turn, can enhance the predictions of the cryptocurrency price developments and potentially increase returns. Furthermore, future research should focus on investigating biases within the behavioral aspect of cryptocurrency market, similar to those observed in the traditional asset market. As the results of this study suggest that the influence of demographic factors and risk preference on individual risk behavior may differ between the cryptocurrency market and the traditional asset market. This finding emphasizes the importance of taking into account the distinctive characteristics and dynamics of the cryptocurrency market when determining the factors that shape investor´s risk behavior. However, it is important to note that risk behavior is influenced by numerous factors, which may vary depending on the specific situation. Therefore, the key to achieving success lies in identifying those factors with the most substantial impact on risk behavior and clearly defining their weights and relationships.

Investors in the cryptocurrency market can benefit from understanding the behavioral tendencies and relationships in between the risk attitude which affecting their decision-making. Awareness of these differences and similarities of the risk attitude in both markets can help them make more informed and rational investment choices.

Moreover, financial institutions and broker in the cryptocurrency market can gain insights into the behavioral patterns of investors. This knowledge can shape the tailored strategies, products and services that address individual´s characteristics, preferences and perceptions. Furthermore, policymakers and regulators can use the findings to have a deeper understanding of the dynamics of the cryptocurrency market and consider appropriate measures to ensure investors protection.

Consequently, the thesis has potential to provide valuable insights and practical implications for investors, financial institutions, policymaker and regulators and is one of the first studies in the cryptocurrency market that refers to the psychological side of investors.

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APPENDICES

Appendix A – Survey

Finance Survey

1. Finance Survey

Dear participant,

this survey is an academic study for a master's thesis that examines risk behavior in the traditional asset market and the cryptocurrency market. The survey should take you only 5 minutes to complete, and your responses are completely anonymous. Thank you in advance for your participation.

Regards,

Lâle Baz
Izmir University of Economics

Prof. Dr. Gülin Vardar
Izmir University of Economics

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2. Card Game

You can now take a card as a part of a card game. There are two piles of cards to choose from (pile A and pile B).

There are four cards in pile A. Two cards lead to a payment of **+4 Dollar** and two cards lead to a payment of **+6 Dollar**.

There are four cards in pile B. Two cards lead to a payment of **+-0 Dollar** and two cards lead to a payment of **+10 Dollar**.

The four cards in pile A.

Information for both piles:
Expected value: +5 Dollar
Best possible event: 50% probability
Worst possible event: 50% probability

The four cards in pile B.

*** 1. Now you have to decide which pile you want to take a card from.**

Make your selection now.

- ◯ I would like to take a card from pile A
- ◯ I would like to take a card from pile B
- ◯ I would like to take a card. I do not mind which pile I take one from.

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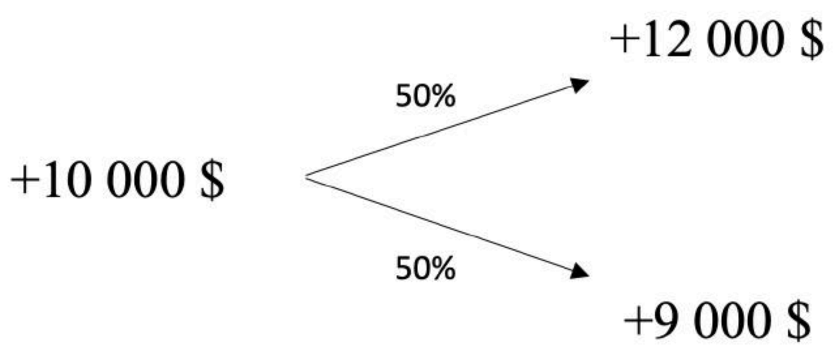
3. Stocks

Information: A stock representing an ownership of a fraction of a company. For example if a company has 1000 stocks and you buy 100 of them you are the owner of 10% of this company´s assets and earnings. Then you have a possible chance receiving dividends or/and if the company is performing well the value of the stocks will rise and you can earn money by selling the stocks.

Consider the following situation:

You have an initial wealth of 10 000 Dollar, which could be invested in **stocks** (risky investment). Your wealth could increase to 12 000 Dollar or decrease to 9 000 Dollar, each with a probability of 50%.



* 1. How do you assess the risk of the mentioned **stocks** (risky investment) on a scale from 0 (no risk at all) to 10 (very high risk).

	(no risk at all) 0	1	2	3	4	5	6	7	8	9	(very high risk) 10
likert-scale	○	○	○	○	○	○	○	○	○	○	○

You could also invest the 10 000 Dollar in a risk free alternative with a safe 3% interest rate.

Risk free Investment	+10 000 $ →	+10 300 $

* 2. Now consider the following scenario: You could invest your initial wealth of 10 000 Dollar in either the **stocks** (risky investment) or in the risk free asset. How much would you invest in the **stocks** (risky investment) and in the risk free investment, respectively?

Please mark your answer on the following scale from 0 to 100, where 0 indicates that the full amount will be invested in the risk free alternative and 100 indicates that the full amount will be invested in the **stocks** (risky alternative).

0 (100% risk free alternative; 0% stocks) — 100 (0% risk free alternative; 100% stocks)

* 3. How would you rate your willingness to take risks when making financial decisions in the **stock** market?

	Very low willingness 0	1	2	3	4	Very high willingness 5
Likert-scale	○	○	○	○	○	○

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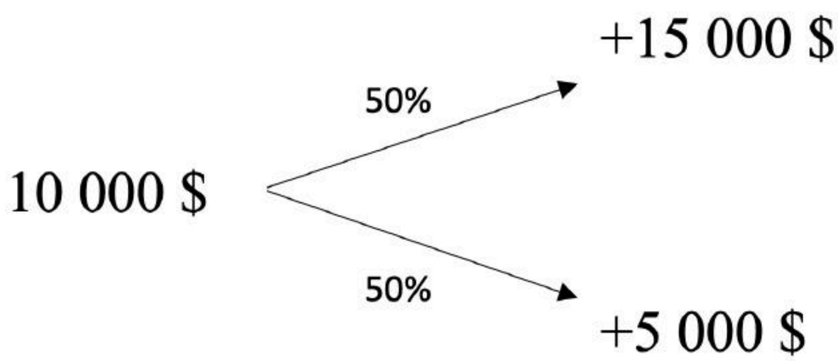
Finance Survey

4. Cryptocurrency

Information: Cryptocurrencies are digital or virtual currencies that use cryptography, a method of protecting information and communications with codes so that only designated individuals can read and process them. Typically, cryptocurrencies are decentralized and thus escape control and regulation by governments and central authorities. The crypto market is usually much more volatile and has no cap. The most well-known cryptocurrencies are: Bitcoin, Ethereum, Litecoin.

Consider the following situation:

You have an initial wealth of 10 000 Dollar, which could be invested in **cryptocurrencies** (risky investment). Your wealth could increase to 15 000 Dollar or decrease to 5 000 Dollar, each with a probability of 50%.



* 1. How do you assess the risk of the mentioned **cryptocurrencies** (risky investment) on a scale from 0 (no risk at all) to 10 (very high risk).

	(no risk at all) 0	1	2	3	4	5	6	7	8	9	(very high risk) 10
likert-scale	○	○	○	○	○	○	○	○	○	○	○

You could also invest the 10 000 Dollar in a risk free alternative with a safe 3% interest rate.

Risk free Investment	+10 000 $ →	+10 300 $

* 2. Now consider the following scenario: You could invest your initial wealth of 10 000 Dollar in either **cryptocurrencies** (risky investment) or in the risk free asset. How much would you invest in **cryptocurrencies** (risky investment) and in the risk free investment, respectively?

Please mark your answer on the following scale from 0 to 100, where 0 indicates that the full amount will be invested in the risk free alternative and 100 indicates that the full amount will be invested in the **cryptocurrencies** (risky alternative).

0 (100% risk free; 0% cryptocurrencies)

100 (0% risk free; 100% cryptocurrencies)

* 3. How would you rate your willingness to take risks when making financial decisions in the **cryptocurrency** market?

	Very low willingness 0	1	2	3	4	Very high willingness 5
Likert-scale	○	○	○	○	○	○

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Finance Survey

5. Demographics

* 1. Have you ever invested in any of the products like: stocks, funds, bonds, certificates?

- Yes
- No

* 2. How many investment products (e.g. stocks, funds, bonds, certificates) did you hold within the last year?

- 0
- 1-5
- 6-10
- More than 10

* 3. Have you ever invested in any of the cryptocurrencies e.g. Bitcoin, Ethereum, Litecoin ?

- Yes
- No

* 4. How many cryptocurrencies did you hold within the last year?

- 0
- 1-5
- 6-10
- More than 10

* 5. What is your highest degree or level of education you have completed?

- [ ] Less than a high school diploma
- [ ] High school degree or equivalent
- [ ] Apprenticeship
- [ ] Bachelor´s degree
- [ ] Master´s degree
- [ ] Doctorate
- [ ] Other (please specify)

* 6. What is your current employee status?

- [ ] Student
- [ ] Employed (part-time, full-time)
- [ ] Unemployed
- [ ] Self employed
- [ ] Retired
- [ ] Other

* 7. What is your relationship status?

- [ ] Single
- [ ] Married
- [ ] Relationship
- [ ] Widowed
- [ ] Divorced

* 8. Do you have children?

- [ ] Yes
- [ ] No

* 9. What is your monthly available income?

- [ ] Less than 4250 TL or less than 1550 €
- [ ] 4251-6000 TL; 1551-3000 €
- [ ] 6001-10000 TL; 3001-5000 €
- [ ] 10001-15000 TL; 5001-7000€
- [ ] above 15001 TL or 7001 €

* 10. What is your sex?

- ◯ Male
- ◯ Female
- ◯ Other

* 11. What is your age?

- ☐ Under 18
- ☐ 18-25 years old
- ☐ 26-35 years old
- ☐ 36-45 years old
- ☐ 46-55 years old
- ☐ Over 55