MASTERARBEIT | MASTER'S THESIS

Titel | Title

Can Copy Trading Beat the Market

verfasst von | submitted by

Dorian Otahal BSc (WU)

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 915
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Betriebswirtschaft
Betreut von | Supervisor:	Assoz. Prof. Steffen Keck PhD

Abstract - English

This thesis, titled "Can Copy Trading Beat the Market?" examines the efficacy of social trading platforms against traditional market benchmarks through both theoretical exploration and empirical analysis. The study scrutinizes various aspects of social trading, including the behavior of individual traders, the mechanics of copy trading, and the impact of factors like trust, transparency, and performance fees on investor returns.

The empirical section tests four key hypotheses to evaluate the potential of social trading to generate superior returns. The findings reveal interesting results. While social trading platforms like eToro and Wikifolio provide novel opportunities for investors, it cannot be consistently said that they outperform the S&P 500 regarding returns. The T-tests showed that the observed difference in performance between the two could indeed be due to random chance. Therefore, it would be inaccurate to claim that the S&P 500 surpasses Wikifolio based on this test even though a higher average performance was measured in the examined period; the results suggest that their performances are statistically similar. In such cases, it can be said that the performances are comparable and that the traditional market index, represented here by the S&P 500, does not statistically outperform the social trading platform under the conditions and period studied. The CAPM analysis gives insights into the risk profile of Wikifolio compared to the S&P 500.

Further analysis shows that the magnitude of invested capital in a social trading product does have a modest but statistically significant impact on average monthly returns. Similarly, the length of time since the wikifolio's initial emission on the platform shows a slight negative influence on performance, suggesting that a longer presence or possibly more experience does not guarantee superior returns. The performance fees, on the other hand, do not have a significant impact on the average monthly returns, challenging the assumption that higher fees correlate with better financial outcomes and also reinforcing the complexity of factors that influence social trading success.

Abstract – German

Diese Arbeit mit dem Titel „Kann Copy Trading den Markt schlagen?“ untersucht die Performance von Social-Trading-Plattformen im Vergleich zu traditionellen Marktbenchmarks sowohl durch theoretische als auch durch empirische Analyse. Die Studie beleuchtet verschiedene Aspekte des Social Tradings, einschließlich des Verhaltens einzelner Trader, der Mechanismen des Copy Tradings sowie der Auswirkungen von Faktoren wie Vertrauen, Transparenz und Handelsgebühren auf die Renditen der Anleger.

Der empirische Teil testet vier zentrale Hypothesen, um das Potenzial von Social Trading zu bewerten. Die Ergebnisse liefern interessante Erkenntnisse. Obwohl Social-Trading-Plattformen wie eToro und Wikifolio neue Möglichkeiten für Anleger bieten, kann nicht durchgängig gesagt werden, dass sie hinsichtlich der Renditen den S&P 500 übertreffen. Die T-Tests zeigten, dass der beobachtete Leistungsunterschied zwischen den beiden tatsächlich zufällig sein könnte. Daher ist es aus dieser Analyse heraus nicht möglich zu behaupten, dass die Sitchprobe an Wikifolios basierend auf diesem Test die Performance des S&P 500 übertrifft, obwohl eine höhere durchschnittliche Leistung auf Seiten des S&P 500 im untersuchten Zeitraum gemessen wurde; die Ergebnisse deuten darauf hin, dass ihre Leistungen statistisch ähnlich sind. Weiters wird eine CAPM-Analyse gemacht die Einblicke in das Risikoprofil von Wikifolio im Vergleich zum S&P 500 liefert.

Weitere Analysen zeigen, dass die Höhe des investierten Kapitals in ein Social Trading Produkt einen geringen, aber statistisch signifikanten Einfluss auf die durchschnittlichen monatlichen Renditen hat. Es zeigt sich weiters, dass der Zeitpunkt der Erstemission einen leicht negativen Einfluss auf die Performance eines Wikifolios hat. Eine längere Marktpräsenz führt also nicht zwangsläufig zu besseren Ergebnissen, stattdessen wirkt sie sich leicht negativ auf die Performance aus. Die Höhe der Handelsgebühren hingegen hat keinen signifikanten Einfluss auf die durchschnittlichen monatlichen Renditen, was die Annahme in Frage stellt, dass höhere Gebühren mit besseren finanziellen Ergebnissen korrelieren, und gleichzeitig die Komplexität der Faktoren unterstreicht, die den Erfolg im Social Trading beeinflussen.

Table of Contents

1 Introduction 6

2 Social Trading Theory 6

2.1 Signal providers and signal followers 7

2.2 The behavior of individual traders 8

2.3 Concept 10

2.4 Copy Trading Feature 11

2.4.1 Imitation 12

2.5 Trust and Transparency 12

2.6 Information spreading and the wisdom of the crowd effect 14

2.7 Risk in social trading networks 16

2.8 Whom to follow - or not to follow 19

2.9 Incentive structures and agency relationship 20

3 Social trading platforms 22

3.1 eToro 23

3.1.1 Features 24

3.1.2 Compensation structure 25

3.2 Wikifolio 26

3.2.1 Features 27

3.2.2 Compensation structure 28

4 Empirical analysis of social trader performance 29

4.1 Hypothesis development 29

4.2 Data 32

4.3 Methodology ... 35

4.4 Empirical results: Hypothesis 1 ... 36

4.4.1 Wikifolio and S&P 500: Return and volatility analysis ... 36

4.4.2 Wikifolio and S&P 500: Discussion of the two sided T-Test Results ... 42

4.4.3 Wikifolio and S&P 500: Discussion of the right sided T-Test Results ... 44

4.4.4 Linear Regression Analysis ... 45

4.4.5 CAPM Analysis of Investment Performance between Wikifolio and S&P 500 ... 50

4.5 Empirical Results: Hypothesis 2 ... 53

4.5.1 Regression Results ... 53

4.5.2 Interpretation ... 54

4.6 Empiricial Results: Hypothesis 3 ... 57

4.6.1 Regression Results ... 57

4.6.2 Interpretation ... 58

4.7 Empirical Results: Hypothesis 4 ... 60

4.7.1 Regression Results ... 61

4.7.2 Interpretation ... 62

5 Limitation ... 65

6 Discussion ... 65

7 Conclusion ... 67

8 References ... 69

Table of Figures

Figure 1 Hypothesis Development 30

Figure 2 Daily Returns of Wikifolio vs. S&P 500 37

Figure 3 S&P 500 Daily Return Distribution 38

Figure 4 Wikifolio Daily Return Distribution 39

Figure 5 Relationship Between S&P 500 and Wikifolio Returns 47

Figure 6 Invested Capital vs. Average Monthly Return 54

Figure 7 Days Since First Emission vs. Average Monthly Return 58

Figure 8 Performance Fee vs. Average Monthly Return 62

1 Introduction

This master thesis is organized as follows. First, an introduction is given, and the concepts of social trading and copy trading are explained. Afterward, aspects of the current literature on the scope of social trading about financial advice and investment decision-making will be discussed. Included closely connected topics, such as information asymmetry, agency problems, incentive structures, and the relationship between different types of investors. Further, the framework of social trading networks will be discussed, as well as the role of the platform operator will be described. Then trading platforms like eToro and Wikifolio that provide investors with social trading functionalities in different ways will be presented. The thesis further explains how investors can use these platforms, how they can make trades, what exactly they are buying, and how they manage relationships between users. The central part of the thesis deals with the research question of whether social trading can be considered an alternative to traditional investments. Hence, the dataset used for this paper to examine this question will be introduced. The following chapters include return characteristics and the risk exposure that signal followers take when they follow signal providers. The social trading performance will be compared to a market risk-adjusted return of alternative investments. The empirical analysis starts and the hypothesis H1-H4 will be tested. It includes several different analysis from T-tests to linear regression analysis. In the last chapters, the findings will be summarized, and some concluding remarks will be provided.

2 Social Trading Theory

Social trading platforms are considered one of the most substantial innovations in online trading (Dorfleitner & Scheckenbach, 2021). Social trading, as it is understood nowadays, is a novel way to participate in financial markets. In terms of transparency and types of relationships, social trading platforms differ substantially from typical trading environments (Glaser & Risius, 2018). Similar to Uber, Twitter, and TripAdvisor, which fundamentally changed entire industries and shaped social interactions, social trading might have a similarly transformative impact on the finance industry (Apesteguia et al., 2020). However, social trading itself is not an entirely new concept. The underlying idea is based on the concept of information sharing among investors, and this has been around for a long time before. Investors have always been communicating with other Investors about investment decisions. Whether in investment clubs where people met physically or later digitally via newsletter, email, and online forums, discussions took place physically or in a virtual environment. When the internet evolved and mass adoption of social media began, people started discussing investments in internet forums, chats, and later within social media groups on platforms like Facebook or Twitter (Reith et al., 2020). Peer opinions come to play a more significant role in financial markets, and according to Chen et al. (2014) the article, one in four adults in the United States directly rely on investment advice from social media platforms and strong growth in relevance to financial markets. On the other hand, Curtis et al. (2014) claims that compared to traditional news sources like Reuters, Bloomberg, etc., with a long history in financial markets, social media is still nascent, but it has an interesting intersection of finance, technology, and social aspects. To sum it up, social media activity can provide a measure of individuals' attention, which can further lead to potentially affecting investment decisions. This is supported by Sprenger et al. (2014), who found that the basic idea of sharing investment ideas, company and stock market-related information, and trading ideas on social media platforms such as Twitter has reached such proportions that effects on the stock market could be proven. It was further proven by them that stock microblogs do contain valuable information for financial professionals.

2.1 Signal providers and signal followers

The social trading literature distinguishes between two parties and follows the idea that there are two groups of individual investors. On the one hand, there are signal providers that share investment ideas with the community. On the other hand, the signal followers who subscribe to the signal providers receive their information and are further able to copy trades in real time

(Doering et al., 2015). Based on that theory and the beginning of online brokerage platforms, today's version of social trading arose. This novel version of a trading platform provides all different kinds of investors with new versions of communication and social interaction. These platforms offer a combination of trading functionalities that are known from online brokers with the communication features of social networks (Glaser & Risius, 2018). It basically combines the advantages of social networks and delegated trading and portfolio management (Reith et al., 2020).

2.2 The behavior of individual traders

Social trading is strongly connected to individual investors' behavior in capital markets and their decision-making (Barber & Odean, 2013). To better understand why social trading is particularly interesting for individual investors, the typical, well-examined investment behavior of individual investors will be discussed. Many characteristics of retail investors are described in papers in the field of behavioral economics and finance. The differences between theoretical investors, who hold well-diversified portfolios and do not frequently trade to minimize transaction costs, and practical, real-world investors, who have many characteristics that let the investor not act in the best financial interests and further tend to make irrational decisions (Barber & Odean, 2013). These characteristics of individual investors will be described to highlight the relevance and importance of studies in the social trading environment and this master's thesis.

Empirical evidence indicates that retail investors earn poor long-run returns and would be better off if they had invested in an index fund. Transaction costs like commissions, transaction taxes, or bid-ask spreads are a significant component that reduces the return (Barber & Odean, 2013). Even-Tov et al. (2022) further examined that commission fees play an influential role and hinder retail investors' participation, trading activity, and diversification. Therefore, platforms like eToro minimize transaction costs and commissions to remove this speed bump for retail investors (*eToro*, 2022).

However, not only transaction costs are the reason for the lower performance of retail investors. Barber & Odean (2013) found further characteristics of individual investors like asymmetric information, which describes the informational disadvantages of individual investors when trading or the effects of overconfidence described by Moore & Healy (2008). They elaborate that people are generally overconfident, which causes them to overestimate their abilities and then could also lead to poor performance.

Another reason for excessive trading and, therefore, the worse performance of individual investors could be the effect of sensation seeking. Papers mentioned by Barber & Odean (2013) from Kumar (2009) and Mitton & Vorkink (2004) hypothesize that retail investors have a taste for stocks similar to lottery-like payoffs. These preferences of high volatility may lead to under-diversification, which could end in lower performance. Another effect that might lead to under-diversification is the familiarity effect. It is described by the informational advantage of individual investors who live or work close to the company they own stocks of. There is disagreement in the literature about whether this supposed information advantage leads to higher or lower performance, as Barber & Odean (2013) mention.

Another effect that leads to poor performance for individuals is the disposition effect. Individual investors strongly prefer selling stocks that have increased in value since they bought and holding stocks for too long that have decreased in value. According to Barber & Odean (2013), the disposition effect is empirically robust. How the effect behaves in the social trading environment will be considered separately later in this master's thesis.

In general, many of these discussed effects lead to under-diversified portfolios. A majority of retail or individual investors hold under-diversified portfolios. Additionally, many uninformed investors trade speculatively to their detriment. However, as a group, individuals make systematic, not random, buying and selling decisions (Barber & Odean, 2013). This insight makes the social-trading topic particularly interesting since it builds on these aspects and further tries to utilize these positive group effects. A study on stock opinions on social media also supports this. Chen et al. (2014) found that the views and opinions on social media platforms can identify future stocks and earnings surprises. Predictability holds even by controlling traditional advice sources like financial analysts and news media. Therefore, it can be said that social media allows investors to generate value-adding information in capital markets (Chen et al., 2014). Given these insights, a social trading strategy might be beneficial to individual investors. It might let them overcome the discussed common behavioral effects that usually result in poorer performance.

2.3 Concept

Different approaches exist to how social trading platforms integrate and combine social aspects with trading and investing functionalities. This thesis will cover two platform implementations more closely and will discuss the differences between the platforms' approaches. However, the concept of social trading platforms nowadays underlies the same ideas. Investors have profiles that are similar to profiles on social network platforms and can further interact with each other by simply following others, writing posts, and commenting on each other's posts. Profiles contain information about the person itself and further about the trading activities, the history and current portfolio performance, and different risk metrics (Glaser & Risius, 2018). With all the information about detailed trading histories, comments from the investors about specific trades, and news related to the investment - a high level of transparency is provided on social trading platforms (Doering et al., 2015). This fact is appealing to signal followers, especially those with less experience who can benefit from the information flow on the platform and the advanced knowledge of the signal providers (Reith et al., 2020). However, not only less experienced investors choose to follow and benefit from their peers as Bursztyn et al. (2014) examined knowledge sharing and social influence on financial decisions. By finding out why a person's choice is affected by his peers, they distinguish between social learning, which means when someone purchases an asset, his peers may also want to purchase it, and social utility, which refers that the possession of the asset directly affects others' utility of owning the same asset. They found that the information provided will not reduce herding even after learning effects.

Thus, financially sophisticated individuals may still choose to follow peers for social utility reasons. Social trading uses these concepts and, combined with a high level of transparency, can lead to lower transaction costs for investors, aka signal followers, which can be a powerful tool for many investors. A further feature that distinguishes the social trading concept from a traditional investment fund is the almost real-time control over the investor's invested capital at any time. This means that a signal follower who invested in a signal provider or followed trades with a certain investment can stop or sell this investment at any time without any restrictions. Hence, social trading networks provide a new and innovative form of delegated portfolio management (Glaser & Risius, 2018).

2.4 Copy Trading Feature

Social trading providers make a feature that is built around imitation of other investors and have built a business model around it. Therefore, one of the most substantial features on social trading platforms that distinguish social trading from other forms of financial trading is the copy trading feature. This feature provides the imitation or the unconditional copying of a signal provider's trades through automatic brokerage execution. Signal providers make their investments publicly available to the other users on the platform – who are able to see the order book and then are able to follow and copy the investment decisions (Oehler et al., 2016). According to Wei Pan and colleagues (2012), this feature enables signal followers to benefit from the wisdom of experienced traders and may also have connections to the wisdom of the crowd in a social trading environment. By following a signal provider, a kind of social relation is entered. Social relations on social trading platforms are different from social relations on conventional social networks. The relational connections created on social trading platforms are not entirely based on social relations but rather on activity relations. This implies that instead of longevity and stable connection between two individuals on social networks, social trading networks are rather short-lived and fragile and explained by the monetary aspects of these relationships (Kapraun & Pelster, 2018). Copying trades manually and automatically must be distinguished in literature.

When trades are copied manually, it can be described as investment advice, and when investment decisions are copied automatically, it can be seen as investment delegation (Doering et al., 2015). Copy trading can further help especially inexperienced investors with little to no knowledge about investing (Pentland, 2013).

2.4.1 Imitation

Imitation as a behavioral heuristic has attracted the attention of economic studies for a long time already (Apesteguia et al., 2020). Imitation can be called the poor man's rationality. If a fully rational decision-maker is capable of making all necessary calculations, there is no need to imitate anyone before making a decision. Therefore, the imitating individual is either incapable of doing all the necessary calculations or does not have the time to do so. This now begs the question of whom to imitate (Offerman & Schotter, 2009). In the context of social learning, studies from Duffy et al. (2019) and Goeree & Yariv (2015) have shown that individuals tend to choose social information instead of private information and follow others even though there is no information on performance. They further show that just following others may make sense as a decision-making shortcut in some circumstances. However, it is often rather costly in terms of individual payoffs. It can be said Copy Trading is a type of imitation, and it is packed as a feature on social trading platforms.

2.5 Trust and Transparency

Social trading networks have gained popularity in recent years due to their potential for increased transparency and the ability for traders to share their knowledge and expertise with a larger audience. However, the success of social trading relies heavily on trust, as investors need to have confidence in the traders they are following and the platform they are using. Together with the global trend towards the disintermediation of financial services such as blockchain technology or more traditional peer-to-peer lending platforms, social trading with a high degree of transparency for investors could play a unique role in the area of investing. Technology like blockchain enables novel systems to no longer require trust from the other party or the middleman because of the algorithmic implementation and built-in governance structure about the conceptualizations of trust and confidence (De Filippi et al., 2020). Social trading platforms, however, do not use blockchain technology as a system to enable trust. There is a high level of transparency between users provided for investors. Furthermore, there is an almost real-time control at any time over the investor's invested capital and it further bypasses unnecessary intermediaries or legal entities. Hence, social trading platforms have the potential to become a real alternative to incumbent financial service providers and investment funds (Glaser & Risius, 2018). When it comes to trust, which is essential in online communities, it is a multidimensional construct including reliability and credibility, emotional comfort, benevolence, quality, and transparency plays a critical role (Shankar et al., 2002).

Trust between the investor and the signal provider is another important aspect. Here the factor trust and risk are also closely related but not as close as someone might assume, as Fama & MacBeth, (1973) show. A low-risk level – so a low maximum drawdown and a high maximum drawdown produce the same outcome in trust. This can be explained by the risk-return trade-offs where the greater the risk, the greater the potential gain, and certain groups of investors might be attracted to high gains, whereas other types prefer less risky options. Thus, the risk is just one of the trust-building factors (Fama & MacBeth, 1973).

Transparency is another critical factor for establishing trust, however, Glaser & Risius (2018) found out that full transparency and exertion of control do not always lead to positive effects. The recognition of being monitored all the time because of the full transparency provided by the social trading platforms, the principal itself could unavoidably induce unfavorable behavior of the agent through the monitoring aspect. This is shown when signal followers con openly compare success measures provided by the platform it could then lead to signal providers trimming their performance metrics even though it might not yield to optimal returns. Especially this kind of social feedback tends to make signal providers act more conservatively which could result in a lower performance. Wohlgemuth et al., (2016) explain, that cognition-based and affect-based signals affects building trust in online communities. This goes along with previous studies in the literature for how trust is being built under an offline context. Thus, it can be said that the decision for copying trades rely on cognition-based and affect-based signals of trustworthiness.

Financial performance is an important factor as well, however research shows that it must complement with these signals of trustworthiness to appear trustworthy for signal followers. It is important to note, that there is not a single signal that can built trust, it is as mentioned multidimensional where several signals are essential to building trust (Wohlgemuth et al., 2016). For operators of copy trading platforms there are several ways to establish trust for the users. From customizing the user interface of the social trading platform and highlight some trust-building features more prominently to providing full names and a profile picture for affect-based signals for establishing trust. Furthermore, remuneration schemes and incentive structures can influence signal providers' behavior and is therefore also subject for trust building (Wohlgemuth et al., 2016).

2.6 Information spreading and the wisdom of the crowd effect

Social interactions are central to how humans gather information and can affect decision-making. Social media has become a source of information in many spheres of life. In current literature, it is controversial whether the information in social networks is actually valuable and can lead to improved decision-making. In previous chapters, it has already been mentioned that social media can contain helpful information for investors. In the financial industry, hedge funds use the information found on social media to make investment decisions (Hossain et al., 2022). This shows that some actors with the right tools can use the vast amount of information in social networks. Given the nature of easy accessibility of social media, retail investors are empowered and have the opportunity to be part of the broader capital market with theoretically a lot of information available. However, Chen et al. (2014) have shown in their study that there is a lack of regulation in social media outlets and emphasize that uninformed actors can easily spread fake "information" among market participants. Another argument against valuable information in social media is that information may just be noise (Hossain et al., 2022). On the other hand, Chen et al. (2014) show that the information that can be found on social media can be valuable to investors because of the higher dissemination of information. They argue that the higher dissemination on social media leads to the early discovery of information by investors, which would further reduce the ability of managers to hoard bad news for a more extended period of time. This is called the *hoarding aversion effect* and is based on the wisdom of the crowd theory, which suggests the value-adding information that can be found in social media. Thus, a social trading platform has the ideal prerequisites for social learning and decision-making in a financial context. A study by Wei Pan et al. (2012) further examines the wisdom of the crowd effect under the context of social trading. They find perfect conditions in a social network where users can communicate, interact and learn with each other and have real cash incentive decision-making for optimal crowd wisdom. In their study, Abbey & Doukas (2015) show that retail forex traders outperform professional forex traders. This, however, comes along with a higher risk-taking behavior because retail traders were using higher leverage than institutional traders and the worst-performing retail forex trader lost significantly more amount of money. However, this study shows that retail traders are quite capable of generating high returns, even beating those of institutional investors - albeit with higher risk and limited to forex. Now one can assume that retail traders have an information advantage and knowledge because of the mentioned wisdom of the crowd effect. The information can be explored through constant social exploration through other retail investors, and hence interesting opportunities can arise in social trading networks. The highest returns and best decisions are made by investors with constant social exploration, which means gathering information and testing out ideas from other people (Pentland, 2013). A key aspect of that is that social embedding substantially impacts on what information is received and how beliefs are formed and decisions are made (Almaatouq et al., 2020). Decision-makers who pay attention to a broad group of people with avoiding following a herd of like-minded people achieve the highest returns. Thus, there is a sweet spot for investors when they balance the right amount of others' ideas, and their own could achieve higher return rates than other investors on social trading platforms. One can therefore say that when investors on social trading platforms remain in the healthy "wisdom of the crowd" sweet spot where diverse opportunities for social learning are provided and at the same time avoid the so-called echo chamber where investors do not benefit from others' ideas anymore because people are too likeminded and the same ideas keep recirculating, they achieve the highest return (Pentland, 2013). Understanding the crowd's wisdom in social trading networks and financial markets is crucial to success and can be turned into hedging and trading strategies (Wei Pan et al., 2012).

Another aspect of higher social media activity is the enhanced market reaction to the news (Curtis et al., 2014). The insights from Curtis et al. (2014) are consistent with examples from Kapraun & Pelster (2018). They show that investment decisions of signal providers, especially opinion leaders, could trigger large cascades of additional buy or sell behavior. The higher dissemination of information on social media makes that possible and could exaggerate investors' negative reactions when the news is disclosed. Interaction-based relations are driven mainly by past performance and hence have the potential to increase market fragility if the community has substantial trading volume. Especially signal providers with high followers may induce volatility, clustering, and herding.

In summary, it is crucial to understand the information spread in social media and the nature of social interaction in financial markets, evaluate potentially "dangerous" events beforehand, make use of the information flow and social learning, and include them in risk analyses.

2.7 Risk in social trading networks

Baghestanian et al. (2014) argue that the social influences in a social trading environment alone affect individual risk-taking. They found evidence that peer information and especially its framing, is an important determinant of risk attitudes. Highlighting the highest-earning investor increases followers' willingness to take risks and elevates average risk exposure. On the other hand, Baghestanian et al. (2014) further indicate that social trading networks may reduce under-diversification and act as a stabilizing factor when social trading platforms also spotlight the worst short-term performing traders or portfolios which would lead to better risk sharing among social traders. When it comes to the individual risk-taking of a signal follower, Apesteguia et al. (2020) showed that by providing investors with trading history and information on previous investment decisions, the success of other investors could lead to an increase in risk-taking. Directly copying trades or indirectly by just using the provided information of a signal provider for own investment decisions may be detrimental to the investor's welfare.

Furthermore, even outside of the copy trading domain, only information on the success of others reduce welfare and may lead to excessive risk-taking (Apesteguia et al., 2020). Offerman & Schotter (2009) show that people tend to be more risk-seeking and make risky decisions after they have observed the behavior of others who have done the same. So, when people have to opportunity to do social sampling, like in a social trading network, based on those findings, they tend to have riskier behavior. Simply imitating the best signal provider appears to be enough for many retail investors, even though it might not be the optimal decision (Offerman & Schotter, 2009). On the other hand another risk that signal providers are exposed to is the fear of the reputational loss of the signaler and the associated loss of performance. Pelster & Hofmann (2018) show in their empirical findings that signal providers are more susceptible to the disposition effect than investors who do not have followers. The disposition effect means that investors tend to sell fewer shares when the price falls, especially when the price is below the purchase price than when the price rises and it is above the purchase price. Thus, a tendency can be observed for investors to sell winners too early and keep losers too long in their portfolios (Weber & Camerer, 1998). This effect is even more substantial in social trading networks with copy trading functionality. There is a strong correlation between the number of signal followers and the disposition effect of the signal provider (Glaser & Risius, 2018). This behavior could be explained by the fear of losing reputation when a signal provider has to admit a bad investment decision. Furthermore, holding to a fallen share signals followers' confidence and trust in their initial investment strategy (Pelster & Hofmann, 2018). Further, Glaser & Risius (2018) found the sensitivity of the disposition effect for signal providers is influenced by the amount of attention or amount of followers or invested capital they receive on social trading platforms. They also conclude that signal providers are affected by behavioral and social biases and found that they try to improve their performance metrics when they receive more attention from the community through invested capital, follower number, etc.

Another interesting aspect of social trading platforms might be how social rankings affect choice behavior and the associated risk assessment of the investors. Bault et al. (2008) show there is a difference between the relative weight of gains and losses in private and social environments. In social environments, rewards are usually distributed on a winner-takes-it-all rule. This underlying rule could also be applied to social trading platforms, giving the signal provider a certain incentive to achieve a higher return through increased risk and thus quickly reach many new followers.

In a private environment, a loss could be particularly harmful and bring an individual investor a relatively risk-averse attitude, according to the motto of the prospect theory, where the focus is on avoiding losses rather than making profits (Kahneman & Tversky, 2013). In a social environment, however, like a social trading platform where the signal provider has a less personal impact when experiencing losses because they do not have any capital invested at all in their wikifolio or less money invested on eToro, the losses do not weigh as much as the gains. Hence, the behavior could be driven more by the prospect of winning than the prospect of losing (Bault et al., 2008).

Another aspect is the risk-shifting behavior of signal providers acting like portfolio managers when subject to an option-based payout structure or convex compensation scheme. This behavior is elaborated in the chapter on incentive structures. However, it should also be mentioned since the initially targeted risk exposure of the signal followers may change considerably over time due to this behavior that was observed by Doering & Jonen (2018).

2.8 Whom to follow - or not to follow

When and why investors decide to follow other investors and become signal followers is the subject of current research and underlies many different variables. In that chapter, it will be discussed under what conditions signal followers decide to follow or unfollow a signal provider and what driving factors lead investors to seek advice or to choose to delegate the investments to a signal provider. Liu et al. (2014) propose three novel behavioral metrics that coincide with the prospect theory. The metrics are naturally risk-adjusted by comparing the typical behavior in winning and losing trades. They are called risk-reward ratio, win-loss holding time ration, and win-loss ROI ratio. These metrics can be used to identify potential winning traders under the many losing traders which minimal risk-reward ratio, as they found out. eToro and wikifolio as well, on the other hand, have both developed their own risk score for each signal provider that should give each signal follower a good picture of how much risk they are taking with their strategy (*eToro*, 2022; *Wikifolio Investments*, 2022). However, since the social trading crowd does not always follow rational thinking (Wei Pan et al., 2012), as mentioned in the previous chapter, trust plays an important role as well. The question of whether the performance or return variable is the driving force behind it will be looked at more closely. DeMarzo and his colleagues (2003) argue that an individual's influence on group opinions depends on how well-connected the individual is in the network and not only on performance. Hence, it could be claimed that since it is a social trading platform investor's influence depends on its audience and the social impact of its members rather than on accuracy, a.k.a return. It further goes along with the persuasion bias, where individuals fail to adjust properly for possible repetitions of information they receive, which plays an important role in the process of social opinion formation (DeMarzo et al., 2003). However, results from Sprenger et al. (2014) show that investors providing above-average investment advice are quoted more often and have more followers, which grants them more social influence.

One could argue now that there could be a positive relationship between the number of followers or invested capital and the returns that are achieved. However, Dorfleitner and his colleagues (2018) show that they cannot find evidence that the crowd can identify superior traders, and no positive relationship between return or popularity of signal providers is given. This cannot be interpreted as there is no wisdom of the crowd effect in general on social trading platforms, as mentioned in a chapter earlier. The basic underlying concept of these social trading platforms is that the collective wisdom of traders (wisdom of the crowd) is superior to the wisdom of one (Almaatouq et al., 2020). Wei Pan and colleagues (2012) found that generally, the crowd does much better than individuals and outperforms individual traders. However, they further mentioned that the social trading crowd is subject to social influence dynamics rather than complete rational thinking, which could change the decision-making process again.

2.9 Incentive structures and agency relationship

Any kind of delegated portfolio management is subject to agency problems. Therefore, it can also be applied to the relationship between a signal provider and a signal follower. When trades are copied through the copy trading feature it can show a classic principal – agent relationship. The principal, the signal follower, bears some risk that the selected agent may engage in actions that are not in the principal's interest. This particular case can be described in the literature as moral hazard (Stoughton, 1993). On social trading platforms, the monitoring capabilities of the principal, or the signal follower to monitor the agent, the signal provider, is fundamentally different compared to traditional asset management. With this level of transparency, moral hazard related issues are significantly more difficult. Whether the signal provider achieves poor trading performance or does not act in the best interest of the agent, signal followers can immediately withdraw their funds and the trader's revenue (compensation) would drop accordingly (Glaser & Risius, 2018).

Further, Doering et al. (2015) elaborate although signalers do not directly receive the invested assets from the followers when trades are copied, they de facto manage a part of the followers' brokerage account which means that it can be considered as delegated portfolio management. In social trading, there are three generic remuneration schemes for brokers: Profit-based, Follower-based, and volume-based. Profit-based remuneration is, as the name says, solely based on the profits that the signal followers' trades make, and the signaler participates in these profits. Follower-based compensation is only based on the number of signal followers. The higher the number, the higher the compensation, the traders' or followers' performance does not matter. For the volume-based remuneration model, copied trades have a price premium, which is then shared between the signal provider and the platform. Hence, in this compensation scheme, active trading is promoted.

Depending on the remuneration and incentive schemes signal providers' risk-taking behavior on social trading platforms is influenced (Glaser & Risius, 2018). What was mentioned in the chapter about trust and transparency Glaser & Risius (2018) state that the agent's behavior is affected by the recognition of being monitored. It was proven that when the social trading community pays more attention to a signal provider, for example, the invested capital increases or the number of followers goes up, the traders try to improve their performance metrics.

Combining these findings now with the different remuneration schemes, it can be said that the behavior of the signal provider is strongly affected by the type of remuneration scheme. Further, Glaser & Risius (2018) found that against the efficient market hypothesis, the performance of the social trader is subject to behavioral, social, and relational biases like the mentioned disposition effect, Moral-hazard, and social feedback. When making performance visible to the community, enabling social feedback from investors, and providing complete transparency signal provider's behavior can be influenced. Social trading platforms can, therefore, promote a specific type of trading behavior and discourage a different kind by changing the incentive structure. By only offering more restrictive attention-signaling features like subjective user ratings, it would promote a higher risk-taking behavior. On the other hand, social feedback mechanisms help to establish risk-aware trading behavior (Glaser & Risius, 2018).

3 Social trading platforms

Social trading platforms try to attract a broader customer base and substantially reduce entry barriers compared to traditional wealth management services (Reith et al., 2020). These platforms offer a wide range of investment opportunities, from regular company shares to investment portfolios to commodities, currencies, and even cryptocurrencies. With this core concept, these platforms want to meet the spirit of the time of social media platforms and combine it with a wide range of financial toolkits to invest money and participate in the capital markets (*eToro*, 2022; *Wikifolio Investments*, 2022). In addition to the trading features, these platforms provide individual investors with different ways to communicate with each other (chat function, public posts, comments) and enable access to information on current and past investments. Typically, as mentioned, the critical feature of these platforms is allowing investors or traders to directly copy the investment choices of other traders (Apesteguia et al., 2020). When it comes to the intentions of which factors predict the intention to use social trading platforms, it varies between experienced and inexperienced users. Whereas advice suitability affects both user groups' choice to use social trading platforms, performance expectancy has the highest impact on the intention of the experienced group, in contrast to the inexperienced group, where performance expectancy has surprisingly no significant effect. Their intentions to use social trading platforms are somewhat affected by individual risk aversion, effort expectancy, and perceived security (Reith et al., 2020). The social trading platform's most prominent feature is to allow traders to observe and copy either automatically or manually the investment decisions of other users. In addition, these platforms offer the basic structure of a social network and all the features and possibilities associated with it that provide comprehensive information about market news, specific stock news, chart analytics, and trader opinions (Kapraun & Pelster, 2018). Several platforms compete with each other; among them, two well-known in German-speaking countries are eToro and wikifolio. These two platforms were chosen for further analysis. While the basic idea of copying investment decisions is the same on these two platforms, they have very different approaches to how this feature is implemented. Additionally, the underlying financial products distinguish substantially from each other. There are further numerous differences in how traders interact with the community and which financial products are ultimately purchased by investors. In the following chapters, the platform-specific differences will be discussed in more detail and a comprehensive insight is given.

3.1 eToro

eToro is a multi-asset investment platform founded in 2007 with the mission to make trading accessible to anyone and reduce dependency on traditional financial institutions. Three years after the launch of eToro, the most popular feature, the CopyTrader, was introduced. It enabled investors to copy other successful traders directly and consequently participate in the performance. By that time, investors were only able to trade commodities and currencies. Three years later, in 2013, a wide selection of stocks was added. Three years later, CopyPortfolios were introduced, which are very similar to investment funds or sector-specific ETFs. CopyPortfolios group assets or investors together on a global trend or business industry like artificial intelligence or renewable energy. In February 2017, eToro added other cryptocurrencies next to bitcoin, like Ethereum, XRP, and other popular coins, so that investors could diversify their portfolios with another asset class further. In January 2022, eToro officially launched stock investments on its platforms (*eToro*, 2022). Initially, investors did not buy actual stocks at eToro. The social trading platform only allowed users to trade contracts for difference (CFD). These CFD products are issued by eToro and participate 1:1 with the underlying asset. It has a small overnight fee and can be leveraged and therefore have a higher risk if the leverage is above 1:1 (Reith et al., 2020). Unlike futures, CFDs don't have an expiry date or a specific contract size. CFDs also have positive effects like lower costs in the form of fewer fees for the investor and the possibility to diversify the individual portfolio with small amounts of money and fractional shares. Furthermore, with CFDs, eToro could guarantee signal followers the same prices as the signal providers when the CopyTrader feature was enabled (Pelster & Hofmann, 2018). On the other hand, by trading CFDs, the investor is exposed to the counterparty risk to eToro, who is the issuer of the CFD, and the investor does not directly own the underlying asset. Additionally, there are small overnight fees when owning a CFD that, according to eToro, reflect the forces of supply and demand driving the financial markets. After the stock investment announcement, eToro still offers CFD trading on the platform. Only stocks that are offered on eToro-supported exchanges can be bought directly, and then the shares are bought in the name of the investor. Other stocks that are not available on certain exchanges or the investor lives in a country where eToro is subject to certain regulations or when investors want to buy commodities, currencies, leveraged trades, or short positions, these transactions are settled as CFDs (*eToro*, 2022).

3.1.1 Features

In terms of the variety of features, eToro is ahead of wikifolio. The overall structure and design of the eToro platform are more related to a social media platform and are also more beginner friendly. It offers various social media tools for interaction, like regular user profiles, follow-user functions, news feeds, comments under user posts, and liking and sharing functionalities. Another important feature is called "Explore," where users can find everything from global markets, stocks, (crypto)currencies, commodities, ETFs, smart portfolios and copyTraders. Furthermore, eToro provides a big financial toolkit as well, where investors have their own watchlist and portfolio where asset prices are shown in real time. When a signal follower now decides to copy the trades of a signal provider with the eToro CopyTrade feature, first, the trader will be chosen. Then the amount of money that the investor wants to invest is determined. 200$ is the minimum amount required to invest in a trader, and two million dollars is the maximum amount that can be invested to copy the trades. Now, every time the signal provider starts a new position, this position will also be entered by the signal follower proportionate to the previously determined investment amount. For example, if the signal provider buys Apple shares with a 5% share in his portfolio, it follows a buy order of the signal follower with a 5% share of the investment amount that was determined when the CopyTrade feature was activated. It is important to note that the current portfolio of the CopyTrader will not be copied. Only new trades of the signal provider are copied. Therefore, it distinguishes itself from mutual funds, ETFs, or CopyPortfolios that er also available on eToro (*eToro*, 2022). Additionally, as Doering et al. (2015) note, the investment of the signal follower does not flow into the signal provider's eToro Portfolio, so the signaler does not have more money to invest. This is a substantial difference and distinguishes this type of investment from a mutual fund or ETF. However, it can still be considered as a novel form of delegated portfolio management.

3.1.2 Compensation structure

eToro follows a follower-based remuneration scheme. The more followers a signal provider has, the higher the monthly remuneration will be. eToro has certain variables like AUC (assets under copy), which is the amount of money copying a portfolio, and a formula to determine the exact amount of monthly payments a signal provider gets. So, depending on the min. Average AUC and min average monthly equity (that is invested by the signal provider) and the signal provider rank of the monthly payment is calculated. This means that the compensation structure of eToro has a convex payoff structure which can potentially increase the incentive to take risks and induce risk-shifting (Panageas & Westerfield, 2009). What is important to note is that according to Doering, Neumann and Paul, 2015 a distinction between different compensation models can be drawn. Signal followers on eToro do not transfer any of their capital into the signal providers' accounts, so signal providers are not considered portfolio managers in a traditional sense. However, they have indirect control over the signal followers' capital because of how the copy trading feature on the social trading platform eToro is designed (Doering et al., 2015). This means when a signal follower starts the copy trade with a certain amount of money, this money is now subject to the investment decisions of the signal provider. So, the risk-shifting theory due to the convex payoff structure can be applied here. Hodder & Jackwerth, (2007) found out that this kind of compensation method induces widely varying risk-taking depending on the terminal date of the portfolio manager. It is further necessary to note that the terminal date of the signal provider's eToro portfolio can be seen as unlimited, which makes a substantial difference in the hedge fund incentive contracts literature. A signal provider's optimal investment strategy is substantially closer to a constant proportional risk-taking when the fund performs reasonably well. However, on the other side, they show that if the fund value has declined substantially and the fund must almost be closed, the manager is moving towards much higher risk-taking (Hodder & Jackwerth, 2007). On eToro, this can be seen as moving from the second lowest rank when the trader has earned a monthly payment to the lowest rank when there is no monthly payment at all anymore. Thus, the step between no compensation and the first rank for compensation can induce the signal provider's risk-taking behavior and directly affect the signal followers. Further, on eToro, there are no direct costs for a signal follower to copy another trader. However, the commission for eToro comes from the SELL/BUY spread of the placed trades. So there is just the regular trading fee hidden in the spread (*eToro*, 2022). Even-Tov et al. (2022) show in their paper that retail investors are highly responsive to changes in trading commission fees.

3.2 Wikifolio

Wikifolio is one of the leading European social trading platforms. Although wikifolio and eToro are in the same social trading industry, they have fundamentally different concepts and therefore work entirely differently for the signal followers and the signal providers. Wikifolio was founded in 2012 and has gained much popularity since then. On Wikifolio, signal providers or wikifolio traders create and publish a so-called wikifolio. This is a portfolio with artificial money where the creator can buy and sell any shares through the wikifolio platform. The trades and holdings of shares are published transparently on the platform. After the creation and after the wikifolio has asserted itself over the community by having enough investor reservations, enough reserved capital collected, and the 21-day period completed, the creator of the wikifolio must get in contact with wikifolio and make up a phone interview. When all these steps are finished, the wikifolio can be the basis for a certificate. This means the wikifolio becomes an ISIN from their partner Lang & Schwarz and can be traded on many different exchanges. Wikifolio itself does not provide any trading on the platform. This leads to a business model that distinguishes fundamentally from the business model of eToro. It is further not possible to directly interact with the creators of the wikifolios. Signal providers only communicate through a news feed of the published wikifolio with their followers. They can give comments to certain investments or trades and can discuss future investment outlooks. However, there is no direct interaction between the signal provider and the signal follower on wikifolio. Due to the nature of a certificate, like CFDs, it is subject to additional risk against the certificate's issuer. So, if an issuing house like Lang & Schwarz cannot meet its payment obligations, every certificate is insured against the issuer's risk (*Wikifolio Investments*, 2022).

3.2.1 Features

Wikifolio's focus is on providing a platform where everyone, after a verification process, is able to create and publish a wikifolio, which is similar to an investment fund. Every investment decision and every trade is entirely transparent and can be seen by everyone. The signal providers communicate through a news channel to the signal followers. Overall the social and communication aspects and other possibilities that users can do on the platform are limited on wikifolio. Wikifolio pursues a fundamentally different business model. While wikifolio is purely a platform for publishing wikifolios and communicating between signal providers and signal followers, it does not offer any other functions. eToro, on the other hand, is a comprehensive trading platform that offers extensive traditional investment opportunities in addition to social trading features. Overall, Wikifolio as a platform has fewer features than eToro. There is no trading functionality on the platform itself. Every trade of a wikifolio takes place on a traditional exchange. Only the ISIN is needed to buy a wikifolio, and every conventional broker can be used to buy the certificate.

Furthermore, the certificates of the underlying wikifolios are not distributed directly by wikifolio but via the partner bank Lang & Schwarz. So, when a signal follower decides to buy or "copy" a wikifolio, a certificate with the direct participation of the portfolio is bought. Every trade of the signal provider and share price change is reflected in the portfolio performance; therefore, the certificate loses or gains in value. Certificates can be traded during the regular opening hours of the supported exchanges.

3.2.2 Compensation structure

Wikifolio's compensation structure follows a more straightforward and transparent approach with a certificate fee of 0.95% per annum. Hence, Wikifolio has a different compensation model, unlike eToro. That fee is similar to a management fee for mutual funds or ETFs and goes directly to wikifolio. Additionally, a performance fee between 5 and 30% is determined by the wikifolio creator that follows a traditional high water mark principle. This means that this fee only applies when the wikifolio has a positive performance and only if it hits a new year high and only on the difference between old and new year highs (*Wikifolio Investments*, 2022). According to Aragon & Nanda (2012) this compensation scheme has a significantly weaker incentive for hedge fund managers to increase the risk to gain greater returns. It could, therefore, also be applied to wikifolio signal providers since wikifolio creators can be seen as portfolio managers, according to Doering et al. (2015). However, on the other hand, Doering & Jonen (2018) found out that portfolio managers tend to increase portfolio risk when they are approaching their HWM (high water mark).

Further, they show no significant difference in risk-shifting behavior between institutional portfolio managers and individual investors. Therefore, these findings can be applied to signal providers on social trading platforms as well. Also, Doering & Jonen (2018) can confirm the subsequently increased portfolio risk when approaching the HWM. Their findings are so interesting because they used data from social trading platforms, especially wikifolio certificates. Therefore, it can be assumed that their sample was mostly non-professional investors. The results of their study show that the closer the individuals are to their high water mark at the end of the month, the more the risk was increased over the subsequent month – same behavior of individual investors like sophisticated hedge fund managers.

4 Empirical analysis of social trader performance

Social trading platforms are particularly interesting to study effects on trading behavior because of key features like transparency, social interaction, and financial incentives (Chen et al., 2014; Liu et al., 2014; Wohlgemuth et al., 2016). The thesis' empirical analysis consists of two parts. Part one compares the performance between the wikifolio social trading platforms and a chosen market benchmark. The risk-adjusted returns are compared, and a t-test is performed to derive a statement. With these findings, it is seen whether a general statement can be made. The second part deals with the other three hypotheses, where a closer look at features and behavior in social trading networks is taken. This research aims to assess the viability of social trading platforms in generating returns that exceed those of traditional market benchmarks. This study seeks not only to evaluate the overall profitability of social trading but also to delve into strategic insights that could guide traders in selecting effective signal providers.

So, as mentioned the research is structured around two primary objectives:

1. **Benchmark Comparison**: To determine if social trading platforms can outperform established market benchmarks, providing a viable alternative for retail and institutional investors.

2. **Performance Factors**: To explore which factors might influence the performance of investments on social trading platforms. This involves a detailed analysis of various characteristics of signal providers, such as the amount of capital invested, the duration since the signal provider's inception, and the structure of performance fees.

The following hypothesis were developed.

4.1 Hypothesis development

In order to address the research question of "Can Copy Trading beat the market" and to be able to derive a general statement, four hypotheses were developed. These hypotheses are tested with the dataset. The hypotheses were derived from the research question, which is "Can investors beat the market with social trading?". Prior research suggests that investors on social trading platforms can achieve higher returns than institutional investors. However, this comes along with higher risk-taking (Abbey & Doukas, 2015). In order to examine this statement more independent, and be able to make a general statement, different aspects of the performance and return characteristics are considered.

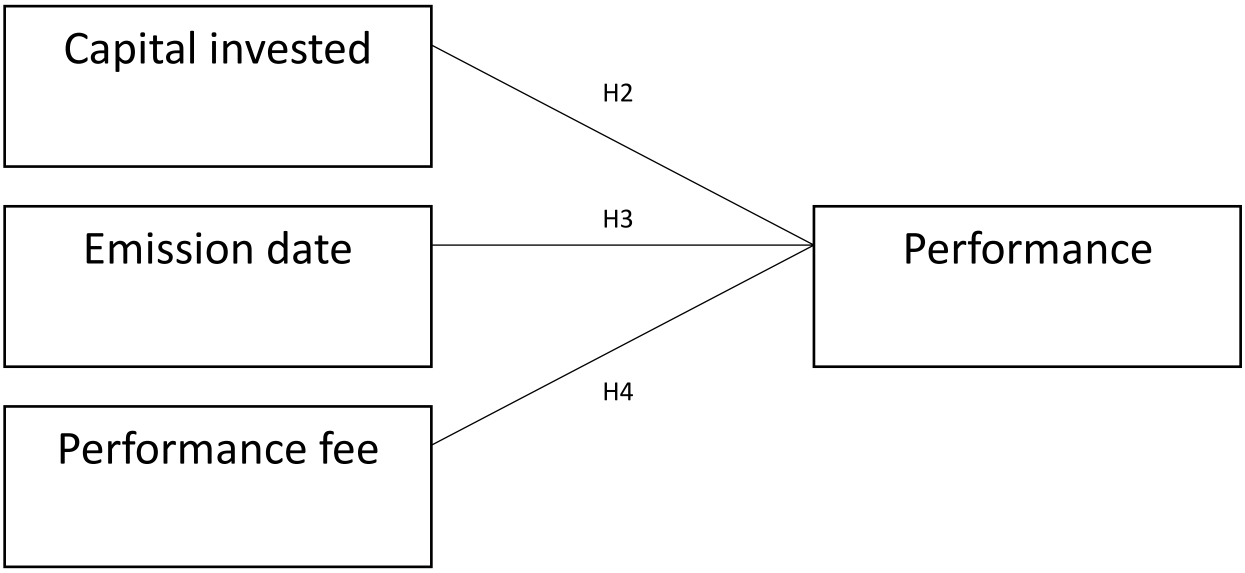

Figure 1 Hypothesis Development

Hypothesis 1: *The avg. monthly return of a wikifolio certificate is higher than the market benchmark*

This hypothesis aims to explore whether wikifolio traders can outperform traditional market indices, suggesting that the strategies employed by these social traders, leveraging real-time information and collective wisdom, potentially yield higher returns. The validation of this hypothesis would not only affirm the efficacy of wikifolio as a competitive investment alternative but also challenge conventional investment paradigms by highlighting the advantages of dynamic and socially-driven trading platforms.

Hypothesis 2: *Wikifolio: Invested capital has no significant impact on the average monthly return*

The second hypothesis focuses on the general invested capital in a wikifolio which can be considered as a proxy variable for the popularity of the wikifolio. It states that the amount of invested capital has no impact on performance. Depending on the test result, a statement could be drawn where a wikifolio with more capital invested can generate a higher return, and conclusions to a more popular wikifolio generate higher returns might be possible.

Hypothesis 3: *Wikifolio: The emission date has no significant impact on the average monthly return*

The third hypothesis focus on the effect of the emission date. H3 tests the assertion that the timing of a Wikifolio's creation—or its "emission date"—does not influence its subsequent average monthly returns. This analysis aims to explore whether the historical context or market conditions at the time of a Wikifolio's launch could affect its performance over time. Demonstrating that emission dates do not affect returns could bolster investor confidence in the stability and predictability of investing in Wikifolios, regardless of market timing or how “old” the wikifolio is and whether investors can expect different future returns depending on the emission date. This hypothesis can help investors investing in new Wikifolios without concern for timing market cycles, focusing instead on long-term strategies and asset allocations.

Hypothesis 4: *Wikifolio: The amount of the performance fee has no significant impact on the average monthly return*

The fourth hypothesis tests the impact of performance fees on performance. Even-Tov et al. (2022) show that retail investors are highly responsive to changes in trading commission fees. At the same time Agarwal et al. (2009) show that incentive fee percentage rate by itself does not explain performance. Which will be examined in the social trading scope with the H4.

The development of the four hypotheses within this thesis introduces a certain limitation due to their exclusive focus on a single social trading platform. This focus may constrain the external validity of the findings, potentially limiting the generalizability of the conclusions drawn. However, interesting insights into the popularity and quality of social traders can be gained and whether it has an effect on performance. Conclusions from the results, in combination with existing literature, can further give valuable insights for future research and lay a groundwork for future research in the field of social trading.

4.2 Data

For the research, a unique dataset that covers the period from the beginning of 2018 to the end of 2020 was used. The data was hand-collected from the website of wikifolio.com .

Data collection from the eToro platform faced significant hurdles and was ultimately discontinued. The inaccessibility of the eToro API as of 2024, combined with the lack of response to requests for data provision, left no official means to gather necessary information. Additionally, the platform's strict security measures and user access limitations hindered manual data collection. Specifically, the platform imposed restrictions on the number of copy trader profiles that could be viewed, and exceeding this limit triggered an IP ban, effectively ending further data collection efforts from eToro. This cessation significantly constrained the research scope and data availability.

Wikifolio provides easier access to collect data on their website. Wikifolios with different categories and metrics can be gathered under the “find wikifolios” section all at once. The daily returns can be downloaded as well on each individual wikifolio website. There are several options to filter wikifolios. To gather relevant, representable data that can be analyzed and compared to market benchmarks, several measures had to introduce to filter out some of the wikifolios. Further, there are several ways to filter and obtain valuable additional data, like the already calculated Sharpe ratio and several performance measures. Only wikifolios that were traded for a minimum of 12 months were included to provide robustness to the results. Another aspect to consider is survivorship bias, which cannot be fully eliminated in the Wikifolio dataset.

An adjustment factor could help mitigate the issue of excluding Wikifolios that failed or closed during the examined period. Estimating the average performance of the non-surviving funds and adjusting the performance of the surviving funds accordingly would be a potential solution. However, these assumptions cannot be made because Wikifolio did not provide the necessary data to establish reference points and make these estimations.

There are 9 756 wikifolios to select from under the wikifolio “Explore” section. Several different filter have been applied to obtain a representative and comparable sample. The filters applied include: exclude traders with fewer than 5 followers, verified status, and a focus on investments in stocks, indices, and ETFs. Below is a detailed explanation of the rationale behind each filter and its importance in creating a meaningful comparison with the S&P 500.

Filter: “only investable wikifolios”

When a wikifolio reaches the status "Investable," it is associated with a corresponding wikifolio certificate, which can be purchased through a bank or online broker. Rationale: Selecting traders with only investable wikifolios create a sample that consists of traders who have demonstrated some level of credibility and appeal to other users on the platform.

Scientific Basis: This filter reduces the risk of selection bias and ensures that the sample reflects individual trading decisions rather than collective behaviors that might not be representative of typical market performance. By focusing on traders with smaller followings, the sample better approximates individual trading strategies, making the results more comparable to a broad market index like the S&P 500, which is not influenced by individual social trading behaviors.

Filter: Investments in Stocks, Indices, and ETFs without leveraged products

Rationale: Limiting the sample to traders who primarily invest in stocks, indices, and ETFs ensures that the asset classes they trade are comparable to those that make up the

S&P 500. This filter excludes traders who focus on other, more speculative asset classes especially with high leverages also potentially including cryptocurrencies or commodities, which do not align with the composition of the S&P 500.

Scientific Basis: The S&P 500 is a market capitalization-weighted index comprising 500 of the largest publicly traded companies in the U.S. The index represents a broad cross-section of the stock market, including sectors like technology, finance, healthcare, and consumer goods. By focusing on traders who primarily invest in similar asset classes (stocks, indices, ETFs), the sample aligns more closely with the S&P 500, enabling a more valid and direct comparison. This filter ensures that the performance metrics are comparable in terms of the underlying assets and market exposures.

In order to obtain a 95 percent confidence interval and a rather small margin of error of around 8%, a sample size of 121 signal providers was chosen on wikifolio.

The data obtained from wikifolio may still be subject to sampling bias and survivorship bias, despite the implementation of several strategies aimed at minimizing these biases. Sampling bias occurs when the selected sample is not representative of the broader population, potentially leading to skewed results. This can arise due to various factors, such as non-random selection or the exclusion of certain segments of the population (Donley, 2012).

In the context of this study, platform-related sampling bias is an inherent limitation, as the data is derived exclusively from a single platform, wikifolio, rather than a broader spectrum of social trading platforms. This limitation constrains the generalizability of the findings to the wikifolio platform alone, rather than to social trading as a whole. Consequently, the hypotheses formulated in this study are explicitly tailored to platform-specific outcomes, acknowledging the limitations imposed by the platform-related sampling bias. By focusing on platform-specific hypotheses, the study aims to provide insights that are valid within the context of wikifolio, while recognizing the limitations in extending these findings to the wider social trading domain.

Survivorship bias is another potential issue in this study, which occurs when only the successful or surviving participants are included in the analysis, potentially overlooking those who have failed or withdrawn. This bias can result in an overestimation of performance metrics and an inaccurate portrayal of the overall population (Elston, 2021). In the context of wikifolio data, traders who have ceased trading or were unsuccessful may be excluded, thus skewing the results toward those with better performance records. While every effort has been made to mitigate these biases, they cannot be entirely eliminated. The study's conclusions should, therefore, be interpreted within the context of these limitations and will also be mentioned again, separately in the Limitations chapter.

The benchmark data of the S&P 500 is obtained through the website investing.com. Several other options were there like the R package quantmod which uses the yahoo finance source for data collection. However, it showed investing.com provided that date in the best way for further data transformation and the following analysis. The data was then used to compare the performance of wikifolio certificates against the S&P 500 as a market benchmark.

4.3 Methodology

In order to determine the performance of wikifolios - Traders, first, the monthly, daily, and log returns for each wikifolio are computed, and the volatility is recorded. Before that, the wikifolio traders' data was combined by the date and summarized with the mean of the daily returns. After that, analysis could begin and the mean return, variance, extreme values, and risk is calculated. The risk of a portfolio can be expressed in different ways. In principle, it can be expressed by the standard deviation. In simple terms, the value of the standard deviation or the measure of dispersion states how high the expected fluctuation range is from the mean value. Another risk measurement variable is the beta coefficient. It plays an important role in this thesis since it measures a portfolio's systematic risk by determining the portfolio's volatility in relation to a particular benchmark (Perold, 2004). Another variable for risk is the Sharpe ratio. It is used to calculate and then compare the risk-adjusted return. With the help of the Sharpe ratio, it is possible to take an equal account of the expected return and the associated risk (Ledoit & Wolf, 2008). In order to further improve the informative value obtained, the returns should be examined in connection with general capital market behavior. Based on the capital asset pricing model (CAPM), a linear regression should provide information about the influence of the market.

A suitable market benchmark for the analysis would be the S&P 500, DAX and MSCI World. In this thesis the S&P 500 was chosen because it is widely recognized as a prime benchmark index, not just for its broad market representation, but also due to its strong historical performance over several decades. This consistent performance makes it a preferred choice for investors employing an ETF strategy, as it offers a reliable reflection of market trends and a diverse portfolio through a single investment vehicle. Its use by a vast array of investment funds as a benchmark for comparing performance underscores its credibility and relevance in financial markets globally.

After the performance and risk of investors on wikifolio have been compared and evaluated with market benchmarks and the first hypotheses has been tested, the other three hypotheses, H2, H3 and H4 are addressed. Another wikifolio dataset will then be used to conduct the analysis about the financial metrics and social trading returns.

4.4 Empirical results: Hypothesis 1

The empirical results of H1 are discussed and presented in the following chapters. First the return, risk and volatility of the social trading samples and the market benchmark are presented. In order to further improve the significance of the information just obtained, the returns are examined in connection with general capital market behavior. Based on the capital asset pricing model (CAPM), a linear regression will be used to provide insight into the market's influence.

4.4.1 Wikifolio and S&P 500: Return and volatility analysis

First the analysis of the statistical summary table will be done. The statistical summary provides key

Data Source	Mean	Median	Std_Dev	Skewness	Kurtosis	5% Quantile	95% Quantile
Daily Return Wikifolio	0.0003815	0.0009845998	0.0076867	-1.0975298	11.20591	-0.011354	0.010220
Daily Return SP500	0.0005796	0.0010714	0.0146214	-0.7052049	18.36698	-0.020966	0.016418

insights into the daily returns of the combined Wikifolio and the S&P 500. In the following chapter a there is a detailed discussion of each metric and its implications is given. Further a boxplot of the wikifolio and the S&P 500 daily returns is provided.

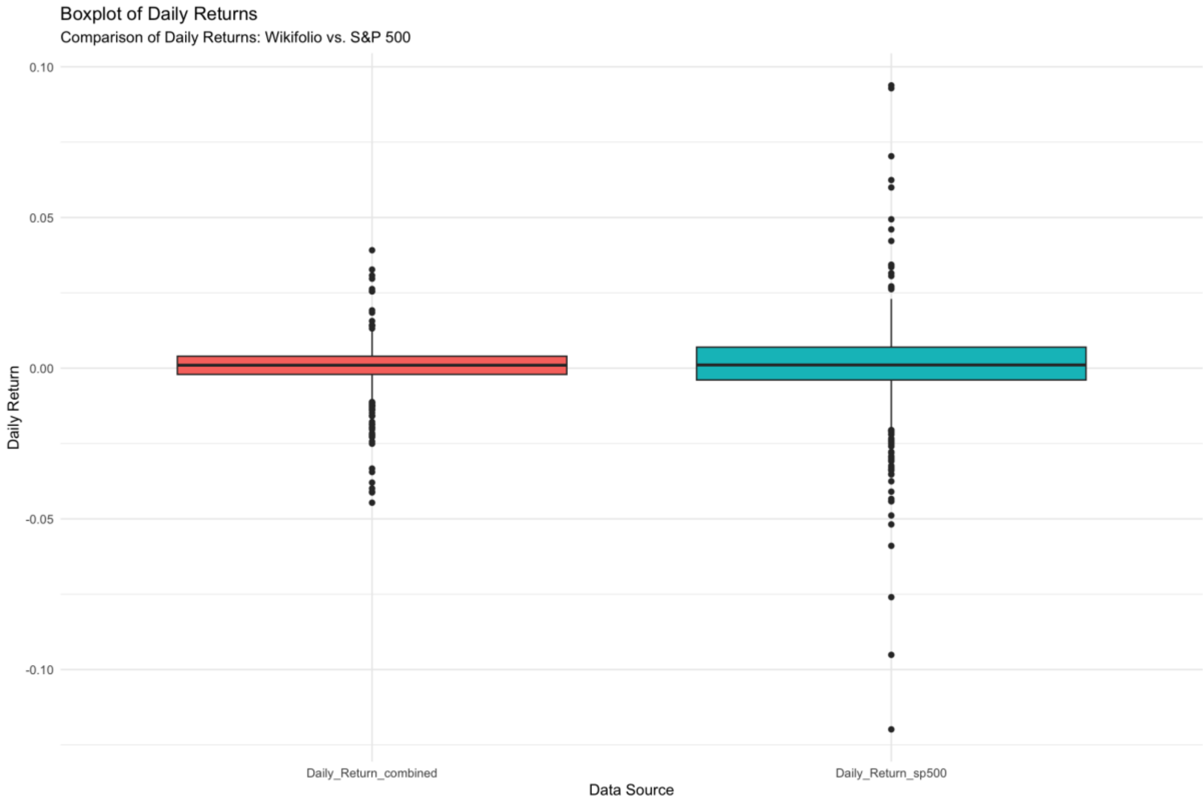

Figure 2 Daily Returns of Wikifolio vs. S&P 500

The boxplot visually compares the distribution of daily returns between Wikifolio and the S&P 500. For Wikifolio, the median return is close to zero, with a narrower interquartile range (IQR), suggesting less return variability. In contrast, the S&P 500 shows a higher median return and a broader IQR, indicating greater volatility. Both distributions exhibit outliers, highlighting extreme gains or losses on particular days.

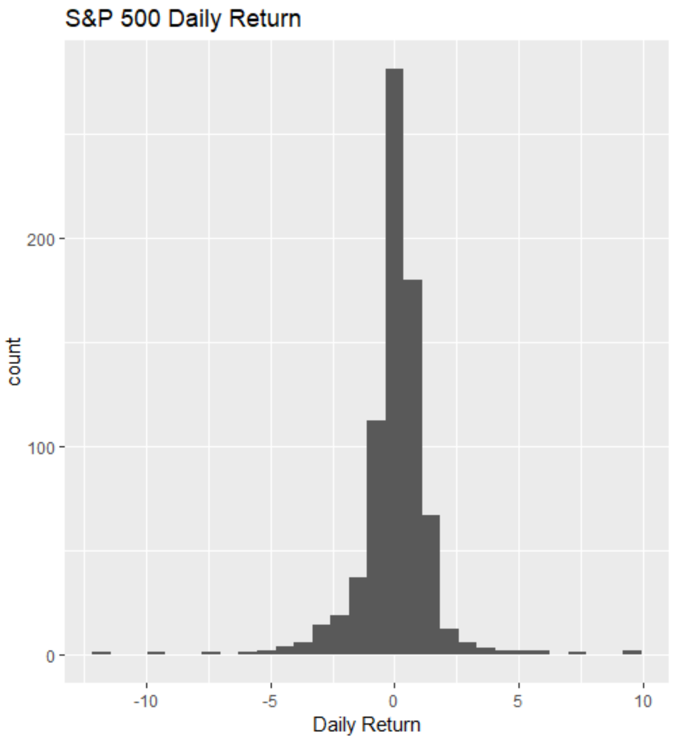

Figure 3 S&P 500 Daily Return Distribution

The histogram of the S&P 500 daily returns shows a distribution that is roughly symmetrical and centered around zero, suggesting that the index typically experiences minimal change in value on most trading days. The bell-like shape of the distribution, which is indicative of a normal distribution, points to the typical behavior expected in financial markets, although it may exhibit "fat tails" that imply a higher occurrence of extreme values than a true normal distribution would suggest. This characteristic highlights the potential for unexpectedly large fluctuations in value, signaling a risk profile important for investors using the S&P 500 as a benchmark to assess volatility and compare with other investment opportunities.

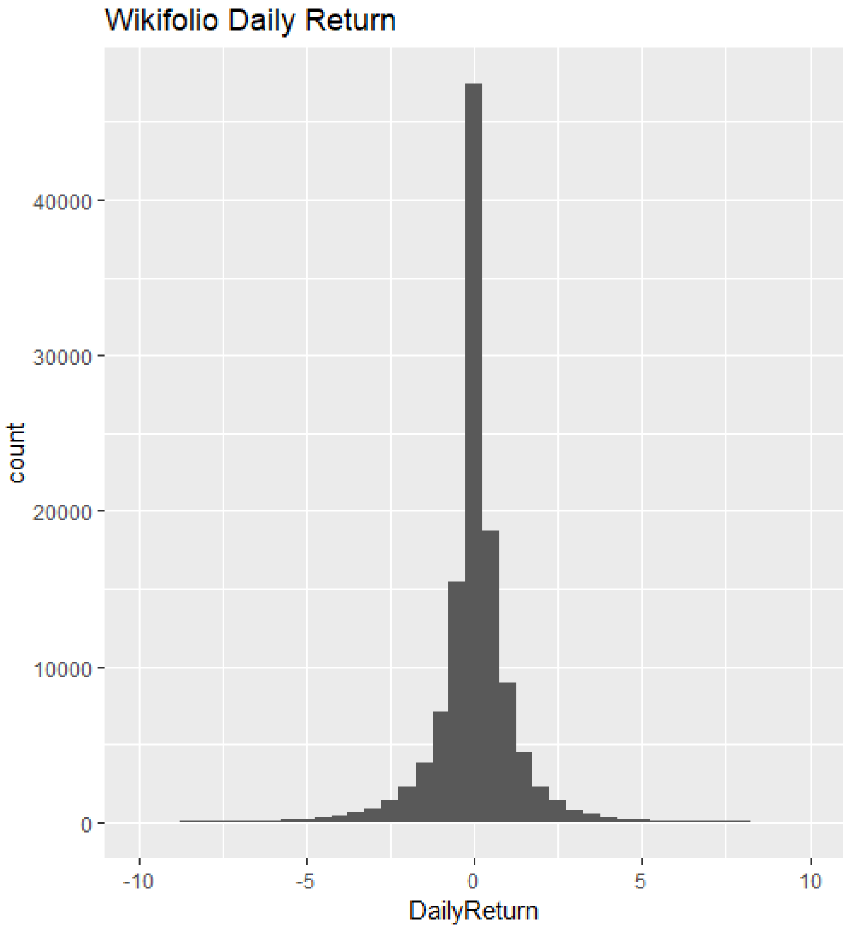

Figure 4 Wikifolio Daily Return Distribution

The histogram of Wikifolio daily returns showcases a distribution that is centered around zero, resembling a normal distribution, though it is significantly more peaked and narrow compared to the S&P 500. This higher concentration of returns close to the median suggests lower volatility, indicative of a more conservative or managed investment approach on social trading platforms like Wikifolio. The distribution's sharp peak and the rapid decline in frequency of returns further from the mean indicate that extreme returns, both positive and negative, are less frequent. Such a pattern could imply that signal providers might opt not to hold assets during volatile market periods to mitigate significant losses, reflecting a potentially risk-averse strategy. This is also supported by Gemayel & Preda (2018) who found out that because of the constant observation the individuals become more self-concious and hence limit their losses to avoid tarnishing their public trading record.

Mean

The mean daily return of the S&P 500 (0.05796%) is slightly higher than that of the combined Wikifolio (0.03815%). However, as our t-tests have shown, this difference is not statistically significant. This suggests that, on average, both investment options can yield similar daily returns.

Median

The median daily return, which represents the midpoint of the data, is very close for both the Wikifolio and the S&P 500. The higher median return for the S&P 500 suggests that more than half of the daily returns are slightly higher compared to the combined Wikifolio. This consistency with the mean supports the overall similar performance of both investments.

Standard Deviation

The standard deviation measures the variability or volatility of the returns. The S&P 500 has a higher standard deviation (1.46%) compared to the Wikifolio (0.77%), indicating that the S&P 500 returns are more volatile. This might suggests that while the S&P 500 may offer slightly higher returns on average, it comes with greater risk.

Skewness

Skewness measures the asymmetry of the return distribution. Both distributions are negatively skewed, meaning that they have a longer tail on the left side. The combined Wikifolio has a more pronounced negative skew (-1.10) compared to the S&P 500 (-0.71), indicating a higher likelihood of experiencing extreme negative returns. This could be a concern for risk-averse investors.

Kurtosis

Kurtosis measures the "tailedness" of the return distribution. Both the Wikifolio and the S&P 500 have high kurtosis values, indicating a high likelihood of extreme returns (either positive or negative). The S&P 500 has a significantly higher kurtosis (18.37) compared to the Wikifolio (11.21), suggesting that the S&P 500 experiences more frequent extreme returns. This could contribute to the higher volatility observed in the S&P 500 returns.

5% Quantile

The 5% quantile represents the value below which 5% of the data falls. For the Wikifolio, this value is -1.14%, while for the S&P 500, it is -2.10%. This indicates that on particularly bad days, the S&P 500 experiences larger negative returns compared to the Wikifolio. This further underscores the higher risk associated with the S&P 500.

95% Quantile

The 95% quantile represents the value below which 95% of the data falls. The S&P 500 has a higher 95% quantile (1.64%) compared to the Wikifolio (1.02%), suggesting that on good days, the S&P 500 achieves higher positive returns. This aligns with the higher average and median returns for the S&P 500.

Implications and Conclusions

<u>Risk and Return Trade-Off:</u> While the S&P 500 shows slightly higher average and median returns compared to the combined Wikifolio, it also exhibits higher volatility and greater risk of extreme negative returns. This highlights the classic risk-return trade-off in finance, where higher returns come with higher risk.

<u>Skewness and Kurtosis Considerations:</u> The negative skewness and high kurtosis in both distributions suggest that both investment options have the potential for extreme negative returns, with the S&P 500 showing a higher propensity for such events. Investors need to consider their risk tolerance when choosing between these options.

Quantiles Analysis: The quantile analysis shows that the S&P 500 can achieve higher returns on good days but also suffers larger losses on bad days. This volatility might be suitable for investors with a higher risk appetite and a longer investment horizon.

In summary, the statistical analysis reveals that while the S&P 500 offers slightly higher mean and median daily returns compared to the combined Wikifolio, it also comes with significantly higher volatility and risk of extreme returns. Both investments exhibit negative skewness and high kurtosis, indicating the potential for extreme negative returns. The S&P 500 tends to have higher positive returns on good days but also larger losses on bad days. These findings suggest that investors must weigh the trade-off between higher potential returns and increased risk when choosing between the combined Wikifolio and the S&P 500. Future research could explore risk-adjusted performance measures and individual Wikifolio strategies to provide a more comprehensive investment analysis.

4.4.2 Wikifolio and S&P 500: Discussion of the two sided T-Test Results

The Welch Two Sample t-test was conducted to compare the daily returns of the combined Wikifolio returns (mean of x) and the S&P 500 returns (mean of y).

Data	Estimate	Statistic	DF	CI_low	CI_high	P_Value
Wikifolio	0.0003815041	-0.3264936	1,120.016	-0.001388789	0.0009925335	0.7441119
S&P 500	0.0005796318	-0.3264936	1,120.016	-0.001388789	0.0009925335	0.7441119

The test produced a t-value of -0.32649 with 1120 degrees of freedom and a p-value of 0.7441.

This test was performed under the null hypothesis (H0) that there is no significant difference in the means of the daily returns between the combined Wikifolio and the S&P 500 index. In simpler terms, this means that, on average, the daily returns (percentage change in price) of the combined Wikifolio are not meaningfully different from those of the S&P 500. The alternative hypothesis (H1) of the two-sided t-test says a significant difference exists between the mean daily returns of the combined Wikifolio and the S&P 500. The meaning of "no significant difference" is that any observed differences in their average returns are likely due to random chance rather than a real underlying difference in performance.

Fundamental Analysis

The t-test result indicates a t-value of -0.326, which falls well within the acceptance range of the null hypothesis. The high p-value of 0.7441, which is significantly above the common thresholds of <0.05 provides strong evidence that we cannot reject the null hypothesis. This implies that there is no statistically significant difference between the daily returns of the combined Wikifolio and the S&P 500 index over the examined period.

Financial Implications

The analysis of the daily returns provides critical insights for investors and portfolio managers evaluating performance benchmarks. The combined Wikifolio exhibits an average daily return of 0.0003815, which is marginally lower than the S&P 500's average of 0.0005796. However, the key takeaway from the statistical analysis is the overlap of the confidence interval (-0.001389 to 0.000993) with zero, indicating no statistically significant difference between the average performances of the combined Wikifolio and the S&P 500. This outcome challenges the presumption that traditional market indices universally outperform social trading platforms and underscores the potential of platforms like Wikifolio as viable alternatives within diversified investment portfolios.

Discussion

The lack of significant difference in returns suggests that the combined Wikifolio's performance is comparable to that of the S&P 500 index. This has practical implications for the diversification and selection strategy of investors. If the combined Wikifolio is constructed based on different strategies or asset selections compared to the S&P 500, it suggests that these strategies do not necessarily lead to superior or inferior performance relative to the broader market index. This insight can be valuable for individual and institutional investors considering Wikifolio as an investment vehicle.

From a statistical standpoint, the use of the Welch t-test accounts for potential differences in variances between the two samples, making the conclusion robust. The non-significant result indicates that any observed difference in mean daily returns is likely due to random variation rather than a systematic performance difference. Thus, investors might consider factors beyond return performance, such as risk tolerance, investment philosophy, and other financial metrics, when comparing the Wikifolio with the S&P 500 index.

In summary, the statistical analysis aligns with the financial understanding that, over the given period, the combined Wikifolio does not exhibit a return pattern significantly different from the S&P 500 index.

4.4.3 Wikifolio and S&P 500: Discussion of the right sided T-Test Results

In this paragraph the the right-sided t-test will be discussed. This test will examine whether the mean of the combined Wikifolio’s daily return is significantly greater than the mean of the S&P 500’ daily return. The use of a right-sided t-test following a non-significant two-sided t-test is justified, especially considering the primary research question of whether “Can copy trading beat the market” like traditional market indices like the S&P 500. While the two-sided test checked for any difference in mean returns between Wikifolio and the S&P 500, the right-sided test specifically explores if Wikifolio’s returns are significantly higher. This targeted approach is critical as it aligns with the thesis objective to determine if social trading platforms can actually yield better returns than the market average.

Since, in the latter section the two sided t-test was discussed already and the conclusion was that there is no significant difference in returns the right-sided t-test we can interpret the results analogously therefore the result discussion will be shortened.

Data	Estimate	Statistic	DF	CI_low	CI_high	P_Value
Wikifolio	0.000381504	-0.3264936	1,120.016	-0.00119710	Inf	0.627944
S&P 500	0.000579631	-0.3264936	1,120.016	-0.00119710	Inf	0.627944

With a p-value of 0.6279 the null hypothesis cannot be rejected. The conclusion is that there is no evidence to suggest that the mean daily return of the Wikifolios is greater than that of the S&P 500.

4.4.4 Linear Regression Analysis

In the linear regression model, the influence of the broader market (as represented by the S&P 500) on the returns generated in the social trading sector (as represented by the Wikifolio returns) is examined. The goal is to understand how strongly returns of the social trading sector are influenced by the movements in a broad market index like the S&P 500 in this study. This model seeks to quantify the effect that fluctuations in the S&P 500 returns have on the returns observed in the Wikifolio.

The results of the Linear regression model can be found in the following tables and are discussed in the following paragraphs.

4.4.4.1 Regression Results

Variable	Estimate	Std..Error	t.value	Pr...t..
(Intercept)	0.000327459	0.0002783103	1.176597	0.239735288584
Daily_Return_sp500	0.093240391	0.0190323134	4.899057	0.000001183827

Min	1Q	Median	3Q	Max
-0.053618	-0.002298	0.000439	0.003519	0.042856

Residual standard error: 0.00757 on 739 degrees of freedom

Multiple R-squared: 0.03146, **Adjusted R-squared:** 0.03015

F-statistic: 24 on 1 and 739 DF, p-value: 0.000001183827

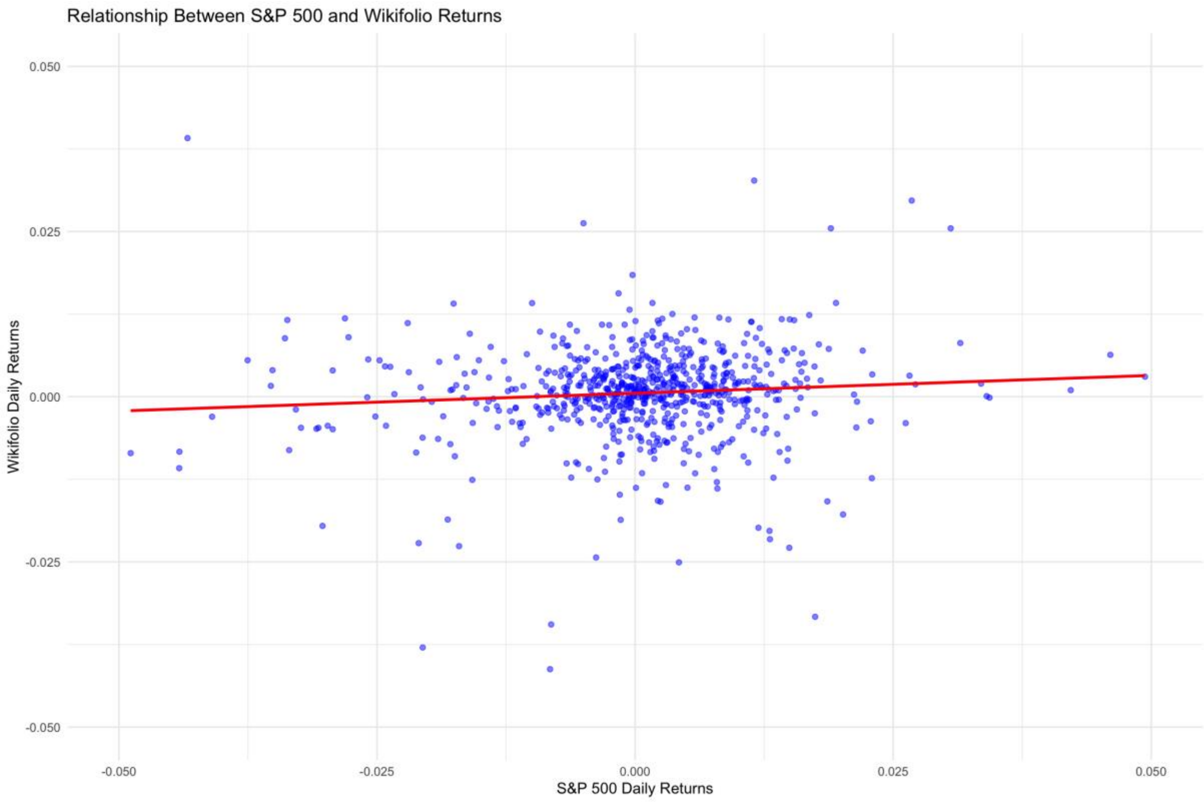

Figure 5 Relationship Between S&P 500 and Wikifolio Returns

The scatter plot visualizing the relationship between the S&P 500 daily returns and the combined Wikifolio returns, augmented by a regression line, suggests a positive but relatively weak linear association. The regression analysis results indicate a statistically significant relationship as reflected by the regression coefficient of 0.0932404 for the S&P 500 daily returns, with a highly significant p-value. This coefficient suggests that for each 1% increase in the S&P 500's returns, the Wikifolio returns increase by about 0.093%. Despite the statistical significance, the practical impact appears modest, with the R-squared value at 0.03146, indicating that only about 3.15% of the variability in Wikifolio returns is explained by changes in the S&P 500. This highlights that while there is a discernible influence of the market as represented by the S&P 500 on Wikifolio returns, a large portion of the return variability is driven by other factors not captured in this model. The spread of residuals also underscores this, showing a range from -0.053618 to 0.042856, which points to substantial unexplained variability in Wikifolio returns.

4.4.4.2 Interpretation

Coefficients

Intercept (0.0003275): This coefficient represents the expected value of the combined Wikifolio returns when the S&P 500 returns are zero. The intercept is small and statistically not significant (p-value = 0.24), suggesting that when there is no movement in the S&P 500, the average return of the combined Wikifolio is close to zero and not different from zero in a statistical sense.

Slope (Daily_Return_sp500 = 0.0932404): This coefficient indicates that for each 1% increase in the S&P 500 returns, the combined Wikifolio returns are expected to increase by approximately 0.09324%. The positive slope is statistically significant (p-value = 0.000001183827), indicating a strong positive relationship between the S&P 500 returns and the combined Wikifolio returns.

Residuals

Residuals represent the difference between the observed values and those predicted by the model. In your model:

- Min and Max Residuals (-0.053618 and 0.042856): These values indicate the largest discrepancies where the model significantly underpredicted or overpredicted the Wikifolio returns. The presence of substantial residuals suggests that certain factors affecting Wikifolio's performance are not captured by the daily returns of the S&P 500 alone.
- Median Residual (0.000439): The median residual being close to zero suggests that, on average, the model does not systematically overestimate or underestimate the returns, pointing to its appropriateness in terms of bias but not necessarily its effectiveness in capturing all variability.

Residual Standard Error (RSE)

- RSE (0.00757): This metric gives an average of the absolute residuals, thus providing a measure of the typical distance between the observed values and the model's predictions. A lower RSE would indicate a better fit of the model to the data. In financial terms, it tells investors about the typical error magnitude they might expect in the predictions of Wikifolio returns based on movements in the S&P 500.

R-squared and Adjusted R-squared

- R-squared (0.03146): This value indicates that only about 3.146% of the variability in Wikifolio returns is explained by the model. It highlights the limited explanatory power of the S&P 500 returns on the variations in Wikifolio returns, suggesting that other unmodeled factors (like specific trading strategies, sectoral effects, or macroeconomic factors) play a more significant role.
- Adjusted R-squared (0.03015): This is a modification of R-squared that adjusts for the number of explanatory terms in a model relative to the number of data points. It provides a more accurate measure of the goodness-of-fit for models with multiple predictors or when comparing models with different numbers of predictors.

F-statistic and p-value

- F-statistic (24 on 1 and 739 DF): The F-statistic tests whether at least one predictor variable has a non-zero coefficient. An F-statistic value of 24 suggests that the overall model is statistically significant.
- P-value (0.000001183827): This very small p-value for the F-test (less than 0.05) indicates that we can reject the null hypothesis that changes in the S&P 500 returns do not explain variations in Wikifolio returns. It confirms that the model is statistically significant, though it explains only a small fraction of the variability in returns.

Conclusion

The analysis suggests that while there is a statistically significant relationship between the returns of the S&P 500 and Wikifolio, the influence of the S&P 500 on Wikifolio returns is relatively minor. It explains that the movements of the market benchmark have a positive impact on the wikifolios.

4.4.5 CAPM Analysis of Investment Performance between Wikifolio and S&P 500

Further financial analysis is done to compare the performance of wikifolio investors and a market benchmark S&P 500. To shed light on their respective risk-return profiles using established financial models like the Capital Asset Pricing Model (CAPM) and the Sharpe Ratio. Doing so can provide empirical evidence crucial for investors seeking to optimize their portfolios in terms of risk and return and further address the research question.

A brief overview of the objectives of the analysis is provided:

Objectives of the Analysis

- **Beta Assessment**: To evaluate the volatility of Wikifolio relative to the S&P 500 and determine its market risk exposure.
- **Expected Return Calculation**: To compute and compare the expected returns of Wikifolio and the S&P 500, providing a foundation for assessing potential wealth generation capabilities.
- **Sharpe Ratio Analysis**: To measure the risk-adjusted returns of both investment options, thereby determining which offers better performance per unit of risk.

Adjustments to Financial Metrics

- Given the historical context of the analysis period (2018-2021), where U.S. government bond yields ranged from 0% to 1%, a **risk-free rate of 1%** is adopted. This adjustment is made to align the financial calculations more closely with the actual economic conditions of the time, ensuring that the results of the CAPM and Sharpe Ratio analyses are both realistic and relevant.

Metric	Wikifolio	S&P 500
Beta	0.0932	1
Expected Return	0.0227	0.146
Sharpe Ratio	0.745	0.634

Here is a detailed interpretation of the metrics from the CAPM analysis and Sharpe Ratio for both Wikifolio and the S&P 500:

Beta

Wikifolio: 0.0932

- This beta value is significantly less than 1, indicating that Wikifolio is much less volatile compared to the broader market (S&P 500). Therefore, on average an investment in Wikifolio would likely experience smaller fluctuations in response to market movements. This suggests that Wikifolio is a low-risk investment relative to the market which would also go in line with the previous findings. A reason for explanation could be the volatile time during the COVID stock market crash. In that time wikifolio investors could have sold their investments and therefore have a lower volatility compared to the market.

S&P 500: 1

- The S&P 500 has a beta of 1, serving as the benchmark for market volatility and risk.

Expected Return

Wikifolio: 2.27%

- Despite its low beta, Wikifolio has an expected annual return of 2.27%. This is a relatively modest return but might be considered attractive given its low risk (beta), especially in a potentially low-return environment or among risk-averse investors.

S&P 500: 14.6%

- The S&P 500 shows a significantly higher expected annual return at 14.6%. This aligns with its role as a market index and reflects the typical risk-return tradeoff: higher potential returns accompanied by higher risk (volatility).

Sharpe Ratio

Wikifolio: 0.745

- The Sharpe Ratio for Wikifolio is 0.745, indicating that it provides a reasonable return per unit of risk. This ratio is above 0. However, it is crucial to compare it to benchmarks or similar investments to fully gauge its attractiveness. The value suggests that the returns, adjusted for risk, are decent, though not exceptional.

S&P 500: 0.634

- The S&P 500 has a Sharpe Ratio of 0.634, which is slightly lower than that of Wikifolio. This suggests that while the market offers higher returns, those returns come with proportionately higher risk, and when adjusted for this risk, the S&P 500 is slightly less efficient in turning risk into return compared to Wikifolio.

Summarize of the findings

The analysis shows a clear tradeoff between risk and return among the two investment options. Wikifolio, with its much lower beta, offers less risk but also lower returns compared to the S&P

500. However, its Sharpe Ratio is higher than that of the S&P 500, suggesting that it may be a more efficient investment on a risk-adjusted basis.

Investors who are particularly risk-averse might find Wikifolio appealing due to its lower volatility and reasonable risk-adjusted returns. In contrast, those seeking higher returns and who are willing to accept higher volatility might prefer investing in the S&P 500.

4.5 Empirical Results: Hypothesis 2

Invested capital has no significant impact on the average monthly return

The Hypothesis H2 will be discussed in the following chapter. Based on the regression results provided for Hypothesis H2, which examines the impact of invested capital on the average monthly return of Wikifolios, we can provide a detailed interpretation of the findings.

4.5.1 Regression Results

Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	40.2698799576369	3.8013181630957	10.593662	0.00000000000000000000000080176
Invested_Capital	0.0000003433934	0.0000000577526	5.945938	0.00000000390002961631998366277

Residual standard error: 113 on 920 degrees of freedom

Multiple R-squared: 0.03701, **Adjusted R-squared:** 0.03596

F-statistic: 35.35 on 1 and 920 DF, **p-value:** 0.0000000039

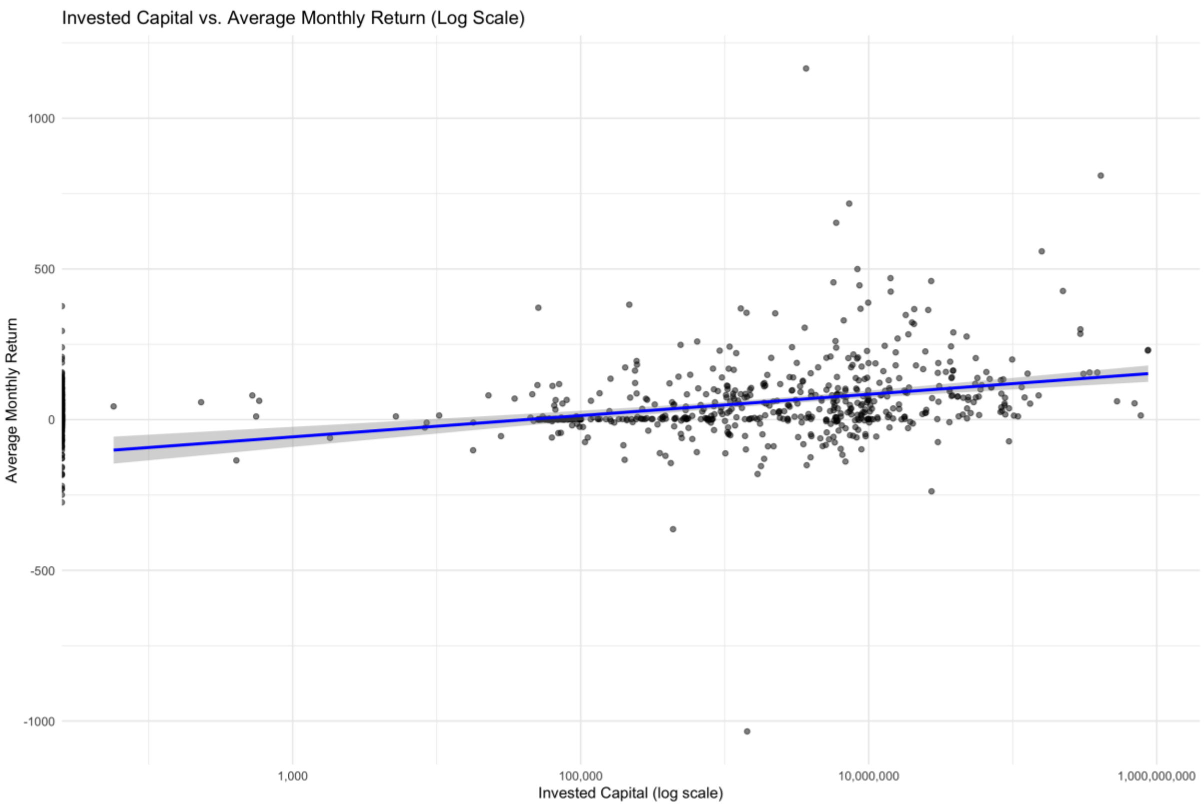

Figure 6 Invested Capital vs. Average Monthly Return

The plot visualizes the relationship between invested capital (on a log scale) and average monthly returns of wikifolio traders. The upward trend indicated by the blue regression line suggests a positive correlation between the amount of capital invested and the average monthly returns, although the spread of data points indicates variability in returns even at higher capital levels. This visualization underscores the influence of invested capital on performance but also highlights that other unaccounted factors likely affect the returns, as evidenced by the dispersion around the trend line.

4.5.2 Interpretation

Coefficients:

- **Intercept (40.27)**: This value represents the expected average monthly return when the invested capital is zero. The high significance (p < 2e-16) of this intercept suggests that there is a substantial baseline average monthly return independent of the invested capital.
- **Invested_Capital (0.0000003434)**: The coefficient indicates that for every additional unit of capital invested, the average monthly return increases by approximately 0.0000003434 units. This effect is statistically significant (p = 0.0000000039), indicating that increases in invested capital are associated with slight increases in average monthly returns.

Standard Error (0.000000058): This measures the average amount that the coefficient estimates vary from the actual average value of our dependent variable. A smaller standard error suggests more precise estimates.

T-value (5.946) for Invested Capital: This indicates that the coefficient for invested capital is 5.946 standard deviations away from zero. Such a high t-value leads us to reject the null hypothesis that this coefficient is zero, meaning there is a statistically significant relationship between invested capital and average monthly returns. In simpler terms, the higher the absolute value of the t-value, the greater the evidence against the null hypothesis, which in this case suggests that changes in invested capital do indeed influence returns, albeit slightly.

P-Value (< 0.0000000039): Indicates the probability of observing the given result, or one more extreme, if the null hypothesis were true. This extremely low p-value further confirms the significance of the invested capital in influencing the average monthly returns.

Residual Standard Error (113): This value indicates the average distance that the data points fall from the regression line. A residual standard error of 113 suggests considerable variability in monthly returns that is not explained by changes in invested capital alone.

R-squared (0.03701) and Adjusted R-squared (0.03596): These metrics indicate that approximately 3.7% and 3.6% of the variation in average monthly returns is explained by variations in invested capital, respectively. While these values might seem low, they are quite common in financial models where returns can be influenced by a multitude of factors — economic conditions, market sentiment, geopolitical events, trader behavior, and many other variables that were not included in this simple model.

F-statistic (35.35): The F-statistic is used to determine whether there is a significant relationship between the dependent variable and the independent variables in a regression model. It essentially asks whether the explained variance in the model is greater than the unexplained variance, given the degrees of freedom and the number of predictors. The extremely low p-value associated with this F-statistic (3.9e-09) indicates that the model as a whole is statistically significant. This means that invested capital, as a factor in the model, does have a significant linear relationship with average monthly returns, although the model explains only a small fraction of the variance in returns.

Discussion and Contextual Interpretation

While the statistical analysis indicates a positive relationship between invested capital and average monthly returns, the practical impact of this relationship appears to be minor given the very small coefficient and low R-squared value. This suggests that while more capital invested in a social trading signal might lead to slightly higher returns, other factors not captured in this model play a more significant role in determining monthly returns.

In the context of social trading:

- **For Investors**: While choosing signal providers with more capital might seem slightly advantageous, it's crucial to consider other factors such as the signal provider's historical performance, risk management strategies, and market conditions.
- **For Signal Providers**: Attracting more capital can lead to better reported average returns, which could help in marketing their strategies, but they should also focus on improving other aspects of their trading to attract and retain savvy investors.

The analysis provides statistically significant insights into how invested capital impacts returns, which, while minor, are nonetheless important for a nuanced understanding of investment strategies on social trading platforms. Investors should consider this as one of many factors in their decision-making processes, and researchers should use these findings as a stepping stone for further investigation into the myriad factors affecting financial returns in social trading environments.

4.6 Empiricial Results: Hypothesis 3

The emission date has no significant impact on the average monthly return

In this chapter, Hypothesis H3 results will be discussed, which assesses the impact of the emission date on the average monthly returns of wikifolio traders. This analysis explores whether the duration since a trader's inception on the platform influences their financial performance, employing a regression model to analyze the relationship between the time active and average returns. This investigation aims to uncover if longstanding traders achieve better outcomes than their newer counterparts.

4.6.1 Regression Results

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	67.7239836	6.87564029	9.849844	0.0000000000000000000007884106
Invested_Capital	-0.0122084	0.00307621	-3.968650	0.0000779073159367092872703772

Residual standard error: 114.2 on 920 degrees of freedom

Multiple R-squared: 0.01683, **Adjusted R-squared:** 0.01576

F-statistic: 15.75 on 1 and 920 DF, **p-value:** 0.00007790

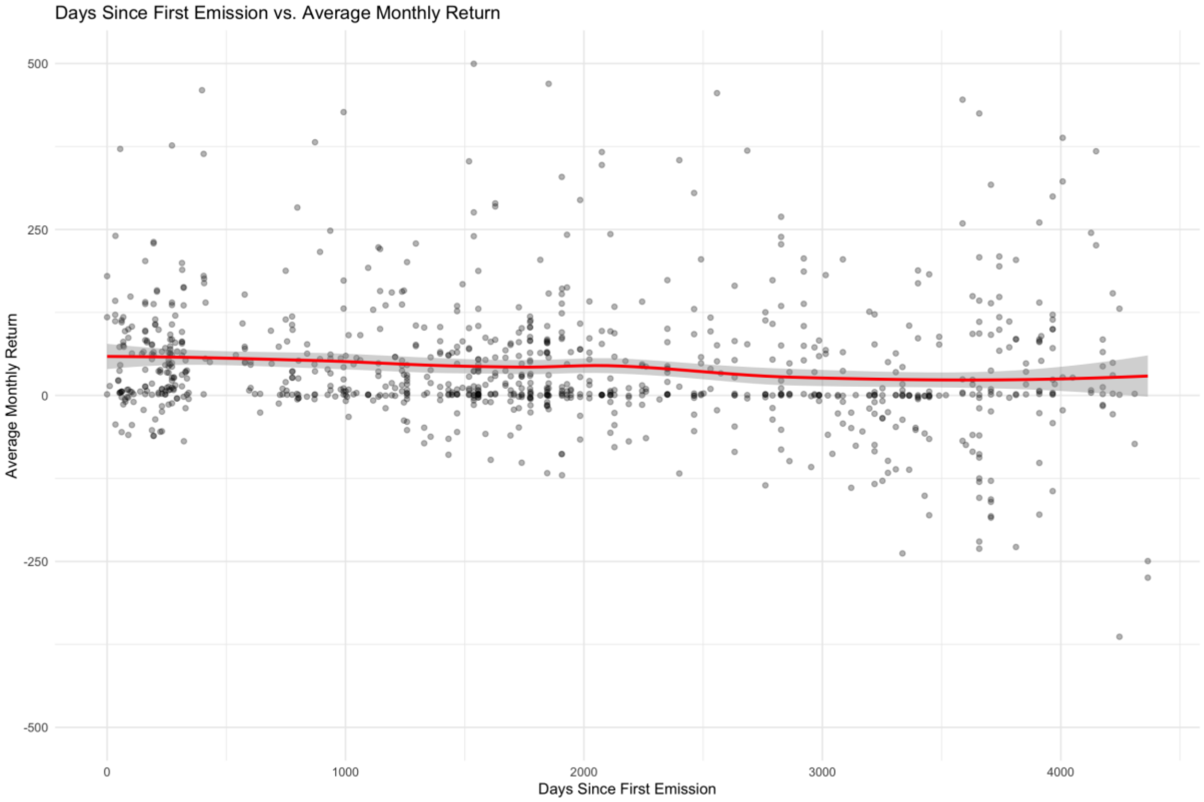

Figure 7 Days Since First Emission vs. Average Monthly Return

The plot visualizes the relationship between the number of days since the first emission of wikifolio traders and their average monthly returns. The red regression line, which is nearly flat, indicates a very slight negative trend, suggesting that longer time since emission does not substantially increase, and may slightly decrease, average monthly returns. This pattern suggests that being active on the platform for a longer time does not necessarily equate to better financial performance. The scatter of data points across the time spectrum highlights considerable variability in returns, reinforcing that factors other than time since emission significantly influence trader performance.

4.6.2 Interpretation

Coefficients

- **Intercept (67.723984)**: This value represents the expected average monthly return when the 'Days_since_First_Emission' is zero, i.e., on the first day of a signal provider's operation. The highly significant t-value (9.850) and <0.05 p-value suggest a substantial baseline average monthly return right at the inception of trading activity.

- **Days_since_First_Emission (-0.012208)**: The negative coefficient indicates that each additional day since the first emission results in a decrease in average monthly return by 0.012208 units. This negative relationship is statistically significant (p = 7.79e-05), suggesting that the longer a signal provider has been active, the slightly lower their average monthly return becomes.

Standard Error (0.003076): The standard error associated with the coefficient for 'Days_since_First_Emission' suggests moderate precision in the estimate. The smaller the standard error relative to the coefficient, the higher the precision of the estimate.

T-value (-3.969): The t-value indicates the coefficient is nearly 4 standard deviations away from zero, providing strong evidence against the null hypothesis that this coefficient is zero (which would imply no effect of duration since emission on returns).

P-Value (0.00007790): The p-value associated with the 'Days_since_First_Emission' coefficient indicates very strong evidence against the null hypothesis, confirming that the duration since inception does have a statistically significant impact on returns.

Residual Standard Error (114.2): This measures the typical deviation of the observed values from the regression line, suggesting that there is still a considerable amount of variability in returns that isn't explained by this model.

R-squared (0.01683) and **Adjusted R-squared (0.01576)**: These values indicate that only about 1.683% and 1.576% of the variance in the average monthly returns is explained by the duration since first emission. This low percentage highlights that other unmodeled factors likely have a more substantial impact on the returns – similar as discussed in h2 which is rather the norm in financial models.

F-statistic (15.75): This tests the overall significance of the regression model, with the associated p-value indicating that the model is statistically significant, suggesting that the duration since inception does indeed impact returns – however, as mentioned in a very small way.

Discussion and Contextual Interpretation

The analysis of Hypothesis H3 indicates a small but statistically significant negative impact of the duration since a signal provider's inception on their average monthly returns. This could suggest that newer signal providers might experience a "honeymoon" period of higher performance, which potentially declines as they age. This decrease might be due to factors such as market adaptation to their strategies, changes in market conditions over time, signal providers becoming less active over time, or a regression towards the mean in trading performance.

For investors on social trading platforms, this finding suggests caution when considering the longevity of a signal provider as a sole indicator of future performance. While experience might imply stability and knowledge, this result indicates that it does not necessarily translate into higher returns over time.

For signal providers, this could underscore the importance of continually adapting and improving strategies, not relying solely on past successes to attract investors.

4.7 Empirical Results: Hypothesis 4

The amount of the performance fee has no significant impact on the average monthly return.

In this section, we explore Hypothesis H4, which scrutinizes the impact of performance fees on the average monthly returns of wikifolio traders. The hypothesis posits that the magnitude of performance fees—often considered a reflection of a trader's confidence in their strategy—should not significantly influence their financial outcomes. By deploying a regression model, this analysis evaluates the actual effect of performance fees on returns, aiming to uncover whether higher fees correlate with superior investment performance or merely reflect a pricing strategy independent of outcome efficacy.

4.7.1 Regression Results

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	46.94704798	6.43115785	7.2999371	0.000000000000622437
Invested_Capital	-0.02386781	0.05995375	-0.3981038	0.690646068358684362

Residual standard error: 115.1 on 920 degrees of freedom

Multiple R-squared: 0.0001722, **Adjusted R-squared:** -0.0009145

F-statistic: 0.1585 on 1 and 920 DF, **p-value:** 0.6906

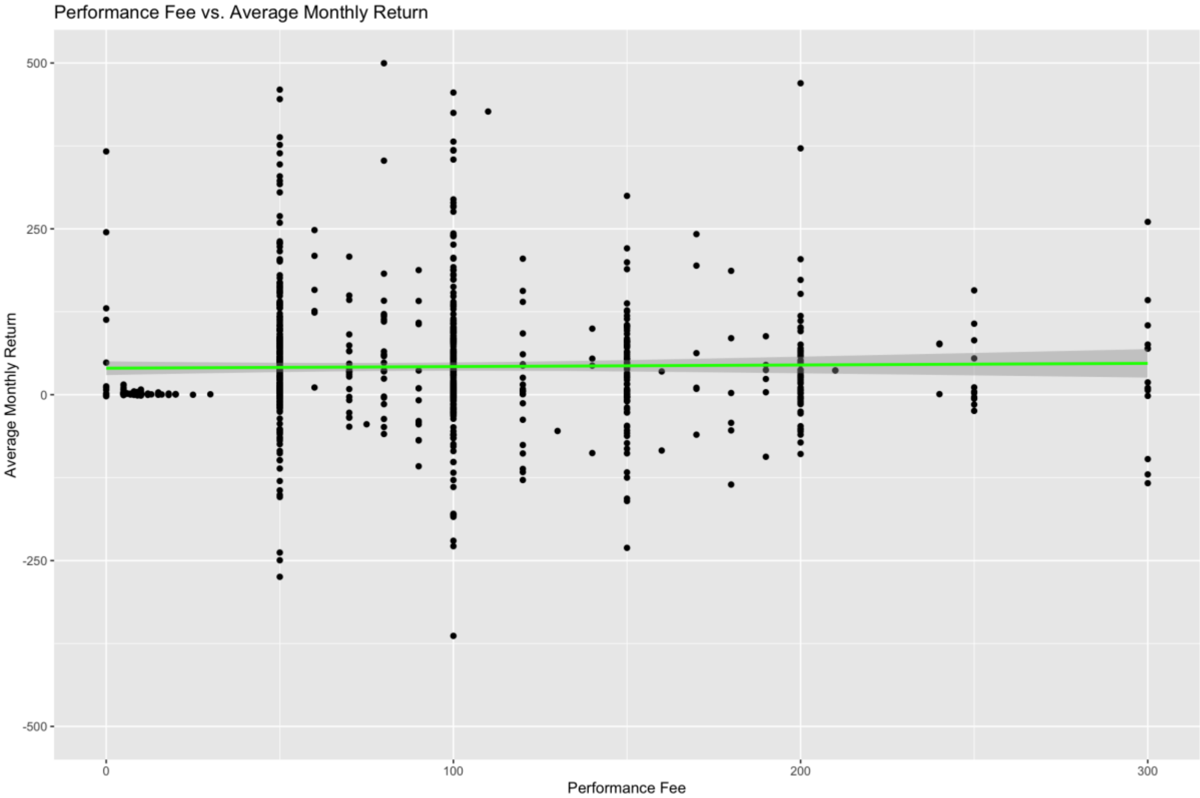

Figure 8 Performance Fee vs. Average Monthly Return

The plot illustrates the relationship between performance fees and average monthly returns among wikifolio traders. The horizontal green line, indicating the regression fit, suggests a minimal to no correlation between the performance fees charged and the returns generated. This lack of a strong trend line indicates that higher fees do not necessarily translate into higher monthly returns, which corroborates the hypothesis that performance fees do not significantly impact financial outcomes. The scattered points across the fee spectrum further highlight the variability in returns, emphasizing that other factors might play a substantial role in determining trader success.

4.7.2 Interpretation

Coefficients

- **Intercept (46.94705)**: The intercept value suggests that when the performance fee is zero, the expected average monthly return is approximately 46.95. The highly significant t-value (7.300) indicates that this intercept is statistically significant, implying a substantial baseline return irrespective of the performance fee.

- **Performance_Fee (-0.02387)**: The negative coefficient for the performance fee suggests a slight decrease in the average monthly return as the performance fee increases. However, the t-value (-0.398) and the associated p-value (0.691) indicate that this effect is not statistically significant. This suggests that variations in performance fees do not have a meaningful impact on monthly returns.

Standard Error (0.05995): This measure indicates the precision of the estimated coefficient for the performance fee. Compared to the coefficient magnitude, the relatively high standard error suggests considerable uncertainty in the effect estimate of performance fees.

T-value (-0.398): The t-value indicates the number of standard deviations the estimated coefficient is from zero. Given that it is less than 1 in absolute value, it does not provide strong evidence against the null hypothesis (that the coefficient is zero).

P-Value (0.691): This high p-value further confirms the lack of statistical significance in the relationship between performance fees and monthly returns, suggesting that fee changes do not significantly affect returns.

Residual Standard Error (115.1): Indicates the typical deviation of the observations from the fitted regression line, with a relatively high value suggesting considerable unexplained variability in monthly returns.

R-squared (0.0001722) and Adjusted R-squared (-0.0009145): Both R-squared values are extremely low, indicating that the model explains virtually none of the variance in average monthly returns based on performance fees. The negative adjusted R-squared suggests that the model might be worse than a simple mean model without predictors.

F-statistic (0.1585): This statistic tests the joint significance of all the coefficients in the regression model, excluding the intercept. The very low F-statistic and its corresponding high p-value (0.6906) further substantiate that the model with performance fee as a predictor does not provide a good fit for explaining variations in monthly returns.

Discussion

This analysis examined the relationship between performance fees and average monthly returns among social trading platforms. Despite intuitive expectations that higher fees might correlate with superior performance—presumably as a premium for higher-quality trading strategies—the statistical findings from this regression model reveal no significant impact. This outcome suggests that the performance fee, as a standalone metric, does not predict the success of trading strategies employed by signal providers. Such a conclusion challenges conventional wisdom in the investment industry, where higher costs often imply superior service or returns. Further, it has to be mentioned that Even-Tov et al., (2022) found out that, retail investors show a very responsive behavior on different trading commission fees.

Appropriateness of Linear Regression Analysis

Performance fees often represent a structured, categorical variable rather than a continuous one, potentially leading to non-linear influences on returns not captured in this linear framework.

- **Categorical Analysis**: Future studies might consider categorizing performance fees into brackets and analyzing their impact using dummy variables in a regression framework. This approach could uncover effects hidden by the averaging of a continuous scale.
- **Non-linear Modelling**: Implementing non-linear regression models or machine learning techniques could help capture more complex relationships that a linear model may overlook.

The results show a fundamental analysis of the effect of performance fees on returns within social trading platforms. While the linear regression model employed did not uncover significant impacts, this result should not be interpreted as conclusive evidence of the irrelevance of performance fees but as an indication of the complexity underlying their relationship with returns. Investors and analysts should consider multiple factors beyond fees when evaluating the potential of signal providers. Moreover, this analysis serves as a benchmark for further research, suggesting a deeper exploration into how different fee structures might influence investor outcomes in varying market conditions.

The findings from this thesis establish a basis for questioning and further investigating traditional fee-performance paradigms in finance, advocating for a better understanding of what drives success in social trading environments. As such, this work contributes to a more informed and critical approach to investment strategy selection on social trading platforms.

5 Limitation

The final chapter of this thesis acknowledges several limitations that may impact the interpretation and generalizability of the findings. One significant limitation is the potential presence of biases inherent in the dataset, specifically selection bias and survivorship bias. Since the data predominantly features wikifolio traders who opt to share their results publicly, it may only comprehensively represent some trading behaviors or outcomes across the platform.

Another limitation is the focus on wikifolio, a platform that may not perfectly mirror the broader universe of social trading environments. While the results provide valuable insights into the dynamics within wikifolio, they might not extend seamlessly to other platforms with different operational mechanisms or trader demographics.

Additionally, although the regression analyses were conducted meticulously, they inherently assume linear relationships and might overlook more complex, non-linear dynamics that could affect returns. This simplification helps understand fundamental relationships but may omit subtler interactions within the data.

Despite these limitations, the research was designed with robust methodological standards, and the findings contribute valuable insights into the effects of invested capital, emission dates, and performance fees on returns within the context of social trading. By acknowledging these limitations, the study underscores the need for cautious interpretation of results. It suggests pathways for future research to explore these dynamics more deeply, enriching the understanding of social trading phenomena.

6 Discussion

In this comprehensive exploration of social trading, the empirical findings challenge and enrich our understanding of signal provider dynamics and their impact on investor returns. The overarching hypothesis, H1, questions whether social trading can consistently outperform traditional market benchmarks. The analysis reveals that, contrary to popular assumptions within retail investing circles, participating in social trading platforms does not guarantee superior returns. This finding echoes the sentiments of Dorfleitner and colleagues (2018) and (Oehler and colleagues (2016), who observed that average participants on social trading platforms do not generally surpass market performance.

Further scrutinizing the factors influencing performance, hypothesis H2 assessed the impact of invested capital on average monthly returns. While a significant relationship was identified, indicating that higher investments might correlate with marginally improved returns, the effect size was minimal. This suggests that while capital injection is a tangible factor, its influence is a fraction of the broader investment outcome, highlighting the multifaceted nature of financial returns that often evade simplistic causal attributions. The findings align with existing studies Glaser and Risius (2018) that hint at a complex interplay of market conditions, trader expertise, and behavioral biases influencing trading success more profoundly than financial inputs alone. Further, it could be interpreted that

Hypothesis H3 and H4 delve deeper into the time aspect and fee-related aspects of trading strategies. The minimal negative impact of emission dates on returns (H3) and the non-significance of performance fees (H4) further punctuate the narrative that external metrics like longevity and fee structures are unreliable predictors of performance. However, Pelster und Breitmayer (2019) show that signal providers' likelihood to obtain copiers increase mainy in their past performance so this would be positive about the time aspect.

Collectively, these results propose a landscape where social trading platforms combine traditional investment principles with the emergent phenomenon of crowd-based decision-making. This study's findings highlight that traditional financial metrics alone offer limited insight into social trading performance, pointing to the need for a more comprehensive discussion.

7 Conclusion

A prevalent misunderstanding suggests that simply replicating the actions of top performers on social trading platforms guarantees increased financial success. This overlooks the possibility that past successes may be more due to luck than skill, making imitation risky. Furthermore, copy trading can lead individuals who are usually risk-averse to adopt riskier financial behaviors as they pursue the potentially misleading success of others. This highlights the complexity and potential pitfalls of basing investment decisions solely on the observed successes of others within social trading environments.

To date, much research has shown that investors are subject to social and behavioral biases. With this thesis, factors influencing performance have been examined. Further, the goal was to show whether a social trading strategy could have higher average returns than a traditional market index. Throughout this investigation, the core hypotheses (H1, H2, H3, H4) aimed to examine the returns of social trading against a traditional market benchmark and the impact of invested capital, emission dates, and performance fees on these returns to understand better how signal followers can navigate on social trading platforms.

The findings from this research are relevant from both a theoretical and practical perspective. The examined data showed that the social traders' performance of wikifolio is not significantly different from the returns from the S&P 500, suggesting that any difference could be due to random chance. Further, the results show that movements in the S&P 500 significantly affect the movements of the wikifolios. The findings of the CAPM analysis further indicate that Wikifolio presents a lower risk and return profile compared to the S&P 500, which might attract risk-averse investors due to its more favorable risk-adjusted returns, as shown by a higher Sharpe Ratio. In contrast, those seeking higher returns may prefer the greater volatility of the S&P 500.

The findings of the analysis of hypothesis H2-H4 suggest that higher capital investments in Wikifolio contribute modestly yet significantly to improved performance, hinting that investing in more popular Wikifolios could yield better returns. Conversely, the research indicates that older Wikifolios tend to underperform relative to newer ones, possibly due to a "honeymoon" effect where returns are initially high. This might also be attributed to signal providers becoming less active over time, which merits further exploration.

Future research could also deepen the understanding of these dynamics by examining the psychological biases impacting decisions on social trading platforms and conducting comparative analyses across different platforms to distinguish how specific features of different platforms affect trader behavior and success. Given the data's restriction to one platform, this could help overcome current limitations related to the generalizability of findings.

In conclusion, this thesis advances the academic dialogue on the functionality and success of social trading and encourages continued research on this topic. The insights provided are valuable for academics and investors as they navigate the evolving investment strategy landscape.

8 References

Abbey, B. S., & Doukas, J. A. (2015). Do individual currency traders make money? *Journal of International Money and Finance*, *56*, 158–177. https://doi.org/10.1016/j.jimonfin.2014.10.003

Agarwal, V., Daniel, N. D., & Naik, N. Y. (2009). Role of Managerial Incentives and Discretion in Hedge Fund Performance. *The Journal of Finance*, *64*(5), 2221–2256. https://doi.org/10.1111/j.1540-6261.2009.01499.x

Almaatouq, A., Noriega-Campero, A., Alotaibi, A., Krafft, P. M., Moussaid, M., & Pentland, A. (2020). Adaptive social networks promote the wisdom of crowds. *Proceedings of the National Academy of Sciences*, *117*(21), 11379–11386. https://doi.org/10.1073/pnas.1917687117

Apesteguia, J., Oechssler, J., & Weidenholzer, S. (2020). Copy Trading. *Management Science*, *66*(12), 5608–5622. https://doi.org/10.1287/mnsc.2019.3508

Aragon, G. O., & Nanda, V. (2012). Tournament Behavior in Hedge Funds: High-water Marks, Fund Liquidation, and Managerial Stake. *Review of Financial Studies*, *25*(3), 937–974. https://doi.org/10.1093/rfs/hhr111

Baghestanian, S., Gortner, P. J., & van der Weele, J. J. (2014). Peer Effects and Risk Sharing in Experimental Asset Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2504541

Barber, B. M., & Odean, T. (2013). The Behavior of Individual Investors. In *Handbook of the Economics of Finance* (Vol. 2, pp. 1533–1570). Elsevier. https://doi.org/10.1016/B978-0-44-459406-8.00022-6

Bault, N., Coricelli, G., & Rustichini, A. (2008). Interdependent Utilities: How Social Ranking Affects Choice Behavior. *PLoS ONE*, *3*(10), e3477. https://doi.org/10.1371/journal.pone.0003477

Bursztyn, L., Ederer, F., Ferman, B., & Yuchtman, N. (2014). Understanding Mechanisms Underlying Peer Effects: Evidence From a Field Experiment on Financial Decisions. *Econometrica*, *82*(4), 1273–1301. https://doi.org/10.3982/ECTA11991

Chen, H., De, P., Hu, Y. (Jeffrey), & Hwang, B.-H. (2014). Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. *Review of Financial Studies*, *27*(5), 1367–1403. https://doi.org/10.1093/rfs/hhu001

Curtis, A., Richardson, V. J., & Schmardebeck, R. (2014). Investor Attention and the Pricing of Earnings News. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2467243

De Filippi, P., Mannan, M., & Reijers, W. (2020). Blockchain as a confidence machine: The problem of trust & challenges of governance. *Technology in Society*, *62*, 101284. https://doi.org/10.1016/j.techsoc.2020.101284

DeMarzo, P. M., Vayanos, D., & Zwiebel, J. (2003). Persuasion Bias, Social Influence, and Unidimensional Opinions. *The Quarterly Journal of Economics*, *118*(3), 909–968. https://doi.org/10.1162/00335530360698469

Doering, P., & Jonen, A. (2018). Risk-Shifting Under Convex Incentives: Evidence from Online-Managed Portfolios. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3234923

Doering, P., Neumann, S., & Paul, S. (2015, May 5). *A Primer on Social Trading Networks – Institutional Aspects and Empirical Evidence*. https://www.efmaefm.org/0efmameetings/EFMA%20ANNUAL%20MEETINGS/2015-Amsterdam/papers/EFMA2015_0306_fullpaper.pdf

Donley, A. M. (2012). *Research Methods*. Facts on File, Inc. https://uaccess.univie.ac.at/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=nlebk&AN=454112&site=ehost-live

Dorfleitner, G., Fischer, L., Lung, C., Willmertinger, P., Stang, N., & Dietrich, N. (2018). To follow or not to follow – An empirical analysis of the returns of actors on social trading platforms. *The Quarterly Review of Economics and Finance*, *70*, 160–171. https://doi.org/10.1016/j.qref.2018.04.009

Dorfleitner, G., & Scheckenbach, I. (2021). Trading activity on social trading platforms – a behavioral approach*. *The Journal of Risk Finance*, *23*(1), 32–54. https://doi.org/10.1108/JRF-11-2020-0230

Duffy, J., Hopkins, E., Kornienko, T., & Ma, M. (2019). Information choice in a social learning experiment. *Games and Economic Behavior, 118*, 295–315. https://doi.org/10.1016/j.geb.2019.06.008

Elston, D. M. (2021). Survivorship bias. *Journal of the American Academy of Dermatology*, S0190962221019861. https://doi.org/10.1016/j.jaad.2021.06.845

eToro. (2022). https://www.etoro.com/de/customer-service/help/trading-investing/

Even-Tov, O., George, K., Kogan, S., & So, E. C. (2022). Fee the People: Retail Investor Behavior and Trading Commission Fees. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4226044

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636. https://doi.org/10.1086/260061

Gemayel, R., & Preda, A. (2018). Does a scopic regime erode the disposition effect? Evidence from a social trading platform. *Journal of Economic Behavior & Organization*, *154*, 175–190. https://doi.org/10.1016/j.jebo.2018.08.014

Glaser, F., & Risius, M. (2018). Effects of Transparency: Analyzing Social Biases on Trader Performance in Social Trading. *Journal of Information Technology*, *33*(1), 19–30. https://doi.org/10.1057/s41265-016-0028-0

Goeree, J. K., & Yariv, L. (2015). Conformity in the lab. *Journal of the Economic Science Association*, *1*(1), 15–28. https://doi.org/10.1007/s40881-015-0001-7

Hodder, J. E., & Jackwerth, J. C. (2007). Incentive Contracts and Hedge Fund Management. *Journal of Financial and Quantitative Analysis*, *42*(4), 811–826. https://doi.org/10.1017/S0022109000003409

Hossain, M. M., Mammadov, B., & Vakilzadeh, H. (2022). Wisdom of the crowd and stock price crash risk: Evidence from social media. *Review of Quantitative Finance and Accounting*, *58*(2), 709–742. https://doi.org/10.1007/s11156-021-01007-x

Kahneman, D., & Tversky, A. (2013). Prospect Theory: An Analysis of Decision Under Risk. In L. C. MacLean & W. T. Ziemba, *World Scientific Handbook in Financial Economics*

Series (Vol. 4, pp. 99–127). WORLD SCIENTIFIC. https://doi.org/10.1142/9789814417358_0006

Kapraun, J., & Pelster, M. (2018). Relying on Others' Investment Skills: About the Dynamics of Relationships in Social Trading Networks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2973194

Kumar, A. (2009). Who Gambles in the Stock Market? *The Journal of Finance*, *64*(4), 1889–1933. https://doi.org/10.1111/j.1540-6261.2009.01483.x

Ledoit, O., & Wolf, M. (2008). Robust performance hypothesis testing with the Sharpe ratio. *Journal of Empirical Finance*, *15*(5), 850–859. https://doi.org/10.1016/j.jempfin.2008.03.002

Liu, Y.-Y., Nacher, J. C., Ochiai, T., Martino, M., & Altshuler, Y. (2014). Prospect Theory for Online Financial Trading. *PLoS ONE*, *9*(10), e109458. https://doi.org/10.1371/journal.pone.0109458

Mitton, T., & Vorkink, K. (2004). Equilibrium Underdiversification and the Preference for Skewness. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.630821

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, *115*, 502–517. https://doi.org/10.1037/0033-295X.115.2.502

Oehler, A., Horn, M., & Wendt, S. (2016). Benefits from social trading? Empirical evidence for certificates on wikifolios. *International Review of Financial Analysis*, *46*, 202–210. https://doi.org/10.1016/j.irfa.2016.05.007

Offerman, T., & Schotter, A. (2009). Imitation and luck: An experimental study on social sampling. *Games and Economic Behavior*, *65*(2), 461–502. https://doi.org/10.1016/j.geb.2008.03.004

Panageas, S., & Westerfield, M. M. (2009). High-Water Marks: High Risk Appetites? Convex Compensation, Long Horizons, and Portfolio Choice. *The Journal of Finance*, *64*(1), 1–36. https://doi.org/10.1111/j.1540-6261.2008.01427.x

Pelster, M., & Breitmayer, B. (2019). Attracting attention from peers: Excitement in social trading. *Journal of Economic Behavior & Organization*, *161*, 158–179. https://doi.org/10.1016/j.jebo.2019.03.010

Pelster, M., & Hofmann, A. (2018). About the fear of reputational loss: Social trading and the disposition effect. *Journal of Banking & Finance*, *94*, 75–88. https://doi.org/10.1016/j.jbankfin.2018.07.003

Pentland, A. (2013). *Beyond the Echo Chamber* (p. 7). Harvard Business Review. https://enterprisersproject.com/sites/default/files/Beyond%20the%20Echo%20Chamber.pdf

Perold, A. F. (2004). The Capital Asset Pricing Model. *Journal of Economic Perspectives*, *18*(3), 3–24. https://doi.org/10.1257/0895330042162340

Reith, R., Fischer, M., & Lis, B. (2020). Explaining the intention to use social trading platforms: An empirical investigation. *Journal of Business Economics*, *90*(3), 427–460. https://doi.org/10.1007/s11573-019-00961-2

Shankar, V., Urban, G. L., & Sultan, F. (2002). Online trust: A stakeholder perspective, concepts, implications, and future directions. *The Journal of Strategic Information Systems*, *11*(3–4), 325–344. https://doi.org/10.1016/S0963-8687(02)00022-7

Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014). Tweets and Trades: The Information Content of Stock Microblogs: Tweets and Trades. *European Financial Management*, *20*(5), 926–957. https://doi.org/10.1111/j.1468-036X.2013.12007.x

Stoughton, N. M. (1993). Moral Hazard and the Portfolio Management Problem. *The Journal of Finance*, *48*(5), 2009–2028. https://doi.org/10.1111/j.1540-6261.1993.tb05140.x

Weber, M., & Camerer, C. F. (1998). The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behavior & Organization*, *33*(2), 167–184. https://doi.org/10.1016/S0167-2681(97)00089-9

Wei Pan, Altshuler, Y., & Pentland, A. (2012). Decoding Social Influence and the Wisdom of the Crowd in Financial Trading Network. *2012 International Conference on Privacy,* *Security, Risk and Trust and 2012 International Confernece on Social Computing*, 203–209. https://doi.org/10.1109/SocialCom-PASSAT.2012.133

Wikifolio investments. (2022). https://help.wikifolio.com/article/26-in-wikifolio-zertifikate-investieren

Wohlgemuth, V., Berger, E. S. C., & Wenzel, M. (2016). More than just financial performance: Trusting investors in social trading. *Journal of Business Research*, *69*(11), 4970–4974. https://doi.org/10.1016/j.jbusres.2016.04.061