Behavioral and environmental aspects of digital finance applications

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Chapter 1

Introduction

1.1 Introductory aspects into digital business models in finance

Since decades the financial industry has faced the challenge to adapt their financial services portfolio in response to advancing technology, global connectivity and increased speed of information (Gomber et al., 2017). As digitalization and social media have entered the financial sector and affected traditional business models, so-called *FinTechs* have arisen providing financial services through the application of modern technology (Mackenzie, 2015). The product portfolios of these new market entrants spans from classical financial services with digital technologies to new product developments (Dorfleitner et al., 2017). FinTechs strive to provide effective solutions in order to facilitate lending and investments for businesses and individuals. In addition, they aim at reducing the costs of payments, increasing the safety of transfer of funds and enhancing the speed of financial transactions (Mackenzie, 2015). The key actors are either start-ups such as Klarna or Ant Group (disruptive FinTechs), or technology corporations that now offer financial products such as Apple or Google and existing financial services providers (sustaining FinTechs) (Gomber et al., 2017). While the majority regards digital, financial startups as the principal FinTech players, other extend the definition by including also the latter ones (Demirguc-Kunt et al., 2018). These innovative companies have initiated a transformation of the financial industry by redefining the way financial firms conduct business, cooperate, and interact with their clients, authorities and competitors (McWaters et al., 2015). They are characterized by bringing together new parties while at the same time eliminating financial intermediaries such as classical banks (Iman, 2020). FinTechs can be defined as "technologically enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services" (European Banking Authority, 2017, p. 4). Brandl and Hornuf (2020), for example, propose a categorization of FinTechs based on their fields of activity: Firstly, the category financing includes business models that provide alternative methods of financing e.g., crowdfunding, crowdlending, and crowdinvesting. Secondly, companies that offer innovative products and tools referring to the consultancy, investment and management of assets belong to the category asset management and comprise robo advisors, social trading and factoring. Furthermore, business models in the payment sector revolve, for instance, around crypto currencies and alternative payment systems. Finally, other FinTechs include the remaining business plans that, for example, operate search engines or provide infrastructures.

The following aspects are regarded as the core differential factors to classic banks and build the basis for their competitive advantages (McWaters et al., 2015; Drummer et al., 2016; European Commission, 2020):

- **Optimized infrastructure:** The implementation of platform-based systems and decentralized technologies such as blockchain create new opportunities for data aggregation and intelligent data analysis while at the same time reducing costs of information acquisition and entailing scalable data management (McWaters et al., 2015).

- **Independence from intermediaries:** Innovative technologies push forward the externalization of existing processes and often lead to the disintermediation of traditional intermediaries (Drummer et al., 2016). Large networks, platforms and decentralized systems establish trustworthy relationships between hitherto unknown parties, provide a cost efficient alternative to intermediaries and, thereby, enhance the scalability of financial services and products (Demirguc-Kunt et al., 2018; Jünger and Mietzner, 2020). Lending and funding platforms, payment applications or innovative investment products such as robo advisors, in particular, build their competitive advantage on the transformed value chains and the associated cost and return potentials (Dorfleitner et al., 2017). Besides, distributed ledger technology offers the potential to enhance the transfer of ownership of all kinds of assets (Mackenzie, 2015).

- **Digitally enabled operations:** Technological advances in information and communication technology such as big data analysis, cloud computing, advanced algorithms and artificial intelligence (AI), Internet of things (IOT), blockchain technology, social networks, peer-to-peer (P2P) technologies, near field communication (NFC), improved mobile devices and data storage possibilities lay the foundation for the automatization of classic financial activities and strengthen the growth performance (Gomber et al., 2017). This development is accompanied by cost reductions, increased transparency for customers, and faster, highly scalable and more user-oriented services and products (McWaters et al., 2015). The flexible scalability coupled with financial innovation by this means paves the way for economic and social transformations (Heap and Pollari, 2020).

- **Intelligent use of data:** Innovative technologies enable the generation of new, distinctive and more comprehensive datasets, the combination of data from multiple sources and the use and analysis of data in real-time and, consequently, create novel insights into customers (McWaters and Galaski, 2017). The strategic use of these data sets proves to be a vital factor in improving customer acquisition and retention, strengthening user loyalty and intensifying customer relationships.

- **Specialized, innovative products:** FinTechs respond to changes in lifestyle and the need for new, transparent, modular and secure financial services by designing a product portfolio for specific target groups placing the focus on individuals rather than institutions (Galvin et al., 2018). Benefiting from the transformed value chain and data based customer relationship, these innovative companies strengthen their brand as they control the distribution and image of their products and services (McWaters and Galaski, 2017). In addition, FinTechs use their lead in knowledge compared to existing financial firms to further tailor their products and services to their customers' needs (Demirguc-Kunt et al., 2018). The development of new consumer functionalities by FinTechs has been accompanied by changes in consumer preferences and behavior (McWaters et al., 2015).

- **Customer empowerment:** As a consequence of decentralized technologies, reduced costs and innovative products, FinTechs greatly enhance the access to finance by mitigating existing barriers, creating new market structures and placing products and services that have not been available before at the disposal of clients (European Commission, 2018). This empowers especially small and medium-sized companies, marginalized investors or developing countries and regions and, thereby, greatly advances financial inclusion (Skoglund et al., 2019). Crowdfunding and crowdlending, for example, constitute alternative lending methods, that provide the opportunity to take up loans, independently from the existing financial resources. Digital currencies and mobile payment function as enablers for financial inclusion and economic growth, in particular, in countries with a high percentage of unbanked citizens (e.g., in Africa and the Middle East) (Haddad and Hornuf, 2019). Increased transparency of information and innovative tools allow customers to gain control over their financial decisions, improve their financial literacy and take on new, more active roles in the financial ecosystem (Mackenzie, 2015).

Haddad and Hornuf (2019) investigate the economic and technological determinants of countries in establishing a successful FinTech ecosystem. They show that thriving economies foster startup formations due to their financial strength. Cumming and Schwienbacher (2018) add that the differences in the heterogenous approaches of implementing financial regulations for startups and financial institutions in the wake of the financial crisis explain partly the distribution of venture capital investments across FinTechs on a global scale. The importance of venture capital is also proven by cumulated global investments into FinTech startups of more than $96 billion between 2011 and 2018. This development is accompanied by an increase in average deal sizes, in particular in Asia, as investors appear to become more selective (Galvin et al., 2018). Capital flows focus on the key players of which the top ten on average raised $1.25 billion in 2019 (Heap and Pollari, 2020). In recent times investors have focused on mature FinTechs that are characterized by successful business models based on unique, heterogenous product portfolios and strategic customer and market expertise (Bose and Berry, 2021). In addition, well established technological infrastructures ensuring secure transactions (e.g., secure internet servers and mobile phone subscriptions) and the availability of talent prove to have a positive influence on the formation of FinTechs. Nevertheless, the decoupling of traditional financial centers and FinTech hubs indicates that the demand for technological financial innovations and flexible market regulations drive the development of the FinTech scene forward (Cumming and Schwienbacher, 2018; Haddad and Hornuf, 2019; Skoglund et al., 2019). Besides, complex regulations explain why the main protagonists are advancing and becoming successful on a regional rather than a global scale (Galvin et al., 2018).

Heap and Pollari (2020) analyze the current FinTech landscape and highlight that the major players are predominantly located in Asia-Pacific, followed by the UK and Europe, the Middle East and Africa, while North and South America are located last on the list. Based on their selection criteria, China still is the dominant player in particular due to its digital ecosystem platforms such as Alipay, though India exhibits a rapid development (e.g., Paytm, Ola or PolicyBazaar) (see also Garvey et al., 2019; Skoglund et al., 2019). Interestingly, the American continent contains the biggest number of Fintech hubs with Brazil and Argentina being dynamic emerging FinTech markets (Skoglund et al., 2019). The UK and Germany are currently leading the FinTech development in Europe, whereby the latter one will probably gain in importance as a consequence of the Brexit (Dorfleitner et al., 2017). Skoglund et al. (2019) conjecture that the diverse product portfolios combined with coordinated commitment and regulation by the European Union continue to be factors of growth for the European FinTech scene.

On a global scale, the majority of FinTech business models focus on the provision of financing services indicating the requirement of innovative alternative financing methods on the demand side. According to Haddad and Hornuf (2019) this can be partly explained by the need for alternative financial resources rooted in the traditional financing gap of smaller companies and funding constraints. Payment services make up the second largest group followed by companies offering other services and innovative firms conducting business in the segment of asset management (Haddad and Hornuf, 2019). In comparison to previous years, FinTechs have been still very active in the fields of payment and transactions, though the ratio of business models dealing with wealth and insurance as well as of FinTechs serving different segments simultaneously has risen (Heap and Pollari, 2020). Recently, platform models offering several different products and services simultaneously, sometimes even connecting different financial institutions, have gained momentum and will play a vital role in the future (McWaters and Galaski, 2017). After successfully launching a digital financial service and establishing a sound customer base, mature FinTechs often move towards a platform model by expanding and diversifying their product portfolio continuously (Bose and Berry, 2021).

FinTech supposedly is one of the fastest growing industries. Dorfleitner et al. (2020) highlight the economic relevance with the example of Germany where the market volume of the FinTech market has increased from 2.3 billion EUR in 2015 to 52.3 billion EUR in 2019, which corresponds to an average annual growth rate of 120%. They show that in 2019 the managed assets of FinTechs of the categories investment and banking amounted to 35.4 billion EUR, while FinTechs in the alternative payment sector created a transaction volume of 24.6 billion EUR, excluding trading with cryptocurrencies. At present more than 500 mineable tokens and coins exist, of which the top 20 cryptocurrencies amount for 98% of the total market capitalization of 152 million EUR in spring 2020 (Gallersdörfer et al., 2020). This growth trend is expected to continue leading to a total market volume of FinTechs of the type financing and asset management – excluding personal financial management services – of approximately 1 trillion EUR in 2035 in Germany (Dorfleitner et al., 2020). Gantori et al. (2019) predict that global trends such as increased urbanization and demographic changes will enforce the positive growth path. They reckon with global FinTech revenues of $265 billion in 2025, implying an average growth rate that is three times higher than the growth rate of the (classic) financial sector. The COVID-19 pandemic has reinforced this path of growth on a global scale (Fu and Mishra, 2020; European Commission, 2020). The Middle East and North Africa stand out with growth rates of 40% in the first half of 2020, followed by North America and Sub-Saharan Africa with 21%. The global pandemic has in particular driven growth in the digital asset management and digital savings sector. On the contrary, FinTechs offering digital lending services experienced negative growth (Ziegler et al., 2020).

Dorfleitner et al. (2017) show that the international FinTech scene is characterized by high dynamics with new market players, technologies and products emerging and incumbents and startups vanishing at a high frequency. By now, a new, more mature phase has begun in which the vast amount of novel technologies and heterogenous products on the market lead to increased competition and consolidation. On the other hand, established financial firms face the challenge of adjusting their business models towards disruptive technologies and strongly rely on tech firms, their infrastructure and expertise in order to adapt to the new market conditions (McWaters and Galaski, 2017). As industry boundaries are becoming blurred, companies from adjacent business divisions e.g., technology firms see the huge potential of discovering new fields of business in the financial services sector. Consequently, big tech companies such as Google, Apple or Facebook by now generate significant shares of their turnover with financial services including alternative payment methods, cryptocurrencies and consumer finance (Heap and Pollari, 2020). Against this background, the incumbent companies have gained access to technologies by entering into strategic alliances with FinTechs to defend and strengthen their market position. FinTechs in return profit from the bigger customer base and availability of banking licenses (Galvin et al., 2018; Brandl and Hornuf, 2020; Bose and Berry, 2021). In addition, they can by this means comply with the legal provisions and reduce the risk of their products being copied by established market participants (Haddad and Hornuf, 2019; Brandl and Hornuf, 2020). At the same time, FinTechs have achieved reasonable levels of growth, expanded their activities to a global scale, received banking licenses, conducted merger and acquisitions, and diversified their product portfolio (Heap and Pollari, 2020; Brandl and Hornuf, 2020; Ziegler et al., 2020).

In comparison with other countries, the most successful FinTechs in China have joined forces with ecosystems such as Alibaba and banks and, thus, profit from increased scalability and rapid innovation (Garvey et al., 2019). According to Garvey et al. (2019) cooperation with other companies, balance between machine and human interaction, cybersecurity, personalization and customization will be the key drivers of future success. Brandl and Hornuf (2020) hypothesize that in the next step FinTechs will seek to promote services and products that transform the current system by eliminating current structures and players. They explain that since their business models will be built on autarchic systems such as blockchains, traditional banks will become superfluous. Technological advancements such as robotic process automation (RPA), voice technology or biometrics identity management can be a catalyst for further financial innovation. On the other hand, the innovative business models entail risks with respect to data usage and cyber security that pose a threat to the stability of financial systems (Gomber et al., 2017; European Commission, 2018; Garvey et al., 2019; Ziegler et al., 2020).Therefore, a sound, efficient and flexible regulatory system is required in order to deal with the emerging risks and security aspects, to protect customers and investors, and to create a base of trust between users, FinTechs, financial firms and legal institutions (McWaters et al., 2015; Demirguc-Kunt et al., 2018). However, it needs to be noted that FinTechs present the opportunity to optimize compliance, reporting and monitoring processes through transparency and automatization (European Commission, 2018). Haddad and Hornuf (2019) highlight the importance of the legal framework and appropriate policy measures for sustainably promoting the FinTech industry, speeding up the implementation rate of innovations and shaping the financial industry (see also Phillippon, 2016; Dorfleitner et al., 2017; Ziegler et al., 2020).

The UK, Singapore and Hong Kong, for example, apply so-called regulatory sandboxes which allow startups to test their business models in a defined framework (Gomber et al., 2017; Ringe and Ruof, 2020). Aiming at intensifying the exchange with the FinTech industry, other countries including Canada, Australia and Japan have set up innovation hubs. The FinTech action plan of the European Union has been designed with the objective to enhance the competitiveness and innovativeness of the European financial market (European Commission, 2018). The measures seek to achieve the following overarching goals: creating an environment that attracts innovative business models and encourages their advancement towards scalability, promoting the implementation of technological innovations within the financial sector, improving the resilience against cyber threats, and safeguarding the integrity and stability of the financial system thereby protecting consumers and investors (European Commission, 2018). In view of recent developments, the European Commission (2020) has established the goal of embracing digital finance in a way that benefits consumers and businesses. The strategic approach is based on the ability of FinTech applications to provide innovative financial products, sustain Europe's economic transformation, reinforce the financial market integration in the Banking and Capital Markets Union and strengthen Europe's open, financial autonomy.

1.2 Research objective of this dissertation

This dissertation focuses on different aspects of digital business models in finance. In particular, FinTechs operating in the field of asset management and payment are at the core of this research project. The fact that the former facilitate the access to financial products regardless of available financial resources has accelerated the growth of this type of FinTech (Haddad and Hornuf, 2019; Dorfleitner et al., 2020). The business model of companies operating in this field revolves around the consultation, investment and management of assets. Different types of asset management FinTechs can be distinguished: social trading platforms, that combine social network aspects with online trading, or robo advisors, that give automated investment advice based on algorithms. Furthermore, personal financial management, and investment and banking are defined as additional business areas (Dorfleitner et al., 2017).

In this regard, the thesis places particular emphasis on social trading platforms that allow investors to benefit from the knowledge of more proficient traders by coping their trades. In addition, social network features enable the communication and interaction between both parties (Dorfleitner et al., 2018). While the availability of large data volumes on social trading platforms has resulted in a rise in research, the behavioral patterns of traders that are induced through the novel dimension of social interaction is still under-researched. Neumann (2014) elaborates on institutional aspects of social trading platforms and investigate whether they constitute an alternative asset class. Apart from return characteristics, social behavioral aspects including herding behavior, investment decisions of followers or communication strategies are studied on these digital trading venues (Liu et al., 2014; Gemayel, 2016; Glaser and Risius, 2016; Röder and Walter, 2019; Lý and Pelster, 2020). In order to evaluate the potential of digital asset management, this thesis explores how the characteristics of these innovative business models effect the investment behavior of their users. The scientific articles of the thesis on social trading platforms aim to generate insights into, firstly, the influence of social interaction triggered by the social network characteristics on the trading activity of signalers. Second, the different investment strategies with particular attention to risk taking behavior of traders are under examination. Based on the results, the thesis tries to answer the question how various behavioral aspects of traders on these platforms can be incorporated in the respective business models in order to avoid biased behavioral patterns and to increase the return of investors. In addition, recommendations for policy implications are provided.

The technological dimension constitutes a central pillar of FinTechs by laying the foundation for various business functions. "Blockchain technology", a form of the distributed ledger technology, is an innovation that has the potential to realize the mentioned change technically and constitutes one of the most promising technologies. The four core attributes of blockchain, namely transparency, immutability, decentralization, and authentication, can address some of the challenges experienced in cooperative, international transactions and advance the implementation of measures in areas outside of business and finance e.g., government and health (Herweijer et al., 2018; Dorfleitner and Braun, 2019). The technological concept of Blockchains does not only significantly enhance the exchange of digital transactions but also creates new opportunities that can be beneficial in other segments (Gomber et al., 2017). The third part of the dissertation deals with blockchain applications, that have the potential to support sustainable development and tackle climate change. The existing literature focuses on performance, obstacles and perspectives as well as on recommendations for actions to enhance the adoption of blockchain technology in digital sustainability actions (Maupin, 2017; Fuessler et al., 2018). This research article intends to review the current integrated application environment in a specially designed, empirical investigation. The objective of this study is to analyze the success determinants of environmentally orientated blockchain applications to assess their current and future contribution to climate protection.

This dissertation contributes to the growing literature on innovative, digital business models in finance. In general, the thesis provides valuable insights into the human-machine-interaction constituting the corner stone of FinTech's success. In the field of asset management FinTechs, the studies emphasize the effect of social network characteristics on trading behavior. The empirical investigation of social trading platforms provides evidence that the social dimension includes parameters that trigger irrational trading activity and influence the trader's risk strategy. With respect to risk taking behavior, the study reveals influential factors of the level of risk as well as risk changes in trading strategies and, thereby, augments the discussion on incentive structures of asset managers. Against the backdrop of the continuously growing FinTech sector, scientific insights on the behavior of individuals applying technology based financial services play an important role in enhancing asset management FinTechs. While startups and financial institutions can apply the findings in the design process of new products and services and optimize their business models accordingly, governmental agencies can further develop the legal framework and derive political measures based on the results of this research project. To our knowledge, this is the first study that draws a profound picture of the current state of green blockchain applications globally. By shedding light on various fields of actions and emphasizing possible, future directions, the findings of this research can enable investors, politicians and citizens in further enhancing mitigation and adaption measures based on blockchain technology. Moreover, the thesis contributes to current research by revealing the determinants of success of green blockchain applications. As a consequence, developers of blockchains, respective companies, and political institutions can build on the results and incorporate the insights acquired in the provision of necessary frameworks and the application development processes. Taken together, as digital technology is changing people's lives, this thesis provides valuable insights on the capabilities of new technologies and innovative business models in the financial sector to shape social, environmental and economic change. In addition, the presentation of opportunities and challenges can be a valuable contribution for actively designing the digital transformation, empowering citizens, and leading the way towards a digital, more sustainable and fair world.

This dissertation consists of three independent research articles with several co-authors.

1. Trading activity and returns on social trading platforms – a behavioral approach

2. The higher you fly, the harder you try not to fall: An analysis of the risk taking behavior in social trading

3. Blockchain applications for climate protection: a global empirical investigation

In the following, a recapitulation of the academic papers, that highlights the research questions, the individual data sets, the applied research methods, the empirical findings, and their contribution, is given. All papers have been published in academic journals at the date of the disputation of this dissertation.

1. Trading activity and returns on social trading platforms – a behavioral approach

This paper studies the trading behavior of trade leaders on two leading social trading platforms in Germany. In particular, the article investigates the irrational factors that influence trading activity derived from the social network characteristics of these platforms, i.e., the number of followers as well as the the rating and compensation framework. The empirical analysis rests upon an extensive set of trading data from the platforms Ayondo and Wikifolio in the observation period from October 2015 to May 2016.

First of all, we add to behavioral finance research by providing evidence of the negative relationship between overconfidence and social trading returns in this innovative online trading environment. As proven by the fixed effects two-stage least squares approach, there are various irrational factors on the platform that result in excessive trading of trade leaders. We find that the social network aspects are significant drivers of the irrational part of trading activity. In particular, the signaler's popularity, either measured by the number of followers or the net change in invested capital, and the ranking of traders, are positively related with the degree of overconfidence. A clear difference is evidenced by the platform specific incentive schemes. While the compensation framework on Ayondo includes strict risk limits and drop-out consequences that appear to reduce the degree of overconfidence, the Wikifolio high watermark reward system does not reveal such an effect. Consequently, the different frameworks of the platforms motivate heterogenous behavioral responses by signal providers.

The empirical findings of this paper are relevant from both a theoretical and practical perspective. First, we contribute to existing literature by investigating the influence of social network features on the trading behavior of trade leaders in an innovative online trading setting. Second, the assessment of two different platforms provides new insights into the importance of the monitoring mechanisms and incentives on the platforms with respect to their effect on the business models. Additionally, we point out that identifying less overconfident traders may be beneficial for followers.

2. The higher you fly, the harder you try not to fall: An analysis of the risk taking behavior in social trading

In this paper, we augment the discussion on incentive structures and risk taking of portfolio managers by empirically analyzing the behavior of asset managers in an innovative online trading setting – a so-called social trading platform. We study whether portfolio managers strategically manage their risk taking behavior in response to their incentive contracts and place a special focus on infinite investment horizons, valuable outside options and platform specific characteristics. Our empirical analysis employs observations from one of the leading German social trading platforms, Wikifolio, in the observation period from April 2012 to April 2016.

We apply a fixed-effects regression model to investigate the influential factors of the level of risk as well as risk changes in trading strategies. The results show that traders dependently choose the absolute and relative risk of the trading strategy on the proximity to the high watermark (HWM). Portfolio managers on this social trading platform act in an infinite investment horizon setting and, therefore, face the HWM incentive scheme as a series of remuneration options on the assets under management. Consequently, they exhibit risk reducing behavior when approaching their HWM. We reason that the increased transparency of information on these platforms intensifying the competition amongst peers and greater reputational risks reinforce this behavioral pattern. In addition, we provide evidence that portfolio managers act strategically taking into account their overall portfolio payoff. Finally, social status indicators such as rankings and communication abilities appear to be significant indicators of risk taking behavior.

Our findings contribute to the discussion on appropriate incentive structures for asset managers with respect to aligning their interests with the investors' interests. In comparison to the majority of existing studies in this field of research, we take an empirical approach and shed light on the factors affecting risk taking behavior on top of incentive contracts. Our empirical findings highlight the importance of considering the investment horizon and outside options of the asset manager when setting up the specific incentive contract. Additionally, we identify various aspects of the trading environment as potential drivers of the portfolio manager's behavior. As a consequence, our study is of interest to platform developers, financial regulators, policy makers and investors.

3. Blockchain applications for climate protection: a global empirical investigation

In this article, we draw a profound picture of the current state of blockchain applications that contribute in a certain way to climate protection. We globally collect data on 85 of such applications following the model of inductive category development (Mayring, 2015) and provide a detailed description of the empirical distribution of different attributes of these applications. Furthermore, we study key determinants of success in the sense of an advanced operational status of the applications distinguishing between application-specific and blockchain-specific characteristics.

In order to gain insights into the factors that promote the performance of an application we perform logistic regressions on the application's success. To begin with, we assess the contribution of these applications to climate protection and identify their future potential. In summary, the consolidation of the green environmentally friendly blockchain applications reveals a diverse portfolio of innovative applications. Since the majority of these is still in the developmental stage, the current contribution to environmental protection can be classified as marginal. With respect to the determinants of success, we prove that the type of activity significantly affects the probability of becoming operational. In addition, we evidence that the choice of the proper consensus mechanism is essential. Neither the implementation of tokens nor the execution of an Initial Coin Offering (ICO) appear to have significant effects on the development of the applications. Interestingly, we observe no differences across the different blockchain types.

Our study contributes to current research by shedding light on the success factors of green blockchain applications. The empirical results provide valuable insights for the developers of blockchains and the respective companies in order to advance the application's development more efficiently. Our findings are especially useful for political institutions for the provision of the necessary legal and political framework for green blockchain applications to thrive.

The remainder of the dissertation is structured as follows. To begin with, chapter 2 constitutes the research paper that analyzes the trading activity of traders on social trading networks in Germany by taking a behavioral approach. In chapter 3 the empirical investigations of risk taking behavior under convex incentives in an innovative online trading setting are scrutinized. Chapter 4 consolidates the actual environment of blockchain applications that contribute in a certain way to climate protection. Moreover, the determinants of success with respect to application-specific and blockchain-specific characteristics are examined. Finally, chapter 5 concludes, discusses theoretical and practical implications of this research project and identifies areas for further research. As a result of the distinct formal requirements by the different journals small differences in the style of the three articles may be present.

Chapter 2

Trading activity and returns on social trading platforms – a behavioral approach

This research project has been carried out jointly by Gregor Dorfleitner and Isabel Scheckenbach. This article has been published as Dorfleitner, G. and Scheckenbach, I., 2021. Trading activity and returns on social trading platforms – a behavioral approach. *Journal of Risk Finance*

Abstract: Social trading platforms are considered to be amongst the major innovations in online trading. The purpose of this article is to analyze the trading activity of traders on social trading networks by taking a behavioral approach. We investigate the factors that influence the irrational part of trading activity derived from the key characteristics of these platforms, i.e., those dealing with social interaction. Our investigation utilizes an extensive set of trading data from two major platforms in Germany to study the trading behavior. We apply a fixed effects two-stage least squares approach to quantify the relationship between trading activity and performance and define overconfidence as the part of trading activity that is irrationally motivated and results in negative returns. Our results provide evidence for the negative relationship between overconfidence and return on social trading platforms. The article finds that the number of followers and some platform-specific features significantly affect the trading behavior of the traders. We contribute to literature by exploring how the novel social interaction characteristics of online trading impact trading activity by giving rise to a new dimension of overconfidence. In addition, we evidence that the different frameworks of the platforms motivate heterogenous behavioral responses by the signalers. Finally, we refine existing studies by applying a distinct methodology for modeling overconfidence.

Keywords: Social trading platforms, overconfidence, social interaction, individual trading behavior, behavioral finance

JEL Classification: G14 G20 G41

2.1 Introduction

Social trading is considered to be one of the major innovations in online trading. Since 2007 an increasing number of platforms offering social trading services has entered the market. These platforms incorporate social network characteristics in online trading. They distinguish themselves from classic trading by providing the possibility of so-called *mirror trading*, which allows users to copy and automatically execute investment strategies of other traders, referred to as *signalers, signal providers* or *trade leaders*. This feature adds a new perspective to the classic principal-agent relationship between investors (*followers*) and fund managers (signalers), as investors can follow their trade leaders and monitor the performances of these in real-time. Information transparency, reduced costs for users and the participation of professionals and media companies have led to an increased level of acceptance of social trading (Glaser and Risius, 2016; Dorfleitner et al., 2017). Social trading, hence, created a new type of market place that adds a new facet to trading by enabling social interaction between signalers and followers for example through the communication of trading strategies and the possibility of rating the signalers. This social dimension implies a novel set of determinants of trading behavior. In this paper we study whether trade leaders on two leading social trading platforms in Germany are affected by the social network aspects and exhibit a behavioral bias known as *overconfidence*. In particular, we investigate the irrational factors that influence trading activity derived from the social network characteristics of these platforms, i.e., the number of followers as well as the rating and compensation framework.

The contribution of this paper is twofold. First, we add to the existing literature by investigating the influence of social network features on the trading behavior of signal providers on social trading platforms. To the best of our knowledge, we are the first to explore how these novel social interaction characteristics of online trading impact trading activity by giving rise to a new dimension of overconfidence. Second, by assessing two heterogenous platforms we generate new insights into the influence of the platform design on individual behavior.

Social trading platforms have aroused researchers' interest as they provide accessibility of an extensive amount of information and trading data to their users. Due to the fact that social interaction can be observed in real-time, they constitute a valuable environment for studying investor behavior. The hitherto best researched platform is eToro, which is also the global market leader. Empirical studies of eToro find, on average, negative returns between 2010 and 2012 (Pan et al., 2012). Dorfleitner et al. (2018) provide empirical evidence showing that only complex trading strategies tailored to platform characteristics are able to provide positive returns (see also Oehler et al., 2016). According to Neumann (2014), the disposition and loss aversion effect explain the return characteristics of social trading returns (see also Liu et al., 2014; Heimer, 2016). Glaser and Risius (2016) observe that the trader's exposure to the disposition effect depends on behavioral and interaction features (see also Pelster and Hofmann, 2017). Contrary to this, Gemayel (2016) indicates that improved information transparency weakens the disposition effect (see also Lukas et al., 2017).

Pan et al. (2012) and Gemayel (2016) provide evidence for a certain level of wisdom of the crowd regarding the followers selecting the right signalers and for a herding behavior of signalers with respect to replicating the strategies of their competitors. Pan et al. (2012) show that investors are influenced by social dynamics such as the number of followers and do not select trade leaders rationally based on performance indicators (see also Röder and Walter, 2019; Kromidha and Li, 2019). Lee and Ma (2015) establish a model to help investors improve the selection of signalers. Wohlgemuth et al. (2016) indicate that both the affect-based and cognition-based signals raise the probability of followers copying their strategies. Ammann and Schaub (2016) find that superior past performance induces increased, positive communication, which, in turn, attracts followers. We extend the findings of Dorfleitner et al. (2018) regarding the negative relationship between high trading activity and social trading returns by analyzing the factors that motivate the irrational part of trading activity of signalers. This article contributes to the stream of literature on overconfidence in a social setting (Bénabou and Tirole, 2002; Pentland, 2013; Proeger and Meub, 2014). Contrary to Proeger and Meub (2014), our study is based on actual trading data from two trading platforms. We emphasize the importance of the platform design and the followers for the behavior of trade leaders.

We apply a two-stage least squares model to overcome the endogeneity of trading activity and to quantify the relationship between trading activity and performance. To this end, we implement an instrumental variable approach endogenizing the trading volume in the first stage. We define overconfidence as the part of trading activity that is irrationally motivated and results in negative returns. Our investigation utilizes an extensive set of trading data from the platforms Ayondo and Wikifolio to study the trading behavior of trade leaders in the observation period from October 2015 to May 2016.

The empirical analysis of the trading activity of signalers on social trading platforms provides new insights. First, we find that overconfident traders on social trading platforms impair their performance through excessive trading, which is consistent with prior research. Second, we show that the social network aspects of these platforms, in particular the number of followers and the ranking of the traders, exhibit a positive relationship with the degree of overconfidence. Third, our findings suggest that the specific incentive schemes of the platforms have diverse impacts. While the incentive scheme on Ayondo includes means that appear to reduce the degree of overconfidence, the Wikifolio reward system does not reveal such an effect. Consequently, our results are not only relevant for traders and investors but also for the operators of social trading platforms.

The remainder of the paper is structured as follows: First, we provide a description of social trading platforms. Building on related literature we derive the hypotheses followed by a description of the data. We subsequently outline our empirical approach in the Section 2.4. We present the results, analyze the differences across the platforms and discuss their theoretical and practical implications in the Section 2.5. Section 2.6 concludes and identifies areas for further research.

2.2 Description of the social trading platforms utilized in the analysis

As digitalization and social media have entered the financial sector and affected traditional business models, so-called *FinTechs* have arisen providing financial services through the application of modern technology (Mackenzie, 2015; Dorfleitner et al., 2017). Social trading platforms combine classic online trading tools with the features of social networks (Neumann, 2014). The design of the platforms enables investors to communicate with each other and to contemplate, scrutinize and copy investment strategies of traders in the network (Pentland, 2013; Liu et al., 2014; Dorfleitner et al., 2017; Gemayel, 2016). The replication of trades in real-time is the distinguishing feature of social trading and provides individuals with the opportunity to profit from more proficient traders, who are compensated for sharing their investment ideas based on performance fees (Pentland, 2013; Doering et al., 2015; Ammann and Schaub, 2016). Although followers do not transfer capital to the signal provider's accounts, the latter de facto act as portfolio managers (Doering et al., 2015, p. 1). Profile pages of signalers display information on the trading strategy, key figures on risk and performance, and social media characteristics such as the number of followers and the ranking (Lee and Ma, 2015; Ammann and Schaub, 2016). Social trading platforms monitor signalers and, depending on the business model, charge users fees, for example spreads or order costs (Neumann, 2014; Doering et al., 2015; Dorfleitner et al., 2017).

This study focuses on Ayondo and Wikifolio since both only allow followers mirror trading and do not provide the option to copy single trades. Both platforms attract heterogenous types of traders based on the differences in the platform design. On Wikifolio, trade leaders (private and professional investors and media companies[1]) create trading strategies by choosing from an investment universe of more than 250,000 shares, exchange traded products, and leveraged products in order to profit from the price development of foreign exchange or commodities (Wikifolio, 2016). After meeting certain criteria, these so-called *wikifolios* become tradable as open-ended index certificates (Dorfleitner et al., 2018). Followers can thereby participate in the performance of the wikifolio (Wikifolio, 2016). Signalers on Ayondo implement their strategies by trading with contracts for difference (CFDs). Buyers of CFDs trade on margins and participate in the changes of the value of the underlying disproportionally (Neumann, 2014). Investors are given the opportunity to invest in up to five traders via CFDs (Ayondo, 2016). Leveraged products especially find favor with social trading because they facilitate the execution of mirror trading (Doering et al., 2015; Dorfleitner et al., 2017). The high flexibility in terms of contract sizes allows for a fractional mapping and ensures an exact proportionality between the signal provider's and followers' accounts (Doering et al., 2015, p.7). While traders on Ayondo can only publish one trading strategy each, signalers on Wikifolio can open several wikifolios. Wikifolio applies a high-water mark (HWM) remuneration scheme, whereas Ayondo compensates its signalers based on the created trading volume and their rating contingent on risk-adjusted performance (Doering et al., 2015). The composition of the ranking constitutes one of the major differences between the platforms. On Ayondo five different career levels (*Level*) are available, which also serve as the basis for the signaler's compensation. The criteria for promotion comprise trading activity and performance figures. To mitigate excessive risk taking, the maximum drawdown (*MDD*) is set to 25% on every level, leading to a demotion from the current level to the basic level in case of exceeding the limit and making promotions in the future impossible (Ayondo, 2016). Wikifolio pursues a different approach and ranks its traders based on *Wikifolio points* that are calculated on a daily basis conditioned to risk, activity, performance, and capital criteria (Wikifolio, 2016). As the HWM compensation principle is already implemented to minimize agency problems, the ranking mechanism appears to be less stringent, allowing signalers to move up and down in the grading scale at any given time.

2.3 Theory and hypotheses

In the following, we build on the existing literature to derive three hypotheses regarding the factors influencing trading behavior on social trading platforms. Hereby, we also account for the different rating and incentivizing features of Ayondo and Wikifolio.

[1] Media companies and financial market magazines such as Börse Online or AnlegerPlus publish their trading strategies on Wikifolio.

Platform design and expectable rational trading behavior A rational signal provider can be characterized by a behavior that maximizes their profits. The compensation strategies of both platforms consist of different elements, which can influence trading behavior. In the case of Ayondo, the trade leader's profits depend directly on the trading volume accountable to him or her, which is created by the number of followers and the degree of his or her trading intensity. This quantity is multiplied by his or her respective level, ranging from 1 to 5 and representing the rating of the trader by Ayondo (Ayondo, 2016). By linking compensation to trading volume, signalers are provided with the incentive to trade in any situation, but with different levels of intensity. At the start of their careers, signalers attempt to establish a sound track record aimed at attracting followers, while not having much to lose. Consequently, signalers will be enticed into trading more, given a smaller number of followers and a lower level (Neumann, 2014). If a signaler advances in the rating system and more followers copy his or her strategy, the signal provider will be able to adapt his or her behavior by reducing his or her trading intensity as he or she profits proportionally from the more followers and the higher level. Higher levels, though, entail the risk of losing more, as the expulsion from the current level to the entry level has strong adverse effects on the rating (due to the irreversibility of the drop) and number of investors. This risk is amplified by the limitation of publishing only one trading strategy. Finally, there is a greater probability of being relegated from the current level due to not meeting the performance criteria because increased trading activity scales down returns by means of transactions costs (Dorfleitner et al., 2018). The strict requirements of the ranking system regarding the maximum drawdown and the risk-adjusted performance support this expected behavior.

There are several major differences on the Wikifolio platform. First, trade leaders receive a performance premium, that partially depends on the capital invested in the signaler's strategy, but only in the case that a new HWM is achieved (Wikifolio, 2016). The option-like character of this compensation can – depending on the time horizon of the trader – induce traders to undertake more risky projects in order to increase the probability of achieving the HWM (Carpenter, 2000; Panageas and Westerfield, 2009). Due to the fact that a minimum of 10,000 EUR must be invested in the wikifolio certificate in order to become eligible for remuneration, signalers can be expected to behave similarly to traders on Ayondo in their early career stage, by seeking the attraction of followers. Once they have an investable portfolio, trade leaders focus rationally on their performance in order to surpass the HWM while aiming at growing capital inflows, which will, in turn, increase their profits. Contrary to Ayondo, neither trading activity nor the rating have a direct impact on the profits of a signal provider. Trading volume, though, partly affects the quantity of Wikifolio points. There is no general incentive to trade more or less in the case of having acquired a certain level of Wikifolio points and following capital. Trade leaders are expected to rationally maintain their trading intensity when moving up in the Wikifolio score, and to exhibit higher levels of volatility. The lack of strict risk and maximum drawdown requirements as well as of penalties in the event of not meeting these criteria supports this expected behavior. Finally, the anticipated behavior of traders, which is similar to that of option holders, is further amplified by the possibility of opening several wikifolios. Signalers are assumed to pursue various trading strategies with different levels of risk until they have created one wikifolio with a broad investor base and good performance. Summarizing, unlike on Ayondo there is no mechanism that incentivizes the traders to trade more on lower promotion levels and to trade less on higher ones.

Popularity and the signaler's trading behavior Thus far, behavioral finance studies have concentrated on the behavior of investors. However, social interaction can alter the traders' conduct as investors learn through observing the behavior of others (Barber and Odean, 2001b; Baker and Nofsinger, 2002; Duflo and Saez, 2002; Seasholes, 2010; Hirshleifer, 2015). The social network features on both platforms give rise to new aspects of social interaction in trading, which have the ability to influence overconfidence. These include, among others, the number of followers that presents an indicator for the popularity of signalers. Kim and Lee (2011) provide proof of the fact that the number of friends on Facebook serves as an affirmation and boost of self-worth. The endeavor to be positively perceived by others can induce overconfidence (Dowling and Lucey, 2010; Burks et al., 2013). Pentland (2013) shows that the confidence of individuals increases when they realize that others pursue strategies akin to their investment ideas. He elaborates by stating that, in the case of limited sources of information, traders consequently face the risk of becoming overconfident. Individuals who are contingent upon self-serving attribution bias, tend to credit past success to their skills and in doing so become more overconfident (Barber and Odean, 2001a; Gervais and Odean, 2001; Hirshleifer, 2001; Puetz and Ruenzi, 2011; Hirshleifer, 2015). As a trade leader cannot directly influence the number of followers or capital invested in his or her trading strategy, the success of the trade leader is partly measured by the ability to entice followers (Doering et al., 2015). Rational signalers who consider the mutual impacts on their profits would, given a certain number of followers, behave in a way as to maintain their performance level and the number of followers. However, all considered, we hypothesize that the popularity of a signaler's strategy is perceived as being a confirmation of his or her skills and thus connected with his or her tendency to trade more. Such a type of irrational behavior is a clear indication of (more) overconfidence.

Hypothesis 1 *The popularity of a trading strategy among followers is positively related with increased trading activity.*

Overconfidence and a trader's return Extensive research has been conducted into the relationship between trading activity and performance. Contrary to rational traders, the overconfident overestimate their expected gains and, hence, trade excessively, resulting in diminished returns compared with benchmarks (Bondt and Thaler, 1995; Daniel et al., 1998; Barber and Odean, 2000; Glaser and Weber, 2007; Grinblatt and Keloharju, 2009). Increased transaction costs for inordinate trading and the lower proficiency levels of the traders can therefore explain the reduced returns of overconfident traders (Barber and Odean, 1999; Shefrin, 2002; Merkle and Weber, 2011; Hirshleifer, 2015). Barber and Odean (2002) show that this relationship is particularly prevalent in online trading due to mitigated market frictions. The enhanced availability of information even augments overconfidence by contributing to the illusion of knowledge and control (Barber and Odean, 2001b; Baker and Nofsinger, 2002; Tsai et al., 2008; Abreu and Mendes, 2012). In the case of Ayondo and Wikifolio, one could argue that the increased trading activity is fostered through the setup of the platforms' compensation rather than being a sign of overconfidence. However, rational trade leaders will take into account that excessive trading entailing negative performance can lead to the loss of followers, capital and rating, and, ultimately, profits. What is more, technical aspects such as the trading strategy or the portfolio composition account for a certain level of trading activity.[2] In addition, trade leaders may see their trading activity as an opportunity to signal their competency and trustworthiness and, hence, adjust their trading behavior accordingly (Burks et al., 2013; Proeger and Meub, 2014; Wohlgemuth et al., 2016). With knowledge of the implied transaction costs, this rational sig-

[2]A trader may, for instance, pursue a strategy close to that of an arbitrageur between an stock index future and the underlying index, forcing him or her to trade a lot. If carried out rationally, though, the strategy should still be so profitable that at least the accruing transactions costs are earned and no negative expected returns emerge as a result from the strategy. However, the generally higher level of trading activity must be accounted for as it is not an expression of overconfidence.

naling strategy should still be profitable, though. Consequently, taking into account all rational factors, we argue that excessive trading activity which is stimulated by irrational factors e.g., increased popularity is connected with negative returns (after transaction costs).

Hypothesis 2 *The increased trading activity due to higher popularity reduces a trader's return.*

Our second hypothesis is, hence, contingent on the first hypothesis. Consequently, only if we find evidence for both hypotheses we have a clear indication of overconfidence, since we define overconfidence as the part of trading activity induced by irrational factors and resulting in negative returns.

Influence of the platform-specific rating and incentivizing methodologies Since social trading platforms prominently display the rating of each signaler, trade leaders strive for good positions in the platform's league table in order to attract new investments (Cheng, 2007; Jin et al., 2016; Gortner and van der Weele, 2019). Both platforms under review reinforce this behavior by suggesting the ranking as one of the key investment criterion, with the result that the predefined search for portfolios in the investigation period has been based on levels and Wikifolio points respectively. A more elaborate analysis of the investment opportunities taking into account risk and performance measures requires additional efforts by the followers. Dowling and Lucey (2010) show that ambitious settings fostering competition among individuals nurture a biased self-attribution (see also Eshraghi and Taffler, 2012; Simon and Heimer, 2015). The social ranking theory contributes by explaining in which way good performances compared with the social environment nourish the signaler's self-perception and result in higher confidence and risk taking (Gilbert et al., 1996; Baker and Nofsinger, 2002). While several studies argue that the scarcity of information in competitive fields augments overconfidence, the immediate feedback on social trading platforms can reduce biased self-attribution as true abilities are revealed (Jin et al., 2016; Heimer, 2016; Gortner and van der Weele, 2019). Moreover, changes in the rating of signalers can be regarded as being a mechanism to supervise signalers and minimize the probability of adverse selection (Neumann, 2014; Glaser and Risius, 2016). In general, we expect that a positive rating (higher levels on Ayondo and more Wikifolio points on Wikifolio) tends to support overconfidence. However, the platform-specific rating and incentive frameworks can influence the way signalers react. The strict limits concerning the maximum drawdown and performance requirements on Ayondo can reduce the overconfidence of trade leaders and might lead to more rational behavior. Signalers do not wish to risk an expulsion to the base level, in particular if they have already achieved a higher position. Not having the option to open a new portfolio emphasizes the effect. Since Wikifolio points are calculated on a daily basis allowing signalers to move up and down the grading scale at any time, we expect that, contrary to Ayondo, the Wikifolio rating scheme will rather foster overconfident behavior. The platform has also not implemented rebalancing measures such as risk limiting mechanisms, which could reduce irrational trading activity. This effect is reinforced by the option of opening several wikifolios.

Hypothesis 3 *The platform-specific rating and incentive features influence the trading activity in a different manner.*

2.4 Data and methodology

2.4.1 Data

We use a comprehensive data set that enables us to measure the relationship between financial activities and social interaction on two major social trading platforms in Germany. The setting of the platforms offers the possibility to simultaneously observe trading activity and individual behavior.

Both platforms publish historical time series of individual trading and performance data on their websites. We downloaded individual daily trading data from Ayondo and Wikifolio during the observation period of November 2015 to May 2016. The dataset includes all portfolios created on Ayondo ever since April 2009 and all portfolios created on Wikifolio ever since September 2011. Furthermore, we manually collected additional information on social interaction such as the number of followers or Wikifolio points on a weekly basis. The dataset employed is similar to but more comprehensive than the dataset utilized by Dorfleitner et al. (2018).

Since the platforms are open to everyone and entry prerequisites are loose, the customer base includes both novices and experts. We adjust the data set by excluding both the demo and inactive accounts to reduce possible biases. Some deficient observations on Ayondo with a maximum drawdown exceeding 100% are deleted. With respect to Wikifolio, we concentrate on the wikifolios that are published and eligible for investment. Finally, we arrive at a data set containing 15,654 weekly performance observations of 1,284 signalers on Ayondo and 106,634 weekly return observations of 4,504 wikifolios of 2,716 signalers on Wikifolio. While some portfolios were created during the observation period, others existed previously, sometimes for months or years. Consequently, the dataset also features traders who do not have any investors yet. Our data do not suffer from survivorship bias, as both the successful and less successful portfolios are retained in the dataset. The platforms disclose information on the trading and social activity of each signaler starting from the beginning of their membership. While Ayondo supplies extensive metric data, Wikifolio provides an insight into quality indicators such as the relationship between risk and return, the traded instruments, and trading style, by using so-called *tags* to categorize wikifolios. We therefore expect – due to disparities in the availability of information as well as in the platform design – Ayondo and Wikifolio to attract different trader and investor groups. Additionally, we assume that the likelihood of errors in the data points is minimal since platform operators advertise the transparency of information and high data quality.

To quantify the returns we follow the platforms, which display the figure *Total performance* as the main performance indicator of trading strategies measuring the performance of the signal provider since the creation of the portfolio to the corresponding day. Weekly performance (*Return*) is calculated based on the relative difference in *Total performance* between the week under consideration and the previous one. To avoid spurious results due to weekend effects, we construct our performance variable on the interval between one Wednesday and the next. Since daily performance figures are not retrievable for every single portfolio, we interpolate performance data on Ayondo and search externally for corresponding prices for wikifolios[3]. Note that the variable *Return* already accounts for transaction costs[4]. As suggested by hypothesis 1,

[3]Interpolated values account for less than 1% of Ayondo performance data.

[4]While Ayondo incorporates transaction costs in the CFD spreads, transaction costs on Wikifolio are a part of the replication strategy in the certificates and thus also already contained in the certificate prices.

we include the popularity of a signaler – measured by the numbers of followers or net cash flows respectively (Sirri and Tufano, 1998). Apart from this we consider the ranking of trade leaders to investigate hypothesis 3. We measure the current *Level* of a trader on Ayondo as well as $Wikifolio\,points$ at the end of one week. In order to control for the effects of the market on returns, we include $Benchmark\,returns$, obtained from Yahoo Finance. We follow a similar approach to Sharpe (1992) and apply asset-specific benchmarks. We account for the focus on trading with (CFDs on) stocks and indices and utilize the return of the MSCI World index in Euro. Moreover, the variable $Volatility$ enters the model to measure risk exposure on performance. By adding lagged returns we account for the past success of signalers. Finally, platform-specific risk and performance key figures as well as social interaction variables i.e., the number of comments published in a week enter the regression.

Table 2.1 and 2.2 provide a detailed description of all explanatory variables as well as additional control variables.

2.4.2 Descriptive statistics

Ayondo Table 2.3 provides descriptive statistics for our sample of 882 signalers on Ayondo in the observation period. As a consequence of trading with CFDs and the disproportional effect of price changes on performance the weekly returns exhibit large variations. We account for the skewness of the return distribution and winsorize weekly returns at the 1% and 99% levels leading to a minimum of −913.11% and a maximum of 703.64%. The resulting average return amounts to −8.4%. In comparison, the mean weekly benchmark performance is −0.33%. We conclude that, on average, signalers underperform the benchmark. Regarding the hypotheses-related variable trades, we observe an average of 18 trades per week. Some traders, though, appear to trade intensively, resulting in a maximum of 839 trades within one week. The risk measure maximum drawdown adds to the presumption of extremely risky trading on Ayondo with a mean of 19.7% and a maximum value of 99.87%. With respect to popularity, signalers have an average of 31 followers. We interpret the skewed distribution as an indicator for herding as investors merely appear to concentrate on a few signalers. An advanced skill level of a trader should be reflected through a higher career level. In fact, the mean of 1.7 suggests that signalers stay in the region of the first and second level. One explanation for this result could be the return of a trader to the initial level in the case of exceeding the maximum drawdown.

Wikifolio Table 2.4 presents the descriptive statistics for the Wikifolio sample comprised of 4,370 wikifolios among 2,670 signalers in the sample period. To begin with, the distribution of returns is skewed to the right as in the case of Ayondo. However, as trading instruments are not restricted to CFDs, the leverage effect in returns is reduced. Nonetheless, a minimum of −19.03% and a maximum of 13.33% is achieved after winsorizing returns at the 1% and 99% levels. Signalers on Wikifolio generate, on average, weekly returns of −0.12%. In comparison, the weekly performance of the benchmark ranges from −6.4% to 4.8% with a mean of −0.07%. Consequently, the traders on Wikifolio appear to perform better than those on Ayondo, although they still underperform the MSCI World Index. The volatility in returns exhibits a mean of 0.0206 and a standard deviation of 0.0709. The positive skewness indicates extreme outliers. We observe an average trading activity of 5.4 trades per week. Consistent with the results on Ayondo, a few signalers appear to trade extensively. The higher level in trading activity on Ayondo compared with Wikifolio can be partially explained by the fact that Ayondo applies a volume-based performance model. Concerning the popularity of wikifolios, the mean net capital

Table 2.1: Definition of the explanatory variables on Ayondo

Data sources: Own calculations based on data from Ayondo and Yahoo Finance. Description of variables following Ayondo (2016).

Variable	**Meaning**	**Description**
$Return_{\text{i,t}}$	Weekly return	Performance of a trader's portfolio in week t, calculated as being the ratio of the weekly net total performance to the previous week's total performance
$Benchmark_{\text{i,t}}$	Benchmark return	Weekly return of the MSCI World Index (in Euro)
$Volatility_{\text{i,t}}$	Volatility	Volatility of daily returns over the last 4 weeks
$Trades_{\text{i,t}}$	Trades per week	Number of trades a trader executed in week t
$TWR_{\text{i,t}}$	Trades-won ratio	Ratio of all previous trades that have been closed with a winning position
$Follower_{\text{i,t}}$	Number of followers	Number of followers following a trader's portfolio measured on a weekly basis
$MDD_{\text{i,t}}$	Maximum drawdown	Maximum drawdown a trader has ever experienced since the beginning of the observation period
$Leverage_{\text{i,t}}$	Leverage ratio	Average leverage of all trades during the previous week
$Short_{\text{i,t}}$	Short ratio	Ratio of securities that have been shortened during the previous week
$HHI_{\text{i,t}}$	Herfindahl-Hirschmann index	Sum of squared portfolio allocations to a specific asset class according to Hoffmann and Shefrin (2011)
$Level_{\text{i,t}}$	Career level	Career level of the trader in categorical values ranging from 1 to 5 (Street Trader, Advanced, Professional, Risk-adjusted, Institutional)
$Experience_{\text{i,t}}$	Experience	Trading experience of the trader in categorical values ranging from 0 to 6 (0 years, 0-1, 1-2, 2-5, 5-10, more than 10 years)
$Week\,dummy_{\text{t}}$	Week	Binary, time identifying variable indicating the week of measurement

Table 2.2: Definition of the explanatory variables on Wikifolio

Data sources: Own calculations based on data from Wikifolio and Yahoo Finance. Description of variables following Wikifolio (2016).

Variable	**Meaning**	**Description**
Metric variables		
$Return_{\mathrm{i,t}}$	Weekly return	Performance of a trader's portfolio in week t, calculated as being the ratio of the weekly net total performance to the previous week's total performance
$Benchmark_{\mathrm{i,t}}$	Benchmark return	Weekly return of the MSCI World Index (in Euro)
$Volatility_{\mathrm{i,t}}$	Volatility	Volatility of daily returns over the last 4 weeks
$Trades_{\mathrm{i,t}}$	Trades per week	Number of trades a trader executed in week t, measured in multiples of 5
$Net\,capital\,change_{\mathrm{i,t}}$	Net change in invested capital	Difference between the total capital invested in the current and in the previous week accounting for capital changes following positive returns
$Comments_{\mathrm{i,t}}$	Number of comments	Number of published comments by the trader in week t, measured in multiples of 5
$WF\,points_{\mathrm{i,t}}$	Wikifolio points	Wikifolio points of the trader in the respective week
$Week\,dummy_{\mathrm{t}}$	Week	Time identifying variable indicating the week of measurement
Wikifolio tags (binary variables)		
$Money\,manager_{\mathrm{i,t}}$	Good money manager	Good money managers accomplished a mean monthly return exceeding 0.3% during a time interval of 6-24 months, while at the same time not experiencing losses above 20% of the portfolio value. In addition, the trader executed more than 35 trades.
$Loyal_{\mathrm{i,t}}$	Loyal investors	More than 15 buy orders have been placed on the wikifolio during the preceding 24 months. In addition, the ratio of sale transactions to total transactions is below 35%.
$Frequently_{\mathrm{i,t}}$	Frequently bought	The difference in the number of purchase requests and sale requests since the emission of the index certificate is higher than 25.
$Heavy_{\mathrm{i,t}}$	Heavy trader	Within the last 49 days, at least 7 times the aggregated portfolio value has been turned around by the trader.
$Performance_{\mathrm{i,t}}$	High performance	The portfolio with the status 'published' or 'investable' achieved a performance of more than 40% in the preceding 12 months and a mean return of more than 4% in the last 6 months.
$Bestseller_{\mathrm{i,t}}$	Bestseller	The index certificate on the wikifolio has been purchased more often than sold within the last two weeks. Furthermore, it is amongst the 25 most highly purchased wikifolios on the platform during the past 14 days.
$Diversified_{\mathrm{i,t}}$	Actively diversified	These types of wikifolios have invested in at least 10 different securities in the last 6 weeks, of which none comprise for more than one fifth of the portfolio value.
$Leveraged_{\mathrm{i,t}}$	Trades leveraged products	The wikifolio can include structured products.

Table 2.3: Descriptive statistics Ayondo

Notes: Descriptive statistics of the Ayondo dataset consisting of 9,522 observations of 882 signalers for the observation period from November 13th 2015 to May 20th 2016. This table contains means and standard deviations (SD) of the variables. Min./Max. refer to the minimum/maximum values of the variables. The variables are defined in Table 2.1.

Variable	**N**	**Min.**	**Mean**	**Max.**	**SD**
$Return_{\mathrm{i,t}}$	9,365	−9.1311	−0.0840	7.0364	1.5544
$Benchmark_{\mathrm{i,t}}$	9,365	−0.0629	−0.0033	0.0477	0.0290
$Benchmark\_USD/EUR_{\mathrm{i,t}}$	9,365	−0.0289	−0.0007	0.0247	0.0134
$Benchmark\_DAX_{\mathrm{i,t}}$	9,365	−0.0623	0.0046	0.0606	0.0338
$Volatility_{\mathrm{i,t}}$	9,365	0.0107	2.1661	1,664.6800	24.6133
$Trades_{\mathrm{i,t}}$	9,365	0.0000	17.7368	839.0000	37.1474
$log(1+Trades)_{\mathrm{i,t}}$	9,365	0.0000	2.0682	6.7334	1.2905
$Follower_{\mathrm{i,t}}$	9,365	0.0000	30.9247	2,165.0000	191.4300
$log(1+Follower)_{\mathrm{i,t}}$	9,365	0.0000	0.9679	7.8876	1.5015
$Level_{\mathrm{i,t}}$	9,365	1.0000	1.6711	5.0000	1.0319
$MDD_{\mathrm{i,t}}$	9,365	0.0000	19.7061	99.8760	24.3581
$TWR_{\mathrm{i,t}}$	9,365	0.0000	0.6209	1.0000	0.3426
$Leverage_{\mathrm{i,t}}$	9,365	0.8000	23.5187	200.0000	37.8622
$Short_{\mathrm{i,t}}$	9,365	0.0000	0.4277	1.0000	0.3490
$HHI_{\mathrm{i,t}}$	9,365	0.0000	0.8982	1.0000	0.2023
$Experience_{\mathrm{i,t}}$	9,365	0.0000	1.7923	5.0000	2.2120

change amounts to 110.947 Euro. While the most successful wikifolio has thus far experienced a maximum of 19,421 Euro worth of net cash inflows, the least favourable wikifolio experienced net cash flows of −14,853 Euro. Based on certain criteria, trading strategies are awarded with Wikifolio points, that are spread between 0 and 8,514 with an average value of 317. Table 2.5 provides insights into the relative frequency of the binary variables.

2.4.3 Methodology

Due to the two-dimensional structure of the data, we perform panel regressions to study our hypotheses. We apply an approach similar to that of Jin et al. (2016) to quantify the relationship between weekly performance (*Return*) and the trading activity (*Trades*). Since only negative returns after transaction costs following increased trading activity initiated by irrational factors are a clear identification of overconfidence, our model considers benchmark return, volatility, and platform-specific variables describing the characteristics of the trading strategies. We follow Gervais and Odean (2001) and Glaser and Weber (2010) and assume that overconfidence is not constant over time as it may be subject to fluctuations conditioned by events that occur within the course of social trading. In light of the skewed distribution of $Trades$ and $Followers$ we logarithmically transform the variables. Since this method is inappropriate for $Net\,capital\,change$, we instead winsorize it at the 1% and 99% level to account for extreme outliers.

Traders differ in unobservable personal traits such as trading ability or the level of overconfidence and are subject to the incentives imposed by the platform. Furthermore, the trading

Table 2.4: Descriptive statistics Wikifolio

Notes: Descriptive statistics of the Wikifolio dataset consisting of 87,128 observations of 4,370 wikifolios of 2,670 signalers for the observation period from November 13th 2015 to May 20th 2016. This table contains means and standard deviations (SD) of the variables. Min./Max. refer to the minimum/maximum values of the variables. The variables are defined in Table 2.2.

Variable	**N**	**Min.**	**Mean**	**Max.**	**SD**
$Return_{\mathrm{i,t}}$	87,031	-0.1903	-0.0012	0.1333	0.0396
$Benchmark_{\mathrm{i,t}}$	87,031	-0.0643	-0.0007	0.0483	0.0279
$Benchmark\_DAX_{\mathrm{i,t}}$	87,031	-0.0832	-0.0013	0.0467	0.0316
$Volatility_{\mathrm{i,t}}$	87,031	0.0000	0.0206	7.1166	0.0709
$Trades_{\mathrm{i,t}}$	87,031	0.0000	5.4017	$1,265.0000$	26.3591
$log(1+Trades)_{\mathrm{i,t}}$	87,031	0.0000	0.6110	7.1436	1.1750
$Net\,capital\,change_{\mathrm{i,t}}$	87,031	$-14,853.0000$	110.9747	$19,421.0000$	$3,014.0000$
$WF\,points_{\mathrm{i,t}}$	87,031	0.0000	317.3683	$8,514.0000$	690.5921
$Comments_{\mathrm{i,t}}$	87,031	0.0000	43.8605	$2,275.0000$	109.1601

Table 2.5: Descriptive statistics of binary variables on Wikifolio

Notes: Descriptive statistics of the Wikifolio dataset consisting of 87,128 observations of 4,370 wikifolios of 2,670 signalers for the observation period from November 13th 2015 to May 20th 2016. This table contains absolute and relative frequencies of the binary variables. *Relative frequency of the variable *Leverage* refers to the overall dataset. The variables are defined in Table 2.2.

Variable	**Observations**	**Relative Frequency in %**
$Money\,manager_{\mathrm{i,t}}$	8,307	9.53
$Loyal_{\mathrm{i,t}}$	5,197	5.96
$Frequently_{\mathrm{i,t}}$	4,665	5.35
$Heavy_{\mathrm{i,t}}$	5,738	6.59
$Performance_{\mathrm{i,t}}$	481	0.55
$Bestseller_{\mathrm{i,t}}$	476	0.55
$Diversified_{\mathrm{i,t}}$	34,499	39.60
$Leverage_{\mathrm{i,t}}$	22,477	0.28*

strategy has an impact on the signaler's general performance, risk taking and trading activity. All these factors give rise to possible endogeneity issues (Heimer, 2016; Glaser and Risius, 2016; Dorfleitner et al., 2018). We therefore employ fixed effects to account for the endogeneity arising from personal characteristics of traders as well as from differences in trading strategies (Hausman and Taylor, 1981). In order to analyze the factors that influence overconfidence and the traders' returns, we implement a two-stage least squares (2SLS) model with fixed effects in both stages. We include rational determinants of trading activity as control variables in the estimation of overconfidence proxied by the part of trading activity that is induced by irrational factors. Besides tackling the endogeneity issue, the instrumental variable (IV) method provides the opportunity to measure the rational and the irrational influences on trading activity in a dynamic setting. In doing so, we distinguish ourselves from existing overconfidence models.

When establishing our conceptual model, we build on behavioral finance literature in order to analyze the irrational factors affecting overconfidence. To begin with, we include lagged variables of the number of followers and net change in invested capital, respectively, as well as the previous rating as instruments to investigate our hypotheses. We account for the different behavioral patterns induced by the platform-specific features by including further variables. Ayondo's incentive and rating system is designed with the objective to mitigate excessive risk taking by the traders by imposing a limit on the maximum drawdown. Therefore, the lagged values of the maximum drawdown are added as instrumental variables. In addition, as overconfidence is associated with a higher inclination towards risk (Odean, 1998; Cheng, 2007), we thereby analyze whether this holds for signalers on Ayondo. Considering the fact that past success may stimulate a trader's confidence (Barber and Odean, 2001b; Statman et al., 2006; O'Connell and Teo, 2009; Dowling and Lucey, 2010; Puetz and Ruenzi, 2011; Hirshleifer, 2015), we incorporate past performance, the lagged trades-won ratio on Ayondo as well as performance related *tags* on Wikifolio as IVs. Finally, we investigate whether the overconfidence of the traders on Ayondo changes over time, based on the experience of the trader (Gervais and Odean, 2001; Glaser and Weber, 2010).

In view of the technical factors influencing trading activity and returns[5], we include lagged variables of leverage and short ratio on Ayondo as well as different Wikifolio *tags* following Dorfleitner et al. (2018). Since traders on Wikifolio can comment on their trading activities, we also include the variable *Comments* in our model to factor in the social network characteristics (Dorfleitner et al., 2018). We account for the relationship between diversification and trading activity by encompassing the lagged Herfindahl-Hirschmann index for Ayondo and the tag *Diversified* for Wikifolio. We also establish the variable *Heavy trader* as control variable in the Wikifolio model.

As a result, the regression models for Ayondo and Wikifolio manifest the following structure, where i represents the signaler and t denotes the time dimension. The terms $\varepsilon_{i,t}$ and $\varphi_{i,t}$ constitute the error terms in the instrumental and reduced form equation respectively.

[5]In comparison to other research such as the study of Oehler et al. (2016), we do not take the approach of applying factor models to analyze returns, but instead base our analysis on the panel data structure and thus follow a rather Fama-MacBeth style approach. By accounting for market returns we implicitly use a beta of 1. In addition, as we consider various influencing factors of returns we do not consider it fruitful to implement additional risk factors.

The **Ayondo 2SLS model** is represented by:

$$\begin{aligned}\log(1+Trades)_{i,t} = {} & \pi_1 \log(1+Follower)_{i,t-1} + \pi_2\, Level_{i,t-1} + \pi_3\, TWR_{i,t-1} \\ & + \pi_4\, MDD_{i,t-1} + \pi_5\, Experience_{i,t-1} + \phi_1\, Benchmark_{i,t} \\ & + \phi_2\, Volatility_{i,t-1} + \phi_3\, Return_{i,t-1} + \phi_4\, Leverage_{i,t-1} + \phi_5\, Short_{i,t-1} \\ & + \phi_6\, HHI_{i,t-1} + \phi_7\, Week_t + \eta_i + \varphi_{i,t}\end{aligned} \tag{2.1}$$

$$\begin{aligned}Return_{i,t} = {} & \gamma_1\, Benchmark_{i,t} + \gamma_2\, Volatility_{i,t-1} + \gamma_3\, Return_{i,t-1} + \gamma_4\, Leverage_{i,t-1} \\ & + \gamma_5\, Short_{i,t-1} + \gamma_6\, HHI_{i,t-1} + \gamma_7\, Week_t + \beta_1 \log(1+Trades)_{i,t} + \upsilon_i + \varepsilon_{i,t}\end{aligned} \tag{2.2}$$

while the **Wikifolio 2SLS model** can be expressed as:

$$\begin{aligned}\log(1+Trades)_{i,t} = {} & \pi_1 \log(1+Net\,capital\,change)_{i,t-1} + \pi_2\, WF\,points_{i,t-1} \\ & + \pi_3\, Money\,manager_{i,t-1} + \phi_1\, Benchmark_{i,t} + \phi_2\, Volatility_{i,t-1} \\ & + \phi_3\, Return_{i,t-1} + \phi_4\, Comments_{i,t} + \phi_5\, Heavy_{i,t-1} \\ & + \phi_6\, Performance_{i,t-1} + \phi_7\, Bestseller_{i,t-1} + \phi_8\, Diversified_{i,t-1} \\ & + \phi_9\, Week_t + \eta_i + \varphi_{i,t}\end{aligned} \tag{2.3}$$

$$\begin{aligned}Return_{i,t} = {} & \gamma_1\, Benchmark_{i,t} + \gamma_2\, Volatility_{i,t-1} + \gamma_3\, Return_{i,t-1} + \gamma_4\, Comments_{i,t} \\ & + \gamma_5\, Heavy_{i,t-1} + \gamma_6\, Performance_{i,t-1} + \gamma_7\, Bestseller_{i,t-1} + \gamma_8\, Diversified_{i,t-1} \\ & + \gamma_9\, Week_t + \beta_1 \log(1+Trades)_{i,t} + \upsilon_i + \varepsilon_{i,t}\end{aligned} \tag{2.4}$$

We use clustered standard errors at the signaler level and include the time variable *Week* to control for the effects of time-series trends. Due to the fact that OLS estimates are likely to be more precise than IV estimates, we check whether the application of the IV approach biases our results. The Hansen's J statistic and endogeneity tests confirm that the econometric estimation procedure satisfies the conditions for efficiently estimating the effect of overconfidence on performance (Hansen and Singleton, 1982; Stock and Yogo, 2005; Kleibergen and Paap, 2006; Baum et al., 2007).

2.5 Results

In this section, we explore the relationship between performance and trading behavior on Ayondo and Wikifolio. We analyze the factors that influence overconfidence with respect to our hypotheses and perform robustness checks. Finally, we discuss the differences between both platforms.

2.5.1 Ayondo

Table 2.6 represents the 2SLS regression results with *Return* as the dependent variable. With respect to the hypothesis-related variable *Level*, regression 1 includes dummy variables for the different career levels, while regression 2 utilizes the continuous variable $Level_{i,t-1}$. To begin with, the auxiliary regression 2.1 provides an insight into the validity of the instruments for overconfidence (*log(1+Trades)*). As suggested by hypothesis 1, the coefficient of the number of followers is positively significant at the 5% level. This result indicates that popularity amongst investors stimulates the overconfidence of traders in their abilities leading to an increase in trading activity. It needs to be noted that this finding is novel, since the development of social trading platforms has introduced the social dimension of followers. In addition, this information is made immediately available to the trade leaders and is able to influence their behavior in this way. Regarding hypothesis 3, we find that the platform-specific ranking and incentive scheme significantly affects trading behavior. The coefficients of the career levels 3 and 4 on Ayondo are positively significant at the 10% level. However, the coefficient is insignificant for the highest level 5. The remuneration model of Ayondo follows a volume-based approach directly aligning the signaler's compensation to his or her position in the platform ranking and the trading volume generated. Due to the fact that traders at a higher level profit proportionally from more followers and the higher level, we interpret this finding as being an indication of the fact that rational traders adapt their trading behavior accordingly. However, the positive, significant coefficient demonstrates that higher positions in the league table tend to nourish the signaler's self-perception and nurture his or her overconfidence, leading to increased trading activity. The insignificant coefficient of *Level 5* can be explained by the fact that this career level entails the risk of losing the most due to the irreversible drop to the entry level. The risk is further amplified by increased trading activity, which, in turn, reduces returns by means of transaction costs. The negative and significant effect of maximum drawdown on overconfidence can be explained by the fact that this figure constitutes one of the main criteria for the assignment of the career level. Since exceeding the limited MDD of 25% will result in an expulsion from the current level back to the initial position, the maximum drawdown serves as a monitor for the level of risk taking. Therefore, the measure maximum drawdown reduces the signalers' propensity towards overconfidence. Looking at the combined effect of Level and MDD shows that the impact of the risk requirement exceeds the positive effect of the rating on overconfidence, leading to a joined negative effect of the ranking and incentive system. Concluding, our results suggest that the ranking system on Ayondo is constructed in a way that mitigates overconfident behavior by making the traders more rational.[6]

The positive development of the trades-won ratio predicts that the signaler will be more greatly exposed to increased trading activity following past success. The coefficient of experience is negatively correlated with overconfidence. With respect to the rational and trading-strategy-related factors affecting trading activity, we find that high leverage ratios, representing the trader's inclination towards risk, have an insignificant impact on trading activity. Traders whose strategies comprise fewer asset classes appear to trade less extensively as compared with signalers who focus on a variety of instruments in their portfolios. Additionally, the portfolio's performance in the previous week is positively significant. Lastly, the week dummies exhibit significant negative coefficients implying that traders reduce trading activity over time.

Finally, when analyzing the second stage regression 2.2, we find that the results support our

[6] If we additionally control for the interaction of *Level 1* and an MDD exceeding 25% (regression not reported here), we observe an insignificant coefficient. Thus, there is no support for the view that those traders that are not anymore subject to the risk limits trade more excessively.

hypothesis 2, being that the trader's performance is adversely affected by overconfidence. The negative and highly significant coefficient of trading activity suggests that overconfident signalers, whose behavior is affected by irrational factors, diminish their returns by trading too much. The interesting aspect in this finding is the fact that overconfidence is still present after controlling for several technical aspects affecting trading activity such as the portfolio concentration, past returns and their volatility as well as the portfolio's strategy. The irrational part of trading intensity can thus be explained by the social interaction dimensions of followers and the rating and incentive scheme. Regarding the benchmark return, we find a negative relationship between the development of the return of the MSCI World Index and a trader's performance, indicating a tendency amongst signalers to short the market. We assume that the insignificant coefficients can be partly explained by the fact that a large part of the return variation due to the weekly market variations is captured by the time dummy. Moreover, we discover a significant negative relationship between past and current performance. Contrary to expectations, the results demonstrate an insignificant risk-reward-relationship. What is more, the leverage and short ratio do not significantly affect social trading returns, while the effect of the portfolio composition is significantly negative. With respect to time series trends, we in fact observe a significant negative coefficient, indicating that signalers impair their performance over time.

Table 2.6: 2SLS regression of $Return_{i,t}$ on trading activity – Ayondo

Notes: This table presents the results of a two-stage least squares fixed effects regression estimating the relationship between $Return_{i,t}$ and trading activity ($(log(1 + Trades)_{i,t})$), instrumented by a set of instrumental variables on Ayondo. $Return_{i,t}$ is winsorized at the 1% and 99% level. While model 1 uses dummy variables for the different $Levels$, model 2 utilizes $Level$ as a continuous variable to measure the effect of rating on trading activity. Models 3 to 4 constitute robustness checks and focus on a subsample of active signalers who have been trading in the previous week. Models 5 to 6 and models 7 to 8 use USD/EUR returns and DAX returns respectively as market returns to investigate the robustness of the regression results. Table 2.1 provides detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered at the signaler level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	2	3	4	5	6	7	8
First stage regression: estimation of the endogenous variable $log(1 + Trades)_{i,t}$								
$log(1 + Follower)_{i,t-1}$	0.0618**	0.0624**	0.0504*	0.0512**	0.0618**	0.0624**	0.0618**	0.0624**
	(0.0276)	(0.0258)	(0.0278)	(0.0258)	(0.0276)	(0.0258)	(0.0276)	(0.0258)
$Level\_2_{i,t-1}$	0.0852		0.0670		0.0852		0.0852	
	(0.0566)		(0.0579)		(0.0566)		(0.0566)	
$Level\_3_{i,t-1}$	0.170**		0.142		0.170**		0.170**	
	(0.0855)		(0.0894)		(0.0855)		(0.0855)	
$Level\_4_{i,t-1}$	0.225*		0.240*		0.225*		0.225*	
	(0.122)		(0.127)		(0.122)		(0.122)	
$Level\_5_{i,t-1}$	0.170		0.177		0.170		0.170	
	(0.235)		(0.202)		(0.235)		(0.235)	
$Level_{i,t-1}$		0.0779**		0.0713*		0.0779**		0.0779**
		(0.0373)		(0.0390)		(0.0373)		(0.0373)
$MDD_{i,t-1}$	−0.016***	−0.016***	−0.015***	−0.015***	−0.016***	−0.016***	−0.016***	−0.016***
	(0.0029)	(0.0029)	(0.0030)	(0.0030)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
$TWR_{i,t-1}$	0.368***	0.368***	0.375***	0.375***	0.368***	0.368***	0.368***	0.368***
	(0.0412)	(0.0412)	(0.0465)	(0.0464)	(0.0412)	(0.0412)	(0.0412)	(0.0412)
$Experience_{i,t-1}$	−0.0004	−0.0005	−0.0003	−0.0003	−0.0004	−0.0005	−0.0004	−0.0005
	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
$Benchmark_{i,t-1}$	−0.501	−0.492	−0.515	−0.510				
	(1.683)	(1.684)	(1.787)	(1.789)				
$Benchmark\_USD/EUR_{i,t-1}$					−5.101	−5.008		
					(17.13)	(17.14)		
$Benchmark\_DAX_{i,t-1}$							−1.166	−1.144
							(3.915)	(3.916)
$Volatility_{i,t-1}$	−0.0004	−0.0005	−0.0001	−0.0001	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$Return_{i,t-1}$	0.0107*	0.0106*	0.0104	0.0104	0.0107*	0.0106*	0.0107*	0.0106*
	(0.0062)	(0.0062)	(0.0064)	(0.0064)	(0.0062)	(0.0062)	(0.0062)	(0.0062)
$Leverage_{i,t-1}$	0.0013	0.0013	0.0007	0.0008	0.0013	0.0013	0.0013	0.0013
	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
$Short_{i,t-1}$	0.0193	0.0186	−0.0226	−0.0239	0.0193	0.0186	0.0193	0.0186
	(0.0356)	(0.0357)	(0.0406)	(0.0407)	(0.0356)	(0.0357)	(0.0356)	(0.0357)
$HHI_{i,t-1}$	−0.483***	−0.482***	−0.429***	−0.430***	−0.483***	−0.482***	−0.483***	−0.482***
	(0.0758)	(0.0759)	(0.0751)	(0.0750)	(0.0758)	(0.0759)	(0.0758)	(0.0759)
Week dummy	yes	yes	yes	yes	yes	yes	yes	yes
Second stage regression: estimation of the exogenous variable $Return_{i,t}$ with $log(1 + Trades)_{i,t}$ instrumented								
$log(1 + Trades)_{i,t}$	−0.806***	−0.806***	−0.801***	−0.796***	−0.806***	−0.806***	−0.806***	−0.806***
	(0.131)	(0.132)	(0.149)	(0.150)	(0.131)	(0.132)	(0.131)	(0.132)
$Benchmark_{i,t-1}$	−4.574	−4.574	−4.335	−4.331				
	(2.830)	(2.830)	(3.063)	(3.059)				
$Benchmark\_USD/EUR_{i,t-1}$					−46.56	−46.56		
					(28.80)	(28.81)		
$Benchmark\_DAX_{i,t-1}$							−10.64	−10.64
							(6.581)	(6.582)
$Volatility_{i,t-1}$	−0.0002	−0.0002	-9.95×10^{-5}	-9.90×10^{-5}	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Return_{i,t-1}$	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***
	(0.0138)	(0.0138)	(0.0147)	(0.0147)	(0.0138)	(0.0138)	(0.0138)	(0.0138)
$Leverage_{i,t-1}$	0.0025	0.0025	0.0018	0.0018	0.0025	0.0025	0.0025	0.0025
	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
$Short_{i,t-1}$	0.0074	0.0074	−0.0003	−0.0002	0.0074	0.0074	0.0074	0.0074
	(0.0615)	(0.0615)	(0.0700)	(0.0700)	(0.0615)	(0.0615)	(0.0615)	(0.0615)
$HHI_{i,t-1}$	−0.438***	−0.439***	−0.424***	−0.422***	−0.438***	−0.439***	−0.438***	−0.439***
	(0.138)	(0.138)	(0.145)	(0.145)	(0.138)	(0.138)	(0.138)	(0.138)
Week dummy	yes	yes	yes	yes	yes	yes	yes	yes
Hansen J statistic	5.39	3.65	8.03	6.49	5.39	3.65	5.39	3.65
$p-value$	0.61	0.45	0.33	0.17	0.61	0.45	0.61	0.46
Endogeneity test	51.77	48.57	39.89	35.87	51.77	48.57	51.77	48.57
$p-value$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	9,365	9,365	8,327	8,327	9,365	9,365	9,365	9,365
Number of signalers	882	882	810	810	882	882	882	882

2.5.2 Wikifolio

The results of the 2SLS regression with *Return* as the dependent variable are reported in Table 2.7. The first column shows the regressions containing the hypotheses-related variables *Net capital change*, *WF Points* and *Money manager*. In the second regression the main model is extended by the instrumental variables *Loyal* and *Frequently*. Starting with the first stage regression 2.3, we assess the validity of our instruments. In line with hypothesis 1, the net capital change positively and significantly affects the degree of overconfidence. These results indicate that subsequent to fund inflows, signalers become more overconfident and trade more actively. The information on the popularity of a trader is displayed prominently and can therefore impact a signaler's behavior. As expected, we find that the ranking system on Wikifolio significantly influences overconfidence, thereby confirming hypothesis 3. Just like on Ayondo, the coefficient of Wikifolio points is positive. This finding implies that a promotion in the league table nourishes the signal provider's self-perception and fosters his or her overconfidence. Contrary to Ayondo, the Wikifolio ranking does not impose a strict restriction on the further progress of the signalers. Since Wikifolio follows the HWM-compensation approach, the incentive system appears to encourage excessive trading activity. The option to open several wikifolios simultaneously adds to this expected behavior. Therefore, we conjecture that the setup of the ranking and incentive system induces overconfident investors to continue in the same manner, as setbacks do not have an educational character and means with a countervailing effect are not in place. In the next step, we examine whether quality tags that indicate the popularity of a wikifolio move overconfidence. We observe a significant positive effect of the reward *Money manager* and a slightly positive effect of the tag *Loyal investors* on overconfidence.

With respect to the effect of rational and trading-strategy-related factors on trading activity the results demonstrate a negative significant relationship between benchmark returns and trading activity. Trade leaders appear to decrease their trading intensity following positive benchmark performances. Contrary to Ayondo, past performance exhibits negative coefficients significant at the 10% level. Besides, we find a negative, yet insignificant correlation between past volatility and trading activity. The number of comments are not significantly related to trading activity. Wikifolio grants portfolios with awards based on quality indicators, the relationship between risk and return, traded instruments and trading style. Among these the tag *Heavy trader* exhibits a positive and significant coefficient, implying the persistence of high trading activity. As is the case with Ayondo, we provide empirical evidence of the positive relationship between past success in terms of risk-return-ratios and trading activity, which is displayed by the significant coefficient of the tag *High performance*. Interestingly, we find that if a wikifolio has been amongst the 25 most frequently purchased strategies within the last two weeks (*Bestseller*), it has a positive, albeit insignificant, effect on trading activity. Finally, trade leaders appear to reduce their trading activity over time – as in the case of Ayondo.

The results from the second stage regression 2.4 add weight to hypothesis 2. The negative and significant coefficient of overconfidence proves that excessive trading by overconfident signalers on Wikifolio reduces returns. We show that after accounting for the rational factors affecting trading activity, namely benchmark returns and volatility of returns as well as the wikifolio characteristics, overconfidence leads to increased trading activity. We provide evidence of the fact that the irrational part of trading intensity can, thus, be explained through the social interaction features of followers and the rating and incentive scheme. When taking into account that we already control for the tag *Heavy trader*, we show that overconfidence is existent beyond this. Contrary to Ayondo, the benchmark return has a positive and significant coefficient. There appears to be evidence of the fact that traders on Wikifolio tend to go long in the market. What is more, past returns have a significant positive relationship with current returns. According to our results, volatility has an insignificant negative effect on performance. Furthermore, since the number of posted comments implies a decrease in social trading returns we assume that experts are more reluctant to communicate their trading strategies. Regarding the wikifolio tags, we do not observe significant effects on social trading returns. Interestingly, the tag *Heavy trader* significantly positively affects a trader's return. Finally, the results indicate that signalers on Wikifolio also impair their performance over time.

Table 2.7: 2SLS regression of $Return_{i,t}$ on trading activity – Wikifolio

Notes: This table presents the results of a two-stage least squares fixed effects regression estimating the relationship between $Return_{i,t}$ and trading activity ($(log(1+Trades)_{i,t})$), instrumented by a set of instrumental variables on Wikifolio. $Return_{i,t}$ is winsorized at the 1% and 99% level and $Net\,capital\,change_{i,t}$ is calculated following Sirri and Tufano (1998). Model 1 represents the core model and is extended by additional social interaction variables in model 2. Models 3 to 4 and models 5 to 6 constitute robustness checks and focus on a subsample of wikifolios trading leveraged products and a subsample of active traders who have been trading in the previous week, respectively. Models 7 to 8 use DAX returns as market return to investigate the robustness of the regression results. Table 2.2 provides detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered at the signaler level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	2	3	4	5	6	7	8
First stage regression: estimation of the endogenous variable $log(1+Trades)_{i,t}$								
$Net\,capital\,change_{i,t-1}$	6.70×10^{-6}***	6.66×10^{-6}***	1.04×10^{-5}***	1.03×10^{-5}***	8.20×10^{-6}***	8.15×10^{-6}***	6.70×10^{-6}***	6.66×10^{-6}***
	(1.23×10^{-6})	(1.23×10^{-6})	(2.13×10^{-6})	(2.12×10^{-6})	(1.80×10^{-6})	(1.79×10^{-6})	(1.23×10^{-6})	(1.23×10^{-6})
$WF\,points_{i,t-1}$	5.00×10^{-5}***	5.05×10^{-5}***	0.0001***	0.0001***	6.14×10^{-5}***	6.21×10^{-5}***	5.00×10^{-5}***	5.05×10^{-5}***
	(1.19×10^{-5})	(1.19×10^{-5})	(3.08×10^{-5})	(3.13×10^{-5})	(1.98×10^{-5})	(1.98×10^{-5})	(1.19×10^{-5})	(1.19×10^{-5})
$Money\,manager_{i,t-1}$	0.0650**	0.0641**	0.113	0.112	0.0738	0.0742	0.0650**	0.0641**
	(0.027 1)	(0.027 1)	(0.071 5)	(0.070 8)	(0.058 1)	(0.058 3)	(0.027 1)	(0.027 1)
$Loyal_{i,t-1}$		0.0996*		0.157		0.0009		0.0996*
		(0.060 4)		(0.096 8)		(0.075 1)		(0.060 4)
$Frequently_{i,t-1}$		−0.0896		−0.168		−0.0408		−0.0896
		(0.110)		(0.181)		(0.131)		(0.110)
$Benchmark_{i,t-1}$	−3.280***	−3.275***	−5.044***	−5.029***	−9.127***	−9.122***		
	(0.725)	(0.725)	(1.515)	(1.516)	(2.902)	(2.902)		
$Benchmark\_DAX_{i,t-1}$							0.224	0.212
							(1.707)	(1.707)
$Volatility_{i,t-1}$	−0.0543	−0.0552	−0.0610	−0.0625	−0.0934	−0.0933	−0.0543	−0.0552
	(0.045 8)	(0.045 5)	(0.047 2)	(0.046 8)	(0.071 4)	(0.071 2)	(0.045 8)	(0.045 5)
$Return_{i,t-1}$	−0.197*	−0.196*	−0.145	−0.143	0.150	0.147	−0.197*	−0.196*
	(0.110)	(0.110)	(0.159)	(0.159)	(0.222)	(0.222)	(0.110)	(0.110)
$Comments_{i,t}$	0.0008	0.0008	-6.84×10^{-5}	-1.53×10^{-5}	0.0007	0.0007	0.0008	0.0008
	(0.000 8)	(0.000 8)	(0.001 3)	(0.001 3)	(0.000 9)	(0.000 9)	(0.000 8)	(0.000 8)
$Heavy_{i,t-1}$	0.256***	0.256***	0.293***	0.294***	0.0539	0.0544	0.256***	0.256***
	(0.038 7)	(0.038 6)	(0.053 6)	(0.053 2)	(0.053 5)	(0.053 5)	(0.038 7)	(0.038 6)
$Performance_{i,t-1}$	0.377***	0.373***	0.427***	0.416***	0.352***	0.350***	0.377***	0.373***
	(0.080 7)	(0.079 7)	(0.110)	(0.107)	(0.105)	(0.104)	(0.080 7)	(0.079 7)
$Bestseller_{i,t-1}$	0.107	0.0987	0.115	0.104	0.117	0.126	0.107	0.0987
	(0.089 1)	(0.087 8)	(0.146)	(0.149)	(0.112)	(0.112)	(0.089 1)	(0.087 8)
$Diversified_{i,t-1}$	0.0135	0.0137	0.0535	0.0547	0.0440	0.0442	0.0135	0.0137
	(0.023 3)	(0.023 3)	(0.049 0)	(0.049 0)	(0.053 1)	(0.053 1)	(0.023 3)	(0.023 3)
$Week\,dummy$	yes	yes	yes	yes	yes	yes	yes	yes
Second stage regression: estimation of the exogenous variable $Return_{i,t}$ with $log(1+Trades)_{i,t}$ instrumented								
$log(1+Trades)_{i,t}$	−0.0366***	−0.0320***	−0.0339***	−0.0266***	−0.0274***	−0.0256***	−0.0366***	−0.0320***
	(0.007 0)	(0.007 0)	(0.008 9)	(0.009 1)	(0.008 8)	(0.008 6)	(0.007 0)	(0.007 0)
$Benchmark_{i,t-1}$	0.496***	0.511***	0.222*	0.260**	−0.250	−0.234		
	(0.047 8)	(0.046 0)	(0.119)	(0.116)	(0.179)	(0.175)		
$Benchmark\_DAX_{i,t-1}$							0.262***	0.262***
							(0.102)	(0.098 0)
$Volatility_{i,t-1}$	−0.0059	−0.0056	−0.0072	−0.0067	−0.0011	−0.0009	−0.0059	−0.0056
	(0.005 3)	(0.005 2)	(0.005 5)	(0.005 3)	(0.003 5)	(0.003 4)	(0.005 3)	(0.005 2)
$Return_{i,t-1}$	0.0256***	0.0270***	0.0159	0.0181	0.001 98	0.002 02	0.0255***	0.0269***
	(0.0100	(0.009 8)	(0.014 7)	(0.014 2)	(0.020 7)	(0.020 6)	(0.010 0)	(0.009 8)
$Comments_{i,t}$	-3.33×10^{-5}	-3.83×10^{-5}	-9.28×10^{-5}	-9.57×10^{-5}*	-4.18×10^{-5}	-4.36×10^{-5}	-3.31×10^{-5}	-3.82×10^{-5}
	(3.62×10^{-5})	(3.33×10^{-5})	(6.31×10^{-5})	(5.60×10^{-5})	(3.79×10^{-5})	(3.67×10^{-5})	(3.62×10^{-5})	(3.33×10^{-5})
$Heavy_{i,t-1}$	0.0084***	0.0072***	0.0103**	0.0082**	0.0013	0.0012	0.0083***	0.0072***
	(0.002 7)	(0.002 7)	(0.004 1)	(0.004 1)	(0.002 6)	(0.002 6)	(0.002 7)	(0.002 7)
$Performance_{i,t-1}$	−0.0016	−0.0034	0.0035	1.59×10^{-5}	−0.0006	−0.0013	−0.0016	−0.0034
	(0.006 1)	(0.005 8)	(0.008 2)	(0.007 8)	(0.008 0)	(0.007 8)	(0.006 1)	(0.005 8)
$Bestseller_{i,t-1}$	−0.0077	−0.0086*	−0.0179**	−0.0196**	−0.0142*	−0.0147*	−0.0077	−0.0086*
	(0.005 2)	(0.005 0)	(0.009 1)	(0.008 9)	(0.007 6)	(0.007 6)	(0.005 2)	(0.005 0)
$Diversified_{i,t-1}$	0.0005	0.0005	0.0021	0.0017	0.0014	0.0014	0.0005	0.0005
	(0.001 0)	(0.000 9)	(0.002 0)	(0.001 8)	(0.002 0)	(0.002 0)	(0.001 0)	(0.000 9)
$Week\,dummy$	yes	yes	yes	yes	yes	yes	yes	yes
Hansen J statistic	1.80	7.24	0.42	6.89	1.52	3.09	1.80	7.22
$p-value$	0.41	0.12	0.81	0.14	0.47	0.54	0.41	0.12
Endogeneity test	106.35	100.37	28.99	24.96	22.09	22.41	106.13	100.19
$p-value$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	87,031	87,031	22,435	22,435	13,097	13,097	87,031	87,031
Number of wikifolios	4,370	4,370	1,181	1,181	1,461	1,461	4,370	4,370
Number of signalers	2,670	2,670	970	970	1,144	1,144	2,670	2,670

2.5.3 Robustness checks

We conduct a series of robustness checks by establishing model variations and calculating the regressions with different subsamples.

Subsample regressions Lastly, traders on Wikifolio decide, at the beginning of their career, whether or not they wish to make use of leveraged products. We account for the high affinity to risk of overconfident traders and analyze overconfidence of those signalers that include leveraged products in their wikifolios (Odean, 1998). In this setting, we can confirm all three hypotheses. We observe that the coefficients of the hypotheses related variables *Net capital change* and *WF points* slightly increase in size (see Table 2.7 models 3–4). However, one has to keep in mind that the traders do not actually have to trade this type of securities during the observation period. One could argue that our results are biased towards extremely active traders. We thus form subsamples by focusing on the active traders who traded in the previous week (see Table 2.6 models 3–4 and Table 2.7 models 5–6). We observe almost identical results for the active subsample compared to the original sample in the case of Ayondo. The main difference lies in the insignificance of the coefficient of *Level 3*. When considering the Wikifolio subsample of active traders, the coefficients of the hypotheses related variables increase slightly in size, while the effect of trading activity on returns is slightly reduced. The effects of past returns and the tag *Heavy trader* become insignificant.

Model variations We follow Dorfleitner et al. (2018) and use the performance of the German stock index (DAX 30) as an alternative measure of benchmark performance to capture possible market and timing effects. In addition, we use USD/EUR return as a benchmark for Ayondo due to the extensive use of forex trading. For both platforms, our results provide evidence for our hypotheses (see Table 2.6 models 5–8 and Table 2.7 models 7–8). Finally, we winsorize the number of comments at the 1% and 99% level to incorporate the skewness of the distribution. Due to the marginal differences in comparison to the main models, we do not report the results here. Altogether, our results substantiate that our indication of overconfidence, namely the irrational part of trading activity, instrumented by a set of variables to account for several dimensions of overconfidence and resulting in negative returns, is a predictive factor for performance and appropriately accounts for endogeneity.

2.6 Conclusion

To date, extensive research has indicated that investors are subject to behavioral and social biases. In this article we analyze aspects of trading behavior on two major social trading platforms in Germany, namely Ayondo and Wikifolio. In particular, we investigate the factors influencing the overconfidence contingent on social interaction features. In contrast to existing overconfidence studies, our data stem from a world external to the laboratory setting. To the best of our knowledge, we are the first to explore how these novel dimensions of online trading impact on overconfidence. We apply a fixed effects two-stage least squares approach to resolve endogeneity issues and confirm our results following a series of robustness checks. By using an exclusive dataset from two leading social trading platforms, we gain insights into the influence of the heterogenous business models. We sustain novel and, to some extent, surprising conclusions.

Above all, we add to behavioral finance research by providing evidence of the negative relationship between overconfidence, proxied by the irrational part of trading activity, and social trading returns in this innovative online trading environment. The negative returns after transaction costs indicate that the increased trading intensity triggered by irrational factors can actually be unequivocally identified as overconfidence. Considering the magnitude of the effect, we find that the coefficient of the endogenous variable is larger in absolute value on Ayondo than on Wikifolio. The difference in trading activity on both platforms could account for this finding. As proven by the IV estimation, there are various irrational factors on the platforms that are significantly related to overconfidence. The signaler's popularity, either measured by the number of followers or the net change in invested capital, reveals itself to be a significant driver of irrational behavior on both platforms. Hence, we conclude that the overconfidence of the traders increases when they receive more attention from the network, as they attribute capital inflows to their abilities. This finding is particularly intriguing as the business model of the platforms is geared to attracting followers. The benefits for investors of investing in sophisticated traders are, to some extent, reduced by the inverse effect of a growing quantity of followers on the overconfidence of signalers. We identify that the platform-specific ranking and incentive system is a significant driver of overconfidence. In general, we find that the rating system nurtures the trade leader's overconfidence. A clear difference is evidenced by the strict risk limits and drop out consequences on Ayondo, which have a significant countervailing effect on excessive trading. On the contrary, the HWM remuneration approach on Wikifolio combined with less prohibitive measures regarding the progression in the rating do not mitigate overconfident behavior. Moreover, we provide insights into the relationship of several factors such as risk, experience and past success with the degree of overconfidence. Taken together, the different frameworks of the platforms motivate heterogenous behavioral responses by the signalers.

Our findings are relevant from both a theoretical and a practical perspective. On the one hand, platform operators aim to attract successful traders, who will in turn entice followers, consequently increasing the operators' revenues. On the other hand, we have proven that the social feedback characteristics can lead to more pronounced overconfidence compared with the standard market setting. Since the overconfident traders experience reduced returns, they may deter prospective customers from joining the platform. Specifically, the more restrictive rating system can be of an advantage for platforms in guiding trader behavior. Even more so, platform operators should be aware of how the monitoring mechanisms and incentives of the platform affect their business models. Investors can refer to our findings when choosing the platform that matches their preferences. Due to the fact that the return of investors is equally affected by the performance of the underlying assets and the behavior of the trader, gaining greater insight into the behavior of signalers can help followers in forming their portfolios.

A limitation of our research lies in the fact that due to lack of data availability, only a few control variables can be used in assessing overconfidence on Wikifolio. The incorporation of additional metric variables would allow us to capture supplementary factors. To improve the generalizability of our findings, future research could investigate additional platforms that differ in products offered, incentive systems, interaction mechanisms, specifically since we demonstrate that the different platform designs shape the behavior of the traders. Summarizing, we expect increasing digitalization combined with changes in the regulatory environment to affect the development of social trading platforms. In conclusion, our article contributes to an improved understanding of the phenomenon of social trading.

Chapter 3

The higher you fly, the harder you try not to fall: An analysis of the risk taking behavior in social trading

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Abstract: In this article, we study the risk taking behavior under convex incentives in an innovative online trading setting. In particular, we empirically analyze how an infinite investment horizon and valuable outside options affect risk taking behavior. We find that traders choose the absolute and relative risk of the trading strategy depending on the proximity to the high watermark (HWM), which represents a series of remuneration options on the assets under management. As a consequence, we observe more risk mitigating behavior the closer the HWM comes. Next, we show that the traders behave strategically and make their risk decisions based on their overall portfolio payoff. Finally, we find that social status indicators such as rankings and communication abilities significantly affect the risk taking behavior.

Keywords: Risk taking, convex incentives, individual trading behavior, social reward mechanisms, social trading platforms

JEL Classification: D81 G11 G23 G41

3.1 Introduction

Delegated portfolio management constitutes an important pillar of wealth management. Consequently, the resulting agency relationship between investors and portfolio managers is a topic of interest in many studies (see Stracca, 2006). Several researchers focus on aligning the portfolio managers' and investors' interests in the form of incentive contracts (see Nalebuff and Stiglitz, 1983; Starks, 1987; Brown et al., 1996; Chevalier and Ellison, 1997; Carpenter, 2000; Berk and Green, 2004; Stracca, 2006). However, the predominant convex remuneration schemes in delegated asset management often create the incentive to pursue short-term profits and to simultaneously increase long-term risk. Such compensation policies can imply excessive risk taking, along with shortcomings in control mechanisms as well as disclosure and transparency issues. These aspects inter alia contributed to the financial crisis in 2008 (see European Commission, 2010; Hopt, 2013; da Silva, 2019). In the aftermath of the crisis investors lost trust in financial institutions, in particular with regards to the incentive schemes of portfolio managers (see European Commission, 2010; Haddad and Hornuf, 2019). The resulting distrust in banks together with increased costs of debts paved the way for a substantial increase in *FinTech* start-ups, which offer financial services by applying modern technology (see Jünger and Mietzner, 2020). In addition, they aim to reduce the information asymmetry between agents and principals through improved information transparency (see Dorfleitner et al., 2017; Haddad and Hornuf, 2019).

In this paper, we augment the discussion on incentive structures and risk taking of portfolio managers by empirically analyzing the behavior of asset managers in an innovative online trading setting – a so-called *social trading platform*. Social trading constitutes an important cornerstone in the FinTech field and challenges asset management companies by offering transparency, trust and digital services (see Glaser and Risius, 2016). These platforms are distinct from classic trading due to the integration of social network features in trading (see Dorfleitner et al., 2017). This new type of platform design allows users to exchange their strategies, chat, and observe the performance of other traders in the network in real-time (see Pentland, 2013; Liu et al., 2014). A distinguishing feature of social trading platforms is the option of mirror trading, which offers the possibility to benefit from the expertise of sophisticated traders, referred to as *signalers* (or *signal providers* or *trade leaders*), whose trading strategies can be copied by investors (or *followers*) and are automatically executed in their trading accounts (see Neumann, 2014). Even though signalers do not directly receive the invested assets of their followers, the former are in fact comparable to portfolio managers (see Doering et al., 2015). Breitmayer et al. (2018) elucidate that the social setting fosters the signaler's risk appetite, which is manifested in increased trading activity and risk taking (see also Schade, 2017; Dorfleitner et al., 2018; Apesteguia et al., 2020; Pelster and Breitmayer, 2019).

Generally, we study whether signalers strategically manage their risk taking behavior in view of their incentive contracts. In addition, we analyze how platform-specific features, i.e., the transparent publication of trading, performance, and risk statistics influence the signaler's behavior. Since this novel setting focuses on social interaction between signalers and followers, we examine whether the social dimensions such as reputation and popularity imply a shift in trading behavior. We explicitly account for the fact that signalers often manage several trading strategies at the same time. On these grounds, we extend the setting of Doering and Jonen (2018) by taking a multi-period approach and considering additional influential factors of risk taking behavior.

The contribution of this paper is twofold. First, we append the existing literature on dynamic risk taking behavior of portfolio managers under convex incentives. While the majority of the studies in this field of research takes a theoretical approach by optimizing standard utility functions, we conduct an empirical study of risk taking behavior. Second, we provide empirical evidence of factors affecting risk taking behavior on top of incentive contracts. Our setting also provides us with the opportunity to shed light on the question of whether increased information transparency affects risk taking behavior. These results can serve as a base for policy makers, regulators and platform operators in improving incentive policies in order to better align the asset manager's and investor's interests and mitigate moral hazard.

Our analysis employs observations from one of the leading German social trading platforms, Wikifolio. We utilize a large data set of trading and performance data in the observation period from April 2012 to April 2016. In this time period we investigate 12.9 million trades of thousands of trading strategies, so-called *wikifolios*. We empirically examine the level of risk as well as changes in the risk of trading strategies with regards to their monetary incentives, the investment horizon, and social dynamics. Our approach is similar to that of Drechsler (2014) since we explicitly account for a multi-period setting as well as for potential outside options of signalers.

According to our results, signalers adjust the levels of risk of a wikifolio in response to the proximity to the high-water mark (HWM). In comparison to other studies on HWM incentive schemes, we evidence that signal providers take into account that they act in an infinite investment horizon framework and, therefore, weigh current payoffs against future payoffs. As a result, we find risk reducing behavior when signalers approach the HWM. In addition, we show that having outside options, meaning alternative trading strategies, and the value of these options, significantly affect their level of risk and risk changing behavior. Finally, we find that signalers react to social reward mechanisms on these platforms. We demonstrate that even though signalers on social trading platforms are not necessarily experienced asset managers, they do, in fact, take a broad set of factors into account when adjusting their risk levels.

The remainder of this article proceeds as follows. In Section 3.2 we provide an insight into the current literature on social trading platforms and risk taking behavior under convex incentives before deriving our hypotheses from theoretical considerations in Section 3.3. Section 3.4 describes our data set and is followed by the descriptive analysis. In Section 3.5 we introduce our empirical methodology and in Section 3.6 we present our results as well as several robustness tests. Section 3.7 concludes, derives policy implications and outlines areas for future research.

3.2 Literature review

3.2.1 Social Trading Platforms

Since the creation of the first social trading platform ZuluTrade in 2007, the number of signal providers, followers, and turnover in social trading have continuously grown (see Glaser and Risius, 2016; Dorfleitner et al., 2018). Doering et al. (2015) elucidate that signalers often implement dynamic strategies and pursuit directional approaches. Moreover, social trading returns exhibit non-normal distributions and high tail risks. Dorfleitner et al. (2018), who analyze different trading strategies ranging from naive to sophisticated trading strategies that account for the characteristic features of the platforms, find that only the latter ones generate positive returns. Based on different risk factor models analyzing returns Oehler et al. (2016) prove that geographically focused trading strategies perform better. According to Neumann (2014), traders on these platforms do not on average outperform their benchmarks, which can be, amongst other things, explained by overconfident behavior and the disposition and loss aversion effect (see also Liu et al., 2014; Heimer, 2016; Oehler et al., 2016; Czaja and Röder, 2020; Breitmayer et al., 2018; Deneke, 2019a). Glaser and Risius (2016) show that social interaction and the aim for a positive social self-image increase the disposition effect (see also Pelster and Hofmann, 2017). Contrary to this, Gemayel (2016) and Lukas et al. (2017) show that the enhanced transparency of information combined with the reputational risk diminish the disposition effect. Lý and Pelster (2020) find that the differences can be explained by the framing of the social status indicators as a result of distinct platform designs.

Lee and Ma (2015) devise a framework so that followers can select the most suitable signal providers. Pan et al. (2012) empirically show that followers rather take social dynamics such as the number of followers into account when selecting their trade leaders and do not only rationally base their investment decisions on performance and risk indicators (see also Röder and Walter, 2019). In addition, Wohlgemuth et al. (2016) demonstrate that signal providers can raise the probability of followers who copy their trading strategies by establishing trust through signaling (see also Kromidha and Li, 2019). Ammann and Schaub (2016) add to this by showing that positive communication significantly increases the amount of followers. With respect to the ability of followers to choose the best signal providers, Dorfleitner et al. (2018) and Deneke (2019b) do not find a significant wisdom-of-the-crowd effect. Moreover, Gemayel (2016) provides evidence of significant and persistent herding behavior. The effect of social learning in social trading, though, is ambiguous (see Pentland, 2013; Zhao et al., 2015; Schade, 2017; Berger et al., 2018; Xuejuna et al., 2019). We distinguish ourselves from existing social trading platforms studies by analyzing the dynamic risk taking behavior – i.e., the level of risk and changes in the level of risk – of signalers under convex incentives. In addition, we investigate additional factors affecting the risk exposure of the trading strategy on top of the incentive contracts and emphasize the effect of transparency and social reward mechanisms.

3.2.2 Funds management behavior under HWM compensations schemes

Social trading platforms remunerate their signal providers for sharing their investment ideas with platform specific performance fees (see Ammann and Schaub, 2016). Since Wikifolio has implemented a HWM compensation scheme to mitigate moral hazard by signalers, our paper is closely related to literature on risk taking under convex incentives (see Brown et al., 1996; Chevalier and Ellison, 1997; Carpenter, 2000; Panageas and Westerfield, 2009). We focus on the HWM literature of hedge funds due to similar return characteristics and framework conditions for the signalers (see Doering et al., 2015; Doering and Jonen, 2018).

Following the establishment of a risk-adjusted performance measure for fund managers by Jensen (1967), many papers investigate the flow-performance relationship of funds (see Sirri and Tufano, 1998; Ferreira et al., 2012; Spiegel and Zhang, 2013). Based on this, Brown et al. (1996) empirically evidence that fund managers whose incentives are linked to the amount of assets under management modify the riskiness of their portfolios in the second half of the year in response to their relative performance from January to June (*tournament behavior*) (see also Clare and Motson, 2009; Cai et al., 2017). Chevalier and Ellison (1997) explain that these incentives, which can be compared to a call option on investor wealth, induce fund managers to either gamble and increase the riskiness of the portfolio or to lock in their gains (see also Hodder and Jackwerth, 2007). Consequently, convex payoffs have the potential to generate a risk-seeking stimulation since the managers are recompensed for gains, though not directly penalized for losses (see Panageas and Westerfield, 2009). Carpenter (2000) applies a theoretical approach and shows that portfolio managers with HWM contracts tailor their volatility toward changes in asset values and even reduce risk when they are far away from the evaluation day or asset values experience strong growth. Brown et al. (2001) add that such variance strategies can be partly explained by the performance comparison with peers and benchmarks, as well as reputation costs (see also Basak et al., 2007; Clare and Motson, 2009). Hodder and Jackwerth (2007) extend these findings by introducing a multi-period setting and examining the effect of the investment horizon and the risk of the fund being closed on risk shifting behavior on a theoretical level (see also Panageas and Westerfield, 2009). They find evidence of "derisking" behavior following fund value increases and extensions to multiple year evaluations. Aragon and Nanda (2011) analyze risk taking behavior of more than 7,000 hedge funds and find that apart from HWM provisions, managerial ownership, and low probabilities of default lead to a more conservative behavior with respect to risk shifting. Drechsler (2014) depicts, in a theoretical framework, that the optimal risk choice can be mapped as a function of the ratio of the fund's assets to its HWM. He outlines how high management fees, strict fund closure policies, or low-valued outside options will result in risk-averse behavior as the fund's value moves further away from the HWM, while volatility increases in the opposite case. With respect to the performance of fund managers, Agarwal et al. (2009) provide empirical evidence that hedge funds with HWM contracts can achieve superior performance. Goetzmann et al. (2003) weigh up the costs and benefits of HWM incentive structures for American hedge fund investors based on their risk attitude and managers' performances (see also Guasoni and Obłój, 2016). Liang and Park (2007) analyze different risk measures including value at risk, expected shortfall and tail risk with respect to their capability to correctly quantify risk considering the higher moments characteristics of hedge funds.

Due to data availability, the majority of these articles establishes theoretical models, while only few empirical studies exist. Our paper is closest to Doering and Jonen (2018), who empirically investigate dynamic risk shifting under convex incentives applying a data set from the social trading platform Wikifolio. They show that managers actively increase risk when they move closer to their current HWM by reducing their cash ratio and portfolio diversification. This behavior is particularly present in the last quarter of the year. We distinguish ourselves from Doering and Jonen (2018) as we explore levels of risk as well as changes in risk to scrutinize all aspects of risk taking. Furthermore, we explicitly take into consideration that signalers act in a multi-period setting. Building on theoretical risk taking models, we analyze whether and how signalers strategically manage their entire portfolio with regards to their risk exposure and compensation. We account for the fact that signal providers can open several wikifolios simultaneously, which provides them with valuable outside options. Finally, we control for additional influencing factors of risk taking behavior such as trading activity or cash ratios.

3.3 Institutional background and hypotheses

In the following, we build on the insights of previous literature and derive our hypotheses regarding the risk-taking behavior of signalers facing convex incentive contracts. To commence, we provide a short introduction to the business model of Wikifolio.

3.3.1 Platform description

Our study focuses on one of the leading social trading platforms in Germany, namely Wikifolio (see Dorfleitner et al., 2017). The platform provides its users (the followers) with the option to profit from more proficient traders (the signalers) by copying their trading strategy, which will automatically be executed in their accounts (see Lukas et al., 2017). Signalers on Wikifolio, who are either private or professional traders, can pursue their trading strategy by drawing on an investment universe of more than 250,000 equities, exchange traded products, and structured products (see Wikifolio, 2016). Contrary to other platforms, signalers can open several wikifolios at the same time. Signal providers must prove the feasibility of their strategy by attracting more than 10 followers and an accumulated investment volume of 2,500 EUR in order to move from the status of *published* to *investable*. Investable wikifolios are then issued as open-ended index certificates by a co-operating bank. Purchasing and selling the wikifolio certificates enables followers to participate in the value development of these trading strategies (see Oehler et al., 2016). In order to facilitate the selection of wikifolios for investors, the platform publishes detailed information on the signaler, the principles of the trading strategy, key performance, and risk indicators, as well as information on the signaler's social status and additional wikifolios in his portfolio (see Wikifolio, 2016). In view of the social dimension of the platform, signal providers can communicate with investors by publishing comments on the development of their trading strategies (see Ammann and Schaub, 2016). The platform operators rank wikifolios on a daily basis resting on so-called Wikifolio points and award labels such as *Bestseller* or *Top ten trader*, which are related to risk and return profiles, trading styles or social attributes (see Dorfleitner et al., 2018).

Due to the fact that Wikifolio follows an HWM remuneration scheme, signalers are only rewarded in the case of exceeding the prior HWM (see Neumann, 2014). The signaler's payoff is tied to his assets under management and a performance fee that the signaler has determined at the setup of the wikifolio. At the end of each calendar year, the platform resets the HWM to the current wikifolio value. It is important to note that signalers are only eligible for compensation if their assets under management exceed 10,000 EUR (see Doering and Jonen, 2018). This innovative online setting differs in two ways from the framework in which the hedge fund manager operates. First, since HWMs are updated on a daily basis and the incentive fee is deducted immediately from the wikifolio value, the incentive option cannot actually be in the money. Second, there is full transparency of information regarding the signaler's trading and performance history and, hence, followers can immediately give feedback on the signaler's strategy by disposing their investments (see Doering and Jonen, 2018).

3.3.2 Hypotheses

Proximity to HWM

Several studies have shown that portfolio managers adjust the level of risk of the portfolio in response to prior performance, due to awareness of the asymmetric flow–performance relationship (see Brown et al., 1996; Chevalier and Ellison, 1997). Clare and Motson (2009) demonstrate that under HWM contracts the manager's risk choices change dynamically depending on the distance to the HWM resulting in either 'gambling' or 'derisking' behavior (see also Drechsler, 2014; Buraschi et al., 2014). Due to the fact that the HWM incentive scheme resembles a call option on the price level, one would expect the signaler to increase risk the more the wikifolio value converges to the HWM as the probability of exceeding the HWM and prospects of remuneration strongly increase (see Doering and Jonen, 2018). Hodder and Jackwerth (2007), however, demonstrate that increased risk-shifting under convex incentives is sensitive to the finiteness of the investment horizon. Panageas and Westerfield (2009) highlight the fact that under HWM contracts introducing an infinite investment horizon has a risk alleviating effect, since the fund manager faces a sequence of options with diverging strike prices and, thus, evaluates the trade-off between current and future payoffs. They explain that while exceeding the current HWM encompasses the payout of the performance fees in proportion to the fund's assets under management (the *scale effect*), the new HWM at the same time reduces the probability of reaching the HWM in the future (the *waiting effect*) (see also Drechsler, 2014). Complementing this finding, Zhao et al. (2018) demonstrates that asset manager strategically adapt their efforts in response to their distance from the HWM striving to preserve the fund and its value. Generally, the investment horizon on Wikifolio is infinite and we presume that signalers are aware of this fact. Rational signal providers are, therefore, supposed to aim at establishing a sound track record with the objective to attract followers and, thereby, increase their assets under management, which will in turn enhance their future potential payoff. Taking into consideration that higher levels of risk may result in an outflow of invested capital, signalers may be induced to implement lower risk levels when approaching the HWM. In addition, gradually approximating the HWM by reducing the risk exposure of the trading strategy enhances the probability of reaching the HWM in the future. Thus, if signalers considered their trading strategy as a one-period investment, they could be expected to increase the riskiness of the wikifolio when they move closer to the HWM. However, as discussed above, in the framework of the Wikifolio platform this is not an expectable behavior. In line with the results of Panageas and Westerfield (2009) and Drechsler (2014), we therefore hypothesize that signalers adjust the riskiness of their wikifolio in relation to their distance from the HWM. The infinite investment horizon has a mitigating effect on signalers' risk choice as they need to weigh current against future payoffs.

Hypothesis 1 *Signalers adjust the volatility of their wikifolios with respect to the proximity to the high-water mark. They generally reduce their exposure to risk when approaching the high-water mark.*

Outside options

Apart from the investment horizon and the HWM, several factors in the portfolio manager's environment can have a significant influence on the level of risk of his portfolio. Drechsler (2014) illustrates the point that especially the value of the outside options are taken into account when implementing risk changes. He finds that valuable outside options and the option to walk away lead to an increase in risk taking. Due to the fact that the signaler decides whether the wikifolio is closed, the exogenous risk of the closure of the fund does not exist. Additionally, the signaler can always choose to walk away and pursue 'external' outside options (see Hodder and Jackwerth, 2007; Aragon and Nanda, 2011). What is more, signalers have the option to open several wikifolios simultaneously, providing them with 'internal' outside options. We anticipate that signalers with at least two wikifolios will act similarly to family fund managers and aim at maximizing the overall portfolio payoff (see Kempf and Ruenzi, 2007). As a consequence, we expect them to choose the level of risk of one wikifolio against the background of the performance and volatility of the other wikifolios in their portfolio. The fact that signalers can pursue different investable trading strategies simultaneously increases the value of the signaler's outside option, since his remuneration is tied to different HWMs and capital levels and, thus, enhances the probability of payoffs (see Carpenter, 2000). A signaler could, for example, manage two or three wikifolios, implement heterogeneous strategies, vary the levels of risks with the objective to reaching a new HWM as soon as possible, and then focus on the most profitable wikifolio. He could also attempt several strategies and, for this purpose, retain the status published. If one of these strategies succeeds, he could then implement the underlying idea in an already investable strategy or apply for investability status of the specific wikifolio. These possibilities for action constitute a valuable outside option for the signalers, which either appreciates or depreciates depending on the performance of the other wikifolios and can thus be accompanied by increased or decreased risk taking. First, the value of the outside option increases with the volatility of the underlying value (see Black and Scholes, 1972). Consequently, we would expect the signaler to increase the wikifolio's risk exposure following an increase in the overall portfolio volatility as the outside option appreciates and will do so even more if the signaler increases risk taking in the specific wikifolio. Second, the option value increases as the likelihood of other wikifolios to reach the HWM increases. We therefore assume that the closer one wikifolio becomes to his HWM, the more riskily the signaler behaves in his other trading strategies. However, reputation and managerial survivorship concerns may have an opposing effect (see Cai et al., 2017). The transparency of information reinforces the reputational risk, as followers can access the wikifolio's performance and risk statistics at any time and shift their cash flows accordingly. In addition, followers can easily compare the performance of one wikifolio with his other wikifolios as well as with peer wikifolios, resulting in increased competition (see Basak et al., 2007). Therefore, it could be beneficial for the signaler to reduce the riskiness of the wikifolio in the case of positive performance of his outside options in the hope of achieving positive spillover effects. We hypothesize that having valuable outside options increases the signaler's risk attitude, although the effect could be diminished by reputational concerns.

Hypothesis 2 *Signalers take the value of their outside options into account when deciding on the risk level of a specific wikifolio. If signalers possess currently valuable outside options, they exhibit risk-increasing behavior.*

3.4 Data

3.4.1 Data

We use an extensive data set from the German social trading platform Wikifolio. The platform discloses detailed, daily trading and performance histories of the signaler's portfolios as well as additional information on the strategy and social interaction indicators on their website (www.wikifolio.com). Our sample contains information on performance fees, the issuance date and trading idea of the wikifolio, an overview of the instruments that will be used to pursue the trading strategy, as well as quantitative information on daily wikifolio values, cash ratios, HWM levels, and trading activity. In 2016, we downloaded these datapoints for the time period of April 27th 2012 to April 15th 2016, totaling 12.9 million trades. The observation period was chosen in the light of the data available and necessary to create the variables of interest. In the case of lacking wikifolio prices, we externally searched for the corresponding price levels to fill the gaps. Our data set includes time series data of all trading strategies that have been developed between September 2011 and May 2016. We have a heterogeneous database including wikifolios that have been recently built as well as wikifolios that have existed for months or years. What is more, the data record includes private and institutional traders, newcomers and experts as well as wikifolios in all of the four statuses ‘published, investable, closing in process’, and ‘closed’. Due to the fact that we retain all wikifolios in our record – notwithstanding their success or failure – we mitigate possible survivorship concerns. At the setup of the wikifolio, signalers determine the initial virtual budget, which Wikifolio recommends as being 100,000 EUR. We exclude observations of wikifolios that have been created before April 2012, since the initial virtual trading cash budget was not published for these strategies. We aggregate daily performance and trading data on a weekly basis. Subsequent to the adjustments, our data set comprises 1.09 million weekly risk data points of 15,636 wikifolios belonging to 7,091 signalers. In addition, we built a subsample of additional quantitative and qualitative data referring to the social network characteristics for the time period from November 2015 to May 2016. These figures were not accessible for the entire observation period and had to be collected manually. This study focuses on the level of risk as well as changes in risk. To quantify risk we compute weekly standard deviations of returns based on daily performance data. In order to prevent a possible downward bias of our risk measure, we exclude wikifolio prices on weekends whose changes are only influenced by the deduction of the certificate fee and do not constitute trading consequences.

Tables 3.1 and 3.2 describe the variables, that are designed on a weekly basis, used in our analysis on the wikifolio and signaler level. The tables contain detailed definitions of all our variables as well as abbreviations used in the later analyses. Table 3.1 displays our variables on the wikifolio level grouped by variables on wikifolio characteristics, trading behavior variables, and performance variables i.e., return, risk and HWM indicators. Table 3.2 defines the variables of interest on the signaler level following the same classification.

Table 3.1: Definition of the explanatory variables on Wikifolio – Wikifolio level

Data sources: Calculations are rested upon data from Wikifolio and Yahoo Finance, the description of variables follows Wikifolio (2016).

Variable	Description
Wikifolio characteristics	
$Perf\_costs$	The performance fee a signaler receives in case of exceeding the HWM (5-30%)
$Days\_start$	The age of the wikifolio as measured by the number of days since the publication of the trading strategy
$Days\_emission$	The age of the wikifolio as measured by the number of days since the emission of the trading strategy, i.e., after it becomes investable
$Diversification$	Constant sum of squared portfolio allocations to the available financial products within each of the 5 asset classes (equities, exchange traded products, funds, investment certificates, and leveraged products) following the Herfindahl-Hirschmann index
$Leverage$	Binary variable that indicates whether the wikifolio can trade structured products
$Investable$	Binary variable that indicates whether the wikifolio is investable (measured at the end of the preceding Friday)
Wikifolio trading behavior variables	
$SecuritiesTurnover$	Sum of purchased and sold securities within the current week
$SecuritiesTurnover\_Ratio$	Sum of purchased and sold securities within the current week in relation to the initial virtual budget ($SecuritiesTurnover/CashBegin$*100,000 EUR)
$CashBegin$	Initial virtual budget chosen by the wikifolio (recommendation by Wikifolio is 100,000 EUR)
$Cash\_norm$	Standardized variable indicating the current cash holdings in relation to the initial virtual budget ($Cash/CashBegin$*100,000 EUR)
$Cash\_Flows\_norm$	Standardized variable indicating the cash flows within the current week in relation to the initial virtual budget ($CashFlows/CashBegin$*100,000 EUR)
$Purchases$	Sum of purchase transactions within the current week
$Sales$	Sum of sale transactions within the current week
$Activity$	Sum of purchase and sale transactions within the current week
HWM	Sum of HWM exceedance within the current week
Wikifolio performance variables	
Rel_Perf	Relative performance of a trader's portfolio in the current week, calculated as being the difference between total performance in the current and the previous week (in each case measured on the basis of Friday wikifolio closing prices)
$Risk$	Volatility of daily returns over the current week (Monday daily returns are calculated as being the difference in the wikifolio's value on Monday and the preceding Friday)
$\Delta\, Risk$	Difference between the current level of risk and the level of risk in the previous week
HWM_score	Current HWM of the wikifolio (measured at the end of the preceding Friday)
$NewHWM$	Binary variable indicating whether a new HWM has been achieved within the current week
$Diff\_HWM\_Min$	Minimum distance to the HWM within the current week
$HWM\_Proximity\_Ratio$	HWM proximity is defined as being the ratio of the current wikifolio value to the current HWM (in each case measured at the end of the preceding Friday)

Table 3.2: Definition of the explanatory variables on Wikifolio – Signaler level

Data sources: Calculations are rested upon data from Wikifolio and Yahoo Finance, the description of variables follows Wikifolio (2016).

Variables	Description
Signaler characteristics	
Number_Wikis	Number of wikifolios the signaler currently manages (published, investable, and closing in process statuses; measured at the end of the preceding Friday)
Number_Wikis_Invest	Number of investable wikifolios the signaler currently manages (measured at the end of the preceding Friday)
Signaler trading behavior variables	
SecuritiesTurnover_Sig	Sum of purchased and sold securities across all wikifolios a signaler manages within the current week
SecuritiesTurnover_Ratio_Sig	Sum of purchased and sold securities across all wikifolios a signaler manages within the current week in relation to the initial virtual budget (*SecuritiesTurnover_Sig*/*CashBegin_Sig**100,000 EUR**Number_Wikis*)
CashBegin_Sig	Sum of the initial virtual budgets of all wikifolios in the current portfolio of the signaler
Cash_norm_Sig	Standardized variable indicating the sum of the current cash holdings across all wikifolios in the signaler's portfolio in relation to the initial virtual budget (*Cash*/*CashBegin_Sig**100,000 EUR**Number_Wikis*)
Cash_Flows_norm_Sig	Standardized variable indicating the sum of the current cash flows across all wikifolios in the signaler's portfolio in relation to the initial virtual budget (*Cash_Flows_Sig*/*CashBegin_Sig**100,000 EUR**Number_Wikis*)
Sum_Purchases_Sig	Sum of purchase transactions the signaler has conducted within the current week
Sum_Sales_Sig	Sum of sale transactions the signaler has conducted within the current week
Activity_Sig	Sum of purchase and sale transactions the signaler has conducted within the current week
Sum_HWM_Sig	Sum of HWM exceedance the signaler has achieved across his wikifolios within the current week
Signaler performance variables	
Mean_RelPerf_Sig	Average, relative performance the signaler has achieved across his wikifolios within the current week t
SD_RelPerf_Sig	Standard deviation of the relative, weekly performances a signaler has achieved across his wikifolios within the current week being an indication of the riskiness of the signaler's portfolio
Max_HWM_Proximity_Ratio_Sig	Maximum proximity of the signaler to his HWMs across his wikifolios within the current week

3.4.2 Descriptive statistics

Descriptive statistics of the 15,636 wikifolios in the observation period dating from April 27th 2012 to April 15th 2016 are reported in Table 3.3. On average, signalers have chosen a performance fee of 11.15%. Wikifolios in our data set are, on average, 423 days old, the oldest even 1,589 days. Interestingly, some wikifolios are published for a very long time period before graduating to the status 'investable'. A share of 26.6% of the examined wikifolios became investable at some point during the observation period. As far as the investment universe is concerned, wikifolios use, on average, 46.3% of the available asset classes. Riskier assets such as knockout products, subscription warrants and other leverage products are generally employed by few signalers, as only 22.2% of the wikifolios are flagged with the option of including leveraged products in their trading strategy.

Regarding the trading-activity-related variables, we observe that wikifolios display, on average, 2.8 trades per week with slightly more purchases than sales. Some wikifolios are extremely active with up to 1,680 trades per week. The initial trading budget is highly skewed with a mean of 429,917 EUR and a maximum of 100 million EUR. We therefore standardize the current cash holdings by dividing the current amount of cash by the chosen budget and multiplying it by the Wikifolio platform advised amount of 100,000 EUR. Similarly, we account for differences in the original trading budget and standardize trading activity related variables accordingly. Wikifolios hold, on average, 26,303 EUR of cash, equaling one quarter of the supposed initial trading budget, the standardized weekly cash flows are highly volatile and range from 0 to 319 million EUR with a mean of 25,437 EUR. When looking at the standardized turnover, one can see signs of a non-normal distribution with a mean of 10,614 traded securities and a standard deviation of 762,230.

Wikifolios, on average, yield weekly returns of 0.13% and show high fluctuations with a minimum of -100% and a maximum of 122,000%. We therefore conclude that – net of all fees – wikifolios achieve close-to-zero performances and only very few skilled traders exhibit high levels of returns. Our risk measure exhibits a mean of 0.012 and standard deviation of 0.0143. Changes in risk compared with the previous week display a mean of 0.0000389. The mean HWM score equals a wikifolio index level of 132.4 and reaches a maximum at 34,834. In addition, the current wikifolio value exhibits a mean of 90.5% of the HWM and the minimum distance to the HWM within the current week on average amounts to -22.28. What is more, a new HWM is reached in 9.6% of the weekly observations.

On average, signalers hold three wikifolios with only one of these being *investable*. We interpret this finding as an indicator that signalers test several trading strategies at the same time, but focus on one strategy that qualifies for remuneration. This could also be a reason why wikifolios are often relatively old at the point when they become investable. Interestingly, the cumulated initial trading budget of a signaler (*CashBegin_ Sig*) exceeds the mean individual initial wikifolio trading budget (*CashBegin*) multiplied by the average number of wikifolios a signaler holds. We therefore assume that signalers pursue different strategies and vary the corresponding cash holdings in each wikifolio. Trading activity and security turnover display similar large variations on the signaler and on the wikifolio level. We observe an average trading activity of signalers of 9.10 trades per week with a standard deviation of 36.10 and a maximum of 1,975. Standardized traded securities per signaler, on average, amount to 79,406 and standardized cash flows per week total a mean of 216,206 EUR. Both variables are highly skewed. These findings add to the presumption that while the majority of signalers trades in a moderate way, a few very active signalers exist.

Signalers generate relative mean performances across their entire wikifolios ranging from -100% to 130,188% with a mean of 0.21%, which is close to the relative performance of a single wikifolio. It seems that signalers only slightly improve their performance by managing more than one wikifolio. The standard deviation of the mean relative performance is, at 0.164, slightly lower than the standard deviation of the relative performance on the wikifolio level and can be interpreted as a form of benefit due to diversification. In addition, the fluctuation range of relative performance is reduced on the signaler level compared with the wikifolio level. Contrary to expectations, the overall risk of returns exceeds the riskiness on the wikifolio level with a mean of 0.0243. In general, the signaler's most successful wikifolios are close to their HWMs with wikifolio values equalling 95.01% of the HWM. In conclusion, trading activity on the signaler level exceeds the anticipated trading activity based on the wikifolio behavior and the average number of wikifolios per signaler. With respect to performance measures, one can observe similar performance levels, although greater risk levels on the signaler level can be found.

3.5 Methodology

The objective of our study is to deduce the factors affecting risk taking behavior of signalers under convex incentives with an infinite investment horizon. To test our hypotheses we employ two approaches and commence with exploring the absolute level of risk before investigating changes in risk compared on a weekly basis. We build on existing risk behavior models in the hedge fund literature and estimate risk choices with respect to the proximity to the HWM, additional factors to verify our hypotheses, and several control variables (see Aragon and Nanda, 2011; Cai et al., 2017). Our risk measure (*Risk*) is calculated on the basis of the volatility of daily returns within the current week. In comparison to other studies we analyze risk behavior on a weekly basis. The weekly view is due to several reasons. First, since the platform provides granular information on the current wikifolio and HWM level to its users – which is examinable for everyone – we expect swift adaption of the signaler's risk taking behavior in reply to this. Second, the majority of the platform's performance and ranking figures are measured on a weekly basis, thereby shaping the frequency of the signaler's activities.[1] We follow current literature such as Aragon and Nanda (2011) and Cai et al. (2017) and define risk changes ($\Delta\, Risk$) as being significant changes in volatility computed as the difference in risk levels between the current and previous week. We winsorize our dependent variables *Risk* and $\Delta\, Risk$ as well as *HWM_Proximity_Ratio* at the 1% and 99% level to mitigate the effect of potential outliers and use logarithmic adjustments for explanatory variables with non-normal distributions.

To explore the effect of convex incentives on risk taking behavior of signalers, we include the variable *HWM_Proximity_Ratio*, which is defined as being the ratio of the current wikifolio value to the present HWM and measured at the end of the previous week. It is important to note that the HWM is updated continuously and performance fees are deducted from the wikifolio value. In addition, the platform resets the HWM to the current wikifolio value at the end of each year. In our baseline model, we estimate the effect of the proximity to the HWM on the wikifolio's risk level controlling for the use of leveraged products and the risk level in the preceding week. Since *Leverage* constitutes a constant variable, it is only included as an interaction term with the HWM measure. Besides, we incorporate lagged risk levels to control for possible mean reversion (Kempf and Ruenzi, 2007; Doering and Jonen, 2018). Furthermore, we account for the fact that only investable wikifolios are eligible for compensation and, thus, wikifolios might exhibit riskier trading activities before coming investable. The fact that signalers can open several wikifolios simultaneously underlines this expected behavior.

[1] While there exists a plethora of risk measures that take into account the behavioral asymmetry of gains and losses (such as value-at-risk, expected shortfall, maximum loss, maximum drawdown), such risk measures are better suited for analyses of longer holding periods compared to the weekly periods of a relatively short observation period we use in this paper. Some risk indicators such as maximum drawdowns are also mostly used by investors. We analyze signaler risk taking behavior, though. Contrary to these measures that investigate risk taking since the beginning of the wikifolio and compare it to reference periods, the focus of this paper is on local risk taking behavior. Based on this, we believe that our measure of risk, namely weekly volatility of wikifolio returns, is perfectly suited to capture the risk taking of signalers in view of the length of the observation period and the frequency of the trading behavior.

Table 3.3: Descriptive statistics

Notes: Descriptive statistics of the Wikifolio data set that contains 1,010,435 observations (N) of 15,636 wikifolios belonging to 7,091 signalers in the observation period from April 27th 2012 to April 15th 2016. This table shows means, standard deviations (SD), minimum (Min.), and maximum (Max.) values of the variables defined in Table 3.1 and 3.2.

Variables	**N**	**Mean**	**SD**	**Min.**	**Max.**
Wikifolio characteristics					
$Perf\_costs$	1,010,435	11.15	7.223	0	30
$Days\_start$	1,010,435	423.33	320.61	9	1,589
$Days\_emission$	404,350	161.117	386.26	-1,628	1,379
$Diversification$	1,010,435	2.315	1.462	0	5
$Leverage$	1,010,435	0.222	0.415	0	1
$Investable$	1,010,435	0.270	0.444	0	1
Wikifolio trading behavior variables					
$SecuritiesTurnover$	1,010,435	75,784.62	13.0 Mn.	0	6.60 Bn.
$SecuritiesTurnover\_Ratio$	876,462	10,615	762,230	0	452 Mn.
$CashBegin$	1,010,435	429,917	5.038 Mn.	0	100 Mn.
$Cash\_norm$	876,462	26,303	73,429	-825,669	33.9 Mn.
$Cash\_Flows\_norm$	876,462	25,437	765,624	0	319 Mn.
$Purchases$	1,010,435	1.588	9.163	0	1,494
$Sales$	1,010,435	1.241	7.029	0	612
$Activity$	1,010,435	2.829	15.487	0	1,680
HWM	1,010,435	0.450	1.031	0	5
Wikifolio performance variables					
Rel_Perf	1,010,435	0.0013	0.190	-1	122
$Risk$	1,010,435	0.0116	0.0143	0.0000197	0.102
$\Delta\ Risk$	1,010,435	0.000039	0.0096	-0.0410	0.0409
HWM_score	1,010,435	132.4297	318.630	0	34,834
$NewHWM$	1,010,435	0.096	0.294	0	1
$Diff\_HWM\_Min$	1,010,435	-22.28	274.61	-30,143	0
$HWM\_Proximity\_Ratio$	1,010,435	0.905	0.156	-1	0.9997
Signaler characteristics					
$Number\_Wikis$	1,010,435	2.972	2.128	1	18
$Number\_Wikis\_Invest$	1,010,435	0.918	1.580	0	18
Signaler trading behavior variables					
$SecuritiesTurnover\_Sig$	1,010,435	288,710	25.8 Mn.	0	6.60 Bn.
$SecuritiesTurnover\_Ratio\_Sig$	907,185	79,405	2.877 Mn.	0	602 Mn.
$CashBegin\_Sig$	1,010,435	1.452 Mn.	13.2 Mn.	0	270 Mn.
$Cash\_norm\_Sig$	907,185	127,716	1.168 Mn.	-533,325	130 Mn.
$Cash\_Flows\_Sig\_norm$	907,185	216,206	6.239 Mn.	0	1.48 Bn.
$Activity\_Sig$	1,010,435	9.10	36.10	0	1,975
Sum_HWM_Sig	1,010,435	1.317	2.841	0	41
Signaler performance variables					
$Mean\_RelPerf\_Sig$	1,006,613	0.0021	0.164	-1	130.1882
$SD\_RelPerf\_Sig$	690,829	0.0243	0.158	0	46.773
$Max\_HWM\_Proxmity\_Ratio\_Sig$	1,010,435	0.950	0.111	0	10.00

Consequently, we implement an interaction term of the dummy variable *Investable* with the *HWM_ Proximity_ Ratio* as well as the dummy variable by itself. This allows us to examine whether differences in behavior exist in the different wikifolio statuses.

In a second step, we take several control factors on the wikifolio level into account that may affect the risk choice of the trade leader in the respective wikifolio. We commence by investigating how the signaler actively manages his level of risk and approximate his decisions through contemporaneous wikifolio activity. Consequently, we include the number of trades, turnover, cash flows and the cash ratio in our panel regression. This is followed by an analysis of the effect of performance related variables on the risk choice of the wikifolio. We utilize measures of returns and HWM closeness within the current week. Since these key figures are transparently published, they not only serve as a basis for investment decisions of followers but also increase the competitive behavior between trading strategies on the platform.

Third, we consider the impact of outside options on risk taking behavior of signalers. To shed light on our second hypothesis, we include performance and activity related variables on the signaler level in our regression framework. To begin with, we implement the number of wikifolios in the signaler's entire portfolio as well as the number of investable wikifolios. In this way, we measure whether the signaler has alternative claims to remuneration. We check for differences in the trading strategies and control for the signaler's entire activity. Consistent with the wikifolio level analysis, we append the baseline model by contemporaneous figures of trading activity, turnover, cash flows, and cash holdings – aggregated at the signaler level. To scrutinize the extent to which the signaler adapts the wikifolio risk with the objecive to maximize portfolio payoffs, we include performance key figures such as his mean portfolio return, the minimum distance to the HWM and the overall portfolio volatility. These performance related variables allow us to gain insights into the profitability and value of the signaler's alternative options.

Finally, we combine our influential factors on the wikifolio and signaler level and measure the combined effect on the riskiness of the wikifolio. What is more, we implement monthly and yearly time dummies to consider seasonal effects and check for tournament behavior in the second half of the year (see Chevalier and Ellison, 1997). With the aim of understanding risk adjustment behavior of signalers, we replace the dependent variable *Risk* by the change in the risk level ($\Delta\, Risk$) in the second part of our analysis (see Aragon and Nanda, 2011; Doering and Jonen, 2018). Our regression models are, thus, presented by:

$$\begin{aligned} Risk_{i,t} = {} & \beta_1\, HWM\_Proximity\_Ratio_{i,t} + \beta_2\, HWM\_Leverage\_Interaction_{i,t} \\ & + \beta_3\, HWM\_Investable\_Interaction_{i,t} + \beta_4\, Investable_{i,t} + \beta_5\, Risk_{i,t-1} \\ & + \delta_i \,\Sigma\, Wikifolio\ var_{i,t} + \gamma_i \,\Sigma\, Signaler\ var_{i,t} + Time\, Dummies + \upsilon_i + \varepsilon_{i,t} \end{aligned} \tag{3.1}$$

$$
\begin{aligned}
\Delta\, Risk_{i,t} = {} & \beta_1\, HWM\_Proximity\_Ratio_{i,t} + \beta_2\, HWM\_Leverage\_Interaction_{i,t} \\
& + \beta_3\, HWM\_Investable\_Interaction_{i,t} + \beta_4\, Investable_{i,t} + \beta_5\, Risk_{i,t-1} \\
& + \delta_i\, \Sigma\, Wikifolio\ var_{i,t} + \gamma_i\, \Sigma\, Signaler\ var_{i,t} + Time\, Dummies + \upsilon_i + \varepsilon_{i,t}
\end{aligned}
\tag{3.2}
$$

We perform standard fixed-effects regressions and cluster standard errors on the signaler level to factor in possible endogeneity issues between risk and HWM proximity resulting from unobservable traits such as trading strategy components, experience or risk aversion (Glaser and Risius, 2016)[2]. The conducted Hausman and Taylor (1981) test substantiates the choice of the fixed-effects over random-effects models.

3.6 Results

In this section, we first analyze the factors influencing a wikifolio's level of risk and then investigate the risk changing behavior exhibited in these trading strategies. Hereafter, we conduct several robustness checks to verify our results.

3.6.1 Regression analysis of the level of risk

The results of our panel regressions with wikifolio risk (*Risk*) as dependent variable are shown in Table 3.4. We extend our baseline model (column 1) by our hypotheses-related variables on the wikifolio and signaler level separately (columns 2–5). Model 6 constitutes our main model that incorporates all control variables on both levels simultaneously. The last column rests upon model 6 and, above this, takes seasonal effects into account.

With respect to our first hypothesis, we find a negative and highly significant relationship between our *HWM_Proximity_Ratio* variable and the wikifolio's level of risk. This result evidences that wikifolios that are closer to their HWM exhibit smaller levels of risk compared with wikifolios that are further away. In view of the infinite, multi-period setting and the tie between the assets under management and the payoff, we interpret this finding as being an indication of the fact that signalers strategically adapt their levels of risk with respect to future payoffs. Rather than increasing the chances of HWM achievements through excessive risk taking, which would be rational behavior in a one-period setting, they appear to evaluate their payoffs against the background of an infinite setting as a sequence of options. Consequently, considering that increased invested capital leads to higher payouts they appear to aim at the maximization of the amount of followers first and, hence, gradually reduce their level of risk when approaching the HWM and, next, at exceeding the HWM when the assets under management are sufficiently large. Therefore, our findings confirm our first hypothesis and are in line with Hodder and Jackwerth (2007) and Zhao et al. (2018). Regarding the option of using leveraged products,

[2] Notice that a Granger causality test as a robustness check to examine causal relationships is not suited for relatively short and wide panels such as ours.

Table 3.4: Fixed-effects regression of *Risk* on the proximity to the HWM

Notes: Analysis of *Risk* – measured by the standard deviations of returns – with respect to the proximity to the HWM using a fixed-effects model. The observation period ranges from April 27th 2012 to April 15th 2016 and contains 15,636 wikifolios belonging to 7,091 signalers. Model 1 includes the main explanatory variables $HWM\_Proximity\_Ratio$, the interaction variables of the $HWM\_Proximity\_Ratio$ with $Leverage$ and $Investable$ and the Dummy Variable $Investable$. Models 2 and 3 expand on the base model through wikifolio specific activity and performance variables. Models 4 and 5 take into consideration that signalers often have several wikifolios, and implement signaler's activity and performance, respectively. Model 6 implements the performance and activity related variables on both wikifolio and signaler perspectives. Model 7 adds to Model 6 with yearly and monthly time dummies. Table 3.1 and Table 3.2 provide detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**	**4**	**5**	**6**	**7**
$HWM\_Proximity\_Ratio_{i,t}$	−0.0089***	−0.0078***	−0.0155***	−0.0082***	−0.0124***	−0.0151***	−0.0154***
	(−31.82)	(−28.19)	(−28.20)	(−28.63)	(−21.77)	(−17.75)	(−17.66)
$HWM\_Investable\_Interaction_{i,t}$	0.0007	0.0001	−0.0013**	−0.0004	0.0015**	−0.0005	−0.0005
	(1.75)	(0.25)	(2.73)	(0.76)	(2.59)	(0.68)	(0.65)
$Investable_{i,t}$	0.0001	0.0009	−0.0008	0.0003	−0.0011	−0.0003	−0.0007
	(0.17)	(1.84)	(−1.64)	(0.63)	(−2.29)	(−0.51)	(−1.04)
$HWM\_Leverage\_Interaction_{i,t}$	0.0012	0.0006	0.0056***	0.0005	0.0033**	0.0060***	0.0054***
	(1.91)	(0.85)	(6.28)	(0.70)	(3.27)	(4.70)	(4.23)
$Risk_{i,t-1}$	0.464***	0.462***	0.456***	0.468***	0.441***	0.433***	0.425***
	(78.16)	(64.84)	(74.18)	(67.21)	(59.62)	(49.39)	(47.28)
Wikifolio level							
$Activity_{i,t}$		3.89×10^{-5}**				4.20×10^{-5}***	4.28×10^{-5}***
		(8.32)				(6.90)	(7.01)
$SecuritiesTurnover\_Ratio_{i,t}$		3.33×10^{-10}**				2.22×10^{-10}*	2.25×10^{-10}*
		(2.61)				(2.11)	(2.12)
$Log\_Cash\_norm_{i,t}$		-6.42×10^{-4}***				-6.01×10^{-4}***	-6.06×10^{-4}***
		(−30.44)				(−21.48)	(−21.51)
$Log\_Cash\_Flows\_norm_{i,t}$		2.39×10^{-4}***				2.57×10^{-4}***	2.61×10^{-4}***
		(22.02)				(17.13)	(17.33)
$Rel\_Perf_{i,t}$			-5.28×10^{-6}			0.0028	0.0027
			(−0.03)			(1.92)	(1.90)
$Diff\_HWM\_Min_{i,t}$			1.04×10^{-6}***			1.14×10^{-6}***	1.17×10^{-7}**
			(6.48)			(4.78)	(4.83)
Signaler level							
$Number\_Wikis_{i,t}$				2.05×10^{-4}***	-6.72×10^{-5}	-7.76×10^{-5}	-1.04×10^{-4}
				(3.35)	(−1.03)	(−1.18)	(−1.58)
$Number\_Wikis\_Invest_{i,t}$				1.71×10^{-4}**	9.15×10^{-5}	1.92×10^{-4}**	4.48×10^{-5}
				(2.86)	(1.70)	(2.99)	(0.71)
$Activity\_Sig_{i,t}$				1.05×10^{-5}***		-3.04×10^{-6}*	-3.36×10^{-6}*
				(6.98)		(−2.07)	(−2.39)
$SecuritiesTurnover\_Ratio\_Sig_{i,t}$				8.21×10^{-11}**		1.31×10^{-11}	1.50×10^{-11}
				(2.89)		(0.64)	(0.76)
$Log\_Cash\_norm\_Sig_{i,t}$				-5.39×10^{-4}***		-8.14×10^{-5}**	-1.32×10^{-4}***
				(−22.22)		(−2.61)	(−4.27)
$Log\_Cash\_Flows\_norm\_Sig_{i,t}$				1.62×10^{-4}***		-8.33×10^{-6}	3.85×10^{-6}
				(19.61)		(−1.03)	(0.47)
$Mean\_RelPerf\_Sig_{i,t}$					−0.0276***	−0.0304***	−0.0296***
					(−18.19)	(−11.27)	(−11.15)
$SD\_RelPerf\_Sig_{i,t}$					0.0209***	0.0215***	0.0210***
					(10.47)	(10.09)	(10.01)
$Max\_HWM\_Proxmity\_Ratio\_Sig_{i,t}$					−0.0021	−0.0014	−0.0007
					(−1.88)	(−0.98)	(−0.51)
Year dummies							yes
Month dummies							yes
_cons	0.0139***	0.0172***	0.0193***	0.0168***	0.0190***	0.0250***	0.0262***
	(53.84)	(49.08)	(41.48)	(45.16)	(18.50)	(18.99)	(19.69)
N	1,010,435	745,545	1,004,647	819,982	690,829	495,145	495,145
$R^2_{overall}$	0.511	0.503	0.495	0.505	0.529	0.515	0.522
R^2_{within}	0.247	0.281	0.251	0.266	0.264	0.299	0.309
$R^2_{between}$	0.911	0.876	0.846	0.895	0.884	0.828	0.831
σ_u	0.0073	0.0056	0.0073	0.0065	0.0070	0.0056	0.0056
σ_e	0.0095	0.0086	0.0094	0.0090	0.0095	0.008	0.0087
ρ	0.374	0.299	0.357	0.340	0.354	0.292	0.297

the coefficients of the interaction variable are significantly positive. Wikifolios that qualify for utilizing structured products display higher levels of risk when they become closer to the HWM. This can be seen as proof, that signalers strategically use structured products when they approach their HWM. Furthermore, signalers of wikifolios that include leverage products may also be either more experienced, less risk averse or both. Since *Leverage* constitutes a constant variable, it is only included as an interaction term with the HWM measure and the individual effect is contained in the fixed effects. Contrary to our expectations, the variable *Investable* as well as the interaction term yield insignificant coefficients implying no apparent difference between the status of the trading strategy and the risk exposure of the wikifolio. Signalers appear to pursue a similar trading strategy even before the wikifolio becomes investable rather than taking a riskier approach in order to achieve investability. The positive, significant coefficient of past risk demonstrates that higher levels of volatility in the preceding week have a positive effect on current risk exposure. We thus infer that signalers who exhibit higher levels of risk do so persistently and investigate this behavior in more detail in Section 3.6.2.

As far as active risk management is concerned, we find positive significant coefficients for the trading activity related control variables (model 2). Wikifolios that trade more and, hence, experience higher turnover and cash flows also display higher levels of risk. Additionally, less active wikifolios with higher cash holdings exhibit lower risk exposure. With reference to the performance related variables and increased competition amongst trading strategies, we find that the current performance displays positive, yet insignificant coefficients in model 6 and 7, which is consistent with the classical risk-return-relationship (see Fama and MacBeth, 1973). Moving to the HWM related performance variable, the coefficient of the minimum distance to the HWM within the current week is positively significant. Based on a mean of -21.93 of $Diff\_HWM\_Min$ we ascertain that wikifolios approaching the HWM reduce their risk exposure on average, therefore providing additional proof of our first hypothesis. This could be explained by the fact that signalers may attempt to exceed their current HWM by strategically gradually adjusting their risk exposure while simultaneously aiming to avoid losing followers due to behavior that is too risky. Building on these results, we deduce that signalers of more active wikifolios exhibit higher levels of risk and reduce risk when approximating the HWM.

Regarding our second hypothesis, we find that the number of investable wikifolios is significantly positively related with the level of risk. Signalers who have outside options thus display riskier trading strategies, since in the case of a failure of one specific strategy, other wikifolios will possibly result in payoffs. It needs to be noted that solely investable wikifolios appear to be respected as outside options since the *Number_ Wikis* doest not significantly affect his behavior in all models. This finding can be explained by the fact that signalers only qualify for remuneration if the wikifolio is investable. Controlling for the aggregated trading activity of the trade leader we observe similar results to those on the wikifolio level. The more active signalers, who are characterized by more trades, higher cash flows, and turnover, as well as fewer holdings in cash, feature higher levels of risk in a specific wikifolio (model 4). While the effect of aggregated signaler trading activity is positive in the individual treatment regression, it becomes negative when wikifolio and seasonal effects are accounted for. As discussed above, we expect signalers with outside options to manage the riskiness of the specific wikifolio considering their overall portfolio payoff. We find that greater portfolio risk measured by *SD_ RelPerf_ Sig*, which is a proxy for more valuable outside options, is significantly positively linked to risk taking behavior of the specific wikifolio, providing evidence in favor of our second hypothesis (model 5). We see this as an indication that signalers adapt higher levels of risk in the specific wikifolio with the objective to increase portfolio volatility and thereby the value of their remuneration option. Moreover, we explore how the maximum closeness of the signaler to the HWMs in his wikifolios affects the level of risk of one specific trading strategy. Being closer on average to one HWM level in the entire portfolio reduces risk taking behavior, though the effect is not significant. We also show that a positive mean signaler performance induces the signaler to reduce the level of risk (model 5–7). These results are not intuitive at first as we would expect signalers to exhibit risk taking behavior when their other wikifolios achieve higher rates of returns and thus chances of exceeding the HWM and qualifying for a remuneration increase. One explanation could be that signalers, who expect capital inflows following good performance, give priority to the enlargement of the capital base for remuneration over HWM exceedance. In addition, the signaler may concentrate on the one strategy that is closest to the HWM and reduce the risk in the other strategies. In doing so he would minimize the potential of capital outflows due to spillover effects between his different wikifolios. Ultimately, the transparency of information on the platform and the framing of social status indicators resulting in increased comparison across peers as well as reputational risks add to considered actions (see Pelster and Hofmann, 2017; Lý and Pelster, 2020).

When considering all aspects, we find mixed evidence regarding our second hypothesis, being that signalers strategically adjust their risk exposure in individual wikifolios in response to the value development of their outside options. We detect two different mechanisms of action. On the one hand, we discover that signalers increase the level of risk if the value of their outside option increases due to greater option volatility (option's vega effect). However, on the other hand, positive overall performance is accompanied by a reduction in the riskiness of the wikifolio, which is, however, less prevalent than the former effect[3]. Finally, we observe that wikifolios significantly increase risk exposure over time, although we find negative significant coefficients of our monthly time dummies, indicating a reduction of volatility within the year. In conclusion, our results indicate that signalers take a series of influencing factors into account when determining their level of risk. First and foremost, they reduce their risk exposure when they approach the HWM. Second, they retain the availability and the value of their outside options in mind.

3.6.2 Regression analysis of changes in the level of risk

We continue our analysis on risk taking behavior and examine changes in the risk level (see Basak et al., 2007; Panageas and Westerfield, 2009). Table 3.5 presents the results of our panel regression of $\Delta\, Risk$ in relation to the previous week. Contrary to Doering and Jonen (2018), we observe significant negative risk adjustments in response to HWM proximity (model 1). The negative changes appear in either of two forms: either the absolute risk level increases less than it did in the previous week or it diminishes. The results underline our theory that signalers reduce their risk exposure when approaching the HWM step by step. This behavior can be interpreted as a sign of balancing the scale effect and waiting effect (see Drechsler, 2014). Therefore, this is further evidence in favor of our first hypothesis being that signalers adjust the degree of risk of their wikifolios in response to their distance from the HWM and, due to the infinite investment horizon, mitigate risk when approaching the HWM. In line with our regression on the absolute level of risk, we observe mostly significant coefficients of the interaction term *HWM_Leverage_Interaction*, which is an indication of generally higher risk adjustments in the case of having the option to use structured products. This result is evidence that signalers, in particular, make use of the leverage option when becoming closer to the

[3]While the effect of portfolio volatility (*SD_RelPerf_Sig*) on risk taking equals 0.0005 (calculated as the product of the regression coefficient of 0.021 and the mean of 0.025), the effect of the *Mean_RelPerf_Sig* equals −0.0000015 (−0.0296*0.00215).

HWM. Once more, the status of the wikifolio does not significantly affect changes in the level of risk. We therefore conclude that the signalers appear to pursue a consistent risk strategy notwithstanding the claims for payment that depend amongst others on the investability of the wikifolio. Finally, higher levels of risk in the previous week have a significant negative effect on changes in wikifolio risk. The results evidence that while higher levels of risk in the previous week lead to increased risk taking in the current week, the risk change is negative.

Furthermore, we control for the impact of the wikifolio's activity on changes in the level of risk. Similar to our regression framework above, increased trading activity, higher turnover, and cash flows as well as fewer cash holdings positively affect risk changes (model 2). This result is obvious, since investing in risky assets compared with holding risk free cash generally is related to higher risk exposure. With respect to relative performance, model 3 demonstrates that while a positive performance has a positive yet insignificant effect on risk change, the effect of the minimum distance to the HWM works in the opposite direction. The coefficients remain significant when all variables on the wikifolio and signaler level are simultaneously considered (model 6 and 7). This behavior can again be attributed to the fact that signalers are aware of the fact that they face a sequence of options and gradually reduce their level of risk when moving closer to the HWM.

In the next step, we test our second hypothesis and investigate the effect of outside options on changes in the level of risk. Through parallelization of the risk level regression, we find a significant, positive effect of the number of invested wikifolios on risk changes. We thus conclude that having outside options that qualify for remuneration leads to larger changes in the level of risk on a weekly basis. Similarly, we control for aggregated trading activity of the signaler on risk changes (model 4). Increased aggregated trading activity, higher turnover, cash flows as well as reduced cash holdings have significant positive effects on changes in wikifolio risk, but their significance is reduced when variables on the wikifolio level are added. We observe how signalers strategically adjust changes in the level of risk in response to the value of their outside options. To begin with, we provide evidence that higher overall portfolio risk induces signalers to increase changes in the riskiness of the wikifolio. This can be explained by the option's vega effect, implying an increase in the outside option's value when portfolio volatility increases (see Black and Scholes, 1972; Drechsler, 2014). Regarding the maximum closeness to the HWM, we observe negative insignificant coefficients for the current proximity to the HWM. In view of signalers' performance, we find a similar picture to that of the one of the risk level regressions. The coefficient of current mean performance is significantly negative (model 5), and this effect is less pronounced than the effect of portfolio volatility[4]. These findings elucidate that if signalers perform well overall, which is proxied by higher average returns and the closeness to the HWMs, they are enticed toward negative risk changes. We argue that this behavior can be ascribed to the fact that signalers expect capital inflows following good past performances. In addition, we regard the increased transparency of information as an additional factor, implying risk mitigating behavior following good performance for signalers with several wikifolios. Consequently, we only find proof to support our hypothesis that signalers exhibit positive risk changes when the value of their outside options increases. Additionally, reputational concerns can have a minimizing effect on risk taking behavior. The monthly dummies display significant negative coefficients, which signify continuous reduction of risk adjustments within the year (model 7).

[4]While the effect of the volatility of the portfolio (*SD_ RelPerf_ Sig*) equals 0.00044, the effect of the mean portfolio performance (*Mean_ RelPerf_ Sig*) adds up to −0.00005.

Table 3.5: Fixed-effects regression of $\Delta\, Risk$ on the proximity to the HWM

Notes: Analysis of changes in risk ($\Delta\, Risk$) compared with the previous week with respect to the proximity to the HWM using a fixed-effects model. The observation period ranges from April 27th 2012 to April 15th 2016 and contains 15,636 wikifolios belonging to 7,091 signalers. Model 1 includes the main explanatory variables $HWM\_Proximity\_Ratio$, the interaction variables of the $HWM\_Proximity\_Ratio$ with $Leverage$ and $Investable$, and the Dummy Variable $Investable$. Models 2 and 3 expand on the base model through wikifolio specific activity and performance variables. Models 4 and 5 take into consideration that signalers often have several wikifolios, and implement signaler's activity and performances, respectively. Model 6 implements the performance and activity related variables on both wikifolio and signaler perspectives. Model 7 adds to Model 6 with time dummies. Table 3.1 and Table 3.2 provide detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**	**4**	**5**	**6**	**7**
$HWM\_Proximity\_Ratio_{i,t}$	−0.0074***	−0.0064***	−0.0122***	−0.0067***	−0.0099***	−0.0115***	−0.0119***
	(−32.42)	(−28.47)	(−27.88)	(−29.02)	(−21.63)	(−16.58)	(−16.73)
$HWM\_Investable\_Interaction_{i,t}$	7.62×10^{-4}*	1.81×10^{-4}	0.0013**	0.0004	0.0013**	0.0005	0.0004
	(2.18)	(0.44)	(3.15)	(0.95)	(2.73)	(0.74)	(0.66)
$Investable_{i,t}$	2.01×10^{-4}	5.37×10^{-4}	-8.87×10^{-4}*	6.05×10^{5}	−0.0011**	3.74×10^{-4}	-5.87×10^{-4}
	(−0.59)	(1.34)	(−2.27)	(0.17)	(−2.62)	(0.70)	(−1.12)
$HWM\_Leverage\_Interaction_{i,t}$	0.0032	0.0005	0.0028***	−0.0007	0.0011	0.0032**	0.0029**
	(−0.63)	(−0.92)	(3.84)	(−1.19)	(1.35)	(3.05)	(2.75)
$Risk_{i,t\text{-}1}$	−0.423***	−0.422***	−0.429***	−0.418***	−0.441***	−0.442***	−0.447***
	(−73.84)	(−61.43)	(−72.10)	(−62.38)	(−61.45)	(−52.58)	(−51.70)
Wikifolio level							
$Activity_{i,t}$		3.15×10^{-5}***				3.32×10^{-5}***	3.38×10^{-5}***
		(7.81)				(6.16)	(6.28)
$SecuritiesTurnover\_Ratio_{i,t}$		2.27×10^{-10}*				1.31×10^{-10}	1.32×10^{-10}
		(2.07)				(1.52)	(1.52)
$Log\_Cash\_norm_{i,t}$		-5.26×10^{-4}***				-4.89×10^{-4}***	-4.92×10^{-4}***
		(−31.10)				(−22.38)	(−22.38)
$Log\_Cash\_Flows\_norm_{i,t}$		1.90×10^{-4}***				1.99×10^{-4}***	2.02×10^{-4}***
		(24.20)				(18.74)	(18.98)
$Rel\_Perf_{i,t}$			7.21×10^{-5}			0.0020	0.0019
			(0.26)			(1.58)	(1.56)
$Diff\_HWM\_Min_{i,t}$			7.98×10^{-7}**			8.21×10^{-7}***	8.60×10^{-7}***
			(5.66)			(3.70)	(3.78)
Signaler level							
$Number\_Wikis_{i,t}$				1.47×10^{-4}**	-8.19×10^{-5}	-8.41×10^{-5}	-1.07×10^{-4}
				(2.91)	(−1.55)	(−1.54)	(−1.96)
$Number\_Wikis\_Invest_{i,t}$				1.32×10^{-4}**	7.32×10^{-5}	1.49×10^{-4}**	4.17×10^{-5}
				(2.66)	(1.63)	(2.81)	(0.81)
$Activity\_Sig_{i,t}$				8.40×10^{-6}***		-2.07×10^{-6}	-2.39×10^{-6}*
				(6.88)		(−1.58)	(−1.90)
$SecuritiesTurnover\_Ratio\_Sig_{i,t}$				6.63×10^{-11}**		1.16×10^{-11}	1.37×10^{-11}
				(3.06)		(0.74)	(0.88)
$Log\_Cash\_norm\_Sig_{i,t}$				-4.44×10^{-4}***		-7.73×10^{-5}*	-1.14×10^{-4}***
				(−21.98)		(−2.99)	(−4.42)
$Log\_Cash\_Flows\_norm\_Sig_{i,t}$				1.31×10^{-4}***		-4.12×10^{-6}	4.65×10^{-6}
				(20.75)		(−0.64)	(0.72)
$Mean\_RelPerf\_Sig_{i,t}$					−0.0228***	−0.0251***	−0.0242***
					(−16.53	(−10.44)	(−10.30)
$SD\_RelPerf\_Sig_{i,t}$					0.0175***	0.0179***	0.0173***
					(10.55)	(9.84)	(9.74)
$Max\_HWM\_Proximity\_Ratio\_Sig_{i,t}$					−0.0017	−0.0018	−0.0013
					(−1.55)	(−1.43)	(−1.07)
$Year\, dummies$							yes
$Month\, dummies$							yes
$\_cons$	0.0115***	0.0142***	0.0156***	0.0140***	0.0156***	0.0207***	0.0218***
	(52.22)	(48.67)	(39.88)	(46.03)	(15.93)	(17.31)	(17.95)
N	1,010,435	745,545	1,004,647	819,982	690,829	495,145	495,145
$R^2_{overall}$	0.138	0.162	0.149	0.148	0.165	0.191	0.201
R^2_{within}	0.225	0.234	0.227	0.227	0.246	0.257	0.269
$R^2_{between}$	0.0049	0.0091	0.0056	0.0006	0.0185	0.0176	0.0170
σ_u	0.0060	0.0044	0.0056	0.0053	0.0058	0.0043	0.0043
σ_e	0.0085	0.0077	0.0085	0.0080	0.0086	0.0078	0.0078
ρ	0.330	0.248	0.306	0.305	0.313	0.233	0.238

When combining the results of Table 3.4 and Table 3.5, we show how the level of risk as well as risk changes are reduced through increased proximity to the HWM. We argue that recognizing the infinite investment horizon can explain this finding. Interestingly, qualifying for remuneration by becoming investable does not have an effect on the risk strategy. In addition, our results suggest that while enhanced performance of the wikifolio is related to increased risk taking, the minimum distance to the HWM in the current week works in the opposite direction. Furthermore, having alternative payment options significantly affects the level of risk. The value of these options – proxied by the overall portfolio volatility of the signaler – influences both the level of and change in risk taking, resulting in higher levels of risk. We find countervailing, though smaller effects of signaler's portfolio performance. Apart from this, we argue that increased transparency of information and the resultant social reputation mechanisms can have a diminishing effect on both the wikifolio's level of risk and changes in risk. Building on the results, we derive that signalers act strategically taking a number of factors into account when deciding on their risk taking behavior.

3.6.3 Robustness checks

In order to substantiate our results, we conduct robustness checks with different model variations as well as a subsample including additional variables to further account for social dynamics.

First, we rebuild our analysis of risk taking behavior following Doering and Jonen (2018), who investigate risk adjustments on a monthly basis with respect to the distance to the HWM in the previous month. They find positive risk changes when wikifolios approximate the HWM. Consequently, we extend our model to explore how signalers tailor the riskiness (*Risk*) of their trading strategy in response to past performance – represented by the performance indicators *HWM_Proximity_Ratio*, relative performance and minimum distance to the HWM of the preceding week – rather than taking a solely contemporaneous view. In comparison to Doering and Jonen (2018), we account for the fact that signalers can manage several trading strategies simultaneously. We adhere to our weekly approach since we showed that signalers frequently adjust the riskiness of their wikifolio in the form of an answer to the innovative platform design[5]. Ultimately, we examine the level of risk as well as changes in risk to obtain a more detailed picture of risk taking behavior with respect to past performance indicators. The results are displayed in Table 3.6 and Table 3.7, respectively. The inclusion of past performance figures yields a significant positive coefficient for the closeness to the HWM in the preceding week in both models, which is consistent with the findings of Doering and Jonen (2018). Signalers increase the riskiness of their trading strategy following higher HWM proximity ratios in the previous week. In contrast, even when accounting for the influence of past HWM proximity, we still confirm a negative relationship between the current proximity to the HWM. This finding can be explained by the fact that signalers face an infinite investment horizon and thus regard their incentive option as a sequence of options. Consequently, they take future payoffs into account when deciding on their levels of risk, resulting in risk mitigating behavior when approaching the HWM instead of increased risk taking which would be optimal in a one period setting. In comparison to Doering and Jonen (2018), our results show two opposing effects: past HWM closeness increases risk taking, whereas the current distance to the HWM has the opposite effect. Furthermore, the contemporaneous effect of the distance to the HWM on risk taking slightly exceeds the past effect. We therefore infer that signalers gear their

[5] We additionally conducted the regressions on a monthly basis yielding similar results.

behavior towards current performance measures due to the fact that at all times both they and their followers are aware of their present HWM distance. Additionally, we find weak evidence supporting our second hypothesis, being that more valuable outside options, measured by the signaler's volatility, portfolio performance and HWM proximity of his portfolio of other wikifolios, lead to increased risk taking. Our results show that increased portfolio volatility positively influences the level of and changes of risk. On the other hand, increased average signaler performance is significantly related to reduced risk taking. The adapted model also displays negative, insignificant coefficients for the maximum closeness of the signaler to his HWMs in the previous week. In conclusion, the model variations confirm risk mitigating behavior in the case of HWM proximity. Moreover, the results can be viewed as an indication that signalers behave strategically by frequently (weekly) adjusting the riskiness of the wikifolio and taking a forward-looking approach rather than focusing on the past. In addition, our results highlight the importance of taking outside options into account when modeling risk taking behavior.

Second, we extend our regression framework by explicitly considering the social network characteristics of the platform. We assume that the differences in the trading environment that foster social interaction, but also increase the risk of reputation and comparison amongst trading strategies, have an effect on signaler's behavior. In addition, since all information is made immediately available to the users, this can lead to instant cash in- and outflows. To explore this matter, we include further variables that measure the social status of the trading strategy. To begin with, we incorporate changes in the assets under management – a proxy for the popularity of the wikifolio –, once as an interaction term with the *HWM_Proximity_Ratio* and once as the variable by itself. We also include wikifolio points that serve as the main basis for the ranking of trading strategies. In addition, we consider the different labels that characterize wikifolios based on the investment focus, trading style, quality or risk, and return figures and thereby serve as social status indicators (see Wikifolio, 2016). Furthermore, we utilize the number of comments to measure the signaler's communication with the followers. Due to the fact that these social network variables have been obtained manually, the observation period is reduced to November 13th 2015 to April 15th 2016 resulting in a smaller subsample of the original dataset including 11,587 wikifolios belonging to 6,229 signalers. Tables 3.8 to 3.11 present the results of the adjusted regressions for the absolute level of risk and risk change. While Tables 3.8 and 3.10 focus on the effect of assets under management on risk taking, Tables 3.9 and 3.11 on top include social network variables.

Table 3.6: Analysis of *Risk* on the proximity to the HWM and past performance figures

Notes: Analysis of *Risk* with respect to the proximity to the HWM using a fixed-effects regression model. We follow Doering and Jonen (2018) and test how past performance affects current risk taking behavior. Model 1 includes the main explanatory variables *HWM_Proximity_Ratio*, the interaction variable of the *HWM_Proximity_Ratio* with *Leverage*, and past risk. Models 2 and 3 expand on the base model through past performance measures on the wikifolio and signaler level, respectively, while model 4 includes performance figures on both levels as well as time dummies. Table 3.1 and Table 3.2 provide detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**	**4**
$HWM\_Proximity\_Ratio_{i,t}$	−0.0109***	−0.0296***	−0.0098***	−0.0253***
	(−19.69)	(−22.93)	(−11.98)	(−11.82)
$HWM\_Investable\_Interaction_{i,t}$	-2.16×10^{-4}	-7.69×10^{-4}	1.72×10^{-4}	−0.0011
	(−0.22)	(−0.77)	(0.14)	(−0.77)
$Investable_{i,t}$	8.20×10^{-4}	0.0013	6.66×10^{-6}	9.20×10^{-4}
	(0.86)	(1.32)	(0.01)	(0.69)
$HWM\_Leverage\_Interaction_{i,t}$	0.0069***	0.0069***	0.0053***	0.0034**
	(8.70)	(8.48)	(5.19)	(2.97)
$Risk_{i,t-1}$	0.466***	0.459***	0.451***	0.440***
	(76.39)	(73.16)	(56.19)	(45.88)
Wikifolio level				
$Activity_{i,t}$				3.86×10^{-5}***
				(6.01)
$SecuritiesTurnover\_Ratio_{i,t}$				2.60×10^{-10}**
				(2.61)
$Log\_Cash\_norm_{i,t}$				-6.25×10^{-4}***
				(−22.11)
$Log\_Cash\_Flows\_norm_{i,t}$				2.53×10^{-4}***
				(17.38)
$Rel\_Perf_{i,t-1}$		5.41×10^{-4}*		0.0019
		(2.26)		(1.38)
$Diff\_HWM\_Min_{i,t-1}$		1.14×10^{-6}***		1.13×10^{-6}***
		(7.18)		(4.73)
$HWM\_Proximity\_Ratio_{i,t-1}$		0.0186***		0.0166***
		(15.57)		(8.20)
Signaler level				
$Number\_Wikis_{i,t}$			-2.92×10^{-5}	-3.51×10^{-5}
			(−0.43)	(−0.50)
$Number\_Wikis\_Invest_{i,t}$			1.52×10^{-4}**	8.81×10^{-5}
			(2.88)	(1.43)
$Activity\_Sig_{i,t}$				-1.96×10^{-6}
				(−1.31)
$SecuritiesTurnover\_Ratio\_Sig_{i,t}$				4.51×10^{-11}*
				(2.16)
$Log\_Cash\_norm\_Sig_{i,t}$				-1.56×10^{-4}***
				(−4.82)
$Log\_Cash\_Flows\_norm\_Sig_{i,t}$				1.65×10^{-5}*
				(1.99)
$Mean\_RelPerf\_Sig_{i,t-1}$			−0.0131***	−0.0068***
			(−9.82)	(−4.60)
$SD\_RelPerf\_Sig_{i,t-1}$			0.0081***	0.0040***
			(9.97)	(4.63)
$Max\_HWM\_Proximity\_Ratio\_Sig_{i,t-1}$			−0.0014	−0.0008
			(−1.15)	(−0.57)
Year dummies				yes
Month dummies				yes
$\_cons$	0.0147***	0.0148***	0.0155***	0.0193***
	(31.32)	(31.95)	(15.79)	(16.41)
N	1,010,435	939,923	647,760	464,676
$R^2_{overall}$	0.477	0.480	0.503	0.519
R^2_{within}	0.244	0.249	0.242	0.289
$R^2_{between}$	0.820	0.826	0.860	0.878
σ_u	0.0073	0.0071	0.0074	0.0058
σ_e	0.0095	0.0094	0.0096	0.0087
ρ	0.368	0.366	0.373	0.303

Table 3.7: Analysis of $\Delta\,Risk$ on the proximity to the HWM and past performance figures

Notes: Analysis of $\Delta\,Risk$ with respect to the proximity to the HWM using a fixed-effects regression model. We follow Doering and Jonen (2018) and test how past performance affects current risk taking behavior. Model 1 includes the main explanatory variables $HWM\_Proximity\_Ratio$, the interaction variable of the $HWM\_Proximity\_Ratio$ with $Leverage$, and past risk. Models 2 and 3 expand on the base model through past performance measures on the wikifolio and signaler level respectively, while model 4 includes performance figures on both levels as well as time dummies. Table 3.1 and Table 3.2 provide detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**	**4**
$HWM\_Proximity\_Ratio_{\text{i,t}}$	−0.0085***	−0.0311***	−0.0075***	−0.0244***
	(−18.55)	(−25.74)	(−10.99)	(−16.55)
$HWM\_Investable\_Interaction_{\text{i,t}}$	2.46×10^{-4}	-2.47×10^{-4}	6.67×10^{-4}	-8.44×10^{-4}
	(0.30)	(−0.29)	(0.64)	(−0.66)
$Investable_{\text{i,t}}$	1.81×10^{-4}	5.97×10^{-4}	-5.79×10^{-4}	6.53×10^{-4}
	(0.22)	(0.72)	(−0.59)	(0.55)
$HWM\_Leverage\_Interaction_{\text{i,t}}$	0.0034***	0.0033***	0.0021*	0.0008
	(5.34)	(5.03)	(2.50)	(0.82)
$Risk_{\text{i,t-1}}$	−0.421***	−0.430***	−0.436***	−0.441***
	(−71.53)	(−71.20)	(−56.57)	(−47.82)
Wikifolio level				
$Activity_{\text{i,t}}$				3.16×10^{-5}***
				(5.31)
$SecuritiesTurnover\_Ratio_{\text{i,t}}$				1.87×10^{-10}*
				(2.10)
$Log\_Cash\_norm_{\text{i,t}}$				-5.11×10^{-4}***
				(−22.98)
$Log\_Cash\_Flows\_norm_{\text{i,t}}$				1.98×10^{-4}***
				(18.82)
$Rel\_Perf_{\text{i,t-1}}$		-3.50×10^{-4}*		1.90×10^{-4}
		(−2.37)		(0.43)
$Diff\_HWM\_Min_{\text{i,t-1}}$		8.73×10^{-7}***		7.65×10^{-7}***
		(6.40)		(3.51)
$HWM\_Proximity\_Ratio_{\text{i,t-1}}$		0.0232***		0.0187***
		(20.42)		(14.33)
Signaler level				
$Number\_Wikis_{\text{i,t}}$			-5.70×10^{-5}	-6.25×10^{-5}
			(−1.05)	(−1.08)
$Number\_Wikis\_Inves_{\text{i,t}}t$			1.19×10^{-4}**	7.54×10^{-5}
			(2.82)	(1.55)
$Activity\_Sig_{\text{i,t}}$				-1.28×10^{-6}
				(−0.92)
$SecuritiesTurnover\_Ratio\_Sig_{\text{i,t}}$				3.53×10^{-11}*
				(2.11)
$Log\_Cash\_norm\_Sig_{\text{i,t}}$				-1.28×10^{-4}***
				(−4.77)
$Log\_Cash\_Flows\_norm\_Sig_{\text{i,t}}$				1.43×10^{-5}*
				(2.18)
$Mean\_RelPerf\_Sig_{\text{i,t-1}}$			−0.0178***	−0.0090***
			(−16.14)	(−8.91)
$SD\_RelPerf\_Sig_{\text{i,t-1}}$			0.0105***	0.0054***
			(16.18)	(8.88)
$Max\_HWM\_Proximity\_Ratio\_Sig_{\text{i,t-1}}$			-5.39×10^{-4}	-7.21×10^{-4}
			(−0.58)	(−0.60)
$Year\,dummies$				yes
$Month\,dummies$				yes
$\_cons$	0.0120***	0.0114***	0.0120***	0.0147***
	(29.86)	(29.01)	(15.71)	(14.71)
N	1,010,435	939,923	647,760	464,676
$R^2_{overall}$	0.139	0.141	0.142	0.172
R^2_{within}	0.221	0.226	0.228	0.249
$R^2_{between}$	0.0053	0.0040	0.0035	0.0011
σ_u	0.0058	0.0059	0.0063	0.0048
σ_e	0.0085	0.0084	0.0086	0.0078
ρ	0.314	0.325	0.348	0.275

Table 3.8: Analysis of *Risk* on the proximity to the HWM & social network characteristics I

Notes: Analysis of *Risk* with respect to the proximity to the HWM and social network characteristics using a fixed-effects regression model. The observation period ranges from November 13th 2015 to April 15th 2016 and observes 11,587 wikifolios of 6,229 signalers. Model 1 constitutes our base model. Additionally, we account for the change in invested capital (for investable wikifolios) or interest value (for published wikifolios) with the variable *CapChange*. Model 2 expands on the base model by wikifolio- and signaler-specific activity and performance variables. Model 3 uses performance variables obtained from the preceding week. Table 3.1 and Table 3.2 provide detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**
$HWM\_Proximity\_Ratio_{i,t}$	−0.0181***	−0.0122**	−0.0440***
	(−7.28)	(−2.92)	(−8.34)
$HWM\_Investable\_Interaction_{i,t}$	0.0107*	0.0080	-9.22×10^{-4}
	(2.01)	(1.03)	(−0.13)
$Investable_{i,t}$	−0.0104*	−0.0081	−0.0016
	(−1.97)	(−1.08)	(−0.24)
$HWM\_Leverage\_Interaction_{i,t}$	0.0292***	0.0330***	0.0327***
	(5.72)	(4.78)	(5.18)
$HWM\_CapChange\_Interaction_{i,t}$	-3.34×10^{-5}	−0.0012	-8.06×10^{-4}
	(−1.44)	(−1.23)	(−0.99)
$Cap\_Change_{i,t}$	2.01×10^{-4}***	0.0012	7.97×10^{-4}
	(8.76)	(1.23)	(1.01)
$Risk_{i,t-1}$	0.158***	0.128***	0.0678**
	(14.05)	(5.87)	(3.02)
Wikifolio level			
$Activity_{i,t}$		-2.13×10^{-6}	1.50×10^{-6}
		(−0.11)	(0.07)
$SecuritiesTurnover\_Ratio_{i,t}$		1.13×10^{-8}	9.94×10^{-9}
		(1.79)	(1.51)
$Log\_Cash\_norm_{i,t}$		-9.73×10^{-4}***	−0.0010***
		(−7.68)	(−7.92)
$Log\_Cash\_Flows\_norm_{i,t}$		2.32×10^{-4}***	2.31×10^{-4}***
		(6.14)	(5.99)
$Rel\_Perf_{i,t}$		0.0154***	
		(6.98)	
$Diff\_HWM\_Min_{i,t}$		6.48×10^{-7}	
		(0.97)	
$Rel\_Perf_{i,t-1}$			0.0155***
			(8.44)
$Diff\_HWM\_Min_{i,t-1}$			3.13×10^{-6}
			(1.74)
$HWM\_Proximity\_Ratio_{i,t-1}$			0.0419***
			(9.19)
Signaler level			
$Number\_Wikis_{i,t}$		-2.59×10^{-4}	-6.92×10^{-4}
		(−0.72)	(−1.83)
$Number\_Wikis\_Invest_{i,t}$		-1.08×10^{-4}	2.60×10^{-4}
		(−0.18)	(0.39)
$Activity\_Sig_{i,t}$		5.09×10^{-7}	-4.96×10^{-8}
		(0.08)	(−0.01)
$SecuritiesTurnover\_Ratio\_Sig_{i,t}$		-4.65×10^{-11}	4.85×10^{-11}*
		(−0.82)	(2.14)
$Log\_Cash\_norm\_Sig_{i,t}$		-1.25×10^{-4}	-4.18×10^{-4}*
		(−0.57)	(−2.04)
$Log\_Cash\_Flows\_norm\_Sig_{i,t}$		4.46×10^{-5}	6.81×10^{-5}*
		(1.49)	(2.18)
$Mean\_RelPerf\_Sig_{i,t}$		−0.0465***	
		(−7.19)	
$SD\_RelPerf\_Sig_{i,t}$		0.0274***	
		(7.16)	
$Max\_HWM\_Proximity\_Ratio\_Sig_{i,t}$		−0.0329***	
		(−6.61)	
$Mean\_RelPerf\_Sig_{i,t-1}$			−0.0136**
			(−2.59)
$SD\_RelPerf\_Sig_{i,t-1}$			0.0079**
			(2.59)
$Max\_HWM\_Proximity\_Ratio\_Sig_{i,t-1}$			9.11×10^{-4}
			(0.11)
Time Dummies		yes	yes
_cons	0.0223***	0.0573***	0.0214**
	(8.26)	(9.26)	(2.94)
N	76,108	29,681	29,706
$R^2_{overall}$	0.0732	0.120	0.0608
σ_u	0.0164	0.0156	0.0167
σ_e	0.0105	0.0087	0.0088
ρ	0.709	0.765	0.783

Table 3.9: Analysis of *Risk* on the proximity to the HWM & social network characteristics II

Notes: Analysis of *Risk* with respect to the proximity to the HWM and social network characteristics using a fixed-effects regression model. The observation period ranges from November 13th 2015 to April 15th 2016 and observes 11,587 wikifolios of 6,229 signalers. Model 1 builds on our base model accounting for the change in invested capital (for investable wikifolios) or interest value (for published wikifolios) and social status indicators. Models 2 to 5 implement ranking and social reward variables following the Wikifolio categorization from the previous week. Model 6 adds the performance and activity related variables. Table 3.1 and Table 3.2 provide descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**	**4**	**5**	**6**
$HWM\_Proximity\_Ratio_{i,t}$	−0.0180*** (−7.27)	−0.0176*** (−7.17)	−0.0179*** (−7.25)	−0.0178*** (−7.20)	−0.0180*** (−7.28)	−0.0120*** (−2.91)
$HWM\_Investable\_Interaction_{i,t}$	0.0109* (2.03)	0.0117* (2.19)	0.0118* (2.23)	0.0116* (2.17)	0.0119* (2.23)	0.0088 (1.13)
$Investable_{i,t}$	−0.009 75 (−1.85)	−0.0102 (−1.95)	−0.0108* (−2.05)	−0.0101 (−1.92)	−0.0107* (−2.02)	−0.0087 (−1.17)
$HWM\_Leverage\_Interaction_{i,t}$	0.0289*** (5.70)	0.0283*** (5.62)	0.0286*** (5.68)	0.0289*** (5.66)	0.0286*** (5.67)	0.0321*** (4.62)
$HWM\_CapChange\_Interaction_{i,t}$	-3.42×10^{-5} (−1.48)	-3.11×10^{-5} (−1.34)	-3.01×10^{-5} (−1.32)	-3.16×10^{-5} (−1.36)	-3.10×10^{-5} (−1.34)	−0.001 23 (−1.21)
$Cap\_Change_{i,t}$	2.01×10^{-5}*** (8.82)	2.00×10^{-5}*** (8.76)	2.01×10^{-5}*** (8.93)	2.00×10^{-5}*** (8.76)	2.00×10^{-5}*** (8.70)	0.0012 (1.22)
$Risk_{i,t-1}$	0.158*** (14.06)	0.158*** (14.04)	0.156*** (13.86)	0.158*** (14.04)	0.157*** (13.90)	0.128*** (5.85)
Wikifolio level						
$Activity_{i,t}$						2.44×10^{-6} (0.13)
$SecuritiesTurnover\_Ratio_{i,t}$						1.10×10^{-8} (1.76)
$Log\_Cash\_norm_{i,t}$						-9.72×10^{-4}*** (−7.69)
$Log\_Cash\_Flows\_norm_{i,t}$						2.29×10^{-4}*** (6.03)
$Rel\_Perf_{i,t}$						0.0155*** (7.01)
$Diff\_HWM\_Min_{i,t}$						6.57×10^{-7} (0.97)
Signaler level						
$Number\_Wikis_{i,t}$						2.56×10^{-4} (0.72)
$Number\_Wikis\_Invest_{i,t}$						-1.15×10^{-4} (−0.20)
$Activity\_Sig_{i,t}$						1.98×10^{-8} (0.00)
$SecuritiesTurnover\_Ratio\_Sig_{i,t}$						-4.46×10^{-11} (−0.79)
$Log\_Cash\_norm\_Sig_{i,t}$						−0.0001 (−0.63)
$Log\_Cash\_Flows\_norm\_Sig_{i,t}$						4.77×10^{-5} (1.60)
$Mean\_RelPerf\_Sig_{i,t}$						−0.0463*** (−7.18)
$SD\_RelPerf\_Sig_{i,t}$						0.0273*** (7.14)
$Max\_HWM\_Proximity\_Ratio\_Sig_{i,t}$						−0.0320*** (−6.46)
Social interaction						
$Comments_{i,t}$	2.45×10^{-5} (0.47)	-6.45×10^{-5}** (−2.70)	-6.13×10^{-5}* (−2.55)	-6.58×10^{-5}** (−2.68)	6.09×10^{-5}* (−2.51)	8.57×10^{-6} (0.28)
$Comments_{i,t-1}$	-9.90×10^{-5}* (−1.99)					
$WF\_points_{i,t}$	-4.61×10^{-6}*** (−7.57)	-2.83×10^{-6}*** (−6.54)	-3.17×10^{-6}*** (−6.63)	-2.89×10^{-6}*** (−6.48)	-3.09×10^{-6}*** (−6.64)	-1.72×10^{-6}*** (−4.58)
$WF\_points_{i,t-1}$	3.05×10^{-6}*** (5.50)					
$Actively\_diversified_{i,t-1}$		3.73×10^{-5} (0.11)			3.12×10^{-5} (0.09)	3.40×10^{-4} (0.85)
$Heavy\_trader_{i,t-1}$		−0.0023* (−2.04)			−0.0024* (−2.21)	−0.0018 (−1.20)
$Medium\_to\_longterm_{i,t-1}$		-8.89×10^{-4}*** (−3.33)				
$Good\_communicator_{i,t-1}$			4.92×10^{-4} (0.72)			
$Regular\_activity_{i,t-1}$			0.0019*** (5.58)		0.0019** (5.73)	2.07×10^{-7} (0.00)
$Bestseller_{i,t-1}$			0.0015 (0.56)		0.0025 (0.92)	0.0058 (1.32)
$Loyal\_investors_{i,t-1}$			0.0039 (1.89)			
$Often\_bought_{i,t-1}$			0.0056* (1.97)		0.0064* (2.25)	0.0031 (0.79)
$Toptentrader_{i,t-1}$			-8.32×10^{-5} (−0.11)			
$Continuous\_growth_{i,t-1}$				0.0024** (2.78)		
$Good\_money\_manager_{i,t-1}$				0.0021*** (5.70)	0.0020*** (5.58)	0.0011** (2.79)
$Highperformance_{i,t-1}$				−0.0045 (−1.90)	−0.0044 (−1.88)	−0.0014 (−0.37)
Time Dummies					yes	
_cons	0.0238*** (8.59)	0.0241*** (8.73)	0.0233*** (8.49)	0.0236*** (8.50)	0.0235*** (8.50)	0.0566*** (8.99)
N	76,108	76,108	76,108	76,108	76,108	29,681
$R^2_{overall}$	0.063	0.064	0.072	0.064	0.067	0.123
σ_u	0.017	0.017	0.017	0.017	0.017	0.015
σ_e	0.011	0.011	0.011	0.011	0.011	0.009
ρ	0.730	0.725	0.720	0.727	0.722	0.760

Table 3.10: Analysis of *Risk* on the proximity to the HWM & social network characteristics I

Notes: Analysis of $\Delta\, Risk$ with respect to the proximity to the HWM and social network characteristics using a fixed-effects regression model. The observation period ranges from November 13th 2015 to April 15th 2016 and observes 11,587 wikifolios of 6,229 signalers. Model 1 constitutes our base model. Additionally, we account for the change in invested capital (for investable wikifolios) or interest value (for published wikifolios) with the variable *CapChange*. Model 2 expands on the base model by wikifolio- and signaler-specific activity and performance variables. Model 3 uses performance variables obtained from the preceding week. Table 3.1 and Table 3.2 provide detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**
$HWM\_Proximity\_Ratio_{i,t}$	−0.0130***	−0.0075	−0.0339***
	(−6.79)	(−1.82)	(−5.76)
$HWM\_Investable\_Interaction_{i,t}$	0.0075	0.0087	0.0035
	(1.96)	(1.29)	(0.52)
$Investable_{i,t}$	−0.0087*	−0.0077	−0.0044
	(−2.28)	(−1.14)	(−0.64)
$HWM\_Leverage\_Interaction_{i,t}$	0.0136***	0.0118*	0.0101
	(4.58)	(2.01)	(1.73)
$HWM\_CapChange\_Interaction_{i,t}$	1.62×10^{-5}	-4.22×10^{-4}**	-5.90×10^{-4}*
	(0.92)	(−2.70)	(−2.14)
$Cap\_Change_{i,t}$	-2.59×10^{-5}***	4.56×10^{-4}**	6.53×10^{-4}*
	(−18.71)	(3.09)	(2.44)
$Risk_{i,t-1}$	−0.675***	−0.704***	−0.750***
	(−56.74)	(−31.92)	(−31.93)
Wikifolio level			
$Activity_{i,t}$		-6.06×10^{-9}	7.27×10^{-7}
		(0.00)	(0.05)
$SecuritiesTurnover\_Ratio_{i,t}$		1.00×10^{-8}	9.29×10^{-9}
		(1.69)	(1.53)
$Log\_Cash\_norm_{i,t}$		-8.27×10^{-4}***	-8.66×10^{-4}***
		(−7.81)	(−7.95)
$Log\_Cash\_Flows\_norm_{i,t}$		1.77×10^{-4}***	1.80×10^{-4}***
		(5.58)	(5.59)
$Rel\_Perf_{i,t}$		0.0040*	
		(2.05)	
$Diff\_HWM\_Min_{i,t}$		3.69×10^{-7}	
		(0.56)	
$Rel\_Perf_{i,t-1}$			0.0040**
			(2.58)
$Diff\_HWM\_Min_{i,t-1}$			1.43×10^{-6}
			(1.91)
$HWM\_Proximity\_Ratio_{i,t-1}$			0.0382***
			(10.22)
Signaler level			
$Number\_Wikis_{i,t}$		-3.55×10^{-4}	-8.19×10^{-4}*
		(−1.05)	(−2.16)
$Number\_Wikis\_Invest_{i,t}$		−0.0011	−0.0010
		(−1.12)	(−0.78)
$Activity\_Sig_{i,t}$		2.83×10^{-6}	2.41×10^{-6}
		(0.45)	(0.43)
$SecuritiesTurnover\_Ratio\_Sig_{i,t}$		-1.81×10^{-11}	3.93×10^{-11}
		(−0.41)	(1.40)
$Log\_Cash\_norm\_Sig_{i,t}$		-1.32×10^{-4}	-3.17×10^{-4}*
		(−0.78)	(−2.02)
$Log\_Cash\_Flows\_norm\_Sig_{i,t}$		4.70×10^{-5}	5.51×10^{-5}
		(1.56)	(1.92)
$Mean\_RelPerf\_Sig_{i,t}$		−0.0257**	
		(−3.27)	
$SD\_RelPerf\_Sig_{i,t}$		0.0151***	
		(3.30)	
$Max\_HWM\_Proximity\_Ratio\_Sig_{i,t}$		−0.0356***	
		(−5.45)	
$Mean\_RelPerf\_Sig_{i,t-1}$			−0.0105*
			(−2.20)
$SD\_RelPerf\_Sig_{i,t-1}$			0.0062*
			(2.23)
$Max\_HWM\_Proximity\_Ratio\_Sig_{i,t-1}$			−0.0046
			(−0.47)
Time Dummies		yes	yes
$\_cons$	0.0191***	0.0584***	0.0228*
	(11.37)	(9.38)	(2.47)
N	76,108	29,681	29,706
$R^2_{overall}$	0.127	0.177	0.151
σ_u	0.0109	0.0093	0.0107
σ_e	0.0096	0.0079	0.0079
ρ	0.566	0.582	0.648

Table 3.11: Analysis of *Risk* on the proximity to the HWM & social network characteristics II

Notes: Analysis of Δ *Risk* with respect to the proximity to the HWM and social network characteristics using a fixed-effects regression model. The observation period ranges from November 13th 2015 to April 15th 2016 and observes 11,587 wikifolios of 6,229 signalers. Model 1 builds on our base model accounting for the change in invested capital (for investable wikifolios) or interest value (for published wikifolios) and social status indicators. Models 2 to 5 implement ranking and social reward variables following the Wikifolio categorization from the previous week. Model 6 adds the performance and activity related variables. Table 3.1 and Table 3.2 provide descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered around signalers. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	**2**	**3**	**4**	**5**	**6**
HWM_Proximity_Ratio$_{i,t}$	−0.0129***	−0.0126***	−0.0128***	−0.0127***	−0.0129***	−0.007 30
	(−6.76)	(−6.63)	(−6.71)	(−6.70)	(−6.76)	(−1.79)
HWM_Investable_Interaction$_{i,t}$	0.0076*	0.0083*	0.0084*	0.0083*	0.0083*	0.0092
	(1.98)	(2.17)	(2.19)	(2.16)	(2.18)	(1.36)
Investable$_{i,t}$	−0.0082*	−0.0085*	−0.0090*	−0.0086*	−0.0088*	−0.0080
	(−2.14)	(−2.23)	(−2.32)	(−2.24)	(−2.30)	(−1.18)
HWM_Leverage_Interaction$_{i,t}$	0.0134***	0.0130***	0.0130***	0.0133***	0.0131***	0.0112
	(4.54)	(4.40)	(4.44)	(4.48)	(4.45)	(1.91)
HWM_CapChange_Interaction$_{i,t}$	1.57×10^{-5}	1.84×10^{-5}	1.92×10^{-5}	1.82×10^{-5}	1.88×10^{-5}	-4.08×10^{-4}**
	(0.91)	(1.05)	(1.12)	(1.04)	(1.09)	(−2.62)
Cap_Change$_{i,t}$	-2.59×10^{-5}***	-2.61×10^{-5}***	-2.60×10^{-5}***	-2.60×10^{-5}***	-2.61×10^{-5}***	4.54×10^{-4}**
	(−18.83)	(−18.57)	(−18.35)	(−18.56)	(−18.77)	(3.04)
Risk$_{i,t-1}$	−0.675***	−0.676***	−0.677***	−0.676***	−0.677***	−0.704***
	(−56.75)	(−56.55)	(−56.92)	(−56.72)	(−56.60)	(−31.84)
Wikifolio level						
Activity$_{i,t}$						3.19×10^{-6}
						(0.21)
SecuritiesTurnover_Ratio$_{i,t}$						9.86×10^{-9}
						(1.67)
Log_Cash_norm$_{i,t}$						-8.29×10^{-4}***
						(−7.84)
Log_Cash_Flows_norm$_{i,t}$						1.75×10^{-4}***
						(5.49)
Rel_Perf$_{i,t}$						0.0040*
						(2.06)
Diff_HWM_Min$_{i,t}$						3.58×10^{-7}
						(0.54)
Signaler level						
Number_Wikis$_{i,t}$						-3.86×10^{-4}
						(−1.13)
Number_Wikis_Invest$_{i,t}$						−0.0011
						(−1.08)
Activity_Sig$_{i,t}$						2.47×10^{-6}
						(0.39)
SecuritiesTurnover_Ratio_Sig$_{i,t}$						-1.64×10^{-11}
						(−0.37)
Log_Cash_norm_Sig$_{i,t}$						-1.39×10^{-4}
						(−0.82)
Log_Cash_Flows_norm_Sig$_{i,t}$						4.87×10^{-5}
						(1.62)
Mean_RelPerf_Sig$_{i,t}$						−0.0255**
						(−3.24)
SD_RelPerf_Sig$_{i,t}$						0.0150**
						(3.28)
Max_HWM_Proximity_Ratio_Sig$_{i,t}$						−0.0347***
						(−5.32)
Social interaction						
Comments$_{i,t}$	1.38×10^{-5}	-4.68×10^{-5}*	-4.26×10^{-5}	-4.65×10^{-5}	4.16×10^{-5}	-1.81×10^{-6}
	(0.26)	(−1.97)	(−1.82)	(−1.95)	(−1.75)	(−0.06)
Comments$_{i,t-1}$	-6.77×10^{-5}					
	(−1.29)					
WF_points$_{i,t}$	-4.43×10^{-6}***	-2.68×10^{-6}***	-2.95×10^{-6}***	-2.77×10^{-6}***	-2.95×10^{-6}***	-1.64×10^{-6}***
	(−7.58)	(−6.32)	(−6.41)	(−6.33)	(−6.45)	(−4.67)
WF_points$_{i,t-1}$	2.99×10^{-6}***					
	(6.09)					
Actively_diversified$_{i,t-1}$		1.73×10^{-5}			1.95×10^{-5}	3.66×10^{-4}
		(0.06)			(0.07)	(1.00)
Heavy_trader$_{i,t-1}$		-3.56×10^{-4}			-5.28×10^{-4}	-2.07×10^{-4}
		(−0.38)			(−0.57)	(−0.18)
Medium_to_longterm$_{i,t-1}$		-6.17×10^{-4}**				
		(−2.58)				
Good_communicator$_{i,t-1}$			2.15×10^{-4}			
			(0.34)			
Regular_activity$_{i,t-1}$			0.0019***		0.0019***	3.92×10^{-4}
			(6.59)		(6.58)	(0.93)
Bestseller$_{i,t-1}$			0.0038		0.0043*	0.0037*
			(1.79)		(2.03)	(1.97)
Loyal_investors$_{i,t-1}$			0.0021			
			(1.28)			
Often_bought$_{i,t-1}$			0.0026		0.0030	0.0019
			(1.23)		(1.41)	(0.72)
Toptentrader$_{i,t-1}$			-3.92×10^{-5}			
			(−0.05)			
Continuous_growth$_{i,t-1}$				0.0025**		
				(2.97)		
Good_money_manager$_{i,t-1}$				0.0023***	0.0022***	0.0014***
				(6.68)	(6.51)	(4.26)
Highperformance$_{i,t-1}$				−0.0020	−0.0020	−0.0010
				(−0.98)	(−0.97)	(−0.27)
Time Dummies					yes	yes
_cons	0.0202***	0.0203***	0.0198***	0.0201***	0.0198***	0.0577***
	(11.60)	(11.65)	(11.43)	(11.54)	(11.39)	(9.19)
N	76,108	76,108	76,108	76,108	76,108	29,681
$R^2_{overall}$	0.115	0.117	0.120	0.116	0.120	0.179
σ_u	0.0117	0.0116	0.0113	0.0116	0.0113	0.0092
σ_e	0.0096	0.0096	0.0096	0.0096	0.0096	0.0079
ρ	0.598	0.592	0.583	0.594	0.584	0.578

Regarding our hypothesis-related variable *HWM_ Proximity_ Ratio*, we once more provide evidence that wikifolios significantly reduce their level of risk when approaching the HWM (see Tables 3.8 and 3.10). Interestingly, the change in assets under management positively and significantly affects the risk exposure of the wikifolio, though the effect is reduced when all variables on the wikifolio and signaler level are included. We argue that this can be explained by the fact that the remuneration is to some extent tied to the assets under management. Increasing the riskiness of the wikifolio in response to cash inflows constitutes rational behavior since surpassing the HWM would be related to increased payouts. With respect to wikifolio and signaler performance, the results reveal themselves to be similar to our regression framework, although some significances disappear when all social interaction variables are considered, which can be ascribed to the quantity of explanatory variables. While the number of investable wikifolios loses its significant influence on the level of risk, the signaler's volatility of returns in fact retains a positive significant effect. Compared to our main regression framework, the *Max_ HWM_ Proximity_ Ratio_ Sig* turns significant and thereby confirms our second hypothesis. In view of the social network characteristics related variables (see Tables 3.9 and 3.11), the amount of comments and wikifolio points are significantly negatively linked to the level of risk. Wikifolios appear to reduce their risk exposure when they attract more attention by followers following an improved ranking or increase in communication activities. In addition, we show that past wikifolio labels influence the level of risk. These include, inter alia, the tags *regular activity, good money manager*, or *heavy trader*. While the tags related to the trading style are negatively significant, risk/return and quality labels are mostly positive significant. Concluding, we show that the social dimension influences the risk taking behavior to a certain degree and that after accounting for these factors our hypotheses still hold.

When looking at risk changing behavior, we still find a negative and significant effect of the proximity to the HWM on risk changes. What is more, changes in the assets under management also significantly affect risk adjustments. Signalers appear to increase the level of risk when they experience capital inflows. However, the changes in the level of risk compared with the previous week become smaller the more assets they manage. Again, the mere availability of outside options does not significantly affect risk changing behavior, but the value of these does, as the significant coefficients of portfolio volatility, performance and maximum HWM proximity show. We also find a significant negative effect of social status represented by wikifolio points on changes in the level of risk. Several tags have a significant effect on changes in wikifolio risk.

Taken together, we confirm our hypotheses when considering social interactions as well as lagged performance effects. The robustness tests provide additional insights into the factors that influence signaler's risk taking behavior. We show that the increased transparency that is implemented by the platform, as well as the social dimension, shapes the signaler's activities and that signal providers appear to be aware of the particularities of the trading environment and to respond accordingly.

3.7 Conclusion

In this article, we study whether portfolio managers strategically tailor their risk taking behavior in response to their incentive contracts. We thereby add to the existing literature on risk taking under convex incentives in the fund literature. In particular, we empirically analyze how both an infinite investment horizon and valuable outside options affect the risk taking behavior of signal providers in an innovative online trading environment. Furthermore, we account for the platform-specific characteristics such as increased transparency of information and social interaction. On these grounds, we extend the findings of Doering and Jonen (2018) by taking a multi-period approach and considering additional influential factors of risk taking behavior. In addition, we not only investigate changes in risk, but also look into levels of risk to provide a more profound picture of risk taking behavior under convex incentives. Our empirical analysis is based on data from the German social trading platform Wikifolio. We apply a fixed-effects regression model to investigate the influential factors of the level of risk as well as risk changes in trading strategies and confirm our results following a series of robustness checks.

Above all, we show that signalers take a complex set of factors into consideration when deciding on their risk strategy. First, we provide evidence that signal providers adapt the absolute and relative risk of the trading strategy to the proximity to the HWM. In a single period setting, signalers increase their risk exposure when they become closer to the HWM, as they do not face any consequences in the subsequent period and are primarily focused on reaching the HWM. Contrary to some existing studies, the Wikifolio portfolio managers are, however, aware of the fact that they act within an infinite investment horizon and comprehend the HWM incentive scheme as a series of remuneration options on the assets under management. Therefore, they weigh up current payoffs (scale effect) against future payoffs (waiting effect). As a consequence, we observe risk mitigating behavior throughout the increasing proximity to the HWM. Second, since signal providers possess the option to open several wikifolios simultaneously, they are provided with outside choices and react in response to the value of these. Being in possession of more valuable outside options, in terms of a higher volatility of the other wikifolios, induces them to increase the riskiness of the trading strategy with the objective to further increase the option's value. However, this effect is mitigated with respect to the moneyness of the outside option in terms of HWM proximity and relative portfolio performance. We thereby show that signalers on Wikifolio in fact behave strategically and take their risk decision in consideration of their overall portfolio payoffs. In addition, we indicate that signalers appear to frequently adapt the exposure of their trading strategies and respond to current performance developments as well as taking a forward-looking approach. Finally, we find that social interaction and status indicators significantly affect risk taking behavior.

Our findings contribute to the discussion on appropriate incentive structures for asset managers. Several studies and practical examples have shown that convex payoffs have the potential to generate risk seeking stimulations since the managers will be recompensed for gains, though, not penalized for losses (see Panageas and Westerfield, 2009). First and foremost, we outline the importance of taking the investment horizon and the presence of outside options of the asset manager into account when determining the specific incentive contract. We thereby provide empirical evidence for theoretical risk taking under convex incentives models (see Hodder and Jackwerth, 2007; Panageas and Westerfield, 2009; Aragon and Nanda, 2011; Drechsler, 2014; Zhao et al., 2018). We also shed light on how setting the right trading environment e.g., through increased transparency of information and social reputation mechanisms can positively affect the portfolio manager's behavior. On the contrary, the option to open several wikifolios simultaneously implies risk taking behavior to a certain degree if these outside options increase in value. Moreover, we contribute on the understanding of private investor behavior since the majority of signal providers on these platforms are not professional asset managers.

Due to the ongoing trend of digitalization and the emergence of new business models as well as increased data availability, our paper is of interest to platform developers, investors and, in particular, financial regulators. Based on our results policy makers can enhance incentive policies in order to better align the asset manager's and investor's interests and mitigate moral hazard. Amending the incentive contracts by designing an infinite investment horizon will reinforce the positive aspects of convex remuneration schemes and reduce excessive risk taking. In addition, allowing for outside options can lead to a more strategic risk approach of the trader. Policy makers should devote particular attention to the set-up of the trading environment. Stricter transparency requirements can improve the level of transparency for the trader and for the investor and, thus, reduce information asymmetry. Together with the introduction of a social dimension, that provides increased opportunities for comparison amongst peers and greater reputational risks, a positive effect on risk taking behavior can be expected. The combination of these policy measures has the potential to benefit all involved parties through the establishment of transparency and trust.

Further studies may analyze how signalers strategically implement different strategies in their portfolio with a focus on the portfolio compositions in greater detail. In addition, further research could investigate the motivation of signalers to forward the application for the investability of a certain trading strategy at a specific point of time. It would be also interesting to know which factors drive signal providers to close wikifolios and withdraw completely. Finally, in view of the social dimension more insights on the impact of social reward mechanisms and social interaction as well as competition amongst peers would be beneficial for platform operators and regulatory offices.

Chapter 4

Blockchain applications for climate protection: a global empirical investigation

This research project has been carried out jointly by Gregor Dorfleitner, Franziska Muck, and Isabel Scheckenbach. This article has been published as Dorfleitner, G., Muck, F., Scheckenbach, I., 2021. Blockchain applications for climate protection: a global empirical investigation. *Renewable and Sustainable Energy Reviews*, 149, 111378

Abstract: Our research consolidates the actual environment of blockchain applications that contribute in a certain way to climate protection. In view of the growing interest in climate change and the need to act on a global scale, knowledge about these applications enables investors, politicians, and citizens to drive this development forward through diverse support opportunities. This article provides an extensive overview of existing mitigation and adaptation measures based on blockchain technology. We collect data on 85 such applications and describe the empirical distributions of different attributes of these applications. In a logit regression, we analyze which application-specific and blockchain-specific characteristics determine the success of an application in the sense of an advanced operational status. We find evidence that applications of the type "energy trading" exhibit reduced chances of success, while green blockchain-based applications implementing a proof-of-stake consensus mechanism are more likely to become operational. Moreover, pursuing an initial coin offering has no significant effect on the success of an application. Our work provides the basis for a better understanding of the success factors of this new technology.

Keywords: Blockchain, distributed ledger, green finance, consensus mechanisms, peer-to-peer transactions, sustainability goals

JEL Classification: O30 Q01 Q54 Q55

4.1 Introduction

In recent years, the debate on climate change has intensified as extremely alarming scientific accounts such as the Intergovernmental Panel on Climate Change (IPCC) report on climate change (IPCC, 2015) have increased people's environmental concerns and expectations. In addition, political events, such as the increased popularity of "green" parties in the EU elections, the attendance of young climate activists at US Congressional hearings, or the presentation of the European Green New Deal in 2019 have strengthened the public discourse (European Commission, 2019; European Parliament, 2020). These developments indicate the demand on the part of society to foster innovation and investments in the area of climate protection. The conclusion of the Paris Agreement in 2015 to collectively implement climate protection measures can be considered as a significant step in this direction (United Nations Framework Convention for Climate Change, 2015). According to Dong et al. (2018), one approach for achieving the proposed objectives revolves around the comprehensive restructuring of climate markets. Advancing these markets to an international, transparent level can promote more efficient and cost-effective trade of climate protection products and services.

"Blockchain technology", a form of the distributed ledger technology, is a promising innovation that has the potential to realize the mentioned change technically. The four core attributes of blockchain, namely transparency, immutability, decentralization, and authentication, can address some of the challenges experienced in cooperative, intergovernmental actions and advance the implementation of measures aimed at tackling climate change and supporting sustainable development (Herweijer et al., 2018; Dorfleitner and Braun, 2019). The United Nations Climate Change (2017) highlights the potential of disruptive technologies such as blockchain technology, the internet of things (IoT), artificial intelligence (AI), and big data in promoting environmental and social sustainability. Several studies outline various fields of applications in which blockchain technology offers the possibility to accelerate climate action (Acharya et al., 2016; Galen et al., 2018; Andoni et al., 2019). The existing literature focuses on performance, obstacles, and perspectives as well as on recommendations for actions to enhance the adoption of blockchain technology in digital sustainability actions (Maupin, 2017; Fuessler et al., 2018). In this article, we build on existing research and oversee the current integrated application environment in a specially designed, empirical investigation. The objective of this research is to present the analysis of the success determinants of environmentally oriented blockchain applications to assess their contributions to climate protection.

Our research is based on a unique dataset of 85 global, green blockchain applications that have been selected following the model of inductive category development (Mayring, 2015). The objective of the study is to gain an insight into the factors that contribute to the performance of an application. Based on application and blockchain characteristics, we perform logistic regressions on the applications' success. We find evidence that the type of activity significantly affects the probability of becoming operational. As a second aspect, we show that selecting the proper consensus mechanism plays a crucial role. In addition, neither the implementation of tokens nor the execution of an Initial Coin Offering (ICO) has an effect on the status of the application. Finally, we demonstrate that differences across blockchain types do not exist.

To our knowledge, this study is the first that draws a profound picture of the current state of green blockchain applications globally. In view of the growing interest in climate change and the need to act on a global scale, we provide an extensive overview of existing mitigation and adaptation measures based on blockchain technology. We therefore illustrate diverse fields of actions and point out possible future directions. It is the knowledge concerning these applications and their potential in tackling climate change that enables investors, politicians, and citizens to drive this development forward through diverse support opportunities. However, the fact that a large portion of the applications under review do not yet take an operational role limits the derivation of insights to some extent. Moreover, we contribute to current research by shedding light on the success factors of blockchain applications. The empirical results provide valuable insights for the developers of blockchains and the respective companies in order to advance the application's development more efficiently. The results are especially useful for political institutions for the provision of the necessary legal and political framework for green blockchain applications to thrive.

The remainder of this paper is organized as follows. In Section 4.2, we outline blockchain technology and climate challenges, and highlight the technological features that serve as a basis for green finance applications. Section 4.3 elaborates on the data collection method and is followed by a description of the data set. After presenting the empirical methodology, we describe the current green blockchain landscape and investigate the success factors of these blockchain applications in Section 4.4. Section 4.5 concludes and provides an outlook for future research.

4.2 Institutional, economic and ecological aspects

4.2.1 Blockchain technology

The McWaters et al. (2015) has declared blockchain technology, the foundation of which was laid by Nakamoto (2009) aided by the development of Bitcoin, to be one of the 10 major technological innovations. The distinguishing feature of this special form of distributed ledger technology (DLT) is the ability to "permanently, immutably and transparently record and store transactions across a peer-to-peer (P2P) network" (Dorfleitner and Braun, 2019, p.219). Market participants carry out transactions by sending them to the nodes of the network for verification. Several transactions are then combined in one time-stamped block and following cryptographic certification attached to previously created blocks, thereby creating a uniform data register, the 'blockchain' (Malherbe et al., 2019; Viriyasitavat and Hoonsopon, 2019). In order to validate and concatenate the transactions, the members of the network square their versions of the blockchain via so-called consensus mechanisms and, in this way, establish consensus on the valid state of the ledger across the whole network (Biais et al., 2019). The proof-of-work (PoW) and proof-of-stake (PoS) mechanisms are the most commonly used consensus algorithms (Herweijer et al., 2018; Shanaev et al., 2019). The former algorithm assigns the concatenation of the new block to the network member who solved a complex cryptographic puzzle with computational processes first and guarantees a high security level. The latter relates the probability of generating a block to the stakes of the nodes, i.e., to the amount of blockchain currency owned and is by design less energy intensive (Nakamoto, 2009; Andoni et al., 2019). Various alternative consensus mechanisms have since arisen, for example, the proof-of-authority (PoA) or the practical Byzantine-fault-tolerance mechanism (PBFT) (Zheng et al., 2018; Pike et al., 2019).

By now, a plethora of blockchain technologies has emerged that vary greatly with respect to the system architecture, the underlying consensus mechanism, speed of transactions, energy consumption, cyber security, governance, and their technical fit for different applications. Special properties of the technology can thus, on the one hand, provide benefits in certain areas while implying negative consequences in others (Zheng et al., 2018). Against the background of the ability to use blockchain applications in dealing with environmental challenges, the following advantages can be summarized: The *immutability of the data* constitutes the fundamental asset of blockchain technology. By lining up interdependent blocks with individual cryptographic encryption, subsequent modification or falsification of data or transactions that have been stored becomes virtually impossible (Neves and Prata, 2018; Dorfleitner and Braun, 2019). Second, *transparency* plays a crucial role. The unrestricted visibility of a blockchain for all participants in the network entails a high degree of transparency, that not only ensures the unchangeability of a blockchain but also reveals opportunistic behaviors of individuals (Risius and Spohrer, 2017; Malherbe et al., 2019). Third, Galen et al. (2018) highlight that blockchains can be built up modularly by means of smart contracts, decentralized applications (dApps) or multi-layer architectures. Consequently, the *scope of applications and utilization possibilities* is customizable and extensively adaptable (Risius and Spohrer, 2017; Zheng et al., 2018). The anonymity of public blockchains resulting from the use of pseudonyms within the network can be seen as an additional benefit with respect to the privacy of individuals (Fabian et al., 2016). Moreover, a key advantage is the *lack of a central authority* within the network. The degree of decentralization and the distribution of decision-making power, though, is strongly dependent on the underlying system architecture (Andoni et al., 2019). Finally, the option of offering tokens provides *new means of payment* on the platform and makes it possible to allocate a *digital value to all types of assets* (Ernst & Young, 2017). The pursuit of an ICO also constitutes an opportunity to rapidly and easily *raise capital* from a P2P network (Masiak et al., 2019; Dorfleitner and Braun, 2019). Investors in turn receive tokens that will transform into cryptocurrency with the launch of the project and can be traded on the secondary market (Neves and Prata, 2018). Adhami et al. (2018) and Fisch (2019) identify increased information transparency, token supply, access to project services, and organized pre-sales as constituting the critical factors for increasing the chances of successful ICOs.

Despite its great potential, blockchain technology faces a number of challenges. For one thing, extremely high computing capacities are required for applications working with the PoW mechanism, resulting in energy inefficiency (Howson, 2019). What is more, technological restrictions such as the limited transaction capacity, increased processing time or scalability, and interoperability with other blockchains as well as with other IT systems can constitute barriers to widespread adoption (Zheng et al., 2018; Herweijer et al., 2018; Andoni et al., 2019). While anonymity is beneficial to some extent, at the same time it can lead to security gaps and conceal illegal behavior (Fabian et al., 2016; Risius and Spohrer, 2017; Bailis et al., 2017). The complexity of the technology calls for a certain level of expertise and can thus prevent potential users from using blockchain applications (Cuccuru, 2017; Shanaev et al., 2019). Blockchain governance, which comprises the diversity of rules and practices that can be deployed to adapt the blockchain following the consensus of the stakeholders and secure its success, can present another challenge. While endogenous governance systems implicitly define the distribution of decision power and incentives through the underlying consensus mechanism, exogenous governance measures are explicitly created either on-chain by encoding it in the infrastructure or off-chain (Beck et al., 2018; Allen and Berg, 2020). However, research on the different governance mechanisms and their advantages and disadvantages in various applications is scarce (Reijers et al., 2018; van Pelt et al., 2021). Finally, regulatory aspects represent one of the biggest challenges. Due to the rapid spread of blockchain technology and its decentralized nature, very few legal regulations exist (Dong et al., 2018).

4.2.2 Environment and climate

The UN General Assembly (2015) names "climate change [as] one of the greatest challenges of our time" and describes how its adverse impacts jeopardize the ability to attain sustainable development (UN General Assembly, 2015, p.5). The IPCC substantiates the anthropogenic influence on the climate system and provides an insight into the contingencies for humans and ecosystems (IPCC, 2015, 2018). They point out that rising sea levels and an increasing occurrence of natural disasters as well as the resulting threat of economic instability, among other things, pertain to the adverse implications (IPCC, 2018; Lenton et al., 2019). Lenton et al. (2019) evidence the heightened likelihood of reaching tipping points and call attention to the irreversible impacts due to the interconnectedness of ecosystems. As a central solution to effectively curb climate change, leading scientists call for a significant reduction of greenhouse gases (UN General Assembly, 2012; UNEP/UNECE, 2016). In the light of the complexity of the anticipated consequences and in view of the urgency of action, the IPCC (2015) proposes complementary mitigation and adaptation strategies that are designed to reinforce the combat against climate change and manage the prospected risks (IPCC, 2018).

The conclusion of the Paris Agreement by 175 nations in 2015 constitutes an important step towards curbing climate change. The most important achievement of this agreement was the creation of the first legally binding contract that defines the common objective of limiting the increase in the global average temperature to significantly below 2°C above the pre-industrial levels and striving for an average temperature rise of only 1.5°C (United Nations Framework Convention for Climate Change, 2015). Model pathways aiming at enhancing the probability of staying below the 2.0°C threshold show the necessity of a decline of 45% in CO_2 emissions between 2010 and 2030, reaching net zero emissions in 2050 (IPCC, 2018). In addition, Article 4 binds the signatory nations to establish and comply with so-called "Nationally Determined Contributions" (NDCs), which are targeted at reducing greenhouse gas emissions (United Nations Framework Convention for Climate Change, 2015). Above all, each nation is committed to adapting its goals to the external circumstances in the country and to making the greatest possible contribution to meeting the 1.5°C target (Dong et al., 2018). Consequently, the agreement obliges industrialized countries to take on leadership roles in combating climate change and in helping developing countries (United Nations Framework Convention for Climate Change, 2015). Article 6 recommends that nations cooperate to accomplish their NDCs, thereby paving the way for carbon dioxide offsetting programs (Neves and Prata, 2018).

Several hurdles are yet to be surmounted in overcoming the current problems in the field of climate change and in proceeding with the implementation of the Paris Agreement. In particular, technical and regulatory barriers have to be removed to facilitate the exchange of CO_2 reduction products as proposed in Article 6 (Dong et al., 2018). Climate markets should be reorganized and connected to each other on an international level because national differences in both tradable assets and in laws can impede international trade (Fuessler et al., 2018; Neves and Prata, 2018). The anticipated benefits include an increase in trading volume and the expansion of the network to small, decentralized actors (Dong et al., 2018; Hagedorn et al., 2019). The control, certification, and management of emission compensation products vary worldwide and incite the risk of double counting. Regulatory transformation and partial standardization of national climate markets would thus constitute the first effective measure to simplify international trade (Chen, 2018). Moreover, governments should develop mechanisms that correctly map, register, and monitor the exchange of CO_2 emissions in a transparent and secure way, thereby laying the foundation for evaluating the implemented measures (Dong et al., 2018). Dong et al. (2018) also propose to enable the management of the resulting data across national borders and corporate sectors. In order to obtain a realistic possibility to limit global warming, enormous financial resources are required for the implementation of the mitigation and adaptation efforts (Acharya et al., 2016; Marke, 2018; Dorfleitner and Braun, 2019). Fuessler et al. (2018), for example, estimate that an investment of USD 3.5 trillion per year solely is required to meet the objectives in the energy sector by 2050. Nassiry (2018) therefore concludes that, aside from government investments, private investors are also an integral part of successfully minimizing CO_2 emissions and reducing the financing gap. The increase in investment volumes, number of climate initiatives, and financing channels has led to a complex climate finance ecosystem that may hinder the success and efficiency of funding (Neves and Prata, 2018). To stimulate new capital expenditure it could be helpful to renew regulatory requirements, provide various incentives for investors, and integrate new technologies into existing processes (Neves and Prata, 2018; Herweijer et al., 2018; Marke, 2018). Dong et al. (2018) argue that innovative forms of investments can increase the number of financial transactions from private investors and effectuate a more secure and less expensive transfer of capital. They consider the spread of an unregulated P2P trade as a possible solution that ensures a realization of these investments.

4.2.3 Blockchain applications to mitigate climate change

One possibility to meet the existing environmental challenges is the implementation of blockchain based applications. The technology's distinctive features can be essential in environmental and climate protection, as they offer wide fields of applications (Neves and Prata, 2018). United Nations Climate Change (2017) identify

- safer and more efficient carbon emission trading and renewable energy trading systems,
- the mobilization of climate finance, as well as
- monitoring frameworks for greenhouse gas emissions

as the key areas in which blockchain applications can be conducive to enhancing climate actions. Pricing mechanisms for CO_2 emissions are regarded as useful tools in realizing emission targets and have been established in over 40 regions, including both cities and entire countries (Chen, 2018; Dong et al., 2018; Banga, 2019). The possibility of a decentralized transfer of data via blockchains corresponds to the current requirements of climate markets in which cost-effective transfers of small amounts of money are becoming increasingly important (Dong et al., 2018). In addition, the tamper-proof storage of data in the blockchain can be used for monitoring, reporting, and validating (MRV) emission compensation products (Fuessler et al., 2018; Braden, 2019). The "Blockchain for Climate Foundation" develops an application with the objective of comprising the NDCs of all nations (see Table 4.6). The distributed consensus algorithm ensures the validity of the registered CO_2 compensation data and reduces manual workload by automating the verification process (Chen, 2018). Constructed upon the measured values, blockchain-based calculations can be executed and, with the help of smart contracts, automated processes can be commenced. Additionally, the carbon offsetting products serve as a tool to raise funds to finance projects in developing countries (Banga, 2019; Dorfleitner and Braun, 2019; Poseidon, 2019). Blockchains also enable the creation of digital assets through the conversion of sustainable initiatives and global public goods into tokens and thereby establish a secondary market for these investments in the form of emission rights or incentive mechanisms (United Nations Climate Change, 2017; Fuessler et al., 2018; Nassiry, 2018; Howson, 2019).

The data transparency and the various access options within a blockchain can simplify the international and cross-sectoral exchange of CO_2 reduction products. The implementation of smart contracts in the climate and renewable energy market also opens up new opportunities (Bailis et al., 2017; Cuccuru, 2017; Marke, 2018). In this field, smart contracts can realize transactions of heterogeneous investment instruments across national borders and regulatory requirements, which will be essential with regard to Article 6 of the Paris Agreement (Herweijer et al., 2018). Additionally, they diminish the risk of contract violations, strengthen trust among the parties involved and reduce the expense of monitoring the proper execution of the contract (Cong and He, 2019). Goranovic et al. (2017) explain how the utilization of smart contracts and dApps building on blockchain can provide efficiency gains in the energy sector (Bahga and Madisetti, 2016; Raval, 2016; EthHub, 2019). The handling of transactions and verification of the origin of electricity paves the way for more individual, decentralized and efficient energy markets, ameliorates the access to electricity and promotes local sustainable energy production and distribution via P2P trading, thereby stimulating demand for renewable energy (Giungato et al., 2017; Herweijer et al., 2018; Fuessler et al., 2018; Galen et al., 2018; Marke, 2018; Andoni et al., 2019). The Swiss application "Quartierstrom", for example, enables decentralized trading of locally produced electricity within the neighborhood. Similar projects can be found in Germany, Australia, Norway, the US or Bangladesh (see Table 4.6).

In addition, Dorfleitner and Braun (2019) show how P2P financing and crowd investments based on blockchain can foster the raising of capital for green projects. The immutability of the financial data and possibility to track whether the financial resources are used for the intended purposes reduces investor risks and mitigates funding barriers (Nassiry, 2018; Schletz et al., 2020). The applications "COCOA", "Waterchain", and "Cryptoleaf" capitalize on these advantages and offer crowdfunding for environmentally friendly projects (see Table 4.6). Financial innovations such as ICOs, digital currencies, and tokens as well as green bonds can also accelerate financial inclusion (Adhami et al., 2018; Galen et al., 2018; Masiak et al., 2019; Chiu and Greene, 2019; Fisch, 2019). Finally, blockchain technology provides opportunities to incentivize environmentally friendly behavior of individuals, for example, by building reward systems based on tokens (Herweijer et al., 2018). Applications in this area include "EnergyCoin", "IXO Foundation", "GreenRide", or "EcoCoin" (see Table 4.6).

However, the current regulatory and legal frameworks in some countries leave room for legal limbo and uncertainty in the use of the technology (Maupin, 2017; Dong et al., 2018). Another problem lies within the data quality in the blockchains, which depends on the quality and accuracy of the data entered and could benefit from increased user training and the integration of external censors (Neves and Prata, 2018). Dong et al. (2018) also cite the small number of experienced blockchain developers as well as the diversity and the associated potential interoperability of individual blockchain technologies as limiting factors. Moreover, they address the lack of interest and technological knowledge regarding DLT amongst the population and potential investors, which can lead to mistrust and rejection of the technology being used in climate markets (Herweijer et al., 2018). Speed and security problems constitute additional challenges whose extent depends on the system architectures used (Fuessler et al., 2018; Andoni et al., 2019).

The energy consumption of blockchains should not be neglected either because it stands in stark contrast to the environmental goals (Giungato et al., 2017). In 2018 the CO_2 emissions from Bitcoin ranged from approximately 22.0 Mt to 22.9 Mt CO_2 (Stoll et al., 2019). These figures, though, strongly depend on the energy mix in the respective countries (Köhler and Pizzol, 2019). Technical factors and economic factors greatly influence the power consumption for using blockchains (Vranken, 2017; Krause and Tolaymat, 2018; Köhler and Pizzol, 2019;

de Vries, 2021). Sedlmeir et al. (2020b) estimate a lower bound of 60 TWh and an upper bound of 120 TWh for the yearly energy consumption of Bitcoin in 2020. The consensus mechanisms and the degree of redundancy, i.e., the number of nodes and the intensity of the processes to perform transactions are the main drivers of electricity consumption (Sedlmeir et al., 2020a). Therefore, the application of alternative consensus mechanisms to PoW represents an integral component for using blockchains to enhance sustainability (Cole and Cheng, 2018; Andoni et al., 2019; Gallersdörfer et al., 2020). While one Bitcoin transaction is assumed to consume 1 GJ, an Ethereum transaction makes up for roughly 0.1 GJ due to its lower market capitalization. In comparison, public permissionless blockchains with a PoS mechanism require only 100 J per transaction. In view of the critics on the PoW mechanism, Ethereum currently prepares to change to PoS (Giungato et al., 2017; Ethereum, 2019; Hertig, 2019). Private permissioned blockchains applying consensus mechanisms such as PoA or PBFT have even lower energy requirements with 1 J per transaction (Sedlmeir et al., 2020b). The energy consumption of blockchains with alternative consensus protocols is thus several orders of magnitude lower than that of PoW blockchains.

4.3 Empirical analysis of the functions and properties of blockchain applications

4.3.1 Research design

In the following, we carry out an empirical investigation of the existing blockchain applications aimed at tackling climate issues. We provide an extensive overview of blockchain applications in green finance, which is one objective of this paper. This overview enables the analysis of the extent to which the theoretical possibilities of the blockchain explained in the previous section are put into practice. Second, we build on these results and establish a logit model in order to obtain a greater understanding of the factors that influence the status of green blockchain applications before obtaining recommendations for action. The first part of the empirical analysis identifies blockchain applications that can effectuate climate mitigation and adaptation strategies. From this point onwards, they are referred to as “green”. The term is derived from the “green finance” definition by Dorfleitner and Braun (2019), in which projects, companies, or technologies are described as being green if they contribute to environmental protection or the containment of climate change. We aim to provide a complete application portfolio including all currently known, blockchain-based green applications. This portfolio serves as the basis for determining the extent to which the advantages of DLT in environmental aspects can be realized and for classifying their contribution to climate protection. In addition, the potential of blockchain technology in the climate markets of the future will be identified.

4.3.2 Data

To begin with, selection criteria for green applications have been defined to create the population of our analysis. Based upon the research objective of this article, the core condition for the inclusion in the data set is the positive contribution to climate protection with the help of blockchain mechanisms. For a superior classification of the selection criteria, three categories have been established. Content-related criteria are linked to the overarching goal of climate protection and require a clear description of the functionality, purpose, and the impact of the blockchain-based application in achieving this objective. Furthermore, the unique carriers in the population need to follow an autonomous business model and, hence, do not belong to a superordinate conglomeration of applications (formal criteria). Clear evidence of the activity of the active application within the past two years as well as a development plan constitute the time-related conditions. During the observation period from April 2019 through July 2019, references to these applications were obtained from scientific literature and from websites. We pursued this information and cross-checked the applications with respect to the specific inclusion requirements. This process results in a population of 85 applications that are listed in Table 4.6.

4.3.3 Methodology

We built on the model of inductive category development following Mayring (2015). Because the information on the applications stems from various sources, ranging from company websites to blog entries, social media statements, white papers, and interview excerpts, all sources are subsumed in one category, and the basic Mayring (2015) model principles have been applied to the dataset. After setting the framework conditions of the analysis, this iterative process explores the information sources and carriers with respect to the selection criteria and level of abstraction, from which features and characteristic values are derived that will serve as the foundation for the analysis and for the interpretation of the applications and their attributes (Mayring, 2015). The construction of five application-specific and four blockchain-based features finalizes this process.

The application-specific features include the 1) type of application, 2) application sector, 3) development status, 4) country of origin, and 5) company characteristics. Considering the primary function of the application as a selection criterion the following characteristic values referring to the type of application can be distinguished: control of electricity networks, reward system, crowdfunding, data verification, emission rights, P2P trading, platform for various applications, and electricity trading. Moreover, we investigate the sector in which the previously determined activity is active and define the characteristic values of *agriculture and forestry*, *general sustainability*, *renewable energies*, *mobility*, and *water management*. Based on the information concerning objectives already achieved and future milestones, the development statuses of *startup phase*, *in preparation* and *operational* are established. Since the size of the companies and their goals can be used as relevant, company-specific characteristics, we combine the information on LinkedIn profiles with the small and medium-sized enterprises definition of the Commission of the European Communities (2003) to create size-related categories. In line with the objectives of the company, additionally both nonprofit organizations and scientifically oriented companies are identified. Finally, we consider the countries in which the individual applications are located. Besides, we account for attributes that are related to the blockchain. The identified features cover 1) the type of blockchain used, 2) the applied consensus mechanism, 3) the issuance of tokens, and 4) the implementation of an ICO. The applications under review rest upon a large spectrum of blockchains with varying properties. Sorted primarily depending on their relevance in both literature and practice, 13 different blockchain technologies including, for example, Ethereum, Stellar, and Hyperledger Fabric, are assayed. We pay particular attention to the consensus mechanism mentioned and do not derive the consensus algorithm from the blockchain used. The inductive categorization yields 11 distinct consensus mechanisms ranging from proof-of-stake to proof-of-work. Further differentiation of the applications can be carried out in relation to the issuance of tokens because not every blockchain-based business model uses those items (Bashir, 2018). The final blockchain-based feature concerns ICOs. In the case of either a successful ICO implementation or an ongoing ICO, the characteristic value "yes" is assigned. Apart from that, the case of unsuccessfully and prematurely terminated ICOs is considered. A detailed description of the selection criteria and characteristic values can be found in Table 4.8 through Table 4.10. Table 4.11 and Table 4.12 display all applications and the application- and blockchain-specific characteristic values. Building on this, the explanatory variables are defined in Table 4.1.

In addition to an isolated frequency analysis, it is also of interest to examine to what extent factors exist that have an impact on the development status of the investigated applications. Such a context-based analysis is particularly relevant for the identification of the potential of blockchain technology in the area of environmental and climate protection. If factors can be determined that are proven to contribute to the operational activity of an application, they can be used for future scientific considerations or to obtain recommendations for newly founded applications. For this purpose, we perform ordered logit regressions to estimate the probability of success of green blockchain applications. The success of an application is proxied with the dependent variable *AppStatus* that distinguishes between the ordered stages of startup phase, in preparation, and operational. The phases in preparation and operational are interpreted as being achievements, albeit to a different degree, since only realized projects can actively contribute to climate protection. The specification of the threshold model based on an unobserved linking variable, which presents the development status of a green blockchain-based application i, is as follows:

$$y_i^* = \beta\, x_i^{'} + \varepsilon_i\,,$$

where $x_i^{'}$ is a vector of observed, explanatory variables describing application-specific characteristics such as the type and sector of activity, origin or company size as well as blockchain-specific characteristics including the employed blockchain technology and consensus mechanism, or the implementation of tokens. The variable β represents a vector of slope coefficients and the term ε_i is the error term. In addition, we assume that while y_i^* cannot be directly observed, we can objectify the three varied categories of development. Consequently, the variable y_i^* is assigned to 1 if the application is in the startup phase, 2 if it is in the preparatory phase, and 3 if it is operational:

$$y_i^* = \begin{cases} 1 & \text{if } y_i^* > cut_1 \\ 2 & \text{if } cut_1 < y_i^* < cut_2 \\ 3 & \text{if } cut_2 < y_i^* \end{cases}$$

where the thresholds cut_i is estimated in the course of the statistical maximum likelihood estimation. We apply Eicke-Huber robust standard errors to all regression models. To begin with, the focus lies on the effect of application-specific and blockchain-specific influential factors individually. In the second setting, both aspects are combined in order to obtain a more complete picture of the determinants. Because the application for an ICO is highly correlated with the implementation of tokens, we analyze the effect of ICOs and tokens separately.

Table 4.1: Definition of the variables

Variable	Description
Application specific variables	
AppStatus	Categorical variable for the current status of the application, classified by the categories startup phase, in preparation, and operational. Reference category: startup phase
AppType	Application types include crowdfunding, data verification, emission rights, platform for various applications, reward system, control of electricity networks & electricity trading, and peer-to-peer (P2P) trading. In the regression dataset platform for various applications and reward system are summarized as platform & reward. Also, P2P trading, control of electricity networks, and electricity trading are aggregated as energy trading. Dummy variables.
AppSector	Categorical variable defining the sectors of activity. Sectors are agriculture & forestry, general sustainability, mobility, renewables, and water management. Agriculture & forestry and water management are subsumed as agriculture & forestry & water in the regression dataset. Reference category: agriculture & forestry & water
Company_specifics	Company specifics refer to the size and properties of the company offering the green blockchain application including very small (<10 employees), small (11-50 employees), medium (51-200 employees), large (>200 employees), scientific, very small nonprofit (<10 employees), small nonprofit (11-50 employees), and unknown. Dummy variables.
Size	Categorical variable based on the variable *Company_ specifics* and distinguishing between company sizes small (very small & small profit & nonprofit as well as scientific companies, <50 employees), medium (51-200 employees), large (>200 employees), and unknown. Reference category: unknown
Country	Country in which the application has been released.
Continent	Continents of origin include Africa, Asia, Australia, Europe, North America, and unknown. The categorical variable in the regression dataset is split between Europe, North America, AfricaAsiaAustralia (Africa, Asia and Australia), and unknown. Reference group: unknown
Blockchain specific variables	
Blockchain	The applied blockchain technologies include Cosmos network, Cosmos network based, Energy Web, Ethereum, Ethereum based, Hyperledger Fabric, Individual blockchain, IOTA, R3 Corda, Skyfiber, SolarCoin, Stellar and Unknown. In the regression dataset the dummy variables Ethereum, Individual, Other (Cosmos, Energy Web, Hyperledger Fabric, IOTA, R3 Corda, Skyfiber, SolarCoin, Stellar), and unknown define the blockchain. The dummy variable alternative blockchain subsumes individual, and other blockchains.
Consensus	The implemented consensus mechanisms are delegated proof-of-stake (DPOS), Federated Byzantine Agreement (FBA), Obelisk, practical Byzantine-fault-tolerance (Practical_BFT), proof-of-authority (POA), proof-of-cooperation (POC), proof-of-fusion (POF), proof-of-production (POP), proof-of-reputation (POR), proof-of-stake (POS), proof-of-stake-time (POST), proof-of-work (POW), and unknown. The categorical variable in the regression dataset distinguishes between the applied consensus mechanisms alternative (FBA, Practical_BFT, POA, POC, POF, POP, POR, Obelisk), POW & POS (POS, POST, DPOS), and unknown. Reference group: unknown
Token	Binary variable with the value of one if the application utilizes tokens ("Yes"), zero otherwise ("No").
TokenType	Variable describing the type of the token. Token types are currency token, equity token, security token, utility token, undefined, and none. Dummy variables. In the regression subsample the dummy variable Other includes security, currency, and unknown token types.
TokenBase	Type of blockchains on which the token is based inlcude Ethereum, Ethereum compliants, individual blockchain, SolarCoin, Stellar, undefined, and none. Categorical variable in the dataset for the token's blockchain base is divided into Ethereum (Ethereum, Ethereum compliant), Other (Individual, SolarCoin, Stellar or undefined), and none. Reference group: none
TokenICO	Variable stating whether the application has either successfully conducted an ICO ("Yes") or not ("No") or "Canceled" the ICO.
ICO	Binary variable with the value of one if the application has conducted an ICO ("Yes", "Canceled"), zero otherwise.

4.4 Results

4.4.1 Descriptive statistics

Our dataset contains both nominally and ordinally scaled characteristics. The descriptive statistics for the dataset are reported in Table 4.2 through Table 4.4. The frequency analysis for the sample of 85 green blockchain applications during the observation period of April 2019 through July 2019 provides an initial indication of the current green blockchain landscape. A short overview of the main results is provided here and an in-depth elaboration follows in Section 4.4.2. It is important to note, however, that individual applications can be assigned to several different types of applications simultaneously. With a modal value of 28.43%, P2P trading represents the biggest field of applications and is followed by crowdfunding, data verification, and emission rights (13.73% each). The majority of applications are found in the sectors of *renewable energies* (61.18%) and *general sustainability* (28.24%). Regarding the development status, we observe that the majority of applications are either in the preparation phase or still in the startup stage. Interestingly, only 15.29% of the applications are already operational.

Due to the fact that one selection criterion involves activity or new information concerning the application within the two preceding years, the distribution can be partially explained by a deficit of information resulting in applications being assigned the latter status. This deficit highlights a general problem concerning many blockchain-based applications. The analysis evidences that the countries of origin of the examined blockchain applications are relatively diverse (see Table 4.3). Furthermore, we find that companies offering green blockchain applications are generally very small or small with fewer than 50 employees, and 10.59% and 2.35% of the companies have a nonprofit or scientific purpose, respectively. With respect to blockchain-specific characteristics, Ethereum constitutes the most commonly used blockchain (42.22%) and is succeeded by the characteristic values of unknown and individual (see Table 4.4). When looking at the consensus mechanisms, the modal value for unknown algorithms equals 64.71%. POW and POA rank second and third. The results can be partially explained by the fact that only consensus mechanisms that are explicitly stated are taken into account. Furthermore, the two-dimensional frequency distribution of 48.24% highlights the importance of implementing an ICO when distributing tokens. The decision to neither apply for an ICO nor to offer tokens constitutes the second most common combination. Owing to the interdependence of issuing tokens and carrying out an ICO, the combination of either conducting an ICO or aborting it while not offering tokens does not exist. Finally, 70.58% of the applications under review utilize tokens.

In the course of the regression analysis, the characteristic values of several features are summarized if the characteristic values exhibit only a small number of observations. With respect to the sector of activity, the sectors *agriculture and forestry* and *water management* are subsumed. We also combine the application types entitled reward system and platform for various applications as both attributes aim at promoting sustainable behavior through various mechanisms. Moreover, P2P trading, electricity trading, and the control of electricity networks are aggregated to energy trading because all activities revolve around the advancement of green energy trading. We group the countries of provenance by assigning them to their respective continents, whereby Russia is included in Europe. Because only very few applications originate from Asia, Australia, or Africa, these observations are combined within one category. We thus use the frequency distribution of the applications in the dataset as the distinguishing feature rather than the population density. In addition, we create the feature size, which is a modi-

Table 4.2: Descriptive statistics of the dataset: Application-specific variables

Notes: The entire data sample contains 85 green blockchain applications. Absolute values and relative values of the variables are displayed. The variables are defined in Table 4.1.

Variable	**Observations**	**Relative frequency in %**
AppType		
AppType_Crowdfunding	14	13.73
AppType_Data verification	14	13.73
AppType_Emission rights	14	13.73
AppType_Platform various applications	10	9.80
AppType_Reward system	11	10.78
AppType_Control of electricity networks	7	6.86
AppType_Electricity trading	3	2.94
AppType_P2P trading	29	28.43
AppSector		
AppSector_Agriculture & forestry	3	3.53
AppSector_Mobility	2	2.35
AppSector_Renewables	52	61.18
AppSector_Water management	4	4.71
AppSector_General sustainability	24	28.24
AppStatus		
AppStatus_Startup phase	16	18.82
AppStatus_In preparation	56	65.88
AppStatus_Operational	13	15.29
Company_specifics		
Company_specifics_Very Small	24	28.24
Company_specifics_Very Small nonprofit	5	5.88
Company_specifics_Small	33	38.82
Company_specifics_Small nonprofit	4	4.71
Company_specifics_Scientific	2	2.35
Company_specifics_Medium	3	3.53
Company_specifics_Large	4	4.71
Company_specifics_Unknown	10	11.76
Continent		
Continent_Africa	2	2.35
Continent_Asia	10	11.76
Continent_Australia	3	3.53
Continent_Europe	45	52.94
Continent_NorthAmerica	19	22.35
Continent_Unknown	6	7.06

Table 4.3: Descriptive statistics of the dataset: *Country*

Notes: The entire data sample contains 85 green blockchain applications. Absolute values and relative values of the variables are displayed. The variables are defined in Table 4.1.

Country	**Observations**	**Relative frequency in %**
Andorra	1	1.18
Australia	3	3.53
Austria	1	1.18
Bangladesh	1	1.18
Belgium	1	1.18
Canada	2	2.35
China	1	1.18
Estonia	1	1.18
France	4	4.71
Great Britain	6	7.06
Germany	10	11.76
HongKong	2	2.35
Ireland	1	1.18
Israel	1	1.18
Italy	1	1.18
Jordan	1	1.18
Lithuania	1	1.18
Malta	1	1.18
Mauritius	1	1.18
Netherlands	5	5.88
Romania	1	1.18
Russia	1	1.18
Singapore	4	4.71
Slovenia	2	2.35
Spain	3	3.53
Sweden	1	1.18
Switzerland	4	4.71
UAE	1	1.18
US	17	20.00
Unknown	6	7.06

fied version of the criterion company-specific characteristics that differentiates between small, medium, and large companies. In view of blockchain technology, a huge variety of different underlying methods is observed.

We build on the frequency distribution and the importance of the blockchains in assigning the observations to new groups. Consequently, we arrive at four different characteristics being the individual blockchain, Ethereum, other blockchain, and unknown blockchain. Some models add other and individual blockchains to the category alternative blockchains. Moreover, proof-of-stake, proof-of-stake-time and delegated proof-of-stake are subsumed under POS and distinguished from POW. The alternative consensus mechanism summarizes all remaining consensus algorithms. Finally, the underlying blockchain types of tokens are aggregated into the categories of Ethereum-based or compliant, other, and unknown. We retain observations with unknown characteristic values as we are interested in whether companies that stand out due to increased information transparency perform better. Table 4.13 presents the resulting descriptive statistics for the regression dataset. Because the regression dataset simply subsumes observations into larger categories, the results are similar to the ones described above.

4.4.2 Analysis of the green blockchain-based applications landscape

In view of the research objective of painting a profound picture of the current state of green blockchain-based applications globally, we build on the descriptive statistics and analyze the extent to which the theoretical potentials of blockchain technology are put into practice. This analysis enables us to assess the current contribution of blockchain applications in the area of environmental and climate protection. To begin with, the main field of applications is P2P trading with 29 applications followed by crowdfunding, data verification, and emission rights with 14 applications respectively. While 61.18% of the applications operate in the sector *renewable energies*, one quarter can be assigned to *general sustainability*. The remaining observations are virtually evenly distributed across *agriculture & forestry*, *water management*, and *mobility*. We identify five major combinations of application type and sector that exhibit the highest two-dimensional frequencies, being P2P trading & *renewable energies* (31.76%), emission rights & *general sustainability* (15.3%), control of electricity networks & *renewable energies* (8.2%), platform for various applications & *renewable energies* (8.2%), and reward system & *renewable energies* (8.2%). Based on the frequency distributions, we identify P2P trading in the renewable energies sector as being a promising application for blockchains due to its decentralized concept. Above all, smarter renewable energy deployment, improved access to electricity, ameliorated, efficient and sustainable energy creation, and distribution prove to be the major benefits. In many parts of the world, the initial operational applications already exist in this field and comprise the majority of observations in our dataset although they are still operating on a small scale or carrying out pilot projects. These include “Brooklyn Microgrid”, “ElonCity”, “Greeneum”, or “WePower”, just to name a few.

Second, the possibility of creating digital assets by converting sustainable projects and global public goods into tokens and creating a secondary market for these investments demonstrates the suitability of blockchains for emission rights in the *general sustainability* sector. The business models of companies such as “1Planet”, “CarbonX”, or “EarthToken” are constructed on these aspects. However, the current contribution to climate protection can be regarded as marginal as in practice the majority of these applications is still in the planning phase. In addition, common combinations in the *renewable energies* sector can be found with applications of the type control of electricity networks, platform for various applications, and reward

Table 4.4: Descriptive statistics of the dataset: Blockchain-specific variables

Notes: The entire data sample contains 85 green blockchain applications. Absolute values and relative values of the variables are displayed. The variables are defined in Table 4.1.

Variable	**Observations**	**Relative frequency in %**
Blockchain		
Blockchain_Cosmos network	2	2.22
Blockchain_Cosmos network based	1	1.11
Blockchain_Energy Web	3	3.33
Blockchain_Ethereum	38	42.22
Blockchain_Ethereum based	5	5.56
Blockchain_Hyperledger Fabric	4	4.44
Blockchain_Individual blockchain	9	10.00
Blockchain_IOTA	1	1.11
Blockchain_R3 Corda	1	1.11
Blockchain_Skyfiber	1	1.11
Blockchain_SolarCoin	2	2.22
Blockchain_Stellar	5	5.56
Blockchain_Unknown	18	20.00
Consensus		
Consensus_DPOS	1	1.18
Consensus_FBA	3	3.53
Consensus_Obelisk	1	1.18
Consensus_POA	5	5.88
Consensus_POC	1	1.18
Consensus_POF	1	1.18
Consensus_POR	1	1.18
Consensus_POP	1	1.18
Consensus_POS	3	3.53
Consensus_POST	2	2.35
Consensus_POW	8	9.41
Consensus_Practical_BFT	3	3.53
Consensus_Unknown	55	64.71
Token	60	70.59
TokenType		
TokenType_Currency	3	3.30
TokenType_Equity	12	13.19
TokenType_Security	6	6.59
TokenType_Utility	38	41.76
TokenType_Undefined	7	7.69
TokenType_None	25	27.47
TokenBase		
TokenBase_Ethereum	25	29.41
TokenBase_Ethereum compliant	5	5.88
TokenBase_Individual blockchain	1	1.18
TokenBase_SolarCoin	1	1.18
TokenBase_Stellar	3	3.53
TokenBase_Undefined	25	29.41
TokenBase_None	25	29.41
TokenICO		
Yes	5	5.88
No	44	51.76
Canceled	36	42.35

system. Blockchains enable the precise traceability of electricity generation or storage, thereby paving the way for more efficient and demand-driven energy supply. Green applications of the crowdfunding type are mainly found in the sectors of *general sustainability* and *renewables* with minor activities in *agriculture* and *water management*, for example with “Poseidon” or “GainForest”. In comparison, data verification activities focus on the sector renewables. Taken together, our dataset provides evidence of a broad spectrum of green blockchain-based applications. Interestingly, the frequency distribution of the fields of activity is consistent with the key areas in which blockchain can be advantageous in enhancing climate actions according to United Nations Climate Change (2017).

While 75% of the applications are based in Europe (52.94%) and North America (22.35%), it is immediately obvious that the supply of green blockchain applications in Central or South America and Africa is virtually non-existent. Even though the dataset evidences the notable focal points US, Germany, Great Britain, and the Netherlands for green blockchain applications, we assess the geographical distribution and consideration of developing countries positively. Moreover, a number of the applications under review include the supporting aspect stated in Article 4 of the Paris Agreement (United Nations Framework Convention for Climate Change, 2015). By raising funds via carbon offsetting products, these applications finance projects in developing countries. Overall, the geographical origin of the applications is not surprising because one cannot expect that financial resources for the implementation of innovative blockchain solutions are available in developing countries.

Furthermore, the high proportion of small companies suggests limited financial strength behind most applications in the dataset. Interestingly, only 9.10% of the applications stemming from scientific and nonprofit organizations are already operational. Medium-sized companies exhibit the highest share of operational applications (33.3%). We can hence deduce that, in particular, private and profit-oriented companies invest in green blockchain applications. The frequency distribution can be seen as an indication of the innovative character and emerging trend of green blockchain applications. The majority of these small companies are startups that have been established specifically for the purpose of developing green applications, whereas large companies often develop the blockchain applications external to their core business. While the use of blockchain by small companies can be regarded as an important opportunity to test varied application possibilities, to gain popularity and to increase user confidence, a closer integration of the technology into green processes of larger companies is desirable, as their financial strength and scope could foster a nationwide implementation. A higher quota of scientifically oriented applications could expand the state of research, which is also beneficial to private companies.

A closer look at the status of the applications under review enables an assessment of the current contribution of green blockchain applications to climate protection. With the majority of applications still being either in the preparatory or in the startup phase, we evaluate the present contribution as being small. Assuming that probably not all of the applications tagged with *in preparation* are still active reduces the estimated contribution to environmental protection.

With regard to the blockchains and employed consensus mechanisms, the extensive variety of 13 different blockchain technologies among the examined applications can be seen positively because the blockchains exemplify customized planning and a wide-ranging level of technological development. We therefore ascertain that green blockchain applications aim at fitting the business model to the most promising system architecture. Over a fifth of all applications investigated do not provide information about the blockchain used, which is a factor that should be viewed critically. There are two ways of explaining this finding. Either the company is still in the preparatory phase and has not yet selected the appropriate blockchain, or the application is based on unsafe or unsustainable blockchain technologies, which complicates the assessment of their environmental contribution. The predominant use of Ethereum can partly be explained by its leading position in the field of smart contracts, which is especially beneficial to applications in the renewables energy sector.

In view of the energy requirements, the actual contribution of these applications to environmental protection is questionable if one assumes that the platforms applying Ethereum follow the PoW mechanism. The plans of Ethereum to move to a PoS mechanism, though, would augment the contribution to sustainability notably. The second most common occurrence is PoW standing at 9.41%, followed by PoA at 5.88%. Our empirical analysis also reveals that a wide range of alternative mechanisms is already employed, which indicates the endeavors to adopt more energy efficient mechanisms and enhance green DLT applications. However, almost 65% of the applications under review do not provide information on the applied consensus mechanism.

Our study reveals that 70.59% of the applications utilize tokens and that almost half of them combine it with the pursuit of an ICO. However, when we take one-dimensional characteristics into account, we find only marginal differences between pursuing and waiving an ICO. We show that a quarter of the applications planning an ICO are either operational or in the startup phase. Assuming that not all ICOs graduate to successful operational activities, the contribution to environmental protection may be reduced. The tokenization of assets such as carbon paves the way for increased interoperability of emission-trading systems and can be a stimulus for data generation and exchange in MRV systems, which is also evidenced by the high ratios of token usage in these application types (85% and 100%). We evidence that these theoretical options are already put into practice with an implementation rate of 85% across crowdfunding applications. Moreover, the data reflect that using tokens to incentivize sustainable actions appears to be a popular measure.

4.4.3 Logit Regressions

To gain further insights into the factors related to the success of green blockchain applications, which is proxied with the dependent variable *AppStatus*, we carry out ordered logit regressions. While models 1 to 2 and models 3 to 4 focus on the effect of application-specific (e.g., type and sector of activity, company size) and blockchain-specific (e.g., blockchain technology, consensus mechanism, tokens) characteristics individually, models 5 and 6 combine both aspects to create a more complex picture of the determinants of operability. The results of the estimated models are presented in Table 4.5.

The effect of application-specific determinants is investigated with the use of several variables. To begin with, neither the continent of origin nor the company size have a significant effect on the development stage of the application. Therefore, we conclude that the economic and social conditions in the respective countries play only a subordinate role with regards to the probability of making a green DLT application marketable. However, one should keep in mind that very few of the applications examined reside in developing countries in Africa or South America. The insignificant coefficients of company size are not intuitive at first as one would expect larger companies to exhibit higher probabilities of success due to their availability of resources. Our findings highlight the accessibility of blockchain technology to all companies regardless of size and origin, and indicate that all types of companies accomplish the launch of green blockchain applications. In view of the portfolio of activities, we find significant negative

Table 4.5: Analysis of the influencing factors of *AppStatus*

Notes: Ordered logit regression analyzing the influencing factors of the ordinal variable *AppStatus* (with the categories of startup phase, in preparation and operational) based on application characteristics (models 1-2) and blockchain characteristics (models 3-4). Models 5 and 6 combine both types of features and account for the implementation of an *ICO* or *Token* respectively. *Z*-statistics are presented within (); *, ** , and *** denote statistical significance at the 10%, 5%, and 1% levels. Eicke-Huber-White heteroskedastic-consistent standard errors are used. R^2 present pseudo MacFadden R^2 values. Variables are defined in Table 4.1.

	1	2	3	4	5	6
Application-specific factors						
Continent_AfricaAustraliaAsia	0.325					
	(0.38)					
Continent_Europe	0.0749	-0.108			-0.306	-0.213
	(0.09)	(-0.20)			(-0.46)	(-0.34)
Continent_NorthAmerica	0.225	-0.0186			-0.471	-0.200
	(0.25)	(-0.03)			(-0.68)	(-0.31)
Size_Small	0.0228	0.0377			0.532	0.445
	(0.02)	(0.05)			(0.72)	(0.59)
Size_Medium	-0.947					
	(-0.33)					
Size_Large	-0.776					
	(-0.60)					
Size_MediumLarge		-0.632			-0.527	-0.688
		(-0.47)			(-0.36)	(-0.45)
AppSector_Mobility	-2.110*	-1.697*			-1.207	-1.418
	(-2.09)	(-2.19)			(-1.17)	(-1.46)
AppSector_General sustainability	-0.976	-0.604			-1.011	-0.925
	(-1.38)	(-0.99)			(-1.53)	(-1.33)
AppSector_Renewables	-1.179	-0.495			-0.504	-0.551
	(-1.03)	(-0.70)			(-0.64)	(-0.70)
AppSector_Water management	-0.965					
	(-0.87)					
AppType_Crowdfunding	-1.383	-1.431			-0.897	-0.912
	(-1.34)	(-1.82)			(-1.08)	(-1.04)
AppType_Data verification	-1.118	-1.409			-1.832	-1.471
	(-1.09)	(-1.47)			(-1.84)	(-1.40)
AppType_Emission rights	-2.275	-2.457*			-1.839	-1.771
	(-1.66)	(-2.13)			(-1.42)	(-1.27)
AppType_P2P trading	-1.508					
	(-1.72)					
AppType_Reward system	-0.769					
	(-0.57)					
AppType_Platform various applications	-0.212					
	(-0.20)					
AppType_Platform & reward		-0.651			-0.563	-0.335
		(-0.67)			(-0.66)	(-0.35)
AppType_Electricity networks & trading	-0.821					
	(-1.14)					
AppType_Energy trading		-2.079**			-2.166**	-1.960*
		(-2.63)			(-2.67)	(-2.45)
Blockchain-specific factors						
Blockchain_Ethereum			-1.335	-0.949	-1.216	-1.263
			(-0.78)	(-0.55)	(-0.78)	(-0.86)
Blockchain_Individual			-1.168	-1.053		
			(-0.73)	(-0.67)		
Blockchain_Other			-0.441	-0.528		
			(-0.28)	(-0.32)		
Blockchain_Alternative					-0.535	-0.644
					(-0.37)	(-0.49)
Blockchain_Unknown			-2.048	-1.462	-1.197	-1.250
			(-1.11)	(-0.81)	(-0.75)	(-0.85)
ICO			0.0847	0.0129	-0.795	
			(0.15)	(0.02)	(-1.16)	
Token						-0.637
						(-0.74)
Consensus_Alternative			-1.109			
			(-1.89)			
Consensus_POS			2.072*	2.410**	2.435**	2.389*
			(2.15)	(2.63)	(2.71)	(2.56)
Consensus_POW			-0.132			
			(-0.12)			
TokenBase_Ethereum			-0.834	-0.941		
			(-0.79)	(-0.86)		
TokenBase_Other			0.118	0.00813		
			(0.13)	(0.01)		
TokenType_Equity			-1.243	-0.964		
			(-1.39)	(-1.19)		
TokenType_Utility			0.515	0.474		
			(0.71)	(0.64)		
TokenType_Other			0.533	0.489		
			(0.83)	(0.74)		
cut_1	-4.138*	-4.148**	-3.223	-2.714	-5.356**	-5.250**
	(-2.28)	(-3.25)	(-1.90)	(-1.59)	(-2.66)	(-2.71)
cut_2	-0.618	-0.581	0.583	1.007	-1.447	-1.378
	(-0.36)	(-0.48)	(0.36)	(0.62)	(-0.78)	(-0.78)
N	85	85	85	85	85	85
R^2	0.0705	0.0776	0.1361	0.1199	0.1509	0.1428
Chi^2	21.28	19.25	25.67	20.31	27.85	28.65
$p > Chi^2$	0.214	0.0828	0.0188	0.0413	0.0467	0.0379

coefficients for energy trading. Green applications conducting business of the type energy trading, i.e., controlling electricity networks, trading energy or participating in P2P trading are, hence, less likely to become operational. This finding is intriguing because companies that are active in these fields will need to employ additional efforts in order to progress. In contrast, the sector in which the application operates has no significant effect. Apart from *mobility*, all sectors exhibit insignificant coefficients in relation to the reference category of *agriculture, forestry & water management*, though the significance becomes indistinguishable in the combined model.

Regarding the blockchain-specific influencing factors, the coefficients of the distinct blockchains are insignificant. This implies that choosing between a well-established blockchain technology such as Ethereum, emerging blockchains, and the development of its own blockchain does not affect the probability of success. In addition, companies that do not report on the applied blockchains do not appear to suffer due to the missing transparency of information in progressing to more elaborated stages. The consensus mechanism constitutes one of the biggest differences across applications. While the coefficients of POW and alternative consensus algorithms exhibit insignificant coefficients, we find significantly positive coefficients for POS mechanisms. One explanation could be that users appreciate the comparatively better energy efficiency of POS mechanisms and the alignment of the superordinate objective of environmental contribution with the technological requirements of the application, which, in turn, may advance the progress of the application. In view of pursuing an ICO, the results do not confirm a significantly positive effect for green blockchain applications. We therefore infer that financial grants from ICOs are not vital as other financing options exist. Our results are, hence, in line with Adhami et al. (2018) and Ernst & Young (2017), who report mixed evidence regarding whether ICOs can be deemed a success factor or not. This finding is particularly interesting because ICOs are also accompanied by risks and costs. Even though almost 71% of the applications under review make use of tokens, we cannot validate that tokens increase the probability of success. Regarding the token types, we do not find significant differences. This finding is interesting as the value of utility tokens, which are not scrutinized by federal laws, is contingent on the amount and activity of the users on the platform, whereas the value of equity tokens is generally more volatile due to its dependence on the success of the application. We also show that whether the token is Ethereum-based or compliant has no impact on the developmental stage.

In models (5) and (6), we conduct a more detailed analysis and combine the application and blockchain dimension to check for possible interdependencies. The results are similar to the individual models. Neither size- nor origin-related characteristics influence the probability of success. With respect to the fields of activity, the negative coefficients of the application type "energy trading" confirms the negative relationship between these types of activity and the chances of becoming operational. The results still hold when blockchain-specifics are factored in. When considering the sector of activities, the combined models exhibit insignificant coefficients. The blockchain-specific variables such as the blockchain technology or the decision to realize an ICO or utilize tokens do not appear to be influential factors. Green applications based on PoS consensus mechanisms have higher probabilities of becoming operational even when accounting for application-specific factors. In total, our results provide valuable insights into answering the question of which characteristics further promote the development of green applications. This answer is of particular interest when evaluating the capability of blockchain applications to drive sustainability.

4.4.4 Discussion of results

Against the background of the empirical results, we identify recommendations for actions to further exploit the potential of blockchain in driving environmental actions. In general, companies of all sizes and origins have the potential to successfully establish green blockchain applications. To date, becoming operational to contribute to sustainability presents the most significant challenge. As the blockchain market is still very young, we assume that the ratio of operational applications will increase in the future. Nevertheless, the ongoing projects provide an excellent opportunity to gain more experience and lay the foundation for more widespread use. We provide evidence that renewable energy trading systems, carbon emission trading schemes, the raising of funds, and the monitoring and reporting frameworks for emissions constitute the key fields of activities of the blockchains applications under review.

While the majority of applications under review operates in the renewables sector, the logit regression model yields reduced chances of success for businesses dealing with energy trading, i.e., controlling electricity networks, trading electricity, and participating in P2P trading. However, adjusting the consensus mechanisms and choosing, for example, a PoS mechanism could enhance the probability of becoming operational. In order to increase their contribution to climate protection, integration into the central power grid is required because these mechanisms have been processed only within microgrids thus far. The passage of the renewable energy directive II and the internal electricity market directive by the European Union, however, are expected to advance the development of grid solutions by promoting innovative, small-scale renewable energy projects, empowering prosumers by strengthening their rights and highlighting related investment opportunities (European Parliament, 2018, 2019). Furthermore, geographic islands in particular have and will benefit from implementing blockchain technology in renewable energy production and trading with regards to monitoring and trading renewable energy, and becoming independent from the mainland. Blockchain-based renewable energy projects such as SkyCoin in Singapore, Community Power on the island of Samsø or Power Ledger in Australia successfully demonstrate positive effects on society, economy, and the environment (Andoni et al., 2019). As power grids are currently centrally powered, the contribution to sustainability can be classified as small. Consequently, we expect no nationwide establishment of blockchain technology in this area.

In view of the importance of data immutability and traceability in successfully establishing emission-trading systems, we suggest intensifying the development of activities in this area. For efficiently using blockchains to trade emission-balancing products among different nations, all players involved should develop a common implementation plan. The field of action is broad and encompasses, among other things, coordinated legislation as the basis for successful trading. A combination of different mechanisms could increase the efficiency of climate markets. Pilot markets should be selected to test blockchain technology under real conditions. It is also important to take into account the future growth of climate markets when creating the technological designs and selecting system architectures.

Blockchain technology enhances financial inclusion through the provision of innovative solutions to raise capital. Based on the frequency analysis, we propose to intensify efforts in this field. In particular, tokens and cryptocurrencies have the potential to improve result-based climate finance through the reduction of costs and increase in efficiency of raising capital, the creation of positive network effects by means of direct P2P transactions, and the facilitation of access to sustainable and new forms of investments which could be essential means in closing the financing gap. In addition, the possibility to transparently track funds flows determines the technology as being highly relevant. Enhancement of supply chain transparency, the potential to revolutionize commodity trade, and the possibility to monitor adaptation measures such as water projects will probably lead to an increase of applications in these fields in the future (Galen et al., 2018; Nassiry, 2018; Neves and Prata, 2018). Besides, applications should continue to integrate developing countries into their business models, thereby bringing this technology closer to the population on the one hand and exploiting the full potentials on a global scale on the other hand.

If applying blockchain technology in government agencies or state apparatus, the utilization of blockchains with restricted access should be considered in order to enable the use of confidential data. In order to ensure the maximum benefits from blockchain implementation, one should check to what extent the decentralized mode of operation of a blockchain matches the respective application and which system architecture provides the best fit. In view of the negative externalities of blockchain technology, the use of the PoW mechanism should be discouraged due to the poor level of energy efficiency. Alternative consensus mechanisms provide more efficient and climate friendly options, and applying the PoS mechanism even has a significant, positive effect on the performance of green applications. In addition, regulatory containments can reinforce the development towards more environmentally friendly consensus mechanisms. Above all, policymakers should establish a solid method to measure the net efficiency of green blockchain applications by comparing the reduction in CO_2 emissions with the CO_2 emissions generated by the blockchain's energy consumption.

Further research on DLT and its compatibility with other industry 4.0 technologies should be conducted to fully exploit the potential of green blockchain applications. We recommend accelerating the advancement of blockchain technology by providing more funding for science. In addition, governments should move DLT more into the public focus aiming at dispelling skepticism concerning the technology and resolving the perceived risk of illegal conduct. Despite the insignificant effect of blockchain technology on the performance of the application, we believe that stricter requirements regarding the applied technology and consensus protocol would improve customers' experience. Flexible legal and regulatory frameworks that do not conflict with regulations from other countries also play a crucial role. Solving the current challenges through stricter and harmonized jurisdictions, information requirements for ICOs, regulatory sandboxes, and investor and governmental education will be essential to further advance the opportunities of tokens and ICOs and, hence, achieve the Paris Agreement targets.

4.5 Conclusion and research outlook

The debate on climate change and on adaptation and mitigation measures has intensified recently. One possible solution to these questions can be seen in blockchain technology. The objective of this study is to consolidate the actual integrated landscape of green blockchain-based applications. We therefore conduct a specially designed empirical investigation following the model of inductive category development (Mayring, 2015). Based on the resulting dataset of 85 applications in the observation period between April 2019 and July 2019, we assess the contribution of these applications to climate protection as well as identifying their potential. Next, we use a logistic regression to analyze the determinants of success of these applications, taking into account application-specific and blockchain-specific characteristics. Finally, we reveal problems and make recommendations for future action.

In summary, the consolidation of the green environmentally friendly blockchain applications reveals a diverse portfolio of innovative applications. A large proportion is still in the developmental stage and operational applications are carried out only on a small scale. The current contribution to environmental protection and the implementation of the goals of the Paris Agreement can therefore be classified as marginal. Nevertheless, the experience gained and knowledge created by these projects proves to be valuable for large-scale implementations in the future. Consequently, the potential of current applications for future climate protection activities should not be underestimated.

The second part of our study builds upon these results and analyzes the factors that contribute to the performance of an application. The objective is to identify the determinants of success to promote blockchain development in digital sustainability actions. While the sector of activity is not predictive for the application's success, we do find evidence that the type of activity significantly affects the probability of becoming operational. Applications conducting business in the area of energy trading, i.e., controlling electricity networks, trading electricity, and participating in P2P trading, are less likely to advance to the operational stage. Company specifics such as the size or origin are not influential factors for the different stages. Our findings highlight the accessibility of blockchain technology for all companies and indicate that all types of companies can accomplish the launch of green blockchain applications. In view of blockchain-specific characteristics, we demonstrate that differences across blockchain types do not exist. However, we show that selecting the correct consensus mechanism plays a crucial role. Choosing a PoS consensus algorithm significantly increases the chances of putting the application into practice. This finding demonstrates a double positive effect as the PoS mechanism is notably more energy efficient and at the same time the probability increases that it will become operational and, thus, contribute to sustainability. Consequently, prioritizing the consensus mechanism issue is fundamental. Finally, neither the implementation of tokens nor the execution of an ICO have an effect on the status of the application. Based on this, emerging companies can weigh up the respective advantages and disadvantages of an ICO, especially since the termination of an ICO can lead to delays or even cancellations of projects, thereby reducing the possible contribution to climate protection.

In conclusion, the empirical findings provide evidence of the opportunities of blockchain technology in driving environmental action. The detailed analysis of the current application portfolio and the identification of success factors generate valuable insights for exploiting the potential of current and future applications for forthcoming climate protection activities. Further research on the technology, legal regulations, governance, and increased user confidence will be able to initiate a large-scale blockchain offensive. In particular, the combination with other technologies such as artificial intelligence, big data, and IoT will reinforce the effect of green blockchain-based applications in driving climate protection.

The contribution of this article is twofold. First, we paint a profound picture of the current state of green blockchain applications in global terms. In view of the growing interest in climate change and the need to act on a global scale, we provide an extensive overview of existing mitigation and adaptation measures based on blockchain technology. We hereby illustrate diverse fields of action and point out possible, future directions. Knowledge about these applications and their potential in tackling climate change enables investors, politicians, and citizens to drive this development forward through diverse support opportunities. Second, we contribute to current research by highlighting the success factors of blockchain applications. The empirical results provide valuable implications for the developers of blockchains and the respective companies, which should aid them in designing the development process more efficiently. Our findings are also of particular interest for political institutions regarding the provision of the necessary legal and political framework for green blockchains applications so that they can thrive.

One possible limitation of the study refers to the relatively small dataset of 85 applications, which also contains a high ratio of applications in the planning phase. Nonetheless, we regard the sample of applications to be representative for the global universe of green finance applications. Since the information quality and variety of many applications are often not comprehensive enough for quantitative analyses, more in-depth qualitative studies of individual applications could uncover further potential. We recommend continuously updating and re-analyzing application portfolios, since the entire field of DLT is still very young and changing rapidly. Regulatory adaptions can lead to the need for further examination. Furthermore, it will be crucial to investigate the energy consumption of the employed consensus mechanisms in deeper detail to be able to relate the carbon-dioxide emission saved by the application to the emissions caused by its implementation. Additionally, long-term studies can be used to identify other success factors for blockchain applications in the area of environmental protection. In order to be able to evaluate the implementation of ICOs and the use of tokens positively or negatively, in-depth studies are required. Further empirical analyses, which consider different forms of financing, prevailing startup capital, and verifiable financial results, could be of interest here. All in all, a sound basis is especially important for the acceptance of the technology and its continuous development.

4.6 Appendix

4.6.1 Data collection method

To begin with, selection criteria for green applications have been defined to create the population of our analysis. Based upon the research objective of this article, the core condition for the inclusion in the data set is the positive contribution to climate protection with the help of blockchain mechanisms. For a superior classification of the selection criteria the three categories content-related, formal and time-related criteria have been established. Content-related criteria are linked to the overarching goal of climate protection and require a clear description of the functionality, purpose and the impact of the blockchain-based application in achieving this objective. The reasoning behind applying blockchain technology and its technical functionality within the application have to be defined whereby the sole payment handling of cryptocurrencies does not qualify for entering the data set. Furthermore, the unique carriers in the population need to follow an autonomous business model and, hence, do not belong to a superordinate conglomeration of applications (formal criteria). In addition, the carrier has not been added to the data set under a different company name. Clear evidence of the activity or the utilization of the active application within the past two years as well as a development plan on the next milestones constitute the time-related conditions. The application is still active and has not been terminated. During the observation period from April 2019 through July 2019, references to these applications were obtained from scientific literature and from websites. We pursued this information and cross-checked the applications with respect to the specific inclusion requirements. This process results in a population of 85 applications that are listed in Table 4.6.

Table 4.6: Overview of the green blockchain-based applications in our dataset

Notes: Overview of the 85 green blockchain-based applications in the dataset in the observation period from April 2019 through July 2019. The companies are listed in alphabetical order. Detailed information can be found on the respective webpages.

Observation No.	Company name	Company webpage
1	1PLANET	https://climatefutures.io/
2	4NEW	https://4new.io
3	Bflow	https://bflow.io/
4	Blockchain for Climate Foundation	https://www.blockchainforclimate.org
5	Brooklyn Microgrid	https://www.brooklyn.energy/
6	Carbon Chain	https://carbonchain.org/
7	Carbon Grid	http://carbongrid.io/
8	Carbonex	https://carbonex.co/#story
9	CarbonX	https://www.carbonx.ca/#zerofootprint
10	Climate Trade	https://climatetrade.com/
11	COCOA	https://www.cocoa-ci.org/
12	Corrently	https://www.corrently.de/
13	Cryptoleaf	https://www.cryptoleaf.io
14	D3A	https://gridsingularity.com/
15	DAO IPCI	https://ipci.io/
16	Earth Token	https://earth-token.com
17	ECO2	https://www.eco2.cc/
18	Elblox	https://www.elblox.com
19	ElectriCChain	https://www.electricchain.org
20	Electron	https://www.electron.org.uk
21	ElonCity	https://eloncity.io
22	Enerchain	https://enerchain.ponton.de
23	EnergiMine	https://energimine.com/energimine
24	Energy Bazaar	https://thespindle.org/project/sinigni/
25	Energy Blockchain Labs	https://www.ibm.com/case-studies/energy-blockchain-labs-inc
26	EnergyCoin Foundation	https://www.energycoinfoundation.org/en/
27	Enosi	https://enosi.io
28	Etiblogg	https://www.etiblogg.com
29	Exergy	https://exergy.energy
30	FlexiDAO	https://www.flexidao.com/
31	freeelio	https://www.freeel.io
32	GainForest	https://gainforest.org
33	Green Assets Wallet	https://stockholmgreenfin.tech/gaw
34	Green Energy Wallet	http://www.greenenergywallet.com
35	Greeneum	https://www.greeneum.net
36	GreenRide	https://gt-int.com/
37	GreenX	https://greenx.network
38	Hive Power	https://www.hivepower.tech
39	Impact PPA	https://www.impactppa.com
40	Inuk	https://www.inuk.co
41	Irene Energy	https://irene.energy
42	IXO Foundation	https://ixo.world
43	KiWi New Energy	http://kiwinewenergy.com
44	KWH Coin	https://www.kwhcoin.com
45	Lition Energie	https://www.lition.de
46	ME SOLshare	https://www.me-solshare.com
47	Nori	https://nori.com
48	NRGcoin	https://nrgcoin.org
49	OLI	https://www.my-oli.com/de
50	Omega Grid	https://www.omegagrid.com
51	OMOS	https://www.omos.io
52	Poseidon	https://poseidon.eco
53	Power2Peer	https://power2peer.com
54	Powerledger	https://www.powerledger.io
55	PowerToShare	https://www.toblockchain.nl
56	Prosume	https://prosume.io
57	Pylon Network	https://pylon-network.org
58	Quartierstrom	https://quartier-strom.ch
59	RED	https://www.redplatform.com
60	Regen Network	https://www.regen.network
61	RobotinaROX	https://robotinarox.io
62	Smart4Hub & Water Credits	http://smart4.tech
63	Solar bankers	https://solarbankers.com/main_block.html
64	Solar DAO	https://www.linkedin.com/company/solar-dao/about/
65	Solara	https://solara.io
66	SolarCoin Foundation	https://solarcoin.org
67	SPEX	https://spectral.energy/solutions/spex
68	Sun Contract	https://suncontract.org
69	Sunchain	https://www.sunchain.fr
70	Swytch	https://swytch.io
71	Synergy	https://www.electrify.asia
72	Tal.Markt	https://talmarkt.wsw-online.de/principle
73	TenneT & sonnen eServices	https://www.linkedin.com/company/tennet/about
74	The Climate Chain	http://www.theclimatechain.org
75	The Eco Coin	https://www.ecocoin.com
76	The Energy Origin (TEO)	https://theenergyorigin.com
77	Veridium Labs	https://www.veridium.io/about.html
78	VLUX	https://vlux.io
79	Water to the World	https://www.waterfortheworld.net
80	Waterchain	https://www.waterchain.io
81	Waterledger	https://waterledger.com
82	WePower	https://wepower.network
83	World Bank Innovation and Technology Lab	https://www.worldbank.org/en/topic
84	XiWATT	https://www.linkedin.com/company/xiwatt/about/
85	Zero Carbon Project	https://www.zerocarbonproject.com

Table 4.7: Selection criteria and characteristic values: Application-specific criteria I

Notes: Overview of the application-specific selection criteria and characteristic values.

Selection criteria & characteristic values	Description
App status	The criterion app status analyzes achieved goals and future milestones to differentiate between various development statuses.
In preparation	This phase is characterized by preparatory measures, in which operational activities are not yet performed. Applications in this stage of development have already drawn up a business concept and in some cases even taken first steps, such as the completion of an ICO, however the planned business activity has not yet been verifiably started.
Startup phase	In this phase, applications have just started to implement parts of their business model on an operational level. Alternatively all planned activities have already taken up, however the application operators still designates these as test activities.
Operational	This phase is reached when feature carriers have already in part or entirely established their business model on the market and these operational activities too demonstrably take place.
App type	The selection criterion app type refers to the primary function of the application as defined in the business model.
Crowdfunding	The field of activity includes all functions with which funds for the financing of projects or other corporate goals are collected. There is no precise specification between donation-based, reward-based crowdfunding or any other type of financing. The goal is solely to generate liquidity.
Data verification	The field of activity includes all functions, with which data or environmental conditions are verified. This can be done, for example, by issuing quality seals or through the provision and compilation of specific data. The objective is the output of data in any form.
Emission rights	The field of activity encompasses all functions related to the allocation of emission rights. The goal is to counter-balance any environmentally harmful behavior through some kind of compensatory measure.
Platform various applications	As part of the activity, a platform is created that enables the development of specific applications within different fields of activity. The aim is to create a foundation that serves as a basis for small, not self-sufficient applications to create a work environment.
Reward system	The field of activity includes all functions that reward users in any manner for specific actions. The goal is to create incentives for certain behavior patterns.
Control of electricity networks	The field of activity includes all functions related to the optimization of electricity grids. These include, for example, the field of microgrids, demand-driven grid feed-in or charging systems as a supplement to power grids. The aim of all functions is the creation of a more efficient power grid.
Electricity trading	The field of activity includes trading electricity, which is explicitly not based on a P2P form. The goal is to sell electricity in exchange for an unspecified compensation.
P2P trading	The field of activity includes all functions that facilitate the trade of unspecified products between different market participants without intermediaries. The goal is to establish a needs-based exchange of various valuables or goods.
App sector	In this case, the selection criterion is the sector in which the previously determined activity is active.
Agriculture & forestry	The sector includes all fields of activity that can be assigned to agricultural and forestry thematic fields. The goal is the sustainable interaction with undeveloped lands.
Mobility	The sector encompasses areas of activity involving environmentally friendly modes of transportation. It should be clearly differentiated from the sector electric mobility. Applications that deal with electric mobility were only used as feature carriers if the for the drive required electricity comes from renewable sources. If this condition, which is also reflected in the selection criterion, is fulfilled, the application is assigned to the sector mobility. The goal is to promote resource-saving transportation.
Renewables	The sector is relevant for applications that operate in the field of renewable energies and do not necessarily focus their actions on one energy source. The aim is to further increase the use of renewable energies and to create an alternative to fossil fuels.
Water management	The sector encompasses areas of activity in which resource-saving use of water is paramount. The goal is to develop methods for reprocessing water in an environmentally friendly manner or for more efficient water handling.
General sustainability	This sector is relevant for applications whose operations are not limited to one sector. These applications carry out activities in a multi-faceted, sustainable manner. The target is to facilitate and promote sustainable actions in general.

Table 4.8: Selection criteria and characteristic values: Application-specific criteria II

Notes: Overview of the application-specific selection criteria and characteristic values.

Selection criteria & characteristic values	**Description**
Company specifics	Relevant, company-specific characteristics can be the size of the company and their goals. The classification of the number of employees in different characteristics is based on the SME definition of the Commission of the European Communities.
Very small	Companies are classified as very small if the number of employees falls below 10.
Small	Companies are classified as small if the number of employees ranges between 11 and 50.
Medium	Companies are classified as small if the number of employees ranges between 51 and 250.
Large	Companies are classified as large if their number of employees exceeds 250.
Nonprofit	Companies that identify themselves as nonprofit organizations on their LinkedIn profile, additionally receive the supplementary characteristic 'nonprofit'.
Scientific	If scientific incentives are the reason for development of the application, the carrier in addition receives the characteristic 'scientific'.
Origin	A final application-specific characteristic is the country where the individual application has its registered office.

Table 4.9: Selection criteria and characteristic values: Blockchain-specific criteria I

Notes: Overview of the blockchain-specific selection criteria and characteristic values.

Selection criteria and characteristic values	**Description**
Blockchain	The criterion blockchain refers to the underlying blockchain technology of the application.
Cosmos network	The underlying blockchain technology is the Cosmos network, a platform for building specific blockchain applications. The consensus mechanism that is mainly used is called Tendermint and a form of PBFT.
Cosmos network based	The underlying blockchain technology is based on the Cosmos network though adaptions and extensions have been made to account for the specifics of the application.
Energy Web	The underlying blockchain technology is the Energy Web, a public blockchain based on Ethereum and specifically developed for the needs of the energy industry. The applied consensus mechanism is PoA.
Ethereum	The underlying blockchain is the Ethereum blockchain, that besides enabling the transfer of the cryptocurrency Ether allows for the coding of decentralized Apps and smart contracts. The current consensus mechanism is PoW, however the move to PoS is planned.
Ethereum-based	The underlying blockchain technology is based on Ethereum though adaptions and extensions have been made to account for the specifics of the application.
Hyperledger Fabric	The underlying blockchain is Hyperledger Fabric, an open-source blockchain supported by the Linux foundation. Depending on the business concept, some form of PBFT consensus mechanism is chosen.
Individual blockchain	DLTs that have been completely redeveloped and are therefore not based on any existing blockchain have been included in the ‘individual blockchain’ category.
IOTA	The underlying blockchain is the open-source blockchain IOTA that uses the distributed ledger technology of ‘Tangle’.
R3 Corda	The underlying blockchain technology is R3 Corda, a blockchain that enables the use of smart contracts. Different consensus mechanism can be chosen.
Skyfiber	The underlying blockchain is Skyfiber, a blockchain technology that creates company-specific solutions and uses the obelisk consensus mechanism.
SolarCoin	The underlying blockchain technology is Solar Coin, that has a public system architecture and applies the PoST consensus.
Stellar	The underlying blockchain is Stellar, a public blockchain that focuses on financial transactions and allows for smart contracts. The Stellar consensus protocol replicates mechanisms of the FBA consensus algorithm.
Unknown	If the intensive research has not yielded viable information on the blockchain technology applied, the characteristic value ‘unknown’ is assigned.

Table 4.10: Selection criteria and characteristic values: Blockchain-specific criteria II

Notes: Overview of the blockchain-specific selection criteria and characteristic values.

Selection criteria and characteristic values	**Description**
Consensus	In this case, the selection criterion is the consensus mechanism applied.
Delegated proof-of-stake	The applied consensus mechanism is the delegated proof-of-stake mechanism (DPOS) that defines so-called voting delegates and witnesses for the validation process. The voting power is linked to the stakes of the nodes.
Federated byzantine agreement	The applied consensus mechanism is the federated byzantine agreement (FBA) where a small group of validators, who have been referred to as trustworthy by the network members, are responsible for the validation of transactions.
Obelisk	The applied consensus mechanism is the Obelisk protocol that distinguishes between block making nodes and consensus nodes.
Proof-of-authority	The applied consensus mechanism is the proof-of-authority protocol (POA) that can be classified as a modification of the proof-of-stake mechanism. The own identity is utilized as a pledge of security rather than the stake and authorizes participants to verify transactions.
Proof-of-cooperation	The applied consensus mechanism is the proof-of-cooperation algorithm (POC). All participants in the network acting as validators are authorized and certified as cooperatively validated nodes. Transactions are validated by the member with the longest elapsed time since the last creation of a block.
Proof-of-reputation	The applied consensus mechanism is the proof-of-reputation mechanism (POR). Authenticated participants are rewarded for their behavior in the network with points. Validation requests are then answered by the participant with the highest amount of points.
Proof-of-production	The applied consensus mechanism is the proof-of-production (POP) that has been specifically developed for saving production data. The data is transmitted via an oracle to the blockchain and automatically verified.
Proof-of-stake	The applied consensus mechanism is the proof-of-stake algorithm (POS) relating the probability of generating a block to the stakes of the nodes, i.e., to the amount of blockchain currency owned. Based on the random principle a user is chosen to add the new block to the existing blockchain.
Proof-of-stake-time	The applied consensus mechanism is the proof-of-stake-time protocol (POST), an adaption of POS that takes into consideration the elapsed time since the validation request.
Proof-of-work	The applied consensus mechanism is the proof-of-work mechanism (POW), that is based on the process of so-called mining. Miners validate transactions, group them into blocks, assign cryptographic signatures, and then need to solve complex mathematical problems with high-performance computers to concatenate these blocks to the existing blockchain.
Practical byzantine-fault-tolerance	The applied consensus mechanism is the practical byzantine-fault-tolerance (PBFT) which is rooted on the solution of the byzantine general problem. The PBFT mechanism is a multi-level validation process in which validators vote on the acceptance of a block.
Unknown	If the consensus algorithm is not explicitly declared, the consensus protocol is not derived from the implemented blockchain technology and the characteristic value 'unknown' is assigned.
Token	Another differentiating selection criterion of blockchain applications constitutes the implementation of tokens.
Yes	These applications use tokens as part of their business model.
No	These operators have not implemented tokens in their applications.
ICO	A final blockchain-based selection criterion is the distinction between the implementation of an initial coin offering (ICO) or the waiver of one.
Yes	If an ICO has already been realized or if the implementation of an ICO is already planned, the carrier receives the characteristic value 'yes'.
No	If the implementation of an ICO is not mentioned in any way by the company or is deliberately excluded, the characteristic value 'No' is assigned.
Canceled	In the event, that an ICO was started earlier, but the process has been prematurely and unsuccessfully aborted, the expression 'canceled' is used.

Table 4.11: Overview of the applications in the dataset: Application-specific characteristic values

	Company	AppType	AppSector	AppStatus	Origin	Company specifics
1	1PLANET	Emission rights	General sustainability, Agriculture & forestry	In preparation	United States	Small
2	4NEW	Control of electricity networks	Renewables	Startup phase	Great Britain	Small
3	Bflow	Data verification	General sustainability	In preparation	United States	Very small
4	Blockchain for Climate Foundation	Emission rights	General sustainability	In preparation	Canada	Small, nonprofit
5	Brooklyn Microgrid	P2P trading	Renewables	Startup phase	United States	Small
6	Carbon Chain	Emission rights	General sustainability	In preparation	Unknown	Small
7	Carbon Grid	Emission rights	General sustainability	In preparation	Singapore	Small
8	Carbonex	Emission rights	General sustainability	In preparation	Unknown	Small
9	CarbonX	Emission rights	General sustainability	Startup phase	Canada	Very small
10	Climate Trade	Emission rights	General sustainability	In preparation	Spain	Very small, nonprofit
11	COCOA	Crowdfunding	General sustainability	In preparation	Netherlands	Unknown
12	Corrently	Reward system, crowdfunding	Renewables	Operational	Germany	Very small
13	Cryptoleaf	Crowdfunding	General sustainability	Startup phase	Ireland	Small
14	D3A	Control of electricity networks, P2P trading	Renewables	In preparation	Germany	Small
15	DAO IPCI	Platform for various applications	General sustainability	Operational	Russia	Very small
16	Earth Token	Crowdfunding, emission rights	General sustainability	Startup phase	Mauritius	Small
17	ECO2	Emission rights	General sustainability	Startup phase	Unknown	Very small
18	Elblox	P2P trading	Renewables	Startup phase	Switzerland	Large
19	ElectriCChain	Data verification	Renewables	Operational	Andorra	Very small, nonprofit
20	Electron	Platform for various applications	Renewables	Operational	Great Britain	Small
21	ElonCity	Control of electricity networks, P2P trading	Renewables	In preparation	Singapore	Small
22	Enerchain	P2P trading	Renewables	Startup phase	Germany	Medium
23	EnergiMine	Reward system, P2P trading	Renewables	Startup phase	Great Britain	Small
24	Energy Bazaar	Control of electricity networks, P2P trading	Renewables	In preparation	Netherlands	Very small
25	Energy Blockchain Labs	Platform for various applications	General sustainability	Operational	China	Unknown

26	EnergyCoin Foundation	Reward system	General sustainability	Operational	United States	Unknown
27	Enosi	P2P trading	Renewables	Startup phase	Australia	Unknown
28	Etiblogg	P2P trading	Renewables	In preparation	Germany	Very small, nonprofit
29	Exergy	Platform for various applications	Renewables	In preparation	United States	Small
30	FlexiDAO	Data verification	Renewables	Operational	Spain	Very small
31	freeelio	Data verification	Renewables	In preparation	Germany	Very small
32	GainForest	Crowdfunding, data verification	Agriculture & forestry	In preparation	Unknown	Small, nonprofit
33	Green Assets Wallet	Crowdfunding, data verification	General sustainability	In preparation	Sweden	Very small, nonprofit
34	Green Energy Wallet	Control of electricity networks	Renewables	In preparation	Austria	Unknown
35	Greeneum	Reward system, P2P trading	Renewables	In preparation	Israel	Small
36	GreenRide	Reward system	Mobility	In preparation	Jordan	Very small
37	GreenX	Crowdfunding	General sustainability	In preparation	Singapore	Small
38	Hive Power	P2P trading	Renewables	In preparation	Switzerland	Very small
39	Impact PPA	Crowdfunding	Renewables	In preparation	United States	Very small
40	Inuk	Emission rights	General sustainability	In preparation	Unknown	Unknown
41	Irene Energy	Platform for various applications	Renewables	In preparation	France	Small
42	IXO Foundation	Reward system, data verification	General sustainability	Startup phase	Switzerland	Small, nonprofit
43	KiWi New Energy	Crowdfunding, P2P trading	Renewables	In preparation	United States	Small
44	KWH Coin	P2P trading	Renewables	Startup phase	United States	Small
45	Lition Energie	P2P trading	Renewables	Operational	Germany	Very small
46	ME SOLshare	P2P trading	Renewables	Operational	Bangladesh	Small
47	Nori	Emission rights	General sustainability	In preparation	United States	Very small
48	NRGcoin	P2P trading	Renewables	In preparation	Belgium	Scientific
49	OLI	P2P trading	Renewables	In preparation	Germany	Small
50	Omega Grid	Control of electricity networks, reward system	Renewables	In preparation	United States	Very small
51	OMOS	Platform for various applications	Mobility	In preparation	Germany	Small
52	Poseidon	Emission rights	Agriculture & forestry	In preparation	Malta	Small, nonprofit
53	Power2Peer	P2P trading	Renewables	In preparation	United States	Very small
54	Powerledger	Platform for various applications	Renewables	In preparation	Australia	Small
55	PowerToShare	Platform for various applications	Renewables	In preparation	Netherlands	Small
56	Prosume	Platform for various applications	Renewables	In preparation	Italy	Small
57	Pylon Network	Data verification	Renewables	In preparation	Spain	Very small

58	Quartierstrom	P2P trading	Renewables	Startup phase	Switzerland	Unknown
59	RED	P2P trading	Renewables	Operational	Romania	Medium
60	Regen Network	Crowdfunding, data verification	Agriculture & forestry	In preparation	Unknown	Small
61	RobotinaROX	Platform for various applications	Renewables	In preparation	Slovenia	Unknown
62	Smart4Hub & Water Credits	P2P trading, data verification	Water management	In preparation	Great Britain	Very small
63	Solar bankers	P2P trading	Renewables	In preparation	United States	Large
64	Solar DAO	Crowdfunding	Renewables	In preparation	Estonia	Very small
65	Solara	Data verification	Renewables	In preparation	Hong Kong	Small
66	SolarCoin Foundation	Reward system	Renewables	Operational	United States	Unknown
67	SPEX	P2P trading	Renewables	In preparation	Netherlands	Small
68	Sun Contract	P2P trading	Renewables	Operational	Slovenia	Small
69	Sunchain	P2P trading	Renewables	In preparation	France	Very small
70	Swytch	Reward system	Renewables	In preparation	United States	Very small
71	Synergy	P2P trading	Renewables	In preparation	Singapore	Small
72	Tal.Markt	Electricity trading	Renewables	Operational	Germany	Small
73	TenneT & sonnen eServices	Control of electricity networks	Renewables	In preparation	Germany	Large
74	The Climate Chain	Data verification	General sustainability	In preparation	France	Scientific
75	The Eco Coin	Reward system	General sustainability	In preparation	Netherlands	Very small, nonprofit
76	The Energy Origin (TEO)	Data verification	Renewables	Startup phase	France	Very small
77	Veridium Labs	Emission rights	General sustainability	In preparation	Hong Kong	Very small
78	VLUX	P2P trading	Renewables	In preparation	Great Britain	Small
79	Water to the World	Data verification	Water management	In preparation	United Arab Emirates	Unknown
80	Waterchain	Crowdfunding	Water management	In preparation	United States	Small
81	Waterledger	P2P trading	Water management	In preparation	Australia	Very small
82	WePower	Crowdfunding, P2P trading	Renewables	Startup phase	Lithuania	Medium
83	World Bank Innovation and Technology Lab	Emission rights	General sustainability	In preparation	United States	Large
84	XiWATT	Crowdfunding, electricity trading	Renewables	In preparation	United States	Very small
85	Zero Carbon Project	Reward system, electricity trading	Renewables	Startup phase	Great Britain	Small

Sources: The applied sources for each application can be found in Table 4.6

Table 4.12: Overview of the applications in the dataset: Blockchain-specific characteristic values

	Company name	Blockchain	Consensus mechanism	Token	Token type	Token base	ICO
1	1PLANET	Ethereum, Hyperledger Fabric	Unknown	Yes	Utility	Ethereum	Yes
2	4NEW	Ethereum	Unknown	Yes	Utility	Ethereum	Yes
3	Bflow	Stellar	Proof-of-reputation	Yes	Utility	Stellar	No
4	Blockchain for Climate Foundation	Ethereum-based	Proof-of-authority	Yes	Security	Unknown	No
5	Brooklyn Microgrid	Individual	Unknown	No	No	No	No
6	Carbon Chain	Ethereum	Unknown	Yes	Security	Ethereum	Canceled
7	Carbon Grid	Ethereum	Proof-of-authority	Yes	Utility	Ethereum	Yes
8	Carbonex	Unknown	Unknown	Yes	Security	Ethereum compliant	Yes
9	CarbonX	Ethereum	Unknown	Yes	Security	Unknown	No
10	Climate Trade	Stellar	Unknown	Yes	Equity	Unknown	Yes
11	COCOA	Unknown	Unknown	No	No	No	No
12	Corrently	Ethereum	Unknown	Yes	Undefined	Unknown	No
13	Cryptoleaf	Ethereum	Unknown	Yes	Equity	Ethereum	Yes
14	D3A	Energy Web	Proof-of-authority	No	No	No	No
15	DAO IPCI	Ethereum	Unknown	Yes	Utility	Unknown	Yes
16	Earth Token	Ethereum	Proof-of-work	Yes	Equity	Ethereum	Yes
17	ECO2	Ethereum	Unknown	Yes	Equity	Ethereum	No
18	Elblox	Ethereum	Proof-of-work	No	No	No	No
19	ElectriCChain	SolarCoin	Proof-of-stake-time	No	No	No	No
20	Electron	Unknown	Unknown	No	No	No	No
21	ElonCity	Ethereum-based	Delegated proof-of-stake	Yes	Utility	Ethereum compliant	Yes
22	Enerchain	Cosmos network	Practical Byzantine-fault-tolerance	No	No	No	No
23	EnergiMine	Unknown	Unknown	Yes	Utility	Ethereum	Yes
24	Energy Bazaar	Ethereum	Unknown	Yes	Utility	Unknown	No
25	Energy Blockchain Labs	Hyperledger Fabric	Unknown	Yes	Undefined	Unknown	No
26	EnergyCoin Foundation	Individual	Proof-of-stake	Yes	Utility	Unknown	No
27	Enosi	Ethereum, R3 Corda	Unknown	No	No	No	No
28	Etiblogg	Unknown	Unknown	No	No	No	No
29	Exergy	Individual	Unknown	Yes	Utility	Unknown	Yes
30	FlexiDAO	Energy Web	Unknown	No	No	No	No

31	freeelio	Energy Web	Unknown	Yes	Undefined	Unknown	No
32	GainForest	Unknown	Unknown	Yes	Undefined	Unknown	No
33	Green Assets Wallet	Individual	Unknown	No	No	No	No
34	Green Energy Wallet	Unknown	Unknown	Yes	Utility	Unknown	Yes
35	Greeneum	Ethereum	Proof-of-work	Yes	Utility	Ethereum	Yes
36	GreenRide	Ethereum	Unknown	Yes	Utility	Ethereum	Yes
37	GreenX	Ethereum	Unknown	Yes	Equity	Ethereum	Yes
38	Hive Power	Ethereum	Unknown	Yes	Utility	Ethereum	Canceled
39	Impact PPA	Ethereum	Unknown	Yes	Equity, currency	Unknown	Yes
40	Inuk	Ethereum-based	Unknown	No	No	No	No
41	Irene Energy	Stellar	Federated Byzantine Agreement	Yes	Utility	Stellar	Yes
42	IXO Foundation	Cosmos network, Ethereum	Practical Byzantine-fault-tolerance	Yes	Utility	Ethereum	No
43	KiWi New Energy	Unknown	Unknown	Yes	Utility	Ethereum	No
44	KWH Coin	Unknown	Unknown	Yes	Utility	Unknown	Yes
45	Lition Energie	Ethereum	Proof-of-stake	No	No	No	No
46	ME SOLshare	Unknown	Unknown	No	No	No	No
47	Nori	Ethereum	Proof-of-work	Yes	Equity	Ethereum	Yes
48	NRGcoin	Ethereum	Unknown	Yes	Utility	Unknown	No
49	OLI	Ethereum-based	Unknown	No	No	No	No
50	Omega Grid	Individual	Proof-of-authority	Yes	Undefined	Unknown	No
51	OMOS	Ethereum	Proof-of-authority	Yes	Currency	Unknown	Yes
52	Poseidon	Stellar	Federated Byzantine Agreement	Yes	Equity, utility	Unknown	Yes
53	Power2Peer	Ethereum	Unknown	Yes	Equity	Unknown	No
54	Powerledger	Ethereum, Individual	Proof-of-work, proof-of-stake	Yes	Utility, currency	Ethereum	Yes
55	PowerToShare	Unknown	Unknown	Yes	Utility	Unknown	No
56	Prosume	Ethereum	Unknown	Yes	Utility	Ethereum	No
57	Pylon Network	Individual	Proof-of-cooperation	Yes	Utility	Ethereum	Yes
58	Quartierstrom	Unknown	Unknown	No	No	No	No
59	RED	Ethereum	Proof-of-work	Yes	Utility	Ethereum	Yes
60	Regen Network	Cosmos network based	Practical Byzantine-fault-tolerance	Yes	Utility	Individual	Yes

61	RobotinaROX	Ethereum	Unknown	Yes	Utility	Ethereum compliant	Yes
62	Smart4Hub & Water Credits	Unknown	Unknown	Yes	Undefined	Unknown	No
63	Solar bankers	Sky Fiber	Obelisk	No	No	No	No
64	Solar DAO	Ethereum	Unknown	Yes	Equity	Unknown	Canceled
65	Solara	Individual	Proof-of-fusion	Yes	Utility	Ethereum	Yes
66	SolarCoin Foundation	SolarCoin	Proof-of-stake-time	Yes	Utility	SolarCoin	No
67	SPEX	Unknown	Unknown	No	No	No	No
68	Sun Contract	Ethereum	Unknown	Yes	Utility	Ethereum	Yes
69	Sunchain	Individual	Unknown	No	No	No	No
70	Swytch	Ethereum	Proof-of-production	Yes	Utility	Ethereum compliant	Yes
71	Synergy	Ethereum	Unknown	Yes	Utility	Ethereum	Yes
72	Tal.Markt	Hyperledger Fabric	Unknown	No	No	No	No
73	TenneT & sonnen eServices	Hyperledger Fabric	Unknown	No	No	No	No
74	The Climate Chain	Unknown	Unknown	No	No	No	No
75	The Eco Coin	Ethereum-based	Proof-of-stake	Yes	Security	Unknown	Yes
76	The Energy Origin (TEO)	Unknown	Unknown	No	No	No	No
77	Veridium Labs	Stellar	Federated Byzantine Agreement	Yes	Security	Stellar	Canceled
78	VLUX	Ethereum	Proof-of-work	Yes	Utility	Ethereum	Yes
79	Water to the World	IOTA protocol	Unknown	Yes	Equity	Unknown	Yes
80	Waterchain	Unknown	Unknown	Yes	Utility	Unknown	Yes
81	Waterledger	Ethereum	Unknown	No	No	No	No
82	WePower	Ethereum	Proof-of-work	Yes	Utility, equity	Ethereum	Yes
83	World Bank Innovation and Technology Lab	Unknown	Unknown	No	No	No	No
84	XiWATT	Ethereum	Unknown	Yes	Undefined	Ethereum compliant	Yes
85	Zero Carbon Project	Ethereum	Unknown	Yes	Utility	Ethereum	Canceled

Sources: The applied sources for each application can be found in Table 4.6

Table 4.13: Descriptive statistics of the regression dataset

Notes: The entire data sample contains 85 green blockchain applications. In comparison with the original dataset the regression subsample subsumes variables into larger categories. Absolute values and relative values of the variables are displayed. The variables are defined in Table 4.1.

	Observations	**Relative frequency in %**
Application specific variables		
AppType		
AppType_Crowdfunding	14	16.47
AppType_Data verification	14	16.47
AppType_Emission rights	14	16.47
AppType_Platform & reward	21	24.71
AppType_Energy trading	36	42.35
AppSector		
AppSector_Agriculture & forestry & water	7	8.24
AppSector_Mobility	2	2.35
AppSector_General sustainability	24	28.24
AppSector_Renewables	52	61.18
AppStatus		
AppStatus_Startup phase	16	18.82
AppStatus_In preparation	56	65.88
AppStatus_Operational	13	15.29
Continent		
Continent_AfricaAustraliaAsia	15	17.65
Continent_Europe	45	52.94
Continent_NorthAmerica	19	22.35
Continent_Unknown	6	7.06
Size		
Size_Small	68	80.00
Size_MediumLarge	7	8.24
Size_Unknown	10	11.76
Blockchain specific variables		
Blockchain		
Blockchain_Ethereum	43	50.59
Blockchain_Individual	9	10.59
Blockchain_Other	20	23.53
Blockchain_Alternative	29	34.12
Blockchain_Unknown	18	21.18
Consensus		
Consensus_Alternative	16	18.82
Consensus_POS	6	7.06
Consensus_POW	8	9.41
Consensus_Unknown	55	64.71
Token/ICO		
Token	60	70.59
ICO	41	48.24
TokenType		
TokenType_Equity	12	14.12
TokenType_Utility	38	44.71
TokenType_Other	16	18.82
TokenBase		
TokenBase_Ethereum	30	35.29
TokenBase_Other	30	35.29
TokenBase_None	25	29.41

4.6.2 Ordered logit model

The specification of the threshold model based on an unobserved linking variable, which presents the development status of a green blockchain-based application i, is as follows:

$$y_i^* = \beta\, x_i^{'} + \varepsilon_i\,,$$

where $x_i^{'}$ is a vector of observed, explanatory variables describing application-specific characteristics such as the type and sector of activity, origin or company size as well as blockchain-specific characteristics including the employed blockchain technology and consensus mechanism, or the implementation of tokens. The variable β represents a vector of slope coefficients and the term ε_i is the error term. In addition, we assume that while y_i^* cannot be directly observed, we can objectify the three varied categories of development. Consequently, the variable y_i^* is assigned to 1 if the application is in the startup phase, 2 if it is in the preparatory phase, and 3 if it is operational:

$$y_i^* = \begin{cases} 1 & \text{if } y_i^* > cut_1 \\ 2 & \text{if } cut_1 < y_i^* < cut_2 \\ 3 & \text{if } cut_2 < y_i^* \end{cases}$$

where the thresholds cut_i is estimated in the course of the statistical maximum likelihood estimation. We apply Eicke-Huber robust standard errors to all regression models. To begin with, the focus lies on the effect of application-specific and blockchain-specific influential factors individually. The respective models are as follows:

$$y_i^* = \beta_1\, i.Continent + \beta_2\, i.Size + \beta_3\, i.AppSector + \beta_4\, i.AppType + \varepsilon_i \tag{4.1}$$

$$\begin{aligned} y_i^* = \gamma_1\, i.Blockchain + \gamma_2\, i.ICO + \gamma_3\, i.Consensus + \gamma_4\, i.TokenBase \\ + \gamma_5\, i.TokenType + \varepsilon_i \end{aligned} \tag{4.2}$$

In the second setting, both aspects are combined in order to obtain a more complete picture of the determinants. It should be noted that the application for an ICO is highly correlated with the implementation of tokens. We therefore analyze the effect of ICOs and tokens separately.

$$\begin{aligned} y_i^* = \beta_1\, i.Continent + \beta_2\, i.Size + \beta_3\, i.AppSector + \beta_4\, i.AppType + \gamma_1\, i.Blockchain + \gamma_2\, i.ICO \\ + \gamma_3\, i.Consensus + \gamma_4\, i.TokenBase + \gamma_5\, i.TokenType + \varepsilon_i \end{aligned} \tag{4.3}$$

$$\begin{aligned} y_i^* = \beta_1\, i.Continent + \beta_2\, i.Size + \beta_3\, i.AppSector + \beta_4\, i.AppType + \gamma_1\, i.Blockchain \\ + \gamma_2\, i.Token + \gamma_3\, i.Consensus + \varepsilon_i \end{aligned} \tag{4.4}$$

Chapter 5

Conclusion

5.1 Contribution of this dissertation

This thesis contributes to the literature on behavioral and environmental aspects of digital finance applications. In particular, FinTechs operating in the field of asset management and payment are at the core of this research project. The three research papers evaluate the potential of technology-based innovative financial services, explore the characteristics of these business models and analyze their effect on the behavior of their users.

The first article investigates the trading behavior of trade leaders in an innovative online trading environment. Using data from two major social trading platforms in Germany, we provide evidence of the negative relationship between overconfidence and social trading returns. Additionally, the social network aspects of these platforms i.e., those dealing with social interaction are identified as the main drivers of the irrational part of trading activity. The signaler's popularity, either measured by the number of followers or the net change in invested capital, and the ranking of traders, are positively related with the degree of overconfidence. A clear difference is evidenced by the platform specific compensation frameworks. While the incentive system on Ayondo entails measures for risk limitation and drop-out consequences that apparently reduce overconfidence, the Wikifolio high watermark reward system does not create this desired effect. The empirical results provide valuable insights into the importance of the monitoring mechanisms and incentive frameworks of these platforms on their business models. Against the background, that platform operators seek to entice successful traders, who in turn will attract followers and, consequently, increase the operators' revenues, understanding the dynamics of user behavior is of utmost importance. We show that the Ayondo compensation model can mitigate excessive irrational trading; however, the opposite appears to be the case for Wikifolio. Investors who have a high interest in investing in profitable traders in order to achieve high returns on their investments can, thus, refer to the findings of this article when deciding on the platform that matches their preferences. Finally, traders can extend their knowledge by observing and assessing their own behavior with regards to the mentioned aspects.

The second research study investigates the influential factors of the level of risk as well as risk changes in trading strategies of portfolio managers. The empirical analysis of the behavior of asset managers in an innovative online trading environment contributes to the discussion on appropriate incentive structures for asset managers with respect to aligning their interests with the investors' interests. Our results show that traders take a complex set of factors into consideration when choosing the level of risk of the trading strategy. We provide evidence that signal providers adapt the absolute and relative risk of the trading strategy to the proximity to the high watermark. Due to the fact, that they act in an infinite investment horizon, they comprehend the HWM incentive scheme as a series of compensation options on the assets under management and, hence, weigh up current payoffs against future payoff. As a consequence, portfolio managers display risk reducing behavior when approaching the HWM. Portfolio managers appear to behave strategically taking into account their overall portfolio payoff. The possession of valuable outside options, in terms of more volatile alternative wikifolios, induces risk taking. However, this effect is mitigated with respect to the moneyness of the outside option in terms of HWM proximity and relative portfolio performance. Besides, platform specific characteristics including, inter alia, social status indicators such as rankings and communication abilities are significant drivers of the level of risk as well as risk changes in trading strategies. Our results highlight the importance of considering the investment horizon and outside options of the asset manager in its incentive contract. By identifying different aspects of the trading venue e.g., social reputation mechanisms or increased transparency of information as influential factors of the portfolio manager's behavior, the empirical findings provide interesting insights for platform developers, financial regulators and investors. Moreover, we add to the understanding of private investor behavior as the majority of platform managers are non-professional investors.

The third paper draws a profound picture of the current state of blockchain applications that contribute in a certain way to climate protection. In view of the need to act on a global scale to mitigate climate change, our empirical findings evidence the opportunities of blockchain technology in empowering environmental action. The detailed analysis of the current application portfolio and the identification of success factors generate valuable insights for exploiting the potential of current and future applications in tackling climate change. To begin with, the consolidation of environmentally orientated blockchain applications discloses a broad spectrum of innovative applications. Since the majority of the applications under review are until now in the initial phase, their environmental contribution is still considered small. However, they have the capabilities to play a major role in implementing mitigation and adaption actions in the future. Besides, we add to existing research by shedding light on the success factors (in the sense of an advanced operational status) of these applications distinguishing between application-specific and blockchain-specific characteristics. We prove, that the type of activity and the applied consensus mechanism significantly affect the probability of becoming operational. By contrast, neither the execution of an ICO nor the implementation of tokens appear to be essential drivers of success. This research project offers a base for strategic thinking and international collaboration, identifies fields of actions and proposes future orientation. The knowledge of strengths and weaknesses of these applications as well as of their potential to tackle climate change can enable investors, developers of blockchains and the respective companies, and citizens to advance the development of green, blockchain-based applications more efficiently. In addition, political institutions can build on our findings in the provision of the necessary legal and political environment that enhances the development of green blockchain applications. In particular, the combination with other technologies such as artificial intelligence, big data, and internet of things will reinforce the potential of green blockchain-based applications in driving climate protection.

As digital technology is changing people's lives, this thesis provides valuable insights on the capabilities of new technologies and innovative business models in the financial sector to shape social, environmental and economic change. In addition, the presentation of opportunities and challenges can be a valuable contribution for actively designing the digital transformation, empowering citizens, and leading the way towards a digital, more sustainable and fair world.

5.2 Limitations and areas for further research

The accelerating pace of technological evolvement combined with reduced costs and risks for implementation speed up the ongoing digital transformation of the financial sector. This development is accompanied by an increased emergence of novel, technologically enabled business models. Technological advancements and scientific research play an important role in tackling the major challenges of our times. Against this background, further research on the FinTech scene and the extensive portfolio of business ideas is essential in order to harness the opportunities that arise as a consequence of technological advancements. In the following the limitations of the three research papers in this dissertation will be discussed:

The first article empirically examines whether social network characteristics on social trading platforms influence the trading behavior of traders. The research model investigates the relationship between trading activity and performance and identifies negative returns after transaction costs following increased trading activity initiated by irrational factors as an indication for overconfidence. Since the model accounts for the part of trading activity that is induced by rational components such as portfolio composition or the ratio of leveraged positions, more detailed, metric information on wikifolios would improve the quality of the results. In view of the diverging effects of platform design on trader behavior, future research could enhance the generalizability of our findings by investigating additional platforms that differ in product portfolio, incentive systems, and social interaction features. In addition, it would be of interest to study how signal providers can acquire more followers.

The second paper provides interesting insights into the risk strategies of traders. The distance to the high-water mark and the value of outside options significantly affect risk taking behavior. Consequently, further studies may assay how signalers adapt distinct risk strategies thereby focusing on portfolio composition. With respect to the different portfolio statuses, future research could examine what motivates signalers to apply for the investability of a certain trading strategy. On the contrary, it can be worth to explore the factors that drive signalers to close wikifolios and withdraw from the trading strategy. Finally, there is substantial room to deepen the knowledge on the relationship between incentive systems and risk taking on innovative trading platforms suggesting to observe these aspects on alternative social trading platforms.

The last research work creates a comprehensive picture of the current landscape of green blockchain applications. Additionally, success factors for the operability of these blockchain applications are determined. More in-depth qualitative studies of individual applications could uncover additional potentials for efficient mitigation and adaptation measures based on blockchain technology. Due to the fact that the field of distributed ledger technology is young and rapidly evolving, a continuous update, extension and re-analysis of the application portfolio is recommended. Furthermore, in order to evaluate the contribution to climate protection more thoroughly a long-term study is essential. It will be crucial to investigate the energy consumption of the employed consensus mechanisms in deeper detail to be able to relate the carbon-dioxide emission saved by the application to the emissions caused by its implementation. With regards to the influencing factors of success, more research should be conducted on the effect of the implementation of ICOs and tokens on the operability of green blockchain based applications. Therefore, it can be worthwhile to further gain insights into the effectiveness of alternative forms of financing, startup capital and verifiable financial results.

These areas for further research highlight important aspects where scientific findings will greatly contribute to the promotion of digital business models in finance, thereby advancing the digital transformation and supporting social, environmental and economic change. Taken together, it remains interesting to see how FinTechs will develop, whether they achieve the desired results with regards to financial inclusion and customer empowerment, and whether businesses and institutions will manage to harness the potential of blockchain technology.

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