Technische Universität München
TUM School of Management

Essays on Digital Finance Innovations:

Decentralized Finance, the Role of Influencers on Investment Decisions, and the Potential of Blockchain Technology for Regenerative Purposes

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Vollständiger Abdruck der von der TUM School of Management der Technischen Universität München zur Erlangung einer Doktorin der Wirtschafts- und Sozialwissenschaften (Dr. rer. pol.) genehmigten Dissertation.

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Die Dissertation wurde am 23.10.2023 bei der Technischen Universität München eingereicht und durch die TUM School of Management am 15.02.2024 angenommen.

Acknowledgements

This dissertation would not have been possible without the help of many people who have supported and influenced me along various steps of my life.

First and foremost, I would like to express my sincere gratitude towards my two academic supervisors and co-authors. Quite certainly, I would not have pursued this dissertation without my supervisor Prof. Dr. Isabell M. Welpe: her enthusiasm and courage to explore new topics which are not yet widely accepted, provide a rare environment for research in innovative and disruptive fields such as that for blockchain-based financial innovations. I am not only thankful for her strong confidence in my dissertation project when I needed it most but also for her encouragement to develop beyond my research, that is as speaker at many practitioners conferences, via contacts to inspiring networks, and support for any local crypto-related initiative setups. I could always rely on her supportive and constructive feedback, and her positive 'can-do' attitude has inspired me beyond this dissertation. Similarly, not only the thesis itself but also the decision to undertake this endeavor is strongly influenced by Prof. Dr. Philipp Sandner. As a pioneer and leading scholar in the field of crypto-assets, he paved my way into the large field of blockchain-based technologies and into the community of like-minded researchers and practitioners. His honest feedback and invaluable guidance have not only tremendously supported me in this dissertation but will also accompany me in future challenges.

I would also like to thank the many colleagues and friends who accompanied the dissertation journey. The TUM School of Management provides an encouraging and inspirational environment, be it at doctoral courses or at the many events and cooperations between different chairs and TUM initiatives. Among the many people who supported me from the university, I would especially like to express my gratitude to a couple of colleagues at the Chair of Strategy and Organization. I thank Prof. Dr. Theresa Treffers for guiding me into how to employ empirical research methods and for providing advice from her many years of academic experience, Eva Pongracz for her continuous, proactive, and always reliable administrative support, as well as my research fellows for the companionship, academic exchange and joyful discussions.

Also, beyond the TUM School of Management, friends and colleagues strongly supported me. Maximilian Krome has accompanied the dissertation from the first day on and I am sincerely grateful for the academic and personal discussions but most importantly for the invaluable support and patience in ups and downs during the dissertation. I also sincerely want to thank Dr. Erik Lenhard for being a great PhD mentor and for providing me with important guidance at various milestones along the dissertation journey.

Finally, I want to thank my personal environment: my parents Dr. Rolf-Volker Meyer and Dr. Elena Meyer for their lifelong support and encouragement to pursue my academic ambitions; my grandparents Prof. Dr. Andrej Askadskij and Dr. Zenaida Gerachenko for exemplifying the reward from academic work; and my close friends for accompanying me along all steps in my life.

Abstract

While most digital innovations are industry-generic, a uniqueness of blockchains is the inherent aim to specifically disrupt the financial industry, that is to replace established intermediaries with decentralized governance mechanisms. The invention of smart contracts on blockchains has decisively contributed to this vision: nowadays, a wide range of existing and new financial services for a magnitude of blockchain-based financial assets run solely code-based, that is intermediary-free, on public blockchains such as Ethereum.

This thesis' starting essay presents the first systematic literature review of the fragmented research field covering the ecosystem of such decentralized financial services, known as 'Decentralized Finance' (DeFi). The essay's most important contributions are twofold. First, DeFi-related literature is clustered into and synthesized within three levels of abstraction (micro, meso, macro) and seven subcategories. Second, four main research avenues are derived, namely concerning i) DeFi protocol interaction and aggregation platforms, ii) decentralized off-chain data integration to DeFi, iii) regulation, and iv) participants and agents in the DeFi system.

The remainder of the thesis uses one secondary (openly available) and two primary (self-gathered) data sets to contribute to the latter research avenue, that is to analyze participants in the DeFi and broader crypto-asset ecosystem.

Specifically, the second and third essay investigate two new phenomena in the financial industry in conjunction, namely that of i) crypto assets and ii) a new, powerful marketing channel: influencers disseminating their investment opinions on social media. Regressing the sentiment in 3.6 million posted viewer comments on the sentiment in the associated 7,740 video titles and transcripts, the second essay finds significant emotional contagion from the seven analyzed YouTube Bitcoin video bloggers (vloggers) onto their audience. However, contrary

to the initial hypothesis, the correlation strength does not increase over time. One possible explanation may be that despite recurrent exposure, emotional bonds and hence contagion do not increase due to poor investment advice. And indeed, neither the third essay’s event study results of viewer-gathered vlog predictions nor those of software-based vlog sentiment measures show evidence that the seven vloggers are correct in their short-term market assessments. Taking the viewers’ emotional susceptibility and vloggers’ inability to correctly predict price movements together, the large audience of such vlogs is advised to be very cautious about adapting any vlogger financial advice.

In contrast to focusing on short-term profits, a DeFi play-off has grown that has made it its highest priority to use blockchain-based financial innovations for regenerative purposes such as environmental protection and fair co-participation of local communities. The final essay of this thesis presents the results from semi-structured interviews with members of the respective ‘Regenerative Finance’, short ‘ReFi’, community. More concretely, the essay presents i) an academic definition of ‘ReFi’, ii) motive forces for ReFi’s emergence, iii) common building blocks along ReFi’s value chain, and iv) overarching goals for ReFi.

Concluding, this thesis presents two sides which emerged around blockchain-based digital finance innovations. Whether long-term aspirations to unlock the technology’s full potential for society can prevail against short-term financial speculators attaching a gambling image to crypto assets in many people’s minds, remains to be seen over the next years.

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List of Abbreviations

ACM ... *Association for Computing Machinery*
AMM ... *Automated Market Maker*
API ... *application programming interface*
B2B ... *Business-to-Business*
B2C ... *Business-to-Consumers*
bn ... *billion*
BTC ... *Bitcoin*
CEX ... *Centralized Exchange*
cf. ... *confer*
DAO ... *Decentralized Autonomous Organizations*
DApps ... *DeFi Decentralized Applications*
DeFi ... *Decentralized Finance*
DEX ... *Decentralized Exchange*
DSL ... *Domain-specific languages*
e.g. ... *exempli gratia*
ERC ... *Ethereum request for comment*
et al. ... *et alia*
etc. ... *et cetera*
ETH ... *Ethereum*
EU ... *European Union*
H.. ... *Hypothesis*
i.e. ... *id est*
IEEE ... *Institute of Electrical and Electronics Engineers*
JEL ... *Journal of Economic Literature*
MEV ... *Miner Extractable Value*
MiCA ... *Regulation on Markets in crypto-assets*
NGO ... *Non-governmental organization*
NLTK ... *Natural Language Toolkit*
OLS ... *Ordinary Least Square*
OTC ... *Over the counter*
p.. ... *Page*
P2P ... *Peer-to-peer*
PoC ... *Proof of concept*
PoS ... *Proof of Stake*
PoW ... *Proof of Work*
PSI ... *parasocial interaction*

PSR .... *parasocial relationship*
ReFi........ *Regenerative Finance*
RQ........ *Research Question*
SDG .... *Sustainable Development Goals*
SEC........ *U.S. Securities and Exchange Commission*
SoK .... *Systemization of Knowledge*
TVL........ *Total Value Locked*
U.N........ *United Nations*
UK .... *United Kingdom*
USA .... *United States of America*
USD .... *United States Dollar*
VADER .... *Valence Aware Dictionary and sEntiment Reasoner*
Vlog .... *video blog*
Vlogger........ *video blogger*
vs. .... *versus*

1 Introduction

1.1. Motivation

Digitization in the financial industry has shifted from improving long-established processes to entirely disrupting financial service business models (Gomber et al., 2017). Next to an enhanced customer experience (Gomber et al., 2018), digital innovations in finance are argued to positively impact the environment (Cao et al., 2021; Liu et al., 2022) and to include previously unbanked people in developing countries to the financial system (Ozili, 2018).

The associated technology-based advancements might be initiated both by established financial service providers to sustain or increase their competitiveness, or by new actors with the aim to disrupt the industry and to rule out incumbent players (Gomber et al., 2017). This thesis focuses on the latter category, that is on new players in the financial industry aiming to entirely change the ways financial services are delivered as well as the parties involved.

More concretely, this thesis focuses on digital finance innovations based on one particular technology, that is on blockchains. The invention of this technology can be rooted back to Nakamoto (2008), introducing the concept of the Bitcoin blockchain, that is the first consensus-governed, decentralized database of cryptographically linked blocks storing and enabling borderless, trustless, all-time available, fast, and digitally signed P2P-transactions. In other words, in the Bitcoin network, one can safely transfer a digital value to any another network user, without relying on a central intermediary. The validity of the transfer is verified and enforced through a network of decentralized validators and can subsequently be viewed and traced by anyone else. The identities of neither the sender nor the receiver are disclosed in the process beyond their blockchain wallet addresses (a string of characters).

So, while former digital finance innovations focused on enabling financial service provisions without the need to visit a bank branch or to deal directly with a financial service provider (Ozili, 2018), the potential of blockchain is another: to make such service institutions obsolete altogether.

A decisive advancement to the Bitcoin blockchain and to accomplishing the idea of a comprehensive, openly accessible, and transparent financial ecosystem that fully functions without traditional intermediaries, came with the Turing-completeness in the script language of the Ethereum blockchain. In doing so, the Ethereum founder, Buterin (2013), established the first practical implementation of smart contracts, i.e., “digital contracts allowing terms contingent on decentralized consensus that are tamper-proof and typically self-enforcing through automated execution” (Cong & He, 2019, pp. 1761–1762).[1]

Given the flexibility of terms written in such contracts, not only can any traditional financial asset (e.g., a security) and service (e.g., lending, trading of complex derivatives) be replicated as a set of smart contracts but also entirely new financial instruments can be created (Schär, 2021)[2].

Intermediaries from traditional finance which have previously coordinated the interests among different market participants become obsolete in such a code-based system of smart contracts (Zetzsche et al., 2020). The independence from coordinating third parties is called making financial services ‘trustless’ (Schär, 2021). Given that all information (e.g., asset ownership, settled transactions) are stored in an underlying blockchain database, smart contract-based financial services may be designed to be publicly open to anyone, fully transparent and all-time

[1] Such smart contracts were first discussed but not implemented in practice by Szabo (1997).

[2] For a detailed overview of smart contract-based financial operations, I refer to Essay I.

operating. The ecosystem which has emerged delivering these services and on which this thesis will mainly focus is known as 'Decentralized Finance', short 'DeFi'.

In order to set a base for this thesis and for future DeFi scholars, the first objective of this thesis is to elaborate on the current state of academic knowledge on Decentralized Finance—research priorly lacking.

RQ1: What is the current state of academic knowledge on Decentralized Finance and what research avenues can be derived from it?

Conducting a comprehensive structured review, DeFi literature is found to be classified into three levels of abstraction and/or perspective. The first one, the micro-level, entails papers which focus on individual components contributing to the functioning of DeFi, that is on smart-contract coding languages, on the various store of value forms which can be built with smart contracts on blockchains (i.e., 'tokens'), as well as on the various financial service applications which can be built in DeFi. The second, the meso-level, entails academic contributions which analyze phenomena and patterns within single DeFi ecosystems such as that on the Ethereum blockchain as well as analyze how those different ecosystems (i.e., being built on distinct blockchains) can be connected with each other and the outside, 'off-chain' world. The third, the macro-level, analyzes characteristics of DeFi as a whole as well as the impact that DeFi has on the broader society.

The remainder of this thesis' research activities can be allocated to the latter, the macro-level. Along with the tremendously growing interest in cryptocurrencies[3] and with DeFi services

[3] See Essay I for more detailed comparisons of cryptocurrency market capitalizations with that of traditional banks and Essay IV for a comparison with the German stock market capitalization.

maturing, the total value locked (TVL) in DeFi smart contracts experienced a remarkable growth in the bull market of 2021. While as of December 2nd, 2020 the TVL in DeFi smart contracts amounted to ‘only’ USD 12.44 billion, exactly one year later, at its peak, the value had almost increased fifteenfold to USD 180.98 billion (DefiLlama, 2023). One year later, however, the TVL has shrunk back to not even a quarter, that is to USD 41.92 billion (DefiLlama, 2023).

Correspondingly, compared to other asset classes, the valuations of crypto assets are considered as highly volatile (Baur & Dimpfl, 2021; Klein et al., 2018). While some price movements can be linked to fundamental events such as crashes of DeFi services (Lee et al., 2022), changes in cryptocurrency appraisals from states (Okorie & Lin, 2020) or even from single individuals such as Elon Musk (Ante, 2023), others are more difficult to comprehend. On the contrary, in fact, the crypto-asset market is rather sentiment- than fundamental-value driven (Naeem et al., 2021).

One industry which is taking advantage of the crypto asset price rollercoaster and associated emotions involved, is that of crypto influencers. On a daily basis, followers can track those influencers’ views on reasons for recent as well as likely patterns for future price movements. A major endeavor of this thesis is to study the impact of those crypto influencers on the crypto-asset industry on the world’s second largest social media platform, that is on YouTube (Kemp, 2022). The collected sample of 52 video bloggers (vloggers) on YouTube focusing on cryptocurrency or blockchain-related content, accumulates more than 21 million subscribers and almost 2 billion views as of September 2022. To examine the role of those influencers in disseminating and shaping the cryptocurrency space, two separate research questions are posed:

RQ2: Do YouTube crypto influencers (emotionally) influence their viewers?

RQ3: Do YouTube crypto influencers correctly analyze future crypto-asset price directions?

Leveraging both software-based sentiment analyses as well as self-gathered data from watching the influencers' videos, the thesis will first examine whether such vloggers emotionally influence their viewers and thus potentially contribute to a sentiment-driven investment space. Finding that the sentiment of vloggers is indeed positively correlated to that of their audience, in a second step, it is analyzed whether the audience can profit from watching the market analyses of such vloggers, i.e., whether abnormal crypto-assets returns are positive (negative) after bullish (bearish) predictions.

Next to a turbulent investment market, also the fundamental development of the crypto-asset and DeFi sector does not follow a steady maturity path. In line with patterns seen in other digital finance innovations, also established financial institutions have started to adopt blockchain technology to streamline their operations and to digitize their services (Guo & Liang, 2016; Hassani et al., 2018; Hütten, 2019). The world's largest bank, JPMorgan Chase, has executed a first trade on a public blockchain (Yang, 2022), Private Equity giants as KKR are experimenting with tokenized funds (KKR, 2022), and security exchanges are investing in and experimenting with blockchain technology to enhance their operations (Deutsche Börse Group, 2023). While the increasing adaption of blockchain technology by financial incumbents might entail benefits for customers and for the integration of DeFi services into the established financial sector, the blockchain adaption by financial institutions yet ironically counteracts the initial goal of DeFi idealists: to make those intermediaries obsolete by using blockchain technology.

Further, also the DeFi ecosystem itself is in some ways impeding its way of providing an alternative, reliable space for decentralized financial services. While in theory, the technology might contribute to financial inclusion (Mavilia & Pisani, 2020; Schuetz & Venkatesh, 2020), tangible case studies of such an impact are yet scarce. On the contrary, some scholars pose that the societal implications of blockchains highly depend on how the technology is utilized and that both incumbent but also some new players are rather employing blockchain-based innovations to reinforce established patterns such as strengthening inequality and centralizing power (Manski, 2017). The final research objective of this thesis is to study how blockchain technology can achieve its promises of positively contributing to society. A group of blockchain entrepreneurs and investors who have committed to put a positive societal contribution before any monetary profits, gathers under the umbrella term 'Regenerative Finance'. This might include one of the inherent DeFi purposes of financial inclusion but also further goals, such as to use blockchain technology for environmental protection endeavors. To understand how this group aims to leverage blockchain-based digital finance innovations for sustainability matters, semi-structured interviews with those stakeholders are conducted. The overarching research questions states:

RQ4: Regenerative Finance: Can blockchain-based financial innovations support in sustainability matters?

Altogether, the thesis' originality beyond answering each individual research question, stems from highlighting and comparing the very different motivations driving the growth and attention of the blockchain-based financial ecosystem. More concretely, this thesis displays two sides of the world which have emerged around blockchain-based digital finance innovations. The one side focuses on individual financial benefits stemming from this new technology, that is trying to identify investment opportunities to participate in the technology's success prospects. Given the high volatility in crypto-asset valuations in combination with 24/7 trading opportunities and a great breadth of investment opportunities in many new crypto-assets, crypto-asset investing can yield big profits but equally large losses. In absence of fundamental valuation techniques, crypto-asset prices are largely dominated by investor sentiment—a fact on which crypto vloggers established a whole industry and to which they even further contribute by emotion-driven vlogging strategies and misleading investment advice. On the other side, a group of ReFi entrepreneurs is working on leveraging the advantages of DeFi (e.g., transaction transparency, liquidity, and composability) to build solutions which contribute to societal matters, such as environmental protection, better than current non-DeFi societal projects.

One of the self-identified risks of the ReFi interviewees in this thesis' last essay as well as of former scholars (e.g., Howson, 2020; Stuit et al., 2022) displays the tension between the two outlined sides in the blockchain-based financial ecosystem: that some entrepreneurs use the disguise of ReFi to build business models to, again, yield a financial benefit for themselves rather than holding up to the promises of contributing to societal matters and to decreasing the inequalities of developed countries and rural communities. Given the opposing interests between both sides, that is decentralizing financial power vs. trying to maximize one's own financial benefits, it will be unlikely for both sides to successfully sustain. Which of both sides will prevail and the associated implications on the blockchain-based financial system, remain to be seen in the future.

1.2. Thesis Structure, Main Results, and Contributions

Apart from the brief introduction section in the present chapter (1.1) and the thesis conclusion (chapter 6), this thesis consists of four essays which each present a scholarly contribution on its own (chapters 2-5). As such, each essay contains its own introduction arguing for the relevance of the essay, a thorough overview of the associated theoretical background and cited references, a detailed and replicable outline of the methodology followed and data used, and a conclusory discussion outlining the essay's theoretical and practical contributions as well as its limitations.

The following provides a summary overview of the research methodologies and the key results and contributions of each of the four essays.

Essay I. DeFi—A Systematic Literature Review and Research Directions

While several authors have provided non-literature guided explanatory overviews of the DeFi space (Chen & Bellavitis, 2020; Jensen et al., 2021; Schär, 2021) as well as systematized academic and practical knowledge of specific DeFi subareas (Bartoletti et al., 2020; Cousaert et al., 2021; Werner et al., 2021), no paper has yet systematically reviewed the accomplishments in academic DeFi research in its whole. However, this research has become highly relevant. Along with the growing attention in practice[4], scholarly DeFi contributions expand rapidly in diverse academic areas such as 'Computer Science', 'Business, Management, and Accounting', or 'Social Science' resulting in a highly fragmented research field. Essay I closes this research gap and provides the first systematic review of Decentralized Finance literature. In doing so, the paper provides DeFi scholars a comprehensive overview of DeFi research to date, derives promising avenues for future research, and offers new scholars a first anchor point to better navigate the different fields of DeFi research.

[4] By the time of writing the essay in November 2021, the market capitalization of the main DeFi blockchain Ethereum ($530bn; DeFi Pulse, 2021) surpassed that of the highest valued bank (JPMorgan Chase$503bn; CompaniesMarketCap, 2021)—not even accounting for the value of the many financial service applications built on top of the Ethereum platform.

The applied methodology follows the guidelines for systematic literature reviews in Webster and Watson (2002), Levy and Ellis (2006), and vom Brocke et al. (2015). In line with the guidelines by vom Brocke et al. (2015), papers were screened based on structured searches on literature data bases. More specifically, to ensure a comprehensive overview, DeFi- and DeFi-describing string searches on seven literature databases were conducted, accompanied by a cross-check for further relevant literature on Google Scholar. The respective search led to 1,006 English, peer-reviewed papers (to ensure all sample papers were subject to quality controls as suggested by Davison et al., 2005) of which 83 were included in the final sample after applying a literature guided definition to delineate DeFi from other finance- and/or blockchain-related research.

The most important contribution of this essay is the coding analysis, structuring DeFi literature into a three-level framework of research perspectives:

i) the micro-level with research around individual DeFi components, namely financial smart contracts, tokens, and decentralized applications (DApps),

ii) the meso-level with research on characteristics within as well as on scaling solutions beyond single-chain systems, and

iii) the holistic-perspective macro-level, conceptualizing the DeFi space as a whole as well as its societal implications and need for regulation.

The subsequent synthetization of papers allocated to the respective (sub-)levels, provides a cross-disciplinary overview and summary of the current state of research.

Finally, by i) identifying non-conclusive or understudied research areas, ii) unveiling inconsistencies among prior research, as well as iii) analyzing comparably merely employed research methodologies such as the usage of primary empirical research data or analyses of DeFi ecosystems other than the Ethereum blockchain, the essay outlines major research avenues to further advance the DeFi space. One of those research avenues constitutes the analyses of participants of the DeFi ecosystem, to which the remaining three essays can be allocated to (studying both crypto-asset investors' and blockchain entrepreneurs' perspectives).

Essay II. High on Bitcoin: Evidence of emotional contagion in the YouTube crypto influencer space

The growth path of blockchain-related innovations has not been steady. While overall experiencing a remarkable value growth, already by three times since its emergence in 2008, the price of the largest cryptocurrency Bitcoin has experienced maximum drawdowns of more than 75% (PortfoliosLab, 2023). Such a high price volatility is unlikely to stem solely from changes in fundamental valuations. Instead, the crypto space has found to be highly driven by market sentiment, up to the point of inducing market bubbles (Chen & Hafner, 2019).

An important social media platform with few opinion leaders reaching a tremendously large audience, has yet not been accounted for in prior academic analyses. Essay II closes this research gap and analyzes a structurally selected sample of 52 YouTube influencers, accumulating more than 21 million subscribers and almost two billion views as of September 2022. While some channels provide educational or news content, many of the YouTube channels conduct 'market analyses', that is analyzing past price patterns and trying to infer future price movements. Although those influencers are obliged to mark their opinions as not being 'financial advice', the assumption underlying this essay is that the videos do influence the sentiment of their viewers, potentially impacting subsequent trades and hence the crypto-asset market.

Measuring the correlation of sentiment in 7,740 video titles and transcripts with that of subsequently posted 3.6 million viewer comments, significant emotional contagion is indeed found from the seven selected Bitcoin vloggers onto their audience. Also, among the audience members themselves, evidence of emotional contagion becomes apparent. To attain said sentiment, the open-source software tool for measuring social-media related sentiment VADER (Valence Aware Dictionary and sEntiment Reasoner; Hutto & Gilbert, 2014) is used. To adjust for the context studied, the underlying lexicon of VADER is extended by the Loughran-McDonald financial sentiment word lists (Loughran & McDonald, 2011).

While finding emotional contagion from vloggers onto their audience as well as among audience members themselves is in line with the derived hypotheses from prior literature, two further findings have been less expected. First, negative emotions are found to be more contagious than positive ones. While those findings are in line with the general negativity bias in emotions (Rozin & Royzman, 2001) and herding behavior research showing that crypto-asset investors are more influenced by negative than positive news (da Gama Silva et al., 2019), they contradict some prior emotional contagion studies in social media (Ferrara & Yang, 2015; Guadagno et al., 2013). Second, given that para-social interactions (friendship-similar feelings between people and media personalities) usually increase with recurring exposure to media personalities (Horton & Wohl, 1956; Rubin & McHugh, 1987), and as stronger para-social interactions tend to lead to stronger emotional contagion (Klimmt et al., 2006), the correlation of sentiment was assumed to become more pronounced in the second halves of a vlogger’s video uploads. However, either no effects or rather even the contrary are found. One possible explanation is that the emotional bonds do not increase despite recurrent exposure to the influencers. A perceived loss of integrity of a trusted influencer can turn into feelings of betrayal (Reinikainen et al., 2021; Tan et al., 2021). In the context studied, a possible trigger for such a loss of integrity might be a track record of poor investment advice (cf. Chen et al., 2014), a hypothesis which the next essay examines in more detail.

Essay III: A "sell grandma, the kids, kitchen, sink kind of opportunity" to buy Bitcoin! Or maybe not? Testing the credibility of crypto influencers.

Essay III builds on the findings of Essay II and validates the track record of influencers conducting daily market analyses on the price of Bitcoin. Again, only the seven vloggers with more than 300,000 subscribers as of September 2021 are considered, limited to a time frame from November 2020 to October 2021.

Two different data sets are gathered and leveraged to analyze whether crypto influencers can correctly predict the short-term price direction of Bitcoin, i.e., for the consecutive 24 hours of a vlog video. First, the in Essay II outlined VADER-based sentiment data is leveraged. However, the software cannot tell whether the vlogger was positive (or negative) specifically about the short-term price direction of Bitcoin or rather about something else. Hence, a second data set contains viewer-gathered data on whether a vlog contained such a short-term price indication or not. Each video was rated by two viewers, independently from one another. Only if both viewers derive the same short-term price prediction for Bitcoin, the observation is considered valid and included in the event study.

Neither of the two data sets suggests that the Bitcoin vloggers are correct in their market assessments. On the contrary, for VADER-based sentiment data, after bullish predictions, the cumulative abnormal return in the 18 hours after the video upload is negative at a 10% significance level.

The implication for the large audience of such vlogs is straightforward: crypto vlog viewers are strongly advised to be very cautious about adapting any financial advice about favorable Bitcoin entry and exit opportunities from such influencers.

Essay IV. Regenerative Finance: A crypto-based approach for a sustainable future

The invention of the blockchain was guided by the intention of creating a better financial system for society, that is eliminating the need of trust in intermediaries (Nakamoto, 2008). In the next evolutionary step of using smart contracts to create any financial service solutions, DeFi advocates have praised that the accessibility, transparency, and immutability of blockchain-based financial services has the potential to facilitate permissionless innovation (Chen & Bellavitis, 2020) and enable financial inclusion for the yet unbanked population (Schuetz & Venkatesh, 2020). A recent group of stakeholders uniting under the umbrella term ‘Regenerative Finance’, short ‘ReFi’, takes the ambitions to use blockchain technology for societal purposes one step further. ReFi entrepreneurs are aiming to use smart contract coordination mechanisms as in DeFi, to better approach sustainability endeavors, such as environmental protection and a fair participation of local communities participating in such endeavors.

Previous academic works have critically evaluated the general potential of leveraging blockchain technology for sustainability missions. While in theory, they confirm the potential to use blockchain technology to coordinate regenerative projects, they largely warn of a scenario in which ReFi projects self-enrich under the guise of regenerative pursuits and at the cost of already disadvantaged local communities (Howson, 2020; Howson et al., 2019; Manski & Bauwens, 2020; Stuit et al., 2022). While those studies constitute important critical case studies and commentaries, no paper has yet set out to structurally gather the views of said ReFi entrepreneurs, that is on their motivations, visions, and plans for the ReFi space. Essay IV closes this research gap and conducts semi-structured interviews with ReFi stakeholders (e.g., entrepreneurs, investors, journalists).

The insights from those interviews offer several contributions to both ReFi academia and practice. First, the essay structurally derives a formal definition for ReFi as well as characteristic building blocks of ReFi projects from ReFi community members. In doing, so the motives of the community, technological and governmental enablers along different value chain steps, and a clear delineation from DeFi projects become apparent. Second, the overarching goals of the ReFi space including required conditions and actions to be taken as well as risks to be mitigated to attain those goals are derived. Here, it becomes clear that ReFi entrepreneurs are well aware of the concerns and risks which former scholars have pointed out. Accordingly, the maintenance of integrity and a careful integration of all stakeholder interests, including that of project suppliers in potentially underdeveloped countries, is named crucial for the ReFi community to both increase demand in and supply of truly regenerative projects. The appearance of bad quality or scam ReFi projects, of which former scholars have warned, are similarly identified as the biggest risks for ReFi by the community itself. To overcome these risks, to advance ReFi solutions, and to measure the actual regenerative impact of ReFi projects on the environment and local communities, the community calls for further academic support. Hence, the Essay serves as groundwork for future studies exploring and measuring how innovative blockchain technology and financial incentives mechanisms can be leveraged to support in solving important societal challenges of our time.

The thesis will conclude with a comprehensive summary of its contributions.

2 Essay I: Decentralized Finance—A Systematic Literature Review and Research Directions

Abstract

Decentralized Finance (DeFi) is the (r)evolutionary movement to create a solely code-based, intermediary-independent financial system—a movement which has grown from $4bn to $104bn in assets locked in the last three years. We present the first systematic literature review of the yet fragmented DeFi research field. By identifying, analyzing, and integrating 83 peer-reviewed DeFi-related publications, our results contribute fivefold. First, we confirm the increasing growth of academic DeFi publications through systematic analysis. Second, we frame DeFi-related literature into three levels of abstraction (micro, meso, and macro) and seven subcategories. Third, we identify Ethereum as the blockchain in main academic focus. Fourth, we show that prototyping is the dominant research method applied whereas only one paper has used primary research data. Fifth, we derive four prioritized research avenues, namely concerning i) DeFi protocol interaction and aggregation platforms, ii) decentralized off-chain data integration to DeFi, iii) DeFi agents, and iv) regulation.

Keywords:	Decentralized Finance, DeFi, Literature Review, Research Directions, Blockchain

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Status:	Published in ECIS Research Papers 2022 (see Meyer et al., 2022)

2.1. Introduction

With the intention to eliminate the need for financial intermediaries by creating a solely code-based, openly accessible, and transparent financial system, Nakamoto (2008) invented the Bitcoin blockchain—the first consensus-governed, decentralized database of cryptographically linked blocks storing and enabling borderless, trustless, all-time available, and digitally signed P2P-transactions. With the Turing-complete script language of the Ethereum blockchain, Buterin (2013) decisively evolved the idea and presented the first practical implication of 'smart contracts' (i.e., code-based agreements executed without human intervention), hence providing the technical foundation for 'Decentralized Finance (DeFi)'—a finance ecosystem enabling complex financial products and transactions in a trustless and borderless manner (e.g., lending/borrowing, derivatives (trading) and borderless stable assets). That this ecosystem is not only an idealistic idea of blockchain utopians but is to be taken seriously is, as of Nov, 5th 2021, reflected in i) Bitcoin's $1,150bn market capitalization (CoinMarketCap, 2021a) exceeding the combined $1,135bn market worth of the world's three highest valued banks , ii) the market capitalization of the main DeFi blockchain Ethereum with $530bn—surpassing that of the highest valued bank and growing tenfold within one year (CoinMarketCap, 2021b), as well as iii) the Total Value Locked in DeFi applications—growing by 26 times in three years from $4bn to $104bn (DeFi Pulse, 2021).

To date, the following papers have provided overviews of the DeFi space: Chen and Bellavitis (2020), Schär (2021), and Jensen et al. (2021) characterize the structure, advantages, challenges, and use cases of DeFi from their own point of view and experience, i.e., not following a systematic, literature-guided approach. Bartoletti et al. (2020b) and Cousaert et al. (2021) present 'Systemizations of Knowledge (SoKs)' for the DeFi subspaces of lending protocols and yield aggregators, respectively. They thereby pursue a mixed approach of synthesizing academic literature and conducting own subspace analyses. Werner et al. (2021) conduct a SoK for the entire DeFi space, however, focusing on security challenges and delineating them into technical and economic ones. Systematic literature reviews, on the other hand, e.g., by Pal et al. (2021) and Ali et al. (2020), have not focused on DeFi but rather on finance blockchain applications in general, i.e., including applications still involving intermediaries. Hence, by the time of our writing and to the best of our knowledge, no study has systematically reviewed the state of increasing academic DeFi contributions—a review highly required to structure this fragmented field of research.

This paper closes this gap and identifies 83 peer-reviewed DeFi-related papers as a basis to address three research questions (RQ):

- RQ1) How can DeFi literature to date be structurally framed and which research methods and blockchain systems have scholars focused on?
- RQ2) Which results and insights can be synthesized from the current state of research?
- RQ3) Which research avenues can be derived?

We thereby help scholars in gaining a systematic and cross-disciplinary overview of DeFi-related literature to date including non-conclusive research results, understudied areas, and underemployed research methods.

Specifically, our paper offers five contributions: First, we confirm through systematic analysis that the number of academic DeFi publications is rapidly increasing. Second, we present the first systematically developed framework of DeFi literature: I.) the micro-level with research on financial a.) smart contracts, b.) tokens, and c) applications; II.) the meso-level with papers on a.) DeFi patterns within and b.) scaling solutions beyond single-chain systems; and III.) the macro-level with holistic research on a.) the DeFi ecosystem (e.g., DeFi participants) and b.) its wider societal impact (e.g., on the legacy financial system and regulatory bodies). Third, we find that scholars have focused on the Ethereum blockchain followed by blockchain system-independent research. Fourth, we show that prototyping/ proof-of-concepts (PoCs) are the dominating research method in this new field. Fifth, we suggest four research avenues to further support DeFi advancements.

The remainder of this paper proceeds as follows: Section 2 provides the theoretical background and research methodology. Section 3 presents the literature framework, applied research methods, and blockchain focuses (RQ1) as well as the synthesis of the current state of DeFi research (RQ2). Section 4 suggests future research avenues (RQ3). Section 5 discusses limitations and concludes.

2.2. Background and Research Methodology

2.2.1. Narrowing of the term 'DeFi' and the scope of this literature review

Based on several scholars' definition, we find that 'DeFi' refers to finance protocols i) built with '**smart contracts'** (Gudgeon et al., 2020a; Zetzsche et al., 2020; Jensen et al., 2021) ii) which are '**trustless**' (Chen and Bellavitis, 2020; Kumar et al., 2020; Werner et al., 2021), i.e., functioning without intermediaries (trusted third parties), and iii) developed on '**permissionless, public blockchains**' (Chen and Bellavitis, 2020; Schär, 2021; Wang, 2020; Popescu, 2020). **Figure 1** illustrates the scope of our review, whereas the following in-depth descriptions help to discriminate DeFi from non-DeFi but blockchain- and finance-related application fields:

‘Smart contract-based’: DeFi stems from but needs to be delineated from the field of non-smart contract based crypto-finance. Only with the introduction of smart contracts—programmatically enforced agreements (Schär, 2021)—the development of conditional, complex financial services was enabled. Similar delineation logic applies to related fields of (non-smart contract enabled) blockchain-native cryptocurrency specifics, e.g., price building of Bitcoin, or crypto-asset trading strategies.

‘Trustless’: While cryptocurrencies were invented to replace trusted third parties, in fact, most volume is stored and traded on ‘centralized exchanges (CEXs)’ (Cong et al., 2019), i.e., undermining the disintermediation aim (Zamyatin et al., 2019). Equally, the enhancement of banks’ processes, new financial services still involving intermediaries (e.g., physically-, third party-backed stablecoins), as well as digital currencies issued by central banks or other third parties are not part of our definition of DeFi.

‘Permissionless, public blockchains’: DeFi is meant to be accessible for everyone, i.e., built on openly accessible (‘permissionless’), public blockchains. Permissioned systems, on the other hand (i.e., private or consortium blockchains), do not only prevent the accessibility for everyone but also contradict decentralization principles since system participants can change the rules of the blockchain, revert transactions, etc. (Buterin, 2015).

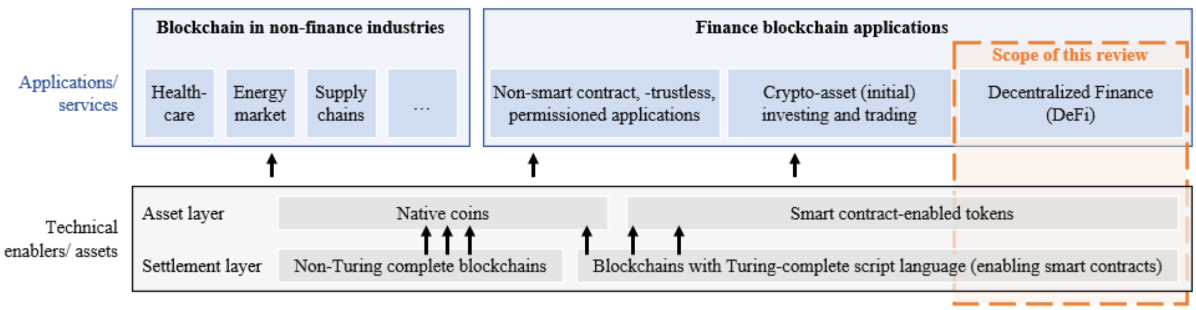

Figure 1. Schematic illustration of the scope of this literature review.

Further, we exclude research related to token investments/ offerings, as this field has been studied in broader depth with own literature reviews (see Moxoto et al., 2021).

2.2.2. Research methodology

To ensure a high-quality review, we followed the research methodologies for systematic literature reviews by Webster and Watson (2002), Levy and Ellis (2006), and vom Brocke et al. (2015).

Our process to identify relevant literature is illustrated in **Figure 2**. As suggested by vom Brocke et al. (2015), our search involved several databases and a combination of search strategies. In total, we screened 7 databases and supplemented a cross-check on Google Scholar. In each database, we conducted a full text search for "Decentralized Finance", "Decentralized Banking" (a synonym) or "Decentralized Exchanges" (DEX) (a delineator from the research field of cryptocurrencies, largely traded on CEXs) in combination with "Blockchain". As outlined by vom Brocke et al. (2015, p. 210), "the number of retrieved publications can be small when new types of technologies ("buzzwords") are studied, which is not uncommon in an IT-oriented discipline […], and it can be large when it turns out that these new technologies have already been studied under different labels". Hence, to not neglect relevant research before the term DeFi entrenched, we added a 'Title, Abstract and Keyword' search for the terms "Smart Contract?", "Financ*" and "Blockchain". In our Google Scholar cross-check, we searched for "Decentralized Finance" or "DeFi" in the title or abstract.

We only included peer-reviewed publications to ensure that all sample papers were subject to quality controls (Davison et al., 2005). Moreover, we included English papers from journals and conferences (or symposiums), as the latter play an important role in the research dissemination process in fast-moving information system fields (Bandara et al., 2011; vom Brocke et al., 2015). Of the 1006 papers matching our criteria, we excluded 228 duplicates. From the remaining 778 papers, we first excluded 549 non-blockchain or non-finance focused papers which also comprised cross-industry research such as on blockchain, smart contract, and governance specifics without a dedicated finance angle. Yet, we acknowledge that those fields are interdependent with DeFi. Second, we excluded 162 papers whose research scope did not cohere to the in section 2.1 discussed DeFi-scope. The resulting list of 67 articles was complemented by 16 articles from backward and forward searches as suggested by Webster and Watson (2002) and Levy and Ellis (2006).

As seen in **Figure 3**, 55 of the 83 papers were published only in 2020 or the first half of 2021. Early papers were mostly published through conferences or symposiums (led by IEEE and ACM conferences), confirming their importance for research dissemination in fast moving fields as DeFi.

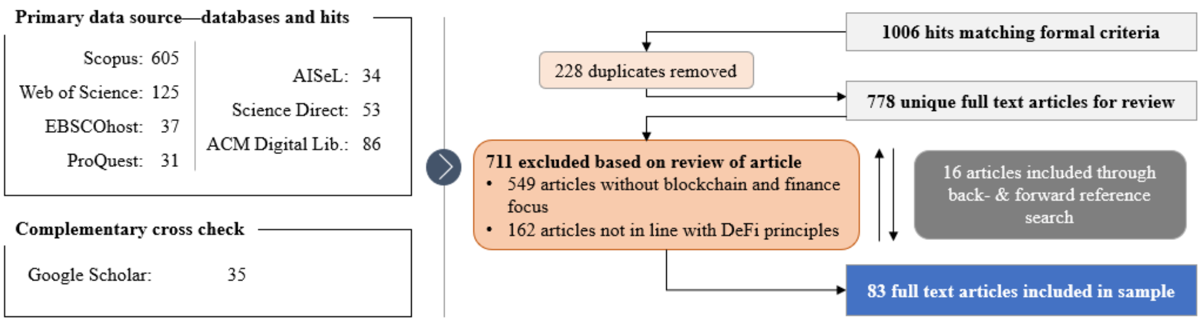

Figure 2. Literature identification and selection process.

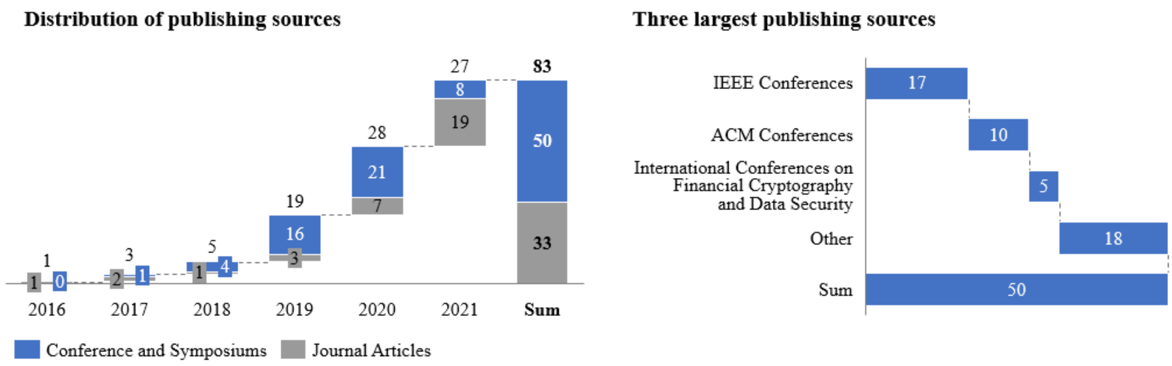

Figure 3. Overview of publishing sources.

Moreover, 63 out of the 83 publishing sources can be (co-)allocated to the subject area of 'Computer Science'. Of those 63 publishing sources, ~10 each are also applicable to the subject areas of 'Economics, Econometrics, and Finance', 'Business Management and Accounting', and 'Decision Science'. Of the remaining 20 sources, 'Business, Management and Accounting' (~10 papers) as well as 'Social Sciences' and 'Economics, Econometrics, and Finance' (~7 papers each) constitute the largest subject areas in accordance with the Scopus data based SCImago Journal Ranking (SCImago, 2020). This width in subject areas affirms that DeFi literature can be considered a cross-disciplinary research field.

To unbiasedly integrate, describe, and summarize the identified 83 papers in a systematic and replicable approach, we followed the literature review specific coding guidelines by Wolfswinkel et al. (2013).

2.3. Results

2.3.1. Literature framework overview

Based on the coding analysis, we frame the current academic DeFi-literature into three levels of abstraction/ perspective and seven subcategories. The framework overview and content-focuses for each of the seven subcategories can be found in Figure 4. On the I.) ‘micro-level’, the largest category with 35 papers (see **Table 1**), academics study aspects of individual components of the DeFi landscape, namely a.) smart contract (language), b.) tokens, and c.) DeFi protocols. With 17 papers, prototype buildings/ PoCs are the most prominent research methodology on the micro-level. Further, in line with real-world applications (Chen and Bellavitis, 2020), scholars largely focus on the Ethereum blockchain (21 papers). On the II.) ‘meso-level’, authors study characteristics within a single blockchain system (e.g., identifying Ponzi scheme patterns) mainly by using empirical Ethereum network data (15 out of 17 papers), or research on opportunities to scale DeFi beyond a single-chain system, namely looking at cross-chain-interoperability or decentralized off-chain data integration possibilities for DeFi applications (13 papers). Lastly, on the III.) ‘macro-level’, authors take a holistic view either by analyzing the entire DeFi ecosystem, e.g., structuring DeFi advantages or use cases (8 papers in total), or the ecosystem’s broader implications on society (e.g., the legacy financial system) and subsequent need for DeFi regulation (10 papers). Studies on the macro-level are mostly blockchain-system independent (10 papers) and hence less Ethereum-focused and mainly use a descriptive research approach (14 papers).

Overall, with 27 papers, prototypes/ PoCs represent the most applied research method, of which 25 papers can be co-allocated to the subject area of ‘Computer Science’ and the other two to ‘Engineering’. Only one paper in our sample, on the other hand, has collected primary data for research. With 49 papers, Ethereum represents the blockchain with most research focus. A comprehensive overview of papers, research methodologies, and blockchain focuses per (sub-)category can be found in **Table 1**. In the following subsections, we present the in-depth content synthesis for each (sub-)category.

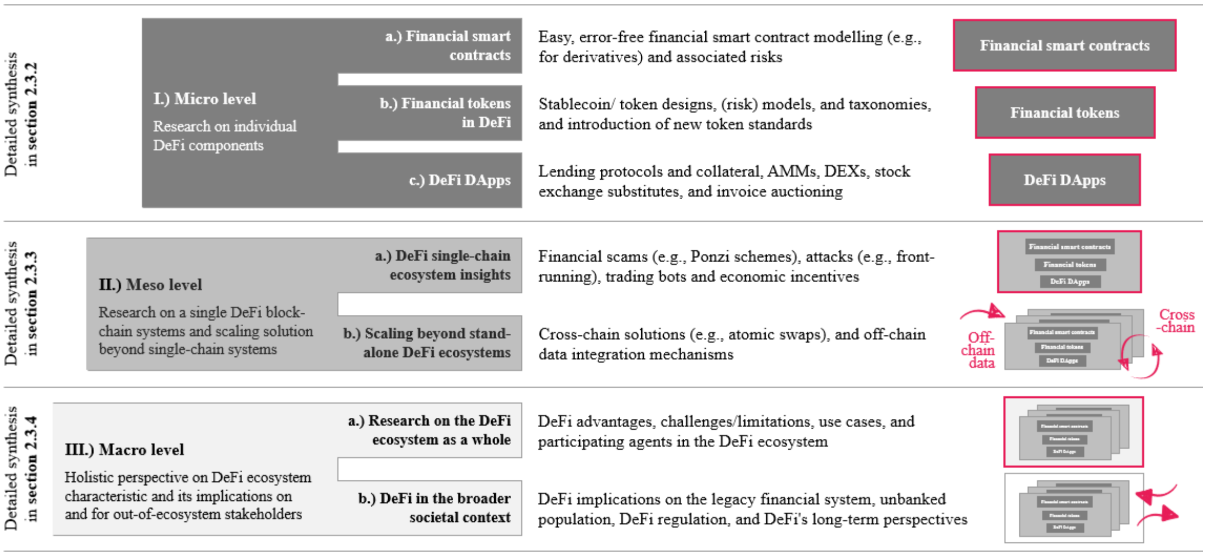

Figure 4. DeFi literature framework.

Table 1. Paper sample, research methods, and blockchain focus per framework (sub-)category.

Framework (sub-) categories	Categorized papers (Note: Multiple research methodologies per paper possible; full table can be provided upon request)	# total paper	Applied research method: Empirical - Primary data	Empirical - Secondary data	Prototype / PoC	Theoretical (modelling)	Descriptive conceptualization	Blockchain focus: Ethereum	Other (e.g. Cardano)	Multiple/ system-independent
Total		**83**	**1**	**21**	**27**	**20**	**20**	**49**	**2**	**32**
I.) Micro level		**35**	**-**	**3**	**17**	**11**	**5**	**21**	**2**	**12**
a.) Financial smart contracts	Arusoaie (2021); Biryukov et al. (2017); Clack (2018); Egelund-Müller et al. (2017); Perera et al. (2020); Seijas et al. (2020); Seijas and Thompson (2018); Skotnica and Pergl (2020); Spiridonov (2021)	**9**	-	-	6	2	1	5	1	3
b.) Financial tokens in DeFi	Davydov et al. (2019); Hu et al. (2019); Klages-Mundt et al. (2020); Liu et al. (2020); Matsuura (2019); Moin et al. (2020); Pernice et al. (2019); van der Merwe (2021)	**8**	-	2	2	2	2	3	1	4
c.) DeFi DApps (decentralized applications)	Angeris and Chitra (2020); Angeris et al. (2019); Bansal et al. (2019); Bartoletti et al. (2021); Kim (2021); Grant et al. (2020); Gudgeon et al. (2020); Guerar et al. (2020); Guerar et al. (2019); Harz et al. (2019); Lin et al. (2019); Okoye and Clark (2019); Pop et al. (2019); Reno et al. (2021); Sridhar et al. (2020); Tien et al. (2020); Tsai et al. (2020); Yang et al. (2019)	**18**	-	1	9	7	2	13	-	5
II.) Meso level		**30**	**-**	**16**	**10**	**8**	**1**	**20**	**-**	**10**
a.) DeFi single-chain ecosystem insights	Bartoletti et al. (2020); Bian et al. (2021); Chen et al. (2021); Chen et al. (2018); Chen et al. (2019b); Daian et al. (2020); Eskandari et al. (2020); Gudgeon et al. (2020); Jung et al. (2019); Lou et al. (2020); Perez et al. (2020); Struchkov et al. (2021); Tien et al. (2020); Victor and Weintraud (2021); Wang et al. (2021a); Wang et al. (2021b); Wu et al. (2021); Zhou et al. (2021)	**17**	-	14	1	3	1	15	-	2
b.) Scaling beyond stand-alone DeFi ecosystems	Borkowski et al. (2019); George and Lesaege (2020); Han et al. (2019); Herlihy (2018); Kumar et al. (2020); Lei et al. (2019); Li et al. (2019); Park et al. (2020); Rueegger and Machado (2020); Shekhawatu et al. (2021); Tefagh et al. (2020); Wang et al. (2021); Zamyatin et al. (2019)	**13**	-	2	9	5	-	5	-	8
III.) Macro level		**18**	**1**	**2**	**-**	**1**	**14**	**8**	**-**	**10**
a.) Research on the DeFi space as a whole	Chen et al. (2020); Jensen et al. (2021); Lockl and Stoetzer (2020); Popescu, 2020; Schär (2021); Stepanova and Eriņš (2021); Smith (2021); Zhang (2021)	**8**	1	-	-	-	7	5	-	3
b.) DeFi in the broader societal context	Abdulhakeem and Hu (2021); Clippinger (2016); Ellul et al. (2020); Duran and Griffin (2021); Guseva (2021); Hütten (2019); Johnson (2021); Larios-Hernández (2017); Paech (2020); Zetzsche et al. (2020)	**10**	-	2	-	1	7	3	-	7

2.3.2. Literature synthesis—Micro level

The 35 papers on the micro-level study aspects of individual components of the DeFi landscape. We cluster this level further into three subcategories differentiated by topic focus: a.) '**Financial smart contract research**', i.e., investigating financial smart contract language designs; b.) '**Financial tokens in DeFi**', i.e., studying the store-of value forms built with smart contracts; and c.) '**DeFi DApps**', i.e., researching and building prototypes of DeFi services. With overall 18 papers, the latter subcategory present the largest one in our framework.

Financial smart contracts

The technical foundation of DeFi is constituted by the underlying blockchain or 'settlement layer' (Schär, 2021) and the incorporated feature of smart contracts. An important question posed here by the 9 papers in our sample, is how complex financial contracts from the traditional world can efficiently, easily, and error-free be transferred to and executed in smart contract programming language (e.g., Skotnica et al. (2020) and Spiridonov (2021)) such that finance managers can focus on the contract specification rather than coding specifics (e.g., Arusoaie (2021) and Spiridonov (2021)). Authors in this field build on pre-blockchain work, which enabled the transition of financial agreements written in natural language towards formal contract languages—also called domain-specific languages (DSLs), pioneered by Arnold et al. (1995) and Jones et al. (2000) (Egelund-Müller et al., 2017). Transferring the idea to the world of smart contracts, several new DSLs for financial contracts such as derivatives have been developed using a PoC research methodology: *Marlowe* for the Cardano chain (Seijas and Thompson, 2018; Seijas et al., 2020) as well as three DSLs for the Ethereum chain, namely i) the unambiguous and composable derivative language *Findel* (Biryukov et al., 2017), ii) the visualization featured language *DasContract* (Skotnica et al., 2020; Skotnica and Pergl, 2020), and iii) a multi-level system that separates DSL-based smart contracts from their execution by Egelund-Müller et al. (2017). Arusoaie (2021) formalize the semantics of *Findel* and develop an infrastructure which tests a list of derived properties which—if fulfilled—exclude security vulnerabilities in *Findel*-based financial derivative contracts. Spiridonov (2021) sketch a theoretical concept for smart contract descriptions based on natural language constructions, leaving a practical testing for later publication.

Financial tokens in DeFi

Based on smart contracts, store of value forms with various functionalities and customization possibilities beyond native blockchain cryptocurrencies such as Ether were invented, summarized under the term 'tokens' (Chen et al., 2019a; Hu et al., 2019; van der Merwe, 2021). The 8 papers in this subcategory conceptualize financial token forms, analyze token characteristics (dominantly of stablecoins) or develop new token standards for DeFi applications.

A highly researched token class are stablecoins, invented to resolve cryptocurrencies' volatility issue—an issue which constitutes a major hindrance to cryptocurrencies' wide-scale adoption (van der Merwe, 2021; Pernice et al., 2019). Klages-Mundt et al. (2020) point out that stablecoins can and already have deviated from their peg and exhibited significant volatility. For non-custodial stablecoins—those adhering to DeFi principles[5]—they formulate risk models to measure incentive-based security and economic stability of stablecoin designs as well as outline how these models can be applied to DeFi applications. Pernice et al. (2019)

[5] Stablecoins can be designed custodial, i.e., utilizing third parties to store the underlying pegged asset of the stablecoin or non-custodial, i.e., implemented solely through smart contracts (Klages-Mundt et al., 2020).

analyze 24 permissionless stablecoin projects and derive a taxonomy based on stabilization techniques, monetary and exchange rate regimes, as well as the degree of decentralization. Moin et al. (2020), on the other hand, propose a taxonomy involving the peg, collateral, price stabilizing, and measurement mechanism used. Both papers point out weaknesses of trustless stablecoins, namely that i) those with digital collateral require well-designed mechanisms to handle volatility swings (Moin et al., 2020), ii) non-collateral-backed, algorithmic stablecoins rely on users' expectations and the issuing mechanism's reliability—which as seen in the case of the protocol *NuBits* might fail (Moin et al., 2020), and that iii) the proxy and self-collateralization rely on margin calls with questionable robustness (Pernice et al., 2019). Further, both agree that decentralized stablecoins depend on well-designed decentral off-chain data integration. A new design for cross-chain stablecoins based on modern risk management is presented by Liu et al. (2020).

New ERC token standards, on the other hand, are developed by Hu et al. (2019) and Davydov et al. (2019). Hu et al. (2019) propose an alternative to stablecoins to resolve the volatility issue of cryptocurrencies. The standard of their *ERC-1* token shifts the exchange risk from merchants and customers to the assumed less risk-averse cryptocurrency issuer. Davydov et al. (2019) propose a token standard (*ERC-T*) which combines characteristics of fungible ERC-20 and non-fungible ERC-721 tokens to enable the fractionalization of unique assets as digital security portfolios and hence ETF-like products in the crypto-asset world.

Matsuura (2019) develops a general token model and interpretation function to support the enablement of more stable finance applications and future academic token research—research which he suggests to be based on open transaction data and in the field of financial engineering.

DeFi decentralized applications (DApps)

The with 18 papers largest subcategory are financial DApps**.** In this area, scholars analyze existing DeFi applications and also often invent own PoCs (9 papers). As in the Ethereum-dominant world of practical applications (Chen and Bellavitis, 2020), DApp research, with 13 papers, does heavily focus on the smart contract pioneer blockchain system.

As in traditional finance, excess assets can generate returns beyond underlying price movements by lending them to someone with shortage of that same asset. Two risks for crypto-asset lending involve the i) volatility-driven monetary instability and ii) counterparty risks between borrowers and lenders (Okoye and Clark, 2018). Hence, DeFi lending services work with overcollateralization requirements for the borrower. One discussed loan service category in the literature sample are P2P mechanisms: a system based on lenders' self-risk assessments of borrowers' collateral certificates (Yang et al., 2019), a P2P lending and bond issuance framework using collateral and insurance in the form of credit default swaps (Okoye and Clark), and a P2P collateral-based lending system with smart-contract-based credit scoring and underwriting mechanisms on loan history transaction records (Reno et al., 2021). An alternative to P2P lending are protocols, in which funds from lenders are pooled and interest rates are derived programmatically by supply and demand. In some sense, these protocols hence replace intermediaries' role of providing a market for loanable funds (Gudgeon et al., 2020b). While the so far discussed loan protocols enable short selling and leveraged long trading, the collateral impedes 'true' borrowing, i.e., entering a position of net debt (Gudgeon et al., 2020b)[6]. Moreover, locked collateral incurs opportunity costs, i.e., the inability to compile returns

[6] An exemption for net borrowing for the duration of one transaction ('flash loans') is discussed on the meso-level.

beyond price changes in the collateral itself (Harz et al., 2019; Kim, 2021). Hence, Harz et al. (2019) present *Balance*, an incentive-based, dynamic collateral design which they show can reduce overcollateralization by 10% while maintaining the same level of utility and security. Tien et al. (2020) implement a solution in which capital locked in smart contracts is supplied to the liquidity pools of *Compound*, providing an historical average annual percentage yield of 4%. Kim (2021), on the other hand, proposes a loan system in which borrowers can increase collateral utility by betting on price movements of their collateral position; yet acknowledging that the approach requires further research to cope with changed scenarios for forced liquidations.

While the so far discussed DApps serve as marketplaces for lenders and borrowers, so called 'Automated Market Makers (AMMs)' serve as an alternative means to increase the time value of money through deposits in fixed ratio 'asset pools' (Angeris and Chitra, 2020). As other parties can swap the deposited tokens of the respective pool (for a rate determined by the liquidity reserve), AMMs also function as DEXs. Moreover, using arbitrage theories, Angeris et al. (2019), Angeris and Chitra (2020), and Bartoletti et al. (2021) are able to show that AMM users are incentivized to perform actions which keep AMMs swap rates in line with actual exchange rates, giving AMMs a third property, namely that of price oracles (mechanisms to feed external data to the blockchain). While AMMs constitute one family of DEXs, the design space of alternative DEXs is large, comprising also order-book and both off-chain and on-chain trade execution mechanisms, all with their own characteristics (Tsai et al., 2020) as well as benefits and trade-offs (Lin et al., 2019).

Further DApp use cases presented are i) protocols to substitute stock exchanges (Pop et al., 2018; Sridhar et al., 2020) including a stock exchange solution based on smart contracts which are accessible by machine learning-based prediction models for stock market prices (Bansal et al., 2019), ii) decentralized auctioning of invoices (Guerar et al., 2020; Guerar et al., 2019), and iii) the proposition to create decentralized structured products (i.e., combinations of instruments such as bonds, stocks, and derivatives) to make this yet to professional investors restricted product class also available for retail investors (Grant et al., 2020).

2.3.3. Literature synthesis—Meso level

The meso-level is subcategorized by the research objective. In the with 17 papers larger subcategory '**DeFi single-chain ecosystem insights**', authors analyze empirical DeFi patterns and focus on the blockchain with the highest amount of transaction data, namely Ethereum (15 papers). The second category ('**Scaling beyond stand-alone DeFi ecosystems**'), entails research on how to interconnect blockchain systems for DeFi (e.g., Ethereum and Cardano) and integrate off-chain data (e.g., non-cryptoasset prices).[7] PoCs present the dominant research method with in total 9 out of 13 papers.

DeFi single-chain ecosystem insights

As traditional finance, DeFi suffers from financial scam constructs. A prominent scam copied to the smart contract world is the 'Ponzi scheme', i.e., 'high yield investment programs' in which investors' return stems only from the investments of further customers joining the scam (Bartoletti et al., 2020a; Lou et al., 2020; Bian et al., 2021; Chen et al., 2019b; Chen et al., 2021). By identifying and analyzing Ponzi schemes on Ethereum and employing a machine-

[7] Here discussed papers focus on decentral, trustless finance applications but the related fields are larger and can for example be read up in the cross-chain interoperability survey by Belchior et al. or the oracle review by Al-Breiki et al. (2020).

learning based detection model, Chen et al. (2019b) estimate that before July 2017, around 500 smart Ponzi schemes were created, accounting for ~0,03% of all Ethereum contracts. Among the papers which develop detection models for Ponzi schemes on Ethereum, the highest F-Score (a measure of a model's accuracy) is reported by Chen et al. (2021). By utilizing a semantic-aware detection approach, the authors suggest a 100% F-score in experimental results, thereby outperforming reported F-Scores from detection tools by Chen et al. (2018), Jung et al. (2019), Lou et al. (2020), and Bian et al. (2021). To avoid Ponzi schemes, Bartoletti et al. (2020a) recommend investors to check the fund's advertisement for too alluring conditions and to analyze the contract code and transaction logs for scam patterns using, for example, the detection tools discussed above. Another financial scam is 'wash trading', in which a group of traders (or a single trader with multiple accounts), trade within their own cycles without eventually changing positions. They thereby manipulate the sentiment of tokens by high trading volumes (Victor and Weintraud, 2021). Analyzing the transactions of two Ethereum DEXs, the authors find that on both DEXs, 30% of tokens have already been wash-traded and that on one of them, 10% of tokens were exclusively subject to wash trading.

A second category of malicious DeFi activity are financial attacks. Daian et al. (2020) find that some of the surging arbitrage bots in DEXs bid up transaction fees to obtain priority ordering in transaction blocks. Further, the authors find that this mechanism, which they call 'priority gas auctions', poses a systemic risk to consensus-layer security and hence the Ethereum ecosystem, since those ordering optimization fees incentivize and enable so called 'miner-extractable-value (MEV)', i.e., value which miners can extract through manipulation of transactions. A phenomenon also assignable to MEV is 'front-running': through access to upcoming transactions, miners can extract privileged information about price slippages and place own transactions before or instead of others in the confirmation block (Struchkov et al., 2021). An extension of 'front-running' is the 'sandwich-attack', in which a miner places one order just before the victim transaction (i.e., front-run) and another one right after it (Zhou et al., 2021). Through transaction sequencing, cryptographic techniques, and appropriate DApp design, front-running risks can yet be reduced (Eskandari et al., 2020). Another vulnerability on DEXs are 'fake deposits', for which Ji et al. (2020) develop *DEPOSafe*, a pattern-based tool to detect such vulnerabilities in ERC-20 smart contracts. A more holistic tool to detect DeFi attacks is *BlockEye*, pursuing end-to-end economic transactions analyses, thereby enabling the identification of whole sequences of malicious transactions and dependencies across DeFi projects (Wang et al., 2021a). As seen in the financial crisis, the failure of a single entity can have huge implications on the financial system as a whole—an interdependency risk which also exists in DeFi: assets created in one protocol (e.g., a stablecoin) are used as collateral or to earn interest in other DApps (Gudgeon et al., 2020a; Tien et al., 2020). If the assets fail, all connected protocols will be affected, potentially leading to a collapse as seen on March, 20th 2020 when the price drop of Ether led to the instability of the stablecoin DAI (Tien et al., 2020). By applying stress-testing mechanisms from traditional finance, Gudgeon et al. (2020a) simulate how a protocol liquidity dry-up could plausibly lead to an undercollateralized and hence insolvent DeFi lending system and a DeFi financial shock. Further, by testing two attack strategies, Gudgeon et al. (2020a) demonstrated the feasibility of attacking *Maker's* governance design, enabling the theft of $0.5bn of collateral within only two blocks. One of the two strategies employed so called 'flash loans'—a solely on blockchains existing method of uncollateralized borrowing under the condition that the borrowed assets are paid back within the same transaction (Wang et al., 2021b).

While the discussed research generates first empirical insights into DeFi activity using network-based 'detection', Wu et al. (2021, p. 18) claim that most studies so far on network 'profiling' (i.e., extracting descriptive information from networks) are not comprehensively discussing the implications of DeFi, which has "seriously affected the shape of the original cryptocurrency market as well as cryptocurrency transaction networks”. One study characterizing transactions statistics of the high-scalability networks of EOSIO, Tezos and XRPL is conducted by Perez et al. (2020). The paper discusses the trade-off of low fees but many low-value spam transactions as in EOSIO and XRPL, or high transaction fees as in Ethereum—co-driven by a DeFi surge—yet in turn deterring a further usage spread. They suggest Tezos as suitable for DApps such as asset tokenization due to its well-defined smart contract semantics and EOSIO for DEXs with on-chain order placements due to the absence of fees and high throughput.

Scaling beyond stand-alone DeFi ecosystems

Operating across blockchain systems poses a complexity for DApps, such that CEXs remain the preferred tool for cross-chain transfers (Bentov et al., 2019; Zamyatin et al., 2019) while DeFi suffers from fragmentation (Borkowski et al., 2019; Han et al., 2019). Hence, scholars in this subcategory have developed prototypes for trustless cross-chain asset exchanges. One area are advancements of the ‘atomic cross-chain swap’, a solution first discussed by Herlihy (2018). Han et al. (2019), Wang et al. (2021c), and Rueegger and Machado (2020) show that the classic atomic swap is equivalent to a premium-free American call option for the swap issuer (given the optionality to abort the swap within a given time frame) and thus unfair for the participant. Hence, the former two papers design and implement swap solutions which estimate the premium value and price it fairly. Further advancements and (technical) alternatives to the atomic swap are presented in i) *XClaim*, a protocol using chain relays and cryptocurrency-backed digital assets to enable trustless cross-chain token issuance, transfer, redemption as well as cheaper and faster exchanges than atomic swaps (Zamyatin et al., 2019); ii) in *DeXTT*, built on top of existing blockchains allowing also for cross-chain one-way transfers by ensuring balance synchronization across the participating blockchains (Borkowski et al., 2019); iii) in *AgentChain*, where users map assets from other blockchains through decentralized trading groups' multi-signature deposit pools (Li et al., 2019); iv) *Xchain*, enabling cross-chain transactions even if they include sequenced and off-chain steps (Shadab et al., 2020); v) and by Lei et al. (2019), discussing a P2P cross-chain trading system with equilibrium pricing techniques. Alternative use cases to swaps and transactions are discussed by Tefagh et al. (2020), proposing the first cross-chain bond issuance protocol *Atomic Bonded Cross-chain Debt* (*ABCD)* and by Shekhawat et al. (2021), suggesting to transfer digital assets and DeFi operations to the cross-chain-interoperable blockchain Polkadot.

Miners verify computations on-chain but there is no built-in mechanism to verify 'real-world' data generated outside the blockchain (George and Lesaege, 2020; Park et al., 2021). So called 'oracles' import verified off-chain information on-chain and are thus a critical bridge for DeFi DApps to integrate data as pegged currency prices or events (Kumar et al., 2020; Park et al., 2021). One class of decentralized oracles are incentive-based voting schemes, e.g., by i) rewarding votes that are coherent with the majority of other votes and vice versa ('Schelling Point' mechanisms), ii) using reputation-based systems for data-feeding nodes as in *Chainlink*, or iii) the approach of *Maker DAO* in which token holders are incentivized to correctly report on the USD price to ensure stability of *Maker DAO's* USD-pegged stablecoin DAI (George and Lesaege, 2020; Park et al., 2021). Another group of oracles are presented by AMMs, discussed earlier—however, they are limited to price reporting of AMM-traded assets.[8]

[8] While there exist further oracles, they are not fully decentral, as in the case of TLS-based schemes, which rely on trusted third-party TLS enabled website (George and Lesaege (2020)) or trusted hardware (Park et al. (2021); Zhang et al. (2016).

2.3.4. Literature synthesis—Macro level

On the macro-level, authors apply a holistic perspective. 8 studies analyze characteristics of the DeFi ecosystem (‘**Research on the DeFi space as a whole**’) and 10 studies investigate DeFi’s out-of-ecosystem impact, i.e., on the financially excluded population, on the legacy financial system, the subsequent need for regulation and likely long-term evolution (‘**DeFi in the broader societal context**’). Most of the in total 18 papers apply a descriptive conceptualization approach (14 papers) and given the holistic perspective, most papers are blockchain system-independent (10 papers).

Research on the DeFi ecosystem as a whole

Authors in this field conceptualize the DeFi ecosystem either by pointing out its benefits and opportunities, deriving risks and challenges, extracting uses cases or by analyzing its agents (i.e., participants in the DeFi ecosystem). Starting with the benefits and opportunities, the most prominent advantages named besides disintermediation are the borderlessness (Chen and Bellavitis, 2020; Popescu, 2020), the openness fostering both trust (Chen and Bellavitis, 2020; Schär, 2021) but also innovation (Chen and Bellavitis, 2020), accessibility for anyone with a smartphone and internet connection (Schär, 2021; Zhang, 2021) as well as the absence of censorship opportunities (Popescu, 2020; Zhang, 2021). Some advantages are simultaneously evaluated as risks or limitations: First, whereas the composability of DeFi primitives is seen as an advantage for accelerated financial innovation (Chen and Bellavitis, 2020; Jensen et al., 2021; Popescu, 2020; Schär, 2021), it can also be viewed as an interdependency and systemic risk, given the high degree of contagion in case of application failures (Jensen et al., 2021). Second, while Schär (2021) argues that smart contract-based financial services increase efficiency, the Ethereum gas costs and network congestion are also posed as key challenges in

DeFi (Chen and Bellavitis, 2020; Jensen et al., 2021). Third, DeFi enhances privacy in the sense that ownerships of wallet addresses are not disclosed (Schär, 2021); however, this may foster illicit activity (Schär, 2021) and on the other hand, privacy is also reduced as all transactions are stored on a public blockchain (Chen and Bellavitis, 2020). That regulatory uncertainty (Chen and Bellavitis, 2020; Popescu, 2020; Smith, 2021), illicit activities (Chen and Bellavitis, 2020; Schär, 2021; Smith, 2021), off-chain data integration (Chen and Bellavitis, 2020; Schär, 2021), governance and operational risks (Jensen et al., 2021; Schär, 2021), as well as the sole reliance on code integrity/ security (Chen and Bellavitis, 2020; Jensen et al., 2021; Schär, 2021; Smith, 2021) pose challenges and risks for DeFi, is agreed upon scholars in this field.

Synthesizing proposed use cases, Chen and Bellavitis (2020) name decentralized currencies, payment services, fundraising, and contracting as major DeFi business models. Schär (2021), Jensen et al. (2021), and Stepanova and Eriņš (2021) further specify the contracting category and analyze the use cases of DEXs and AMMs, lending platforms, derivatives, and automated on-chain asset management. While the use cases largely fit to the micro-level findings of this literature review, the latter two, i.e., derivatives and on-chain asset management, are less covered in our sample. Moreover, Schär (2021) proposes a DeFi stack, comprised of five layers: the i) settlement layer (relatable to the here discussed 'Financial smart contracts' subcategory), ii) asset layer (relatable to this review's 'Financial tokens in DeFi'), iii) protocol layer (relatable to the proposed 'Financial DApps' bucket, iv) application, and the v) aggregation layer. While the first three layers are researched in further depth by papers in this review's sample, the application and aggregation layer are not yet specifically covered by other authors.

Two papers in our sample conduct research on DeFi agents. The paper by Jensen et al. (2021) conceptually categorizes DeFi agents into four groups: i) users, ii) liquidity providers, iii) arbitrageurs, and iv) application designers. The paper by Lockl and Stoetzer (2021) focuses on the first group, i.e., DeFi users: by gathering primary data among DeFi users, the authors test whether blockchain pioneers' driver, i.e., distrust in financial institutions, positively affects DeFi adoption—a relation they cannot confirm.

DeFi in the broader societal context

Referring to the work of Yaga et al. (2018), Abdulhakeem and Hu (2021) suggest that blockchain is the technology to likely impact our lives the most for the next decades. One discussed impact is the financial inclusion of the unbanked population—representing ~bn 1.7 people as of 2017 (Abdulhakeem and Hu, 2021; Demirgüç-Kunt et al., 2020). To support successful financial inclusion solutions, Larios-Hernández (2017) analyzes habit-based sensitives towards financial services of the unbanked and conclude that 'semi-formal'-services (i.e., in the middle ground of full decentralization and incumbents' financial services) are most prone to succeed. Clippinger (2016) and Duran and Griffin (2021) study DeFi's impact on legacy financial intermediaries. Clippinger (2016) finds that the digital disruption in the newspaper industry holds analogies with the threat of smart contract enabled services on banking. As a survival strategy he suggests banks to authentically work on behalf of customers' interests and names lack of trust in institutions' proper personal data management as an important challenge to solve. This yet contradicts Lockl and Stoetzer (2021) who do not confirm a positive relation between distrust in financial institutions and DeFi adoption. Duran and Griffin (2021), on the other hand, find that similar factors contributing to the financial crisis, can also be found in the automated and interconnected smart contract world, potentially impacting the stability of the global financial system. By pressing for technical improvements, better monitoring, and robust standards, they suggest regulatory bodies could reduce these risks, yet claiming that if smart contracts are used in high volumes to hold funds in escrow and facilitate transfers, it may be better to require certain settlement types via central counterparties or consortiums instead of following a fully decentralized approach**.**

That DeFi regulation is important, is agreed upon scholars (e.g., Ellul et al. (2020), Paech (2017), Larios-Hernández (2017), Duran and Griffin (2021)). However, regulating DeFi is non-trivial, mainly driven by i) the difficulty of determining the applicable jurisdiction and law in a borderless market (Zetzsche et al., 2020), ii) lack of enforcement power in the absence of clear accountabilities (Zetzsche et al., 2020), and iii) censorship resistance, i.e., preventing third parties to confiscate assets (Johnson, 2021). Guseva (2020) analyzes empirical data in the US and finds that the SEC's flexible enforcement approach is not suitable anymore after the SEC's inconsistent game-theoretic behavior in three recent legislation cases, leading to increased uncertainty of market participants. With DeFi protocols issuing governance tokens, she suggests aiming for more formal regulation. Evaluating the ecosystem from a tech side, Ellul et al. (2020) point out that jurisdictions have so far mainly focused on financial aspects as cryptocurrency usage and have put insufficient focus on regulating the technological risks stemming from blockchains and smart contracts, hence proposing a technology assurance regulatory environment. A related thought is taken by Zetzsche et al. (2020), proposing an 'embedded regulation' for DeFi, meaning that regulatory requirements are to be integrated in the technological structures which enable DeFi in the first place. The integration could be enforced through an external guarantor, i.e., a "platform where the regulation is embedded and that facilitates supervisory cooperation" (Zetzsche et al., 2020, p. 202). However, the authors argue that while this would enable effective oversight and risk control, it would require a small part of the value chain to become reconcentrated—a state which they claim to be inevitable.

Overall, a common theme emerges in DeFi studies in the broader societal context: the questionability of large-scale enforceability of a fully decentralized financial system. Paech (2017) provide further support, arguing that finance will largely continue to rely on an intermediary-client approach, e.g., as individual clients are subject to private and thus local law irrespective of alternative code-based network rules. Hütten (2019) adds another angle and points out that the DeFi space itself becomes less decentralized as blockchain utopians' commitment to strictly adhere to code-based governance has crumbled after the failure of the DeFi protocol *The DAO*. Further, Hütten (2019) poses that the very institutions that blockchain pioneers meant to replace, embrace the technology for their own operations, leading to an evolution of financial capitalism rather than a revolution. Similarly, Paech (2017) predicts that the expected revolution will primarily introduce new technologies enabling the current financial market model to become more efficient, and Abdulhakeem and Hu (2021) propose that blockchain technology does not necessarily need to overthrow the incumbent system but rather complement it.

2.4. Fields for further research

To derive fields for further research, we applied three angles to our literature synthesis. First, within our framework's subcategories, we identified understudied areas or those with non-conclusive findings as in the case of DeFi network profiling studies or DeFi regulation research. Second, across our framework, we searched for inconsistencies among papers as in the case of authors pointing out the importance of oracles or the existence of an aggregation layer and on-chain asset management, but with few or no relatable research in our sample. Third, we added the angle of research methodologies and blockchain focuses applied and derived areas with room for more academic efforts. While, in the accelerating DeFi space, we expect further research in all discussed framework buckets, our analysis suggests four research directions which will best support the further advancement of the DeFi space:

Research on DeFi protocol interaction and aggregation layers

Whereas the DeFi framework of Schär (2020) states that on top of DeFi protocols there are other layers of user-friendly DeFi service applications and aggregation DApps (and real-world protocols as *YearnFinance* show those aggregation platforms indeed exist), we did not find respective peer-reviewed research. The same reasoning applies to on-chain derivatives and asset management research—use cases in which scholars could prove the praised potential of DeFi composability. We propose to utilize openly accessible transaction records (secondary data) to provide insights on i) how different DeFi DApps empirically interact, ii) find yield farming patterns across and beyond the here discussed lending and liquidity pool rewards (e.g., also involving staking), iii) as well as empirically analyze the associated role of aggregation protocols.

Decentralized oracle applications and their integration to DeFi DApps

Scholars agree that off-chain data integration poses a challenge for DeFi: Chen and Bellavitis (2020) derive that the inability to objectively codify off-chain data on the blockchain, may limit the efficiency and usefulness of a decentralized system of distributed trust. Further, Schär (2021) points out that the dependency on oracles for off-chain data integration introduces dependencies and implies risks of centralized contract execution. Schär (2021) suggests that these risks may be mitigated by decentralized oracles, however, scientific research on fully decentralized oracle designs for DeFi DApps is yet scarce. Some oracle designs discussed in the DeFi context are not fully decentral, as in the case of TLS-based schemes which rely on trusted third-party TLS enabled websites (George and Lesaege, 2020) or trusted hardware (Zhang et al., 2016; Park et al., 2021). To enable more use case opportunities involving off-chain data, we therefore suggest further proof-of-concept research on decentralized oracle integration to DeFi DApps.

Agents/ participants in the DeFi ecosystem

So far, only little light has been shed on DeFi ecosystem participants. In our literature sample, Jensen et al. (2021) conceptually divide DeFi agents into users, liquidity providers, arbitrageurs, and application designers, whereas papers as for example by Angeris and Chitra (2020) and Harz et al. (2019) model incentive-based behavior of different agents on specific DApp categories as AMMs, DEXs or liquidity pools. We suggest further research in this area, especially by conducting primary and secondary data studies. A related study using primary data can be found by Tana et al. (2019), conducting an ethnographic study among miners, traders, and developers. However, in their resulting typology of agents, namely 'Novice' (54%), 'Fortune Hunter' (21%), 'Knowledge-Seeker' (17%), and 'Visionary' (6%), they only discuss the latter in conjunction with DeFi. For secondary data studies, Wu et al. (2021) point out that most papers extracting descriptive information from cryptocurrency networks, are not comprehensively enough discussing the implications of the emergence of DeFi. One study that can be related to this claim and which can be used as a springboard for DeFi-specific studies is the one by Liu et al. (2021), analyzing Ethereum token transactions—i.e., excluding ether transfers and (highly DeFi relevant) smart contract calls—to identify economic agents. Gaining a better view on DeFi agents will improve our understanding of the ecosystem's dynamics, adaptors' motivations (which as shown by Lockl and Stoetzer (2021) is not solely driven by distrust in intermediaries), and enable a targeted derivation of key levers to further advance this still emerging ecosystem.

Regulation of DeFi

Research non-conclusively answers how DeFi can effectively be regulated. The book chapter contribution by Maia (2021) suggests that while the European proposal for a 'Regulation on Markets in Crypto-assets (MiCA)' is a first step to regulating non-trustless crypto-asset markets, the regulation does not address the early-state DeFi trend. For upcoming legislation, Maia (2021) suggests that besides establishing incentives for self-regulatory contributions, authorities should integrate efforts with private bodies to establish public entities which, e.g., through governance tokens, can actively participate in DeFi-protocols and monitor and steer the protocol's risks as well as report systematic risks to authorities. However, the exact design is still unspecified. As long as DeFi operates under regulatory uncertainty, many entrepreneurs, developers, investors, and users will refrain from entering the space. Finding supra-regional solutions for the borderless DeFi space makes the challenge even more complex and requires academic support. As so many stakeholders are involved, we propose this field as a good area for primary data research—of which only one study exists so far.

2.5. Discussion and concluding remarks

Our review offers five distinct contributions. First, we show that the number of DeFi publications is rising with 55 out of 83 articles only published in 2020 and the first half of 2021. 50 out of the 83 papers were published via conferences, which is an expected dynamic in rapidly evolving information system research fields. Second, we present a framework structuring DeFi research into three levels of perspective: i) the micro-level with research around individual DeFi components, namely financial smart contracts, tokens, and DApps, ii) the meso-level with research on characteristics within as well as on scaling solutions beyond single-chain systems, and iii) the holistic-perspective macro-level, conceptualizing the DeFi space as a whole as well as its societal implications and need for regulation. Third, in line with applications in practical use, academia has focused on the Ethereum blockchain so far with 49 out of 83 papers. Fourth, we find that prototyping/ PoCs are the dominating research methodology whereas openly available, secondary transaction data is so far merely used for fraud detection studies and only one paper has used primary data. Finally, we identify four research avenues to further advance the DeFi space, namely i) research on DeFi protocol interaction and aggregation DApps, ii) improvements of decentralized oracles and their integration to DeFi DApps, iii) analyses on participants of the DeFi ecosystem, and iv) practical suggestions for effective DeFi regulation.

We thereby provide the first systematic overview of academic DeFi literature to date and derive research avenues in this yet fragmented scientific field. There are two limitations which we want to point out. First, like other systematic reviews, our paper may suffer from biases, e.g., in sample selection and data interpretation. Second, we needed to ensure a manageable number of papers. Therefore, we excluded i) adjacent, interdependent research such as on non-finance specific smart contract, decentralized governance, and blockchain-related studies as well as ii) DeFi book publications and recent DeFi-related legislations. An inclusion of those sources would extent the comprehension of this review even further and is thus suggested for further reviews in this field.

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3 Essay II: High on Bitcoin: Evidence of Emotional Contagion in the YouTube Crypto influencer space

Abstract

Video blogs (vlogs) on content sharing platforms continue to grow in importance in online marketing. We show the strong influence that vloggers exert on their audience in the quickly expanding blockchain, crypto-assets, and Web3 industry. Measuring the correlation of sentiment in the title and transcript of 11,954 videos to that of cumulatively 3.6 million viewer comments, we find significant emotional contagion across all seven selected YouTube Bitcoin vlogs, all of which—in line with the gender imbalance of both Web3 and the YouTube influencer sphere—are hosted by men. The effect of emotional contagion is more pronounced for negative than positive emotions, and, although emotional bonds are said to intensify with recurring exposure to an influencer, it does not increase over time. The findings are relevant for marketers in blockchain-based markets, for financial regulators to understand the disruption potential exerted by crypto vloggers, and for crypto vlog viewers.

Keywords:	Emotional Contagion, Crypto-assets, Blockchain, YouTube, Vlogs, Online Influencer Marketing

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Current Status:	Published in the Journal of Business Research (see Meyer et al., 2023)

3.1. Introduction

Already 30 years ago, Hatfield, Cacioppo, and Rapson (1993) recognized celebrities and the mass media as agencies of large-scale emotional and cognitive contagion continuously expanding their capacities to define reality for billions of people. As of 2022, with 4.59 billion people or 60% of the world's population using social media (Statista, 2022), this forecast has now become a reality. Given the importance of social media platforms and the considerable amount of time users spend on them, these networks have become ubiquitous in digital marketing in various B2C industries, from classic consumer goods to digital innovations such as crypto-assets.

One popular form of online marketing consists in leveraging opinion leaders or influencers (Leung, Gu, & Palmatier, 2022). Through their central position in a network and considerable audience reach, they represent an essential source of advice for many potential consumers and are an effective form of product diffusion (Casaló, Flavián, & Ibáñez-Sánchez, 2020; Rogers, 1983; Tsang & Zhou, 2005). A fundamental driver of success for influencer marketing is so-called para-social interaction (PSI), referring to friendship-similar feelings between people and media personalities (Horton & Wohl, 1956). The thereupon emerging para-social relationships (PSR) positively affect the perception of the influencer-endorsed products (Reinikainen, Tan, Luoma-aho, & Salo, 2021) as well as subsequent purchase intentions (Sokolova & Kefi, 2020; Yuan & Lou, 2020).

Along with the rising popularity of vlogs (video blogs) on content sharing platforms, as seen through the dominance of YouTube and the rise of TikTok and Reels on Instagram, various studies have also found evidence for the effectiveness of PSI and PSR in vlog marketing (Kurtin, O'Brien, Roy, & Dam, 2018; Lee & Watkins, 2016; Reinikainen, Munnukka, Maity, & Luoma-aho, 2020). The influence exerted on consumers occurs at various levels, one of them being the transferal of emotions (Klimmt, Hartmann, & Schramm, 2006), better known as emotional contagion (Rosenbusch, Evans, & Zeelenberg, 2019). In fact, viewers of social media influencers identify emotional contagion as a central determinant to a vlogger's viewer and subscriber performance, with content being less important (Lee & Theokary, 2021).

One industry that is especially emotion-driven is the crypto-asset industry. Several studies have found social media sentiment to drive crypto-asset prices (Drobetz, Momtaz, & Schröder, 2019; Kraaijeveld & De Smedt, 2020) even to the point of inducing market bubbles (Chen & Hafner, 2019). In fact, crypto-asset returns seem driven more by social-media sentiment than fundamental factors such as macroeconomic news (Naeem, Mbarki, & Shahzad, 2021).

So, while prior studies find evidence for vloggers' emotional influence (Rosenbusch et al., 2019) and sentiment-driven dynamics in the crypto space (e.g., Kraaijeveld & De Smedt, 2020), no study has looked at the intersection, namely, the emotional impact which few crypto YouTube influencers have on their millions of viewers. This is highly relevant mainly due to two reasons. First, the dynamics of emotional contagion might be different in the financial service and tech industry than for consumption products on which former influencer marketing literature has largely focused. Second, the consequences of regular and sustained emotional contagion would be substantially different given that subsequent, emotion-influenced investment decisions might lead to severe financial losses for individuals and contribute to the sentiment-driven crypto market.

We close this research gap and offer five contributions. First, with more than 21 million subscribers and almost 2 billion views, we reveal the vast impact a compiled set of 52 crypto influencers have built in recent years and outline some of the characteristics of the crypto vlogging industry, such as their male dominance. Second, we confirm previous research findings of influencer-initiated emotional contagion within this new, impactful industry: the sentiment from video titles and video transcripts of seven structurally selected Bitcoin vloggers positively correlates with the sentiment in viewers' comments. Sentiment is thereby measured using the open-source framework VADER (Valence Aware Dictionary and sEntiment Reasoner; Hutto & Gilbert, 2014), a software tool that is specifically attuned to evaluating sentiments expressed in social media, and using a finance context-adjusted word lexicon (Loughran & McDonald, 2011). Third, we show that the communities emerging on these vlogs provide a platform for further emotional contagion between the audience members themselves. Fourth, we employ real-world, longitudinal sentiment data to compare contagion effects over time. Against the hypothesis that emotional contagion increases with a vlog's maturity as PSR develops over time (Horton & Wohl, 1956; Rubin & McHugh, 1987) and as higher PSR relates to stronger emotional contagion (Klimmt et al., 2006), we find that for the crypto vlogger space, the effects are non-existent or reversed. Fifth, in line with the general negativity bias in emotion contagion (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Rozin & Royzman, 2001) but in contrast to some prior social media emotional contagion research (Bösch, Müller, & Schneider, 2018; Coviello et al., 2014; Ferrara & Yang, 2015) we find that, in the Bitcoin vlogging context, negative emotions seem to be more contagious than positive ones.

Studying the crypto vlogger industry and the emotional contagion therein is also highly relevant for practitioners, mainly along three dimensions. First, emotionally influencing millions of viewers and providing community platforms for further peer influence, we identify a substantial source of social capital for digital influencer marketing in the virtual-asset industry that is projected to grow to a $150-300 billion market by 2025 (BCG, 2022). Second, given that the reputation of vloggers closely interdepends with that of their associated brands and vice versa (Reinikainen et al., 2021), we call for caution and due diligence before collaborating with Web3 influencers who provide financial advice-similar content while deploying means of emotional contagion to generate more views. Third, to give marketers assurance in cooperating with crypto influencers and simultaneously protect YouTube consumers from sentiment-driven trading advice, we call regulators to reassess and extend their role in regulating crypto influencers spreading investment opinions.

3.2. Theoretical Background and Conceptual Framework

Online influencer marketing has become an essential component in brands' strategies to promote their offerings, with video-based content formats gaining in popularity (Leung et al., 2022). One format of video-based content is that of video blogs, short vlogs, serving as a means for any type and form of user-generated, video-based content sharing and the ability for viewers to subscribe, share, and comment on the content (Gao, Tian, Huang, & Yang, 2010; Snelson, 2015). Most vlogs are owned and authored by individuals who focus on a personal theme and broadcast their opinions, ideas, and personal lives, or who summarize and comment on news on certain topics (Molyneaux, O'Donnell, Gibson, & Singer, 2008). Constituting the second largest social media platform worldwide (Kemp, 2022), YouTube remains the largest sharing platform for such vlogs.

The vlogging space is dominated by men (Wotanis & McMillan, 2014), who not only produce more content than women but are also more likely to regularly view and comment on vlogs (Molyneaux et al., 2008). The average vlog participant is rather young at 23 years old (Molyneaux et al., 2008), however, the regular consumption of vlog content and susceptibility towards vlogging influencers has even been found in children of only ten years old (Folkvord, Bevelander, Rozendaal, & Hermans, 2019; de Veirman, Hudders, & Nelson, 2019).

Simultaneously, younger users have also been found to be more susceptible to peer influence on social media, and men to be more influential than women (Aral & Walker, 2012).

With several million subscribers and viewers, some vloggers can be considered as influencers and to have reached celebrity status (Berryman & Kavka, 2017), recognized also beyond YouTube (Lange, 2007). Marketers increasingly leverage this immense source of social capital through collaborations with vloggers, believing that this novel form of advertising effectively influences consumers' purchase intention at a comparably low cost (Hill, Troshani, & Chandrasekar, 2020). And indeed, brand perception and purchase intentions for experimental groups watching brand-endorsing vlogs are shown to be higher than for the control groups (Lee & Watkins, 2016).

Next to and interdependent with factors such as credibility (Xiao, Wang, & Chan-Olmsted, 2018) and the homophily between a vlogger and the audience (Ladhari, Massa, & Skandrani, 2020), particularly the degree of para-social interaction (PSI) and thereof emerging para-social relationships (PSR) with the audience have been shown to play an important role in the success of vlogger influence. PSI is thereby understood as the feeling of affective ties with a media personality (Horton & Wohl, 1956). The higher the PSI/PSR, the higher the influencer's desirability and ability to convince followers (Reinikainen et al., 2021) and the stronger the perceived relationship importance of viewers towards the vlogger (Kurtin et al., 2018). Accordingly, establishing strong PSR is a key goal for vloggers (Chen, 2016).

The ability to build a strong emotional connection with their viewers is also reflected in the marketing performance of collaborating brands: the stronger the PSR of brand-endorsing vloggers with their audience, the better the perception of the endorsed brand and/or product as well as, in turn, the higher the subsequent purchase intention (Lee & Watkins, 2016; Reinikainen et al., 2021; Sokolova & Kefi, 2020; Yuan & Lou, 2020). Antecedents such as perceived shared values between the audience and a vlogger (Ladhari et al., 2020), attitude homophily (Ladhari et al., 2020; Lee & Watkins, 2016; Sokolova & Kefi, 2020), and the homophily-related (Lee & Watkins, 2016; Turner, 1993) social attractiveness of a vlogger (Lee & Watkins, 2016; Liu, Liu, & Zhang, 2019; Sokolova & Kefi, 2020) support PSI building and the vlogger-endorsed brand and product perceptions. Employing vlogging tactics such as interactive audience participation (Munnukka, Maity, Reinikainen, & Luoma-aho, 2019) and lg interactions and other people's opinions and expressed feelings, emotions have also been found to be contagious in the digital world (Goldenberg & Gross, 2020). On Facebook, for example, users are more likely to adopt positive or negative emotions if these are over-expressed in their social network (Kramer et al., 2014), and bad weather does not only negatively influence the affected persons but also the emotional expressions of on average one or two other users in the affected person's Facebook network (Coviello et al., 2014). The stronger the relationship ties between users, the stronger the degree of emotional contagion (Lin & Utz, 2015).

The results also hold true on Twitter: while there is a linear relationship between the average emotional polarity of the tweets someone is exposed to and their own subsequent tweets, the results yet differ depending on the susceptibility to emotional contagion of the respective users (Ferrara & Yang, 2015). As for vloggers, viewers even identify emotional contagion and linguistic styles as central determinants to viewer and subscriber performance, while content and production expertise being peripheral (Lee & Theokary, 2021). Viewers thereby tend to choose vloggers with similar traits in the first place: the homophily among vloggers and their audience adds to the observation of similar emotions expressed (Rosenbusch et al., 2019).

Transferring these prior research findings to the context at hand, we expect to find emotional contagion from crypto vloggers onto their audience (see **Figure 5**):

H1. Audience sentiment correlates with the sentiment of the crypto vlogger.

Given the high levels of interactive features and the opportunity to self-contribute, YouTube vlogs represent more than a mere medium for individual content creators to reach a large viewer base. In addition, vlogs are considered as networks to maintain social relationships (Lange, 2007) and connected communities (Gao et al., 2010). Apart from solely following the vlog content, audience members can thus also consume the shared reactions of other audience members, such as their opinions on the subject matter or vlog. The comparison of one's own opinions and feelings about the vlogger and video content to that of others, has been shown to impact the perceived information credibility of the vlogger (Xiao et al., 2018) as well as to even positively moderate the PSR between a vlogger and the audience (Reinikainen et al., 2020). Extending the definition of PSI to "interpersonal involvement of the media user with what he or she consumes" (Rubin, Perse, & Powell, 1985, p. 156), the context of influencing relationships in the vlogger space can hence be extended from a solely influencer-follower to also including follower-follower relationships.

Related emotional contagion processes have been found among users of various social networks (Goldenberg & Gross, 2020) and also seem to play a role in vlog-comparable environments: in the e-commerce context, viewers are emotionally influenced not only by the content shown but also by other audience members (Meng, Duan, Zhao, Lü, & Chen, 2021). Accordingly, the consideration of follower-follower relationships among crypto vlogs consumers is expected to impact emotional contagion dynamics in that audience members also transfer emotions between each other:

H2. Audience sentiment is correlated to audience sentiment in prior videos of the same vlogger.

The stronger the relationship ties between social network users (Lin & Utz, 2015) as well as the stronger the para-social relationship between a media personality and the consumer

(Klimmt et al., 2006), the stronger the emotional contagion. Similar to interpersonal relationships, PSI-based connections develop and intensify with frequent exposure over time as uncertainty reduces and perceived similarities with the media personality increase (Eyal & Rubin, 2003; Horton & Wohl, 1956; Rubin & McHugh, 1987). Accordingly, the frequency and duration of YouTube exposure were found to be associated with PSR (Kneisel & Sternadori, 2022; Kurtin et al., 2018) as well as the social attraction towards a vlogger (Kurtin et al., 2018), and is further believed to be associated with the emotional attachment to the influencer (Golbeck, 2016; Ladhari et al., 2020). Similarly, frequent exposure to an online social network can result in stronger relationships among users and a stronger identification with the community (Ballantine & Martin, 2005; Tsiotsou, 2015).

Hence, both the effect of emotional contagion by crypto vloggers as well as among vlog audience members are expected to increase over time as the vlog matures.

H3. The effects of H1 and H2 increase over time.

Little consensus has been reached on which type of valence in emotions leads to stronger contagion in digital media (Goldenberg & Gross, 2020). Early research has found negative emotions to be more contagious than positive ones (Baumeister et al., 2001; Rozin & Royzman, 2001). In the digital media context, however, scholars either do not find evidence in favor of the negativity bias (Kramer et al., 2014) or rather evidence refuting it on social media platforms such as Twitter (Ferrara & Yang, 2015) or Facebook (Coviello et al., 2014) as well as for online newspapers (Bösch et al., 2018). Positive messages are also shown to be more engaging (Goldenberg & Gross, 2020) and viral (Berger & Milkman, 2012; Choi & Toma, 2014; Gruzd, Doiron, & Mai, 2011; Guadagno, Rempala, Murphy, & Okdie, 2013) and while Fan, Xu, and Zhao (2016) found anger to be more contagious than joy, the latter still highly outperformed the negative emotions of disgust and sadness in terms of contagiousness. Referring to the context of this paper, crypto investors tend to be more impacted by negative information in their investment decisions (da Gama Silva, Klotzle, Pinto, & Gomes, 2019), however, the content sharing platform YouTube is rather a place of positive emotions (Goldenberg & Gross, 2020; Reinecke & Trepte, 2014; Waterloo, Baumgartner, Peter, & Valkenburg, 2018) on which positive emotions also positively affect consumer engagement such as commenting (Hughes, Swaminathan, & Brooks, 2019). We hence test whether positive or negative sentiments are more contagious, formulating the hypothesis towards the social media context:

H4. The effects of H1 and H2 are stronger for positive than for negative vlog sentiment.

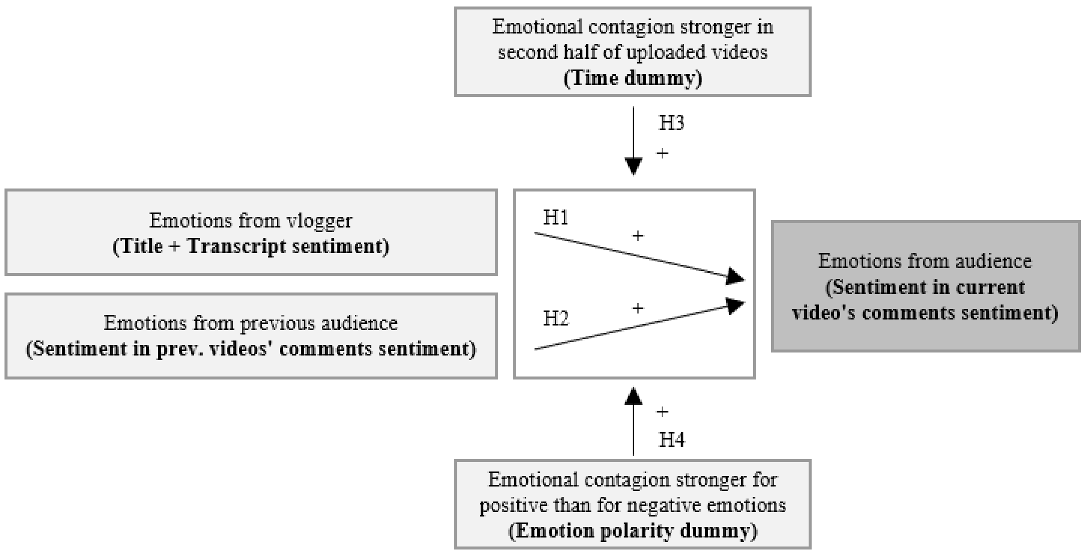

Figure 5. Conceptual model: Hypotheses for emotional contagion in the crypto-assets / Bitcoin vlogger space

3.3. Data and methodology

3.3.1. Identification of crypto vlogs

Three sources were used to obtain a comprehensive overview of the YouTube vlogger space for blockchain and crypto content: i) a post and respective thread *"Crypto Youtubers Tier List"* from the Reddit community "*r/CryptoCurrency*" with around 1,500 comments about the quality of different YouTube crypto vloggers (reddit, 2021), ii) online-articles for vlogger recommendations (CryptoWeekly, 2021; Freutel, 2021), and iii) YouTube itself, i.e., directly searching with the use of keywords such as "crypto(currencies)", "blockchain", or "bitcoin". In doing so, a minimum of 30,000 subscribers as of September 2021 was set to ensure a comprehensive set of crypto content channels above a specified threshold. Channels with a focus other than crypto-related content were omitted. The resulting sample constitutes a list of 52 crypto channels (see **Table 6**).

To analyze emotional contagion in the vlogger space, the sample was further narrowed down to channels with continuously repeated but emotionally loaded product content: daily market analyses on the most prominent cryptocurrency, Bitcoin. The selection of vlogs with mainly Bitcoin content reduced the risk of a difference in comments' emotional state due to a change in the product or service covered. The intrinsic nature of Bitcoin remains stable, with no changes in the functionality or purpose of the base blockchain during the examined time frame. However, despite its stable functionality, Bitcoin constitutes a highly volatile asset (Baur & Dimpfl, 2021; Klein, Pham Thu, & Walther, 2018). The drastic price fluctuations represent the nutrient substrate for crypto YouTubers conducting market analyses. They can frequently update their opinion on the same cryptocurrency and utilize the emotions from the valuation rollercoaster to generate more views. The lack of large-scale agreed and applied fundamental valuation models and evidence of sentiment-driven pricing (Naeem et al., 2021) further contributes to the argument of crypto-assets being an emotionally loaded investment space and hence a viable opportunity to study the effect of emotional contagion. To ensure an analysis of far-reaching influencers and a sufficient number of comments per video to analyze, the threshold of subscribers for the emotional contagion analyses was further increased to 300,000 as of February 2022. The seven channels which matched these criteria in our data set along with key performance metrics are displayed in **Table 7**.

3.3.2. Collection of crypto vlog video data

Over the Google YouTube Data API, data on the number of views, likes, and comments as well as all openly available video identifiers and titles per channel were obtained. From a total of 52,878 videos, the seven selected channels for the emotional contagion analysis comprised 12,934 videos. Video transcripts and comments were accessible for 11,954 videos (with a total of 3.6 million comments) and gathered by developing a custom python web scraper that interfaces with the YouTube API through open-source python libraries. To increase accuracy in the subsequent emotion polarity evaluation, text cleaning functions from the NLTK library were leveraged to remove YouTube-specific words such as hashtags, hyperlinks, and other unwanted characters, as well as to split transcript and comment sentences for further processing. To ensure videos covered Bitcoin, the script also identified bitcoin mentions (e.g., “bitcoin”, “Bitcoins”), keywords (BTC, $BTC, XBT), and coin pairs (e.g., BTC/ETH) in the video titles. The assumption is that a video relating primarily to Bitcoin would mention the word or a synonym in its title for increased visibility on the YouTube platform, which overall applied to 7,740 videos.

3.3.3. Sentiment analysis of vlog content

Researchers refer to sentiment analysis, also called opinion mining, as the automated process of identifying opinions expressed in a piece of text, such as a comment or a transcript, to determine the writer's attitude towards a particular topic and categorizing its polarity in its simplest form on a positive, neutral, or negative scale (Preethi, Uma, & Kumar, 2015).

This research uses the open-source framework VADER (Hutto & Gilbert, 2014) to run sentiment analysis both due to its performance, versatility, and simplicity of use but more importantly due to its recognition as one of the most accurate sentiment analysis tools using lexicon-based analysis in a social media context (Al-Shabi, 2020; Bonta, Kumaresh, & Janardhan, 2019; Sohangir, Petty, & Wang, 2018). VADER generates a sentiment compound score that i) sums the numerical sentiment values of all words and symbols from a sentence which match the used word lexicon and ii) normalizes it between -1 and 1. VADER's developers have recommended the usage of a polarity range describing anything scoring above 0.05 in compound score as positive and conversely scoring below -0.05 as negative, the range in between being labelled as neutral (Al-Shabi, 2020; Hutto & Gilbert, 2014; Pano & Kashef, 2020). The positive or negative compound scores were averaged across all sentences to attain an overall score if a measured text contained multiple sentences (i.e., for transcripts and most comments).

While the prepackaged, open-source lexicon of VADER is well suited for analyzing text in a social media context (including slang, emoticons, and acronyms), it does not account for context-specific expressions. In their research on sentiment-guided adversarial learning, Zhang, Li, Wang, and Choi (2021) demonstrated the utility of extending the VADER lexicon to better fit specific subdomains such as finance and cryptocurrencies to improve its accuracy. To achieve this, we leveraged the Loughran-McDonald Financial Sentiment Word Lists, which contains many of the expressions used by analysts in stock recommendations and financial reports (Loughran & McDonald, 2011). The dictionary is split across 7 categories, from which we retained 2 for our analysis, namely the 'positive' and 'negative' lists. The VADER framework attaches a numerical sentiment value to every expression in its lexicon, determining how positive or negative the word is. To extend it effectively with the positive and negative lists from Loughran and McDonald (2011), we reproduced the methodology developed by Zhang et al. (2021) and attached a numerical value of +1.5 to every positive word and -1.5 to negative words. Among 863 duplicates between the two lexicons, only 21 words were found to have conflicting polarity (i.e., one being perceived negative and the other one positive). For these 21 words, VADER, being domain-independent, misestimates the polarity in a financial context and we hence adapted said polarity to the interpretation from the Loughran-McDonald lexicon. For instance, the word ‘challenge’ in VADER has a positive connotation, whereas in the financial world, the word can often be associated with legal troubles or a difficult economic landscape and is therefore assigned a negative polarity in the Loughran-McDonald lexicon. For the remaining 841 words with matching polarity, priority was given to the interpretation from the VADER lexicon as its numerical sentiment values offer a more precise evaluation of the magnitude of emotions associated with each word. The final Loughran-McDonald enhanced VADER lexicon contains 9,349 words—3,494 positives and 5,855 negatives.

3.3.4. Definition of variables

The dependent variable in all hypotheses, audience sentiment during or after watching a video, is measured by the text-based sentiment in viewers’ comments. Audience members can show their appreciation to other viewers' comments by so-called upvoting, which is comparable to a like. Yet, upvotes were not considered as vloggers themselves regularly interact with their audience by commenting on their own videos and as they receive a disproportionately high number of upvotes. A respective weighting might thus distort the reflection of the audience's sentiment.

To test whether emotions from vloggers influence their audiences, their sentiment is approximated by the text-based sentiment in the video title and transcript. Video descriptions are omitted from the analyses as vloggers often reuse the same text patterns in their descriptions which does not provide relevant or additional sentiment information. As the chronological ordering among comments for individual videos was not attainable, previous audience emotions are proxied by comments' sentiment from a vlog's preceding videos. The duration, for which emotions last, depends on many factors and differs across a variety of emotions beyond 'positive' and 'negative' ones (Verduyn & Lavrijsen, 2015). Also, the duration for emotional contagion can vary: "People can 'catch' emotional states they observe in others over time frames ranging from seconds to weeks" (Fowler & Christakis, 2008, p. 1). Given the absence of clear guidance on which preceding time range to use, a self-considered parameter needed to be developed. With emotional contagion processes ranging from seconds to weeks, a time frame of approximately one week seems reasonable. Since, on average, one video per day is uploaded by the seven vloggers in this sample, the average comments' sentiment of the preceding seven videos is considered for 'prior audience sentiment'. Other time frames (i.e., 1, 3, 5, 10, 15, 20, 30 days) were tested for robustness.

Furthermore, several control variables are considered. As shown by Veirman, Cauberghe, and Hudders (2017), the performance metrics of a vlogger (e.g., number of viewers) can influence the consumers' perception and perceived opinion leadership of the vlogger and hence potentially the degree of emotional contagion. Additionally, as Casaló et al. (2020) have shown in the context of Instagram, followers can be co-involved in the influencer's value creation process by, for example, interacting with the account or recommending it. Hence, if a viewer strongly associates with the vlogger, the viewer's mood might be affected by the performance metrics of the vlogger. Consequently, the video performance statistics of 'view counts', 'comment counts', and 'likes per views' are considered control variables. The latter is thereby constructed as a substitute for absolute like counts, given the high correlation of like and view counts.

Shared experiences or contextual factors in the vlog network are also considered since disregarding them could lead to an overestimation of emotional contagion (Cohen-Cole & Fletcher, 2008). An important factor in this context is the crypto market sentiment, i.e., whether the market is in an upward or downward motion. For example, if prices have been increasing for a while, chances are that both the vloggers' and viewers' moods will be more positive than if the crypto market is experiencing a crash. Thus, to control for the general crypto market condition, daily and weekly returns of Bitcoin are considered. To mitigate a potential reverse causality, i.e., that sentiment from vloggers and viewers would impact Bitcoin returns (as Kraaijeveld and De Smedt (2020) have shown for Twitter sentiment), daily and weekly returns were derived from Bitcoin's daily opening prices (CoinGecko, 2022), i.e., price realizations before any video uploads on the same day.

3.4. Results

The section starts with an overview of the outreach and characteristics of the crypto vlogger market before presenting the results to each tested hypothesis and performed robustness tests.

3.4.1. Overview of the crypto vlogger market

As of September 2022, the 52 channels accumulated almost two billion views and a subscriber base of more than 21 million, thereby representing the largest influencer space within the crypto world. In comparison, while the 52 vlogs generated a total of ~36.5 million views in August 2022 alone, prominent crypto news and information outlets such as CoinTelegraph, CoinDesk, Bitcoin.com, or Bitcointalk received less than 10 million visitors over the same period (Similarweb, 2022). Also, compared to other social media platforms, YouTube presents a dominant position in the crypto space. While as of September 2022, the 52 YouTube vloggers cumulated a total subscriber base of 21.0 million, the same influencers only reached 13.9 million followers on Twitter.[9] The two Reddit communities 'r/CryptoCurrency' and 'r/Bitcoin' counted only 5.4 million and 4.6 million members, respectively (reddit, 2022a; reddit, 2022b).[10]

Some commonalities appeared among the 52 vlogs: More than half of the vloggers are US-based, eight are UK-based, while all others are scattered across different countries. 50 vlogs publish English content irrespective of their origin, the other two originate from Germany. The rather male characterization of the crypto (Bannier, Meyll, Röder, & Walter, 2019; Henry, Huynh, & Nicholls, 2018) and YouTube space (Molyneaux et al., 2008; Wotanis & McMillan, 2014) is also reflected in the gender distribution of crypto vloggers: only two vlogs are led by females. 27 vlogs upload content daily or even multiple times a day, the remaining ones on a weekly or monthly basis. Most channels cover one or two of the following content categories: i) market analyses on various crypto-assets, ii) educational blockchain and crypto content, and iii) news updates about the crypto space. To monetarize the content, various strategies are employed, among them i) premium memberships such as access to a vlogger's gated crypto community, ii) affiliation links, displayed in the videos' description and advertised by the vlogger, and iii) crypto projects or services introduced and promoted in the videos, some of which the vloggers supposedly co-produced.

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9 The 52 YouTube crypto vloggers do not constitute a comprehensive overview of all crypto influencers on Twitter. The number of Twitter followers was collected via the Python package *Snscrape* (JustAnotherArchivist, 2021).

10 Further cryptocurrency-related subreddits exist, but to the best of our knowledge, they are by far smaller.

3.4.2. Descriptive analysis of sentiment data

Table 2 shows the descriptive statistics for the videos included in the analysis. Comment sentiment, title sentiment, and transcript sentiment evaluations without a VADER score, i.e., where the Loughran-McDonald enhanced VADER lexicon did not find a word match, were omitted from the analysis. Given that the title usually consists of only one sentence, the probability of a word match within the lexicon is the lowest for this variable, leading to the smallest number of videos with a valid score (4,180 videos). The highest average sentiment score, with 0.274, can be found in the comments, driven partly by the ever-present appreciation reflected in positive wording toward the vlogger. The lowest average and median sentiment scores occur in the title sentiment, with -0.101 and -0.333, respectively. An explanation can be found in vloggers' strategy to attain more viewers with sensationalist headlines. The usage of emotionally loaded headlines is also observable in the high standard deviation of 0.541 and the presence of extremes: with scores ranging from -0.948 to 0.924, the titles nearly utilize the entire sentiment span from -1 to 1. As the transcript sentiment is consolidated as an average from the sentiment scores of many sentences, the scores are most moderate, e.g., showing the lowest standard deviation of 0.080. Interestingly, while the titles are constructed to play with negative emotions, the mean and median transcript scores are positive again, with 0.158 and 0.163, respectively.

With an average score of 0.351, the most positive comments are found in the vlog of *Crypto Capital Venture*; the lowest but still positive mean comment score with 0.204 is found in the vlog of *CryptoRUs* (see **Table 8**). The variable showing the widest range among individual vloggers is the t*itle sentiment scores*. Three vloggers who use sensationalist headline strategies the most are *Lark Davis, MMCrypto, and The Moon:* the average title compounds are negative (< -0.05), and the standard deviations are among the highest in this sample. On the other side

Table 2. Variables and descriptive statistics

Variable	N	Mean	Median	St. Dev.	Min	Max
Dependent variable: Comment sentiment						
Comment sentiment	7,736	0.274	0.277	0.138	−0.769	0.856
Independent variables: Sentiment from vlogger and previous audience						
Title sentiment	4,180	−0.101	-0.333	0.541	−0.948	0.924
Transcript sentiment	7,731	0.158	0.163	0.080	−0.555	0.625
Previous comment sentiment (7 videos)	7,663	0.277	0.283	0.104	−0.268	0.571
Control variables: Video performance statistics and crypto market performance						
View count (log)	7,740	10.331	10.584	1.263	4.890	13.525
Likes per view	7,740	0.071	0.067	0.022	0.010	0.265
Comment count (log)	7,737	5.299	5.371	1.059	0.000	8.961
Daily Bitcoin return	7,740	0.002	0.002	0.041	−0.352	0.192
Weekly Bitcoin return	7,740	0.012	0.007	0.110	−0.431	0.470

Notes: Comment sentiment measures the emotional expressions of the audience in a video's comments. Title and transcript sentiment measure emotional expressions from the vlogger. Previous comment sentiment (7 videos) measures the emotions from the audiences of preceding videos. 'Likes per view' measures of how many people watching a video clicked on the like function. Sentiment scores of 0 (no lexicon match) in the title, transcript, or comments of the 7,740 Bitcoin-related videos are omitted from the analyses.

of the spectrum, *Benjamin Cowen* is the most moderate vlog in this sample when considering standard deviations and min-max ranges in title and transcript sentiments. Interestingly, this matches with the evaluation of the Reddit crypto community "*r/CryptoCurrency*" discussing the quality of different crypto vloggers: among the seven channels, *Benjamin Cowen* is the only vlog receiving the highest possible rating by the community ("S-Tier" referring to superior quality) and is described to always keeping a "calm head in this crazy market" (reddit, 2021).

While some variables are significantly correlated, the variance inflation factors are all below 3.14 and indicate that multicollinearity should not affect the results of the OLS regression.

3.4.3. Emotional contagion results overall and for each individual vlog

Table 3 shows four different models. The first three test the impact of each of the three independent variables in isolation from each other ((1) Title sentiment, (2) Transcript sentiment, (3) Previous comment sentiment). The last model (4) tests all three independent variables in combination. With an adjusted R^2 of 0.48, the model fit for the combined model (4) is considerable.

Both i) sentiments from the vloggers' titles and transcripts as well as ii) audience sentiment in a vlog's preceding seven videos affect the emotions in audience comments in a positive linear relationship. The audience's sentiment in the previous seven videos has the highest effect on the comments of the current video. In isolation from the other two independent variables, an increase of 1 in the preceding audience sentiment leads to an on average 0.72 higher comment sentiment score. Including the emotional contagion from the vlogger (4), the estimated coefficient slightly decreases to 0.69. The effect is significant in both tested variants ($p < 0.01$). From the influence exerted by the vlogger, the transcript plays a more critical role: in isolation, a one-point increase in sentiment leads to an on average 0.36 increase in the respective video's comment sentiment; for the titles only to a 0.05 increase. In the combined model, the coefficients slightly decrease to 0.26 and 0.03, respectively, yet both influences are significant in all tested models ($p < 0.01$).

Also, certain control variables significantly correlate with the audience's emotions. For example, a higher view count negatively correlates with audience sentiment ($p < 0.01$). A possible explanation is that the ratio of core followers to occasional viewers decreases with more viewers. If core followers are more likely to comment positively, let alone express their

Table 3. Emotional contagion among vloggers and audience - OLS regressions

	Dependent variable: Audience sentiment measured by emotions in a video's comments			
	(1) Title sentiment	(2) Transcript sentiment	(3) Prev. comment sentiment	(4) Combined model
Independent variables: Sentiment from vlogger and previous audience				
Title sentiment	0.05***			0.03***
	(0.003)			(0.003)
Transcript sentiment		0.36***		0.26***
		(0.02)		(0.02)
Previous comment sentiment (7 videos)			0.72***	0.69***
			(0.01)	(0.02)
Control variables: Video performance statistics and crypto market performance				
View count (log)	-0.05***	-0.06***	-0.01***	-0.01***
	(0.002)	(0.002)	(0.002)	(0.002)
Likes per views	1.06***	0.90***	0.76***	0.70***
	(0.09)	(0.07)	(0.06)	(0.08)
Comment count (log)	0.03***	0.03***	-0.0003	0.01**
	(0.003)	(0.002)	(0.002)	(0.003)
Daily Bitcoin return	0.07	0.04	0.17***	0.12***
	(0.05)	(0.04)	(0.03)	(0.04)
Weekly Bitcoin return	0.17***	0.13***	0.02*	0.02
	(0.02)	(0.01)	(0.01)	(0.02)
Constant	0.56***	0.57***	0.14***	0.11***
	(0.02)	(0.01)	(0.02)	(0.02)
Observations	4,178	7,727	7,660	4,143
R^2	0.25	0.27	0.43	0.48
Adjusted R^2	0.25	0.27	0.43	0.48
Residual Std. Error	0.12 (df = 4171)	0.12 (df = 7720)	0.10 (df = 7653)	0.10 (df = 4134)
F Statistic	235.02*** (df = 6; 4171)	481.95*** (df = 6; 7720)	956.85*** (df = 6; 7653)	470.17*** (df = 8; 4134)

Notes: Comment sentiment measures the emotional expressions of the audience in a video's comments. Title sentiment (1) and transcript sentiment (2) measure emotional expressions from the vlogger. Previous comment sentiment (7 videos) (3) measures the emotions from the audiences of preceding videos. The combined model (4) tests all three variables in combination. The control variable 'Likes per views' constitutes a measure of how many people on average who watched a video clicked on the like function. Sentiment scores of 0 (no lexicon match) in the title, transcript, or comments of the 7,740 Bitcoin-related videos are omitted from the analyses. *p<0.1; **p<0.05; ***p<0.01.

appreciation towards the vlogger, the density of positive comments decreases. A reverse logic applies to audience engagement. Both comment counts and likes per view positively relate to audience sentiment ($p < 0.01$). The results can be interpreted in several ways. First, they complement prior findings that consumer engagement is higher for positive content messages (Goldenberg & Gross, 2020) in that it is also specifically higher when the consumer sentiment itself is positive. Second, if other viewers consider a high ratio of likes to views as a mood indicator of other audience members, it might further lead to an emotional contagion from previous viewers to later viewers.

Also, the crypto market performance plays a significant role. In the combined model, daily Bitcoin returns positively correlate with audience sentiment ($p < 0.01$). Weekly Bitcoin returns, on the other hand, positively relate to audience sentiment when omitting the sentiment of the last seven videos ($p < 0.01$). Given that returns from the preceding week will, to some degree, already be reflected in the audience sentiment of the preceding seven videos, this observation is comprehensible.

The results of emotional contagion also hold for each individual channel (see Table 9). All three independent variables positively correlate with comment sentiment. The highest degree of emotional contagion is observable for the vlogger *CryptoRUs* (title sentiment: 0.05, $p < 0.01$; transcript sentiment 0.64, $p < 0.01$), the lowest for *Crypto Capital Venture* (title sentiment: 0.02, $p < 0.05$; transcript sentiment 0.18, $p < 0.01$). The influence from prior audience sentiment is most pronounced for *Benjamin Cowen* (0.83, $p < 0.01$), less pronounced again for *Crypto Capital Venture* (0.33, $p < 0.01$). Interestingly, while being the least extreme in diverging emotions (cf. **Table 8**), *Benjamin Cowen* is also the channel with the highest model fit (adjusted R^2 of 0.59). Per the relatively weak emotional contagion coefficients, the model fits least for *Crypto Capital Venture* (adjusted R^2 of 0.16), yet the F-Statistics still being significant ($p < 0.01$).

Hence, both H1 and H2 are thereby supported among and for each individual vlog.

3.4.4. Emotional contagion results over time

To test the hypothesis that the effect of emotional contagion increases over time (H3), a dummy variable was constructed, dividing the video sample per vlogger into two halves depending on their time of upload, i.e., early videos (first half) and later videos (second half). Based on the binary variable, three moderators were constructed and tested: (1) *'Title sentiment * Time dummy'* to test whether the emotional contagion from the title is stronger in the second halves of a vlog's videos; (2) *'Transcript sentiment * Time dummy'*, testing the same for transcript-originated emotional contagion; (3) *'Prev. comment sentiment * Time dummy'*, testing the same for audience-based emotional contagion. Contrary to the expectation that emotional contagion is more pronounced in the second halves (H3), no change in time or even a decreasing degree of emotional contagion is found (see). The only vlog and independent variable showing a significant increase in emotional contagion over time is the title sentiment for the vlog *CryptoRUs* ($p < 0.1$). The emotional contagion effect from transcripts, on the other hand, is decreasing over time for *BitBoy Crypto* ($p < 0.05$), *CryptoRUs* ($p < 0.05$), *and Lark Davis* ($p < 0.05$). For previous comments' sentiment, no significant change over time is observable. H3 is accordingly rejected.

Table 4. Emotional contagion over time - OLS regressions with time dummy moderators

	Dependent variable: Audience sentiment measured by emotions in a video's comments						
	(1) Benjamin Cowen	(2) BitBoy Crypto	(3) CryptoRUs	(4) Lark Davis	(5) Crypto Cap. Venture	(6) MMCrypto	(7) The Moon
Independent variables: Sentiment from vlogger and previous audience							
Title sentiment	0.03	0.04***	0.04***	0.05***	0.04**	0.02***	0.01*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
*Title sentiment * Time Dummy*	-0.01	-0.005	0.04*	-0.0002	-0.03	-0.02	0.01
	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Transcript sentiment	0.23**	0.39***	0.77***	0.42***	0.18*	0.28***	0.34***
	(0.11)	(0.07)	(0.10)	(0.06)	(0.10)	(0.07)	(0.06)
*Transcript sentiment * Time Dummy*	-0.06	-0.20**	-0.33**	-0.19**	-0.02	-0.03	-0.11
	(0.15)	(0.08)	(0.13)	(0.08)	(0.15)	(0.10)	(0.08)
Previous comment sentiment (7 videos)	0.82***	0.42***	0.32***	0.59***	0.34***	0.71***	0.47***
	(0.08)	(0.05)	(0.08)	(0.06)	(0.12)	(0.06)	(0.06)
*Previous comment sentiment (7 videos) **	0.01	0.04	0.11	-0.01	-0.01	-0.05	0.02
Time Dummy	(0.08)	(0.07)	(0.11)	(0.05)	(0.07)	(0.06)	(0.06)
Control variables: Video performance statistics and crypto market performance							
View count (log)	-0.01	-0.02***	0.02	-0.01	-0.005	0.003	-0.01
	(0.01)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Likes per views	0.82	0.11	1.55***	0.96***	1.16***	0.75***	1.04***
	(0.50)	(0.18)	(0.54)	(0.25)	(0.31)	(0.16)	(0.16)
Comment count (log)	-0.003	0.01*	-0.02*	-0.0001	-0.0002	-0.001	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Daily Bitcoin return	-0.05	0.18**	0.02	0.11	-0.05	0.07	0.16*
	(0.13)	(0.09)	(0.10)	(0.09)	(0.14)	(0.09)	(0.08)
Weekly Bitcoin return	-0.02	0.09**	-0.05	0.03	0.13**	0.01	0.02
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
Constant	0.04	0.25***	-0.14	0.07	0.17	-0.04	0.09
	(0.13)	(0.04)	(0.11)	(0.08)	(0.11)	(0.07)	(0.09)
Observations	452	972	458	588	380	513	780
R^2	0.60	0.42	0.48	0.48	0.18	0.45	0.33
Adjusted R^2	0.59	0.41	0.47	0.47	0.15	0.44	0.32
Residual Std. Error	0.11 (df = 440)	0.11 (df = 960)	0.08 (df = 446)	0.09 (df = 576)	0.10 (df = 368)	0.07 (df = 501)	0.09 (df = 768)
F Statistic	60.51*** (df = 11; 440)	63.29*** (df = 11; 960)	37.78*** (df = 11; 446)	47.98*** (df = 11; 576)	7.29*** (df = 11; 368)	37.79*** (df = 11; 501)	35.03*** (df = 11; 768)

Notes: The 'Time dummy' divides videos per vlogger into two halves depending on their time of upload: 1) the first 50 % of videos uploaded in vlog (dummy = 0); 2) the second 50 % of videos uploaded in vlog (dummy = 1). The time dummy in combination with the respective sentiment score (title, transcript, audience comments) builds a moderator to test whether contagion effects are stronger in the second halves of uploaded videos per vlog. Sentiment scores of 0 (no lexicon match) in the title, transcript, or comments of the 7,740 Bitcoin-related videos are omitted from analyses. *p<0.1; **p<0.05; ***p<0.01.

3.4.5. Emotional contagion results for positive and negative emotions

To test an effect difference in emotional contagion for positive versus negative emotions, four dummy variables were constructed: a polarity dummy each for i) whether the title sentiment, ii) transcript sentiment, iii) both title and transcript, iv) and previous videos' comment sentiment is positive (i.e., larger than 0.05). The dummies were used to build moderators with their respective sentiment counterpart scores, translating into four tested moderator models: (1) whether the effect of emotional contagion from a video's title is stronger for positive than for negative titles, (2) the analog for transcript sentiment, (3) whether emotional contagion from title and transcript is stronger if both are positive, (4) the analog for comment sentiment. **Table 5** shows the respective results of the four models: stronger emotional contagion effects are not found for positive but for negative emotions instead such that H4 is rejected. The moderator '*Title sentiment * Title polarity*' is negative on a 10% significance level, and for the sentiment from previous videos' comments, emotional contagion is more pronounced for negative than for positive preceding comment sentiment on a 1% significance level. For transcript sentiment, there seems to be no difference in emotion polarity. The results contradict prior findings in social media-related emotional contagion research. While prior social media studies find a stronger emotional contagion for positive emotions (Ferrara & Yang, 2015; Guadagno et al., 2013), the opposite holds true in the crypto or, more specifically the Bitcoin influencer space: in line with Rozin and Royzman (2001) and Baumeister et al. (2001), negative emotions seem to be more contagious than positive ones.

Table 5. Emotional contagion for positive vs. negative emotions - OLS regressions with polarity dummy moderators

	Dependent variable: Audience sentiment measured by emotions in a video's comments			
	(1)	(2)	(3)	(4)
Independent variables: Sentiment from vlogger and previous audience				
Title sentiment	0.05***		0.04***	0.03***
	(0.01)		(0.01)	(0.003)
Title sentiment	-0.03*			
** Title polarity*	(0.02)			
Title sentiment			-0.01	
** Title and transcript polarity*			(0.01)	
Transcript sentiment		0.33***	0.28***	0.27***
		(0.06)	(0.02)	(0.02)
Transcript sentiment		-0.04		
** Transcript polarity*		(0.06)		
Transcript sentiment			-0.04	
** Title and transcript polarity*			(0.03)	
Previous comment sentiment (7 videos)	0.71***	0.70***	0.69***	1.08***
	(0.02)	(0.01)	(0.02)	(0.09)
Previous comment sentiment (7 videos)				-0.43***
** Polarity*				(0.10)
Control variables: Video performance statistics and crypto market performance				
View count (log)	-0.01***	-0.01***	-0.01***	-0.02***
	(0.002)	(0.002)	(0.002)	(0.002)
Likes per views	0.80***	0.72***	0.69***	0.72***
	(0.08)	(0.06)	(0.08)	(0.08)
Comment count (log)	0.003	0.003	0.01**	0.01***
	(0.003)	(0.002)	(0.003)	(0.003)
Daily Bitcoin return	0.15***	0.13***	0.12***	0.12***
	(0.04)	(0.03)	(0.04)	(0.04)
Weekly Bitcoin return	0.03**	0.01	0.02	0.03*
	(0.02)	(0.01)	(0.02)	(0.02)
Constant	0.13***	0.11***	0.11***	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	4,146	7,651	4,143	4,143
R^2	0.45	0.46	0.48	0.48
Adjusted R^2	0.45	0.46	0.48	0.48
Residual Std. Error	0.10 (df = 4137)	0.10 (df = 7642)	0.10 (df = 4132)	0.10 (df = 4133)
F Statistic	430.84*** (df = 8; 4137)	801.69*** (df = 8; 7642)	376.58***(df = 10; 4132)	422.14*** (df = 9; 4133)

Notes: The polarity dummies divide video titles, transcripts, and comments to a boolean variable (1 for positive emotions, i.e., sentiment scores > 0.05 and 0 for negative emotions, i.e., sentiment scores < 0.05); Title and Transcript polarity refers to both title and transcript sentiment scores being positive (> 0.05); the dummy for previous audience sentiment tests whether the average comments' sentiment score of the preceding 7 videos is positive or negative. Sentiment scores of 0 (no lexicon match) in the title, transcript, or comments of the 7,740 Bitcoin-related videos are omitted from analyses. ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

3.4.6. Robustness tests

In the preceding analyses, carefully considered variables and data were used to estimate emotional contagion in the context of crypto vlogging. This section presents the associated robustness tests.

Only Bitcoin-focused videos were considered to ensure that changes in audience emotions did not occur due to a change in subject covered. Although the analyzed vlogs focus primarily on Bitcoin, they occasionally include non-Bitcoin-related crypto-asset content. Testing emotional contagion for those 4,214 non-Bitcoin-related videos, the model fit in the combined regression model (cf. **Table 3**, (4)) is still considerable with an adjusted R^2 of 0.45. Also, all three independent variables still show a significant effect ($p < 0.01$). Similarly, a decrease of emotional contagion in the second halves of the vlogs' video uploads (H3) as well as for positive emotions (H4) still holds.

In the absence of clear guidance from prior literature on the duration of emotional contagion or on how many previous interactions with an influencer are still present in one's mind, a carefully considered time range of seven preceding videos was selected to estimate past audience sentiment. Other time frames (1, 3, 5, 10, 15, 20, and 30 preceding videos) were tested for robustness and show similar results in terms of significant emotional contagion from previous comments' sentiment onto current comments' sentiment ($p < 0.01$), yet with differing model fits and coefficient estimates. The highest model fit with an adjusted R^2 of 0.49 can be found for the preceding 15 videos. Overall, the robustness test shows that the selected time frame of 7 preceding videos did not change the nature and interpretation of results compared to other time frames.

3.5. Discussion

3.5.1. Theoretical contributions

This study presented important influencer marketing research in a new but powerful market. Digital products have become more and more important in our economy as the growing dominance of tech companies shows. One of the latest technological advancements is the blockchain, enabling the emergence of the crypto-assets industry and promise of a large-scale decentralized internet, or Web3, in which power and ownership are given back to users (Momtaz, 2022). As our results show, examining prior scientific findings in these new markets is paramount: whereas some results are in line with prior influencer-marketing studies, others stand in contradiction.

First, we confirm our hypothesis that crypto vloggers transfer their emotions to their audiences (H1) and show that they are likely to play with emotions purposefully. The standard deviations and min-max ranges in the title sentiments, i.e., the observable video information before a potential viewer decides to watch the video, are considerably more extreme than in the transcripts. Further, while the mean and median for transcript sentiment are both positive, the two statistics are negative for title sentiments, with the median even being significantly lower than the mean. The strategy seems to play off: view counts negatively correlate with all sentiment variables, including the title sentiment. Hence, complementing prior findings in the broader YouTube vlogger context that a vlogger's ability of emotional contagion and linguistic styles is perceived as central to a vlogger's success (Lee & Theokary, 2021), we show that crypto vloggers are likely to use rather negative and often sensationalist headlines to generate more views.

Second, considering YouTube vlogs not as mere one-sided platforms for vloggers to reach an audience but as interactive content sharing networks to maintain social relationships (Gao et al., 2010; Lange, 2007), we confirm our hypothesis that, on top of transferring their own emotions via videos, vloggers also provide community platforms for further emotional contagion among audience members (H2). The results match with prior studies of emotional contagion among members of social media platforms (Goldenberg & Gross, 2020) and extend observations in vlogger-related research, namely i) that other audience members' comments moderate the effect of PSR on perceived vlogger credibility (Reinikainen et al., 2020) and ii) that audience members emotionally influence other viewers in the context of E-Commerce (Meng et al., 2021).

Yet, the effects of emotional contagion behave differently than expected over time. Given that PSI intensifies with recurring exposure to a celebrity (Horton & Wohl, 1956; Rubin & McHugh, 1987) and those levels of PSI positively relate to the degree of emotional contagion (Klimmt et al., 2006), emotional contagion was expected to be higher in the second halves of a vlogger's video uploads. Rather the contrary or no effects are found in this study, such that H3 is rejected. One possible explanation is offered in the rapidly increasing number of viewers who might dilute the more intense PSI of a vlogger's early core community. Another possibility is that specific vlog characteristics or events have counteracted long-term PSR. In the present context, a poor track record in investment evaluations could explain why we see less agreement between a vlogger and the audience (cf. Chen, De, Hu, & Hwang, 2014), potentially also impacting the peer relationships among audience members.

Further, we contribute to the unsettled debate on whether positive or negative emotions are more contagious. While influencer marketing and vlogger literature have so far often focused on 'feel-good' industries such as fashion or beauty, we examined a much more volatile (Baur & Dimpfl, 2021), emotionally loaded, and sentiment-driven industry (Drobetz et al., 2019; Kraaijeveld & De Smedt, 2020). In the crypto vlogging context, we find emotional contagion to be more pronounced for negative emotions. While these findings contradict some earlier social media-related emotional contagion studies (Ferrara & Yang, 2015; Guadagno et al., 2013), they are yet in line with pre-social media research saying that negative entities are more contagious than positive ones (Rozin & Royzman, 2001) as well as crypto market herding literature saying that investors are more affected by negative than by positive information (da Gama Silva et al., 2019).

In faith of an increase in asset value, Bitcoin and other crypto-assets constitute financial investment opportunities for vloggers and their millions of viewers alike. An actual or anticipated reversal of asset value increase is associated with fear of financial losses and disappointment. In the absence of large-scale applied fundamental valuation techniques as in the stock market, single tweets as by Elon Musk, few trades by large-scale crypto-investors, or simply a change in social-media sentiment might induce large price fluctuations (Kraaijeveld & De Smedt, 2020)— making the causes of volatility difficult to comprehend and further contributing to a sentiment-driven investment behavior. Hence, a more pronounced spread of negative emotions is generally plausible in this uncertain and volatile environment and indicates that our findings can better be explained by the market characteristics of the crypto industry and the overall negative bias in emotion spreads rather than by positive mood characteristics (e.g., Goldenberg & Gross, 2020) and the stronger virality of positive emotions in social media (Berger & Milkman, 2012; Guadagno et al., 2013).

3.5.2. Managerial implications

Our findings also offer several practical contributions. Online influencer marketing has become an integral component of brands' marketing strategies (Leung et al., 2022), and we introduced an important space of social capital for influencer marketing in the crypto-asset industry, which is projected to grow tremendously. Although it is somewhat ironic that rather than building on the promoted decentralized blockchain technology for marketing processes (cf. Tan & Saraniemi, 2022), information dissemination in Web3 is still very much performed in a Web2 manner: the gathered sample of 52 influencers accumulated more than 21 million subscribers and almost 2 billion views by the time of writing. Demonstrating their ability to emotionally influence their viewers and providing community platforms for further peer influence, substantiates crypto vloggers representing powerful marketing resources. Considering crypto influencers collaborating with other parties via affiliation links and/or service promotions, shows that some marketers already leverage this source of capital.

Yet, given the risks associated with the highly sentiment-driven crypto-assets industry, we call for attention to possible hazards emerging from these influencers. Investors in the crypto-asset markets are mainly comprised of younger generations (Naeem et al., 2021), who are also most susceptible to peer influence on social media (Aral & Walker, 2012). Although former SEC Chairman Jay Clayton poses that “the idea that we’re going to regulate retail investor opinion on stocks is a difficult one for people to get their head around” (Reinicke, 2021), we argue that both marketers but also regulators should be aware of the vast impact that a few ‘retail investor opinions’ can have on the mass market – even when they pledge ‘not to provide financial advice’. As prior research on herding behavior in financial markets shows, peer influence also affects investment behavior: the social contacts and the communities one engages with have a significant effect not only on the likelihood of investing in financial instruments but also on the specific choice of assets being purchased (Brown, Ivković, Smith, & Weisbenner, 2008; Bursztyn, Ederer, Ferman, & Yuchtman, 2014; Fenzl & Pelzmann, 2012; Hong, Kubik, & Stein, 2004). The fact that YouTube crypto influencers emotionally influence millions of viewers and even purposefully use sensationalist video titles to generate more views while reviewing crypto-assets products and services might further play into a sentiment-driven and no level-headed investment behavior—potentially leading to individual and large-scale financial losses. A transgression, e.g., as recently seen in the case of influencer Kim Kardashian, promoting a crypto-asset to her followers without disclosing the payment received for the promotion and being charged (SEC, 2022), thereby negatively affects both the influencer as also the endorsed products and brands (Reinikainen et al., 2021). We hence call marketers for caution and due diligence before collaborating with Web3 influencers and urge regulators to reevaluate the need for guidelines for influencers that disseminate their investment and market opinions to a larger audience and utilize emotion-guided strategies to do so. In the meantime, we advise crypto vlog viewers to be aware of the emotional influence they are exposed to, especially before engaging in any form of financial investment.

3.5.3. Limitations and further research

We want to point out some limitations, each translating into a call for further research. First, many cues in vlogger content will not be adequately reflected in the title and transcript sentiment, e.g., thumbnails, video images, a vlogger's pitch, or facial expressions. Video-based sentiment software tools with potentially more accurate results would possibly reveal that vloggers' emotional contagion is even more pronounced. Similarly, a reflection of the chronological order of comments within a video will likely increase the model fit for the emotional contagion regression.

Second, there are other psychological constructs that interdepend with emotional contagion. Distinguishing between the various affective influences that might be exerted, i.e., emotional contagion, empathy, and viewer-generated emotions (Klimmt et al., 2006), could provide a more differentiated explanation on why we observe similar emotions expressed among a crypto vlogger and audience members. Similarly, accounting for homophily among vloggers and viewers (Rosenbusch et al., 2019) might provide further insights into the affective influences found.

Third, our research concentrated on English-speaking, male, and popular vlogs in terms of subscribers. The expression of affective responses might differ across cultural backgrounds (Matsumoto, Yoo, Hirayama, & Petrova, 2005) and for larger vs. smaller crypto vlog community sizes (Lin, Tov, & Qiu, 2014). So, while English is the dominant language in the international crypto market, it might still be interesting to study local crypto vlogs with fewer subscribers and compare respective results in affective influences. Apart from the emotional contagion context, scholars might also want to further investigate causes and consequences, that from as many as 52 crypto influencers accumulating almost 2bn views, only two were found to be female.

Lastly, while we present evidence for emotional contagion exerted from crypto vloggers, we can only assume but do not know much for certain about the respective consequences yet. Hence, we call for research on i) the impact of crypto vloggers' emotional contagion on subsequent trading behavior, ii) on associated benefits and risks for individual investors as well as financial markets at large, iii) on the track record of those vloggers and the respective impacts on PSR and emotional contagion, and iv) on the impact on the associated long-term (brand) perception of endorsed Web3 securities and services.

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3.7. Appendix

3.7.1. Appendix A

Table 6. Names of 52 crypto vlogs in sample.

1	99Bitcoins	14	Coin Bureau	27	Data Dash	40	MDX Crypto
2	Aantonop	15	Colin Talks Crypto	28	denome	41	Millennial Money
3	Alexander Lorenzo	16	Jordan Lindsey	29	Digital Asset News	42	MMCrypto
4	Altcoin Buzz	17	Crazy 4 Cryptos	30	Dr. Julian Hosp	43	My Financial Friend
5	Altcoin Daily	18	Crypto Banter	31	EllioTrades Crypto	44	Satoshi Stacker
6	Anthony Pompliano	19	Crypto Capital Venture	32	Finematics	45	Sheldon Evans
7	Bankless	20	Crypto Casey	33	Hashoshi	46	The Bitcoin Express
8	Benjamin Cowen	21	Crypto Daily	34	InvestAnswers	47	The Modern Investor
9	BitBoy Crypto	22	Crypto Kirby Trading	35	Ivan on Tech	48	The Moon
10	Blocktrainer	23	Crypto Zombie	36	Jason Pizzino	49	Token Metrics
11	Bob Loukas	24	CryptoBusy	37	JRNY Crypto	50	Tyler S
12	Box Mining	25	CryptoRUs	38	Lark Davis	51	Unchained Podcast
13	Charles Hoskinson	26	Daap University	39	Max Maher	52	What Bitcoin Did

3.7.2. Appendix B. Performance metrics, descriptive statistics, and regression results per vlog

Table 7. Performance metrics of seven shortlisted Bitcoin vloggers.

	Benjamin Cowen	BitBoyCrypto	CryptoRUs	Lark Davis	CCV	MMCrypto	The Moon	**Total**
Subscribers (k)	769	1,440	327	651	486	565	562	4,800
Total videos	1,702	3,364	1,306	2,041	1,423	1,279	1,819	12,934
Total views (m)	84.87	215.09	106.60	58.21	28.26	84.49	89.29	666.79
Ø views per video	49,863	63,938	81,625	28,520	19,858	66,057	49,085	51,554
Total likes (m)	5.10	12.40	5.76	3.84	1.82	7.96	5.97	42.85
Ø likes per video	2,996	3,686	4,411	1,883	1,278	6,221	3,283	3,313
Ø likes per view	0.06	0.06	0.05	0.07	0.06	0.09	0.07	0.06
Total comments (k)	317.22	942.41	432.04	599.19	242.50	973.85	543.63	4,050.82
Ø comments per video	186	280	331	294	170	761	299	313.24

Table 8. Variables and descriptive statistics per vlog.

Variable	N	Mean	St. Dev.	Min	Max
Benjamin Cowen					
Comment sentiment	1,050	0.259	0.180	−0.473	0.749
Title sentiment	454	0.063	0.423	−0.751	0.772
Transcript sentiment	1,050	0.143	0.070	−0.232	0.354
Previous comment sentiment (7 videos)	1,043	0.260	0.147	−0.271	0.469
BitBoy Crypto					
Comment sentiment	1,408	0.263	0.152	−0.769	0.804
Title sentiment	979	−0.041	0.552	−0.948	0.915
Transcript sentiment	1,407	0.171	0.085	−0.499	0.564
Previous comment sentiment (7 videos)	1,395	0.261	0.105	0.028	0.548
CryptoRUs					
Comment sentiment	989	0.204	0.123	−0.110	0.856
Title sentiment	463	−0.034	0.440	−0.883	0.924
Transcript sentiment	989	0.162	0.059	−0.079	0.625
Previous comment sentiment (7 videos)	982	0.203	0.084	0.022	0.477
Lark Davis					
Comment sentiment	1,041	0.320	0.125	−0.208	0.838
Title sentiment	591	−0.112	0.540	−0.933	0.883
Transcript sentiment	1,042	0.160	0.098	−0.555	0.390
Previous comment sentiment (7 videos)	1,028	0.319	0.083	0.072	0.495
Crypto Capital Venture					
Comment sentiment	810	0.351	0.106	−0.085	0.739
Title sentiment	385	−0.066	0.477	−0.883	0.836
Transcript sentiment	803	0.145	0.079	−0.204	0.419
Previous comment sentiment (7 videos)	803	0.351	0.051	0.155	0.501
MM Crypto					
Comment sentiment	1,079	0.315	0.092	−0.011	0.629
Title sentiment	515	−0.375	0.530	−0.940	0.912
Transcript sentiment	1,079	0.163	0.071	−0.079	0.567
Previous comment sentiment (7 videos)	1,072	0.315	0.064	0.139	0.448
The Moon					
Comment sentiment	1,359	0.233	0.107	−0.108	0.647
Title sentiment	793	−0.140	0.609	−0.942	0.899
Transcript sentiment	1,361	0.154	0.085	−0.149	0.599
Previous comment sentiment (7 videos)	1,340	0.233	0.068	0.070	0.460

Notes: Comment sentiment measures the emotional expressions of the audience in a video’s comments. Title sentiment and transcript sentiment measure emotional expressions from the vlogger. Previous comment sentiment (7 videos) measures the emotions from the audiences of preceding videos. Sentiment scores of 0 (no lexicon match) in the title, transcript, or comments of the overall 7,740 Bitcoin-related videos are omitted from the analyses.

Table 9. Emotional contagion among vloggers and audience per vlogger - OLS regressions

	Dependent variable: Audience sentiment measured by emotions in a video's comments						
	(1) Benjamin Cowen	(2) BitBoy Crypto	(3) CryptoRUs	(4) Lark Davis	(5) Crypto Capital Venture	(6) MMCrypto	(7) The Moon
Independent variables: Sentiment from vlogger and previous audience							
Title sentiment	0.03*	0.04***	0.05***	0.05***	0.02**	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Transcript sentiment	0.19**	0.29***	0.64***	0.31***	0.18**	0.26***	0.26***
	(0.08)	(0.05)	(0.09)	(0.04)	(0.07)	(0.05)	(0.04)
Previous comment sentiment (7 videos)	0.83***	0.49***	0.48***	0.61***	0.33***	0.71***	0.50***
	(0.04)	(0.05)	(0.06)	(0.06)	(0.11)	(0.06)	(0.05)
Control variables: Video performance statistics and crypto market performance							
View count (log)	-0.01	-0.02***	0.01	-0.02**	-0.01	-0.01	-0.02**
	(0.01)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Likes per views	0.79	0.03	1.34**	0.78***	1.12***	0.72***	1.05***
	(0.49)	(0.18)	(0.53)	(0.24)	(0.25)	(0.16)	(0.16)
Comment count (log)	-0.003	0.02***	-0.01	0.001	0.0005	0.001	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Daily Bitcoin return	-0.05	0.19**	0.004	0.10	-0.04	0.07	0.16*
	(0.13)	(0.09)	(0.10)	(0.10)	(0.14)	(0.09)	(0.08)
Weekly Bitcoin return	-0.01	0.09**	-0.07	0.02	0.13**	0.01	0.03
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
Constant	0.06	0.25***	-0.10	0.21***	0.19**	0.04	0.15**
	(0.10)	(0.04)	(0.10)	(0.07)	(0.08)	(0.06)	(0.06)
Observations	452	972	458	588	380	513	780
R^2	0.60	0.41	0.47	0.47	0.18	0.45	0.33
Adjusted R^2	0.59	0.41	0.46	0.46	0.16	0.44	0.32
Residual Std. Error	0.11 (df = 443)	0.11 (df = 963)	0.08 (df = 449)	0.09 (df = 579)	0.10 (df = 371)	0.07 (df = 504)	0.09 (df = 771)
F Statistic	83.61*** (df = 8; 443)	84.19*** (df = 8; 963)	48.81*** (df = 8; 449)	63.73*** (df = 8; 579)	9.85*** (df = 8; 371)	51.24*** (df = 8; 504)	47.45*** (df = 8; 771)

Notes: Comment sentiment measures the emotional expressions of the audience in a video's comments. Title and transcript sentiment measure emotional expressions from the vlogger. Previous comment sentiment (7 videos) measures the emotions from the audiences of preceding videos. The table shows the combined model testing all three independent variables in combination per each individual vlog. 'Likes per views' constitutes a measure of how many people on average who watched a video clicked on the like function. Sentiment scores of 0 (no lexicon match) in the title, transcript, or comments of the 7,740 Bitcoin-related videos are omitted from the analyses. *p<0.1; **p<0.05; ***p<0.01.

4 Essay III: A “sell grandma, the kids, kitchen, sink kind of opportunity” to buy Bitcoin! Or maybe not? Testing the credibility of crypto influencers.

Abstract

Against widespread investment advice, crypto-asset retail investors are trying to yield superior investment returns by ‘crypto-asset picking’ or market timing. One group taking advantage thereof and even fueling such aspirations is that of crypto influencers on YouTube conducting crypto market analyses. To test the value of such analyses for retail investors, we derive short-term Bitcoin price analyses from a sample of seven influencers with each more than 300,000 subscribers over a one-year time frame. Both, viewer-gathered data from the overall 4,607 videos as well as software-based sentiment measurement, do not indicate such influencers being correct in their daily analyses. On the contrary, if anything, the event study suggests those influencers being wrong. We conclude that the many subscribers and viewers are strongly encouraged to refrain from taking any investment advice from the YouTube crypto influencers.

Keywords: Crypto-assets, Bitcoin, Influencer, Prediction Accuracy, YouTube

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Current Status: Working Paper, Submitted to Finance Research Letters (VHB: B)

4.1. Introduction

Textbook investments guides backed by scientific evidence suggest retail investors to perform best when investing into broad index funds, and, in line with modern portfolio theory, to diversify across different asset classes (Malkiel, 1996). Risk-tolerant investors can also benefit from investing a portion of their portfolio to the new, volatile crypto asset class (Andrianto, 2017; Kuo Chuen et al., 2017; Trimborn et al., 2020), again, advised to diversify across the many different types of crypto-assets already existing (W. Liu, 2019). The reality of many crypto-asset retail investors is yet another. They try to outperform the wider market by timing favorable entry and exit points or by identifying a specific asset which will lead a fortune. The guiding motto reads: ‘To the Moon’.

One stakeholder group encouraging such notions by conducting daily market analyses and showing off alleged success stories, is that of crypto influencers on YouTube. Given that a gathered set of such video bloggers (vloggers)[11] accumulates almost 2 billion views and no less than 21 million subscribers, it is fair to assume that some of the viewers will likely be influenced by the vloggers’ analyses in their crypto-asset investment decisions. Indeed, on samples of respectively 60 and 305 videos, Lath (2022) and Moser and Brauneis (2022) find significant positive abnormal returns for small-cap crypto-assets after they are mentioned in YouTube crypto vlogs. The two papers are yet at odds on whether the price performance sustains (Lath, 2022) or reverses shortly after the mention (Moser & Brauneis, 2022).

[11] Meyer et al. (2023) show that a gathered sample of 52 blockchain and crypto vloggers accumulated 21 million subscribers and almost 2 billion views as of September 2022.

The current paper aims to answer if deriving investment inspiration from seven of such influencers over a one-year time frame, translating into a total of 4,607 under consideration, can be valuable in identifying profitable buy- and sell opportunities for the largest crypto-currency Bitcoin.

Prior scientific research is pointing towards both directions. On the one hand, neither active funds are found to consistently succeed in market timing in the stock market (Jiang, 2003) nor are retail investors in the crypto-asset market (Pursiainen & Toczynski, 2022). On the other hand, technical analysis (Gerritsen et al., 2020), social media sentiment (Kraaijeveld & De Smedt, 2020; Naeem et al., 2021), as well as crypto experts such as analysts (Gerritsen et al., 2022) have actually been found able to predict Bitcoin prices.

We contribute to this literature by showing that YouTube crypto influencers are most likely not able to predict short-term Bitcoin price movements. On the contrary, our results rather indicate vloggers rather being significantly incorrect in their market assessments. We support this claim with an event study covering seven Bitcoin vloggers, a one-year timeframe, and two types of data sets: i) a self-gathered sample of respectively two raters extracting short-term Bitcoin investment advice from each video and ii) the videos' title and transcript sentiment measured with the software VADER (Valence Aware Dictionary and sEntiment Reasoner; Hutto & Gilbert, 2014).

4.2. Data and methodology

4.2.1. Collection and processing of viewer-rated data

In line with the rationale and methodology described in Meyer et al. (2023), we aim for YouTube channels that conduct daily market analyses on the most well-known crypto-asset

Bitcoin and that accumulate more than 300,000 subscribers (as of September 2021) to ensure an analysis of far-reaching influencers. Seven YouTube channels match these criteria: *Benjamin Cowen, BitBoy Crypto, CryptoRUs, Crypto Capital Venture (CCV), Lark Davis, MMCrypto,* and *The Moon*. Each video from November 2020 to October 2021 was evaluated by two distinct raters on whether it contains a prediction on the Bitcoin price from the respective vlogger (i.e., excluding opinions from potential vlog guests) for the consecutive 24 hours (a common analysis time frame for vloggers publishing daily market analyses). In line with former classification categories (Barber et al., 2001; Stickel, 1995), the raters applied a 5-point scale ranging from bullish to bearish for the asset price. Over the overall 4,607 videos attainable over the one-year time frame from the seven vloggers, 2,769 videos were found to contain a short-term analysis for the price of Bitcoin by one of the two viewers. For 638 videos both raters agreed on the vlogger's price indication for Bitcoin in the consecutive 24 hours (see **Table 10**, Panel A).

For a consecutive test, the 5-point scale was conferred to a 3-point scale as used in Gerritsen et al. (2022), i.e., merging 'bullish' and 'neutral-bullish' into one 'bullish' category; analogue for 'bearish' and 'neutral-bearish'. Given that a differentiation between 'bullish' and 'neutral-bullish' (equally for 'bearish' and 'neutral-bearish') might be very nuanced and viewer subjective, the rate of agreement on the vloggers' prediction (1,012 videos), was higher than for the 5-rate scale. Overall, there is a slight trend towards rather bullish than bearish short-term predictions observable (488 total bullish vs. 323 bearish predictions on a 3-rate scale[12]).

[12] On longer horizons than 24 hours, the vloggers were predominantly bullish on the Bitcoin price.

A vlogger's change of mind from 'bullish' to 'neutral' or to 'bearish' as well as from 'neutral' to 'bearish' is considered a 'downward revision' (vice versa for an 'upward revision') in the scale of 3 prediction categories. Overall, we identified 296 upward, and 295 downward revisions.

4.2.2. Sentiment-based prediction data

As a second test, we analyze whether software-based sentiment data on the vlogger's titles and transcripts indicates the direction of the short-term Bitcoin price. Sentiment is measured with the open-source framework VADER (Hutto & Gilbert, 2014); yet extending the VADER-proprietary lexicon with the finance-specific lexicon by Loughran and McDonald (2011) to account for the context at hand. Following the methodology by Meyer et al. (2023), a sentiment score between -1 (very negative) and 1 (very positive) is derived for the titles and transcripts in each video of the seven vloggers for which transcript data was retrievable via a Python script and that contains a bitcoin mention (e.g., "bitcoin", "Bitcoins"), a Bitcoin keyword (BTC, $BTC, XBT), or a coin pair containing Bitcoin (e.g., BTC/ETH) in the video title. Although VADER's developers recommend anything above a score of 0.05 (-0.05) to be labelled as positive (negative), we set the thresholds to 0.15 and -0.15 respectively, to ensure a more nuanced differentiation between positive and negative sentiment. Further, we require both, the title and transcript sentiment scores to exceed 0.15 for a video to be considered as positive, and hence as 'bullish'. Similarly, both title and transcript sentiment need to score below -0.15 to be considered as negative, that is 'bearish'. All other values are considered 'neutral'. Up- and downward revisions are computed similarly as for viewer-rated data. A descriptive overview of videos assigned to each group can be found in **Table 10**, Panel B.

Table 10. Descriptive data overview of vloggers' short-term Bitcoin price predictions

Panel A: Viewer-rated prediction data

	Benjamin Cowen	BitBoy Crypto	CCV	CryptoRUs	Lark Davis	MMCrypto	The Moon	Total
Total videos Nov 2020 – Oct 2021	899	1.137	634	425	320	545	647	4.607
Videos with short-term BTC prediction	364	377	548	207	207	471	595	2.769
Total agreed predictions (5-rate)	58	30	133	65	61	105	186	638
Bullish	7	9	48	2	6	42	23	137
Neutral-bullish	18	5	12	17	15	28	17	112
Neutral	12	5	49	12	13	11	99	201
Neutral-bearish	13	4	5	23	25	13	25	108
Bearish	8	7	19	11	2	11	22	80
Total agreed predictions (3-rate)	90	58	216	104	81	224	239	1.012
Bullish & Neutral-bullish	46	31	130	39	26	147	69	488
Neutral	12	5	49	12	13	11	99	201
Bearish & Neutral-bearish	32	22	37	53	42	66	71	323
Total revisions (3-rate)	58	33	127	64	52	112	145	591
Upward revisions	29	16	61	34	26	56	74	296
Downward revisions	29	17	66	30	26	56	71	295

Panel B: VADER-sentiment-based prediction data

	Benjamin Cowen	BitBoy Crypto	CCV	CryptoRUs	Lark Davis	MMCrypto	The Moon	Total
Total videos Nov 2020 – Oct 2021	864	968	614	371	310	476	559	4.162
Videos with BTC mention in title	511	545	470	221	211	439	504	2.901
Total predictions (3-rate)	511	545	470	221	211	439	504	2.901

Bullish	89	193	107	48	34	18	83	572
Neutral	298	288	280	138	116	330	317	1.767
Bearish	124	64	83	35	61	91	104	562
Total revisions (3-rate)	284	306	248	124	119	168	266	1.515
Upward revisions	148	152	126	61	63	84	137	771
Downward revisions	136	154	122	63	56	84	129	744

4.2.3. Event study methodology

To analyze the validity of vlogger predictions, we pursue an event study, that is studying whether the cumulative abnormal returns before and after a bullish (bearish) prediction are positive (negative); analogue for up- and downward revisions.

Given the short time frame of only 24 hours that the predictions target, we leverage hourly Bitcoin prices from the exchange *Bitstamp*, retrieved from cryptodatadownload.com[13]. Hourly log returns are derived as $R_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$, where p_t present the Bitcoin closing price at an hour t (UTC). To control observed for expected returns, we use the mean-adjusted model. The expected return, $\widehat{R_t}$, is derived as the mean log return from an estimation window of 2 to 50 days prior to a video upload, in hourly terms translating to $(-48, -1{,}200)$.[14] The abnormal return (AR) at time *t* is derived as $AR_t = R_t - \hat{R}_t$, cumulative abnormal returns (CAR) from

[13] Bitstamp is one of the largest Bitcoin exchanges (Brandvold et al., 2015) and has been used for Bitcoin studies before (Hudson and Urquhart, 2021).

[14] Methodological guidance on event studies suggest an estimation window dating back at least 100 days, however, given the 24/7 trading opportunity, the high volatility in the Bitcoin market, and the fact that we conduct a short-term analysis based on hourly data, led us to decide for dating back 50 days, being also more in line with comparable Bitcoin event studies by Gerritsen et al. (2022).

the event hour *0* to an hour n as $CAR_{0,n} = \sum_{t=0}^{n} AR_t$. The event window is set as 24h prior to a video upload (the time frame on which on average the prior vlog video has been uploaded) and 24 hours subsequent to a video upload (the time frame for which the prediction is derived). The hour of the video upload is set as $t = 0$ (e.g., 15:00 UCT for a video uploaded at 15:45 UCT) as videos are usually pre-recorded and hence the price changes of the hour of upload can be considered as covered by the 24h prediction. Considering that some viewers, if pursuing a subsequent trade after a certain prediction, might hold their position a little longer, also a post-event window of two further days is shown.

4.3. Results

Our results are displayed in **Table 11** and show that the seven vloggers in our sample are not able to structurally predict the short-term price of Bitcoin correctly. On the contrary, following the vloggers' investment opinion might rather yield negative abnormal returns. Applying the original gathered 5-rate scale, the average CAR for the 18 hours after a bullish price prediction is negative with -0.97% ($p < 0.1$). On the consolidated 3-rate scale, the respective figure corresponds to -0.55% ($p < 0.1$). Overall, the CARs after (neutral-)bullish predictions or upward revisions appear to be on average lower than that after (neutral-)bearish prediction or downwards revision. Also, on an individual level, no vlogger is found to be able to correctly analyze short-term price movements of Bitcoin.

Table 11. Event study results based on viewer-rated prediction data

Average cumulative abnormal returns before and after vlogger predictions on which both raters agree on. Standard deviations are displayed in parentheses. The asterisks *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively.

	5-rate scale					3-rate scale			Revisions 3-rate scale	
CAR as of t=0	Bullish	Bullish-Neutral	Neutral	Bearish-Neutral	Bearish	Bullish	Neutral	Bearish	Upward	Downward
-24	0.75 (0.53)	0.61 (0.58)	0.07 (0.46)	0.19 (0.63)	0.52 (0.71)	0.48 (0.3)	0.07 (0.46)	0.11 (0.36)	0.70 (0.37)	0.07 (0.39)
-18	0.52 (0.43)	0.48 (0.51)	0.09 (0.4)	0.27 (0.58)	0.98 (0.61)	0.19 (0.25)	0.09 (0.40)	0.43 (0.31)	0.26 (0.32)	0.25 (0.34)
-12	0.38 (0.36)	0.04 (0.41)	-0.13 (0.3)	0.32 (0.44)	1.46 ** (0.5)	-0.06 (0.2)	-0.13 (0.30)	0.56 * (0.26)	-0.19 (0.25)	0.30 (0.27)
-6	0.26 (0.28)	-0.15 (0.31)	-0.14 (0.21)	0.13 (0.34)	0.90 ** (0.34)	-0.12 (0.15)	-0.14 (0.21)	0.33 (0.19)	-0.18 (0.18)	0.24 (0.2)
+6	-0.18 (0.28)	0.08 (0.31)	-0.02 (0.22)	0.38 (0.32)	-0.06 (0.33)	-0.19 (0.14)	-0.02 (0.22)	0.24 (0.18)	-0.23 (0.19)	0.22 (0.19)
+12	-0.6 (0.38)	0.25 (0.38)	-0.19 (0.31)	0.28 (0.50)	0.11 (0.47)	-0.25 (0.19)	-0.19 (0.31)	0.03 (0.26)	-0.20 (0.26)	0.08 (0.26)
+18	-0.97 * (0.47)	-0.17 (0.52)	-0.08 (0.35)	0.59 (0.56)	0.04 (0.61)	-0.55 * (0.23)	-0.08 (0.35)	0.03 (0.32)	-0.38 (0.31)	0.15 (0.32)
+24	-0.98 (0.6)	0.03 (0.57)	-0.34 (0.42)	0.49 (0.62)	0.04 (0.70)	-0.5 (0.28)	-0.34 (0.42)	-0.18 (0.37)	-0.38 (0.35)	-0.27 (0.38)
+48	-0.75 (0.73)	0.17 (0.77)	-0.21 (0.61)	1.00 (0.90)	-0.45 (1.03)	-0.28 (0.37)	-0.21 (0.61)	-0.61 (0.52)	-0.43 (0.49)	-0.90 (0.52)
+72	-1.18 (0.83)	0.47 (1.02)	-0.85 (0.7)	0.58 (1.15)	-0.38 (1.38)	-0.65 (0.45)	-0.85 (0.7)	-0.56 (0.65)	-1.15 (0.59)	-0.69 (0.63)

Also, the VADER-based sentiment data does not suggest that vloggers provide valuable Bitcoin price information (see **Table 12**). Neither the cumulative abnormal returns for bullish or bearish, nor for upward and downward revisions are found significant. Hence, also an automated trading strategy leveraging vlogger sentiment does, most likely, not outperform the market.

Table 12. Event study results based on VADER-measured sentiment data

Average cumulative abnormal returns before and after Bitcoin-related vlog videos with bullish (title and transcript sentiment > 0.15) or bearish (title and transcript sentiment < 0.15) sentiment. The neutral category comprises any Bitcoin-related videos, not considered as bullish or bearish. Standard deviations are displayed in parentheses. The asterisks *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively.

	3-rate scale			Revisions 3-rate scale	
CAR as of t=0	Bullish	Neutral	Bearish	Upward	Downward
-24	0.14 (0.26)	0.18 (0.15)	0.11 (0.25)	0.01 (0.23)	0.23 (0.23)
-18	0.12 (0.23)	0.08 (0.13)	0.19 (0.22)	0.05 (0.19)	0.33 (0.20)
-12	0.10 (0.19)	0.00 (0.10)	0.14 (0.17)	0.02 (0.17)	0.17 (0.15)
-6	-0.01 (0.13)	-0.03 (0.07)	-0.11 (0.13)	-0.12 (0.12)	-0.09 (0.11)
+6	0.20 (0.13)	-0.04 (0.07)	0.10 (0.13)	0.17 (0.11)	0.14 (0.11)
+12	0.16 (0.18)	-0.10 (0.10)	0.13 (0.18)	0.08 (0.15)	0.08 (0.15)
+18	0.41 (0.23)	-0.08 (0.13)	-0.25 (0.22)	0.24 (0.19)	-0.07 (0.19)
+24	0.29 (0.26)	-0.07 (0.15)	-0.31 (0.25)	0.19 (0.22)	-0.05 (0.22)
+48	0.35 (0.36)	-0.02 (0.20)	-0.34 (0.36)	0.49 (0.31)	0.04 (0.31)
+72	0.65 (0.43)	-0.05 (0.25)	-0.32 (0.45)	0.55 (0.37)	0.07 (0.39)

4.4. Discussion and Conclusion

Even though crypto vloggers are found to influence short-term price movements and trading volumes for small cap coins (Lath, 2022; Moser & Brauneis, 2022) and crypto experts to be able to correctly predict Bitcoin price directions (Gerritsen et al., 2022), we cannot confirm such a positive track record for crypto vloggers for the largest cryptocurrency Bitcoin.

Considering that the time frame under review has rather been characterized by price increases[15], one could argue that it would be hard to correctly predict positive CARs by bullish predictions. However, also bearish predictions are not followed by negative cumulative abnormal returns, such that it is fair to derive that crypto vloggers cannot structurally tell in which direction the short-term Bitcoin price evolves. Even though only videos for which both raters agreed on the short-term prediction were considered, one might argue that a viewer's understanding of the direction of a vlogger's market analysis is still subjective. However, also a software-based sentiment measure of the videos does not indicate that rather positive (negative) vlog titles and transcripts are followed by positive (negative) CARs. Hence, also an automated trading strategy based on vlogger sentiment, e.g., as successfully working for Twitter sentiment (Kraaijeveld & De Smedt, 2020), will most likely not outperform a buy-and -hold benchmark. We conclude that crypto vlog viewers, especially as they have been found to be emotionally susceptible to YouTube crypto influencers (Meyer et al., 2023), are strongly advised to be very cautious to adapt any vlogger price direction predictions, and if anything, to view such videos as pure entertainment.

Future papers might build upon our findings and provide further insights into the price prediction ability of vloggers and respective consequences, e.g., examining circumstances under which vloggers are more likely to correctly predict price movements, consequences on viewer behavior after periods of false or correct predictions as well as the effect of vloggers on the investment behavior of their viewers.

[15] In the considered timeframe from November 1st, 2020, to October 31st, 2021, the Bitcoin price increased from USD 13,734 to USD 61,359.

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5 Essay IV: Regenerative Finance: A crypto-based approach for a sustainable future

Abstract

‘Regenerative Finance’ (‘ReFi’) projects are gaining increasing traction. At their core stands the mission to positively contribute to societal matters, currently dominated by environmental protection efforts and a fair co-participation of local communities in the projects’ design and implementation. Blockchain technology is used to accomplish these regenerative endeavors in a more efficient, transparent, and equitable way than legacy regenerative projects. Based on semi-structured interviews with members of the ReFi community, we i) derive a definition for ‘ReFi’, ii) describe motive forces for its emergence, iii) derive common building blocks along ReFi’s value chain, and iv) synthesize the overarching goals of the ReFi community including required actions and associated risks to attain these goals. The consolidation of ReFi experts’ perspectives, visions, and concerns lay the groundwork for further scholars to quantify the accomplishment of ReFi’s societal impact ambitions, to reveal limitations in current business models, and to support enhancing them.

Keywords: Regenerative Finance, ReFi, Decentralized Finance, Blockchain, Crypto, Sustainability

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Current Status: **Forthcoming in** ‘The Elgar Companion to Decentralized Finance, Digital Assets and Blockchain Technologies’ edited by Henrik Cronqvist and Desiree-Jessica Pely (2024)

5.1. Introduction

The blockchain sector has developed into a considerable industry, impacting various areas of society. At its peak in November 2021, the overall cryptocurrency market capitalization exceeded 3 trillion USD (CoinGecko, 2022) and thereby that of the German stock market of ‘only’ 2.3 trillion USD in 2020 (Worldbank, 2022). Renowned brands such as Nike, Gucci, and Tiffany have entered the world of NFTs; the largest bank by market capitalization (CompaniesMarketCap.com, 2022), JPMorgan, has executed their first Decentralized Finance (DeFi) trade on a public blockchain; and the opportunity to build a decentralized, crypto-based Web3 is widely discussed. On the contrary, recent events in 2022, such as the failure of Terra-Luna (cf. Briola et al., 2022) or the implosion of the crypto exchange FTX with an associated loss of several billion USD in customer funds, have reinsured crypto critiques that the crypto space is to be taken with caution and that it constitutes a risky, gambling-dominated sphere with no positive long-term value.[16]

A growing crypto-based development called ‘Regenerative Finance,’ ‘ReFi’ for short, has set out to maximize the positive contribution that it can make: to positively add to real-world societal matters. Such matters might include de-carbonization (e.g., through reforestation and carbon offsetting), ocean conservation, or the improvement of soil and water quality. Concrete ReFi projects include, for instance, the KlimaDAO (KlimaDAO, 2022), the Toucan protocol (Toucan, 2022), and the Regen Network (Regen Network, 2022). In other words, the ReFi community refocuses on the very roots of the crypto space; that is, to use blockchain technology

[16] Ironically, the misusage and subsequent loss of customer funds by central intermediaries such as FTX, is exactly one of the incidents which Nakamoto (2008) aimed to prevent by inventing the blockchain.

to create (financial) service solutions that serve society better than legacy systems. For 2023, a Forbes article projects ReFi as a key Web3 trend (Marr, 2022).

To the best of our knowledge, there is no former paper which has used the term 'ReFi' under which the field of blockchain- and token-based projects for environmental and societal purposes is currently gaining new traction. However, previous research exists on ReFi-related themes which evaluate how blockchain-based projects can facilitate sustainability endeavors. While most authors conclude that, in theory, the technology has the potential to provide a transparent, trust- and borderless coordination mechanism for regenerative projects, they yet warn of a scenario in which crypto projects self-enrich under the guise of sustainable pursuits: Howson (2019) and Howson et al. (2019) introduce first blockchain projects related to carbon offsetting and deforestation, and critically review their accomplishments in generating a surplus to climate change mitigation and to fairly involve local communities. Howson (2020) warns of so-called "crypto-colonialism," referring to blockchain platforms that extract economic benefits from already disadvantaged people and further increase the power asymmetry between the Global North and South under climate change mitigation credentials.

Similarly, through the investigation of 27 blockchain-based environmental and conservation initiatives, Stuit et al. (2022) critically claim that the drivers for these projects have so far rather stemmed from blockchain entrepreneurs' motivation to invent new crypto services than from a sustainability mission, as well as that the environmental success is yet lacking. To ensure that blockchain-based projects with a regenerative imperative succeed in a positive societal contribution, they propose to more closely involve on-the-ground stakeholders in the projects' design processes. Manski and Bauwens (2020), Thomason et al. (2018), and Chapron (2017) support this call to action for blockchain entrepreneurs to connect with the development and sustainability community to design true regenerative social and economic systems. This also includes a fair and equitable co-involvement of the affected communities in the design and decision process (Pschetz et al., 2020). In doing so, blockchain technology could offer a means to address both climate change and growing levels of poverty (Thomason et al., 2018). If not done properly, the opportunities emerging from blockchain technology might perish to the foreclosing of blockchains' material agency by a small powerful elite (Manski & Bauwens, 2020).

The research related to ReFi so far mainly builds upon outside-in commentaries and case-studies. However, we are not aware of any research that has interviewed ReFi entrepreneurs and supporters to structurally gather their views on ReFi—research that also Stuit et al. (2022) propose to better understand the mentalities, rationale, and motivation of ReFi project creators. Moreover, to the best of our knowledge, there is no scientific work which has systematically defined and conceptualized nor used the term 'Regenerative Finance' so far. This paper fills these gaps. In synthesizing the perspectives from eleven semi-structured interviews with ReFi experts, we derive an understanding of the umbrella term 'ReFi' and what its prospects look like.

More concretely, our contributions are fourfold. First, we define the term 'Regenerative Finance' as *'any form of business models or activities which employ economic incentive systems, constructed and enforced through DeFi tools, to positively contribute towards environmental and/or other societal matters.'* Second, we derive hypotheses for three driving forces leading to the emergence of ReFi: i) the urgency to combat climate change, ii) the dissatisfaction with how legacy systems contribute to environmental protection, and iii) the failure to date of DeFi to deliver on its promises of presenting a better financial system for society. In combination with DeFi reaching a level of technological maturity able to enter real-world territories, ReFi is aiming to develop solutions addressing those three motive forces. Our third contribution is to structure common building blocks of ReFi. Leveraging the property of 'composability,' that is, similarly as in DeFi to seamlessly integrate various projects with each other, our interviewees argue that ReFi is better understood along the building blocks of the entire value chain than of individual projects. As the key differentiator to DeFi, the ReFi value chain will always start with some real-world project which presents the means to implement a regenerative mission. Each step of the value chain has its own technological enablers. While the governance form of Decentralized Autonomous Organizations (DAOs) facilitates globally distributed co-involvement and community building, it reaches its limits when it comes to cooperating with real-world legal entities. Fourth, we take a look forward and derive the overarching goals of the community (increasing both the regenerative project supply and demand), respective enablers to reach those goals (e.g., ReFi regulation) as well as the main risks for the ReFi space (e.g., a loss of integrity due to ReFi scam projects).

Our results are relevant for both academia and practitioners. We offer the first academic work to structurally derive an understanding of the term 'ReFi' from members of the ReFi community and to synthesize both required actions and risks to be mitigated to grow ReFi's positive impact. We thereby provide the basis for future academic efforts in the field, for example, to support the development of enhanced blockchain-based solutions with a regenerative impact, to facilitate dialogue among required ReFi stakeholders, or to independently assess the actual societal impact of ReFi projects and prevent potential risks from misconduct. In fact, our interviewees identified such academic support as an important enabler to increase ReFi's adaption.

The paper proceeds as follows. We start by outlining the applied methodology for our research. Subsequently, we present the results from the interview inputs before discussing the results and concluding.[17]

5.2. Data and Methodology

We initiated our research with two objectives: to conceptualize the ReFi community's current understanding, driving motives, and functionalities of ReFi and to derive its potential pathway. As the field of ReFi is only emerging, there is yet no extensive research to build on to address these two research objectives. When a (new) phenomenon is yet poorly understood, explorative studies provide a means to inductively derive generalizations about it (Stebbins, 2001). Hence, to approach our research objectives, we pursued an explorative research design leveraging the expertise of early ReFi pioneers. A suitable means to obtain in-depth information on experts' experiences and viewpoints on a particular topic is to conduct interviews (Turner, 2010). One of the most widely applied interview methods is the use of open-ended questions in semi-structured interviews, allowing experts to fully elaborate on their viewpoints and provide an extended reflection in comparison to yes or no questions (Knott et al., 2022; Turner, 2010). Researchers can hence ensure to address specific dimensions of a research question while still leaving opportunities for interviewees to offer new meaning to the topic of study (Galletta, 2013).

[17] For a better understanding of crypto-native terminologies used here, we refer to the following works: Meyer et al. (2022) present the current academic understanding of DeFi; Morrow and Zarrebini (2019) outline how tokenization works, its societal applications, and potential use cases; Kampakis (2018) provides an overview of how tokenomics can be used for various forms of incentive setting via the analysis of three case studies; Ziegler and Welpe (2022) define and derive a taxonomy of DAOs. For a more pronounced background on Regenerative Economics, we refer to Fullterton (2015).

In line with the guidance of Creswell and Poth (2007), we developed the interview questions to be a narrowing of the central research questions in our study. The interview guide was hence organized around four broad topics, which were refined through a pilot testing. The first two aimed at answering our first research objective, namely, to conceptualize ReFi: asking participants about i) their understanding of ReFi and ii) a common denominator of building blocks that ReFi projects usually entail. The latter two topics aimed at deriving future avenues for ReFi: asking ReFi experts i) about their view on the future of ReFi and ii) about potential risks for a scaling of ReFi. All interviews were conducted by either one or two researchers, audio-taped with the authorization of the participants, transcribed, and, if required, translated into English for further processing. To analyze the information input, we applied the coding guidelines for building grounded theory dating back to Glaser and Strauss (1967), allowing us to systematically and inductively develop a theory around the phenomenon under study (Creswell & Poth, 2007).

To identify an appropriate set of experts with a background in ReFi, we searched for experts via Google and LinkedIn using the keywords ‘Regenerative Finance’ and ‘ReFi’ as well as leveraged conference and social network information on people with ReFi content coverage. Overall, we identified and contacted 49 potential interview candidates of which thirteen agreed to speak with us. Eventually, two interviews were omitted from the coding analysis due to the poor insights they provided on the posed questions. The participants from the remaining eleven interviews engaged with ReFi related topics from various professional angles, including founders of (multiple) ReFi projects, project engineers, VC investors, journalists or podcast producers, and academic researchers at the intersection of sustainability and blockchain applications—sometimes combining multiple angles in one person. Geographically, the interview participants were based in the US, India, and Germany. All interviews approximately stayed within the targeted range of thirty minutes.

5.3. Results

The coding analysis revealed common patterns in the interviewees' responses towards both of our research objectives. This section starts with the conceptualization of ReFi and continues with the prospects of the space. All results and statements proposed in the following are solely based on the input from the eleven expert interviews.

5.3.1. Conceptualization of Regenerative Finance

The conceptualization of ReFi is divided into three parts. First, we derive a common definition of the term 'ReFi.' Second, we explain how the interviewees explain the emergence of ReFi. Third, we present common building blocks which characterize ReFi-related projects or activities.

Definition of Regenerative Finance

Three common threads emerged for defining the term 'ReFi.' The first surrounds the ultimate purpose of ReFi projects. While environmental topics are yet dominating the ReFi ecosystem, the interviewees largely agreed that ReFi projects may relate to any outcome which is not only non-extracting but even beneficial to real-world societal matters, spanning from environment, social, to governance topics. Some interviewees specified ReFi projects as aiming to contribute to the Sustainable Development Goals.

The other two common threads can be categorized into means of establishing these goals: i) the deployment of common capitalistic incentives to steer behaviors which ultimately pay back to the aforementioned societal goals, and ii) the usage of DeFi tools (e.g., tokenization and smart contract-based protocols) to implement and enforce these incentive structures. The form of implementation can vary, such as representing a whole business model, a financial application as part of a larger value chain, or even an event. Taken together, we propose the following definition of ReFi emerging from the expert interviewees:

'Regenerative Finance describes any form of business models or activities which employ economic incentive systems, constructed and enforced through DeFi tools, to positively contribute towards environmental and/or societal matters.'

Drivers for the emergence of Regenerative Finance

As the definition shows, ReFi projects use smart contract implementation and enforcement mechanisms from the longer existing DeFi space. A delineation between both can be drawn along two criteria. The first relates to the purpose of the respective projects. While a positive contribution to the aforementioned societal matters is the core of ReFi projects, DeFi projects are rather mission-neutral or often driven by financial-based success. The second criterion refers to the nature of the underlying assets that DeFi and ReFi are built on. DeFi protocols are often projects which exist fully 'on-chain' – that is, the underlying assets that are traded were constructed solely with the help of a blockchain and can exist detached from real world, non-blockchain based phenomena.[18] ReFi projects, on the other hand, are always based on 'off-chain' projects (e.g., a reforestation venture) which provides the means to positively add back to society. In other words, while DeFi can exist on virtual assets only, ReFi projects always rely on real-world (i.e., off-chain) assets.

Most interviewees hence do not see ReFi as a subcategory of DeFi but rather as a play-off. Some of the interviewed experts even described ReFi as a response to DeFi, constituting one of the motive forces for establishing the ReFi space: while DeFi proponents have often praised the technology to enable financial inclusion by only requiring an internet connection and being permissionless, in fact, DeFi has not yet lived up to its promises. The congestion on the Ethereum blockchain has made simple transactions a costly, high-barrier endeavor and so far, the beneficiaries of DeFi have not been the unbanked people in developing countries but crypto-native protocol developers and investors. The ReFi community aims to return to the early goals of crypto and DeFi pioneers in using the technology to solve societal issues.

As a trailblazer for ReFi, the decrease of blockchains' own energy-consumption is put forward, namely the transition from power-intensive Proof-of-Work (PoW) to energy-friendly Proof-of-Stake (PoS) block validation mechanisms. While this change reduces the environmental impact of blockchains themselves, ReFi strives for more: building business models that not only cause no harm, but also even positively add to societal interests. Most ReFi stakeholders thereby view the combat of climate change as one of the most urgent issues of our time. Legacy systems of

[18] In some cases, also DeFi protocols are attached to a real-world asset, e.g., some stablecoins are backed by the real currency which they are pegged to.

carbon offsetting systems are perceived as not being able to scale their climate protection measures to the required value: they involve too many intermediaries and are processed over cumbersome processes and OTC-deals—resulting in illiquidity, high transaction costs, and inefficient price building of natural assets. ReFi proponents see DeFi tools as a means to overcome these issues, making them one of the key building blocks in ReFi-related projects as outlined in the next section. A summarizing illustration of the driving forces and proposed definition of ReFi is depicted in **Figure 6**.

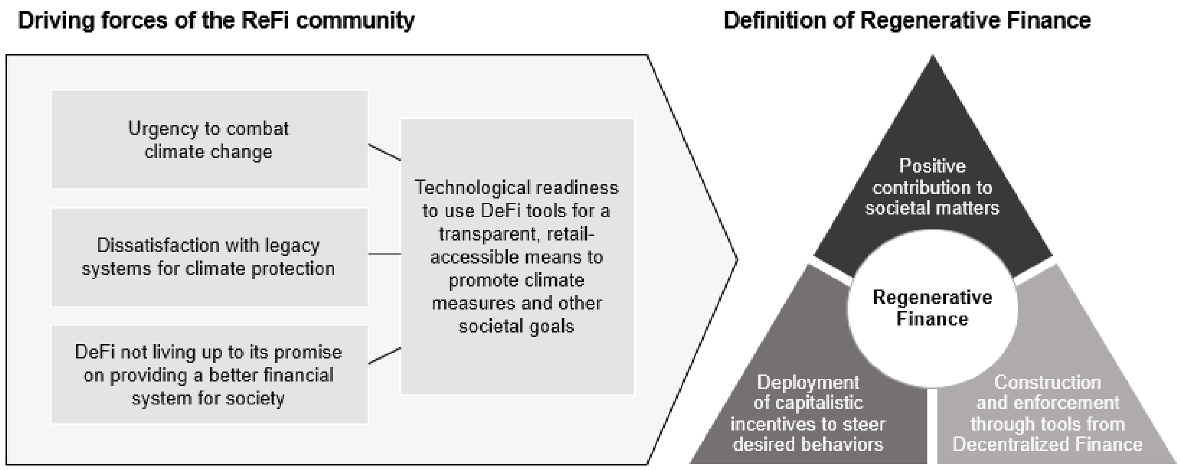

Figure 6. Driving forces for the ReFi community and proposed definition of ReFi.

Building blocks of ReFi projects

As derived from the definition of ReFi and elaborated previously, the common building block across ReFi projects is their underlying mission to positively contribute to societal matters. The characterization of the remaining building blocks yet differs as a result of the most often stated advantage of using DeFi tools: composability. The possibility to integrate and interoperate different DeFi protocols (e.g., exchanges, marketplaces) and tokens due to commonly used standards, allows the emergence of what some of our interviewees call 'Nature Lego.' As a founder of a ReFi protocol puts forward, 'it is very easy to pick up somewhere and build on something and just work on a part of the puzzle, not work on everything.'[19] Consequently, the discussion of common building blocks surrounded the typical value chain of ReFi and the various technological and governance enablers leveraged in each of its steps. A graphical overview is depicted in **Figure 7**.

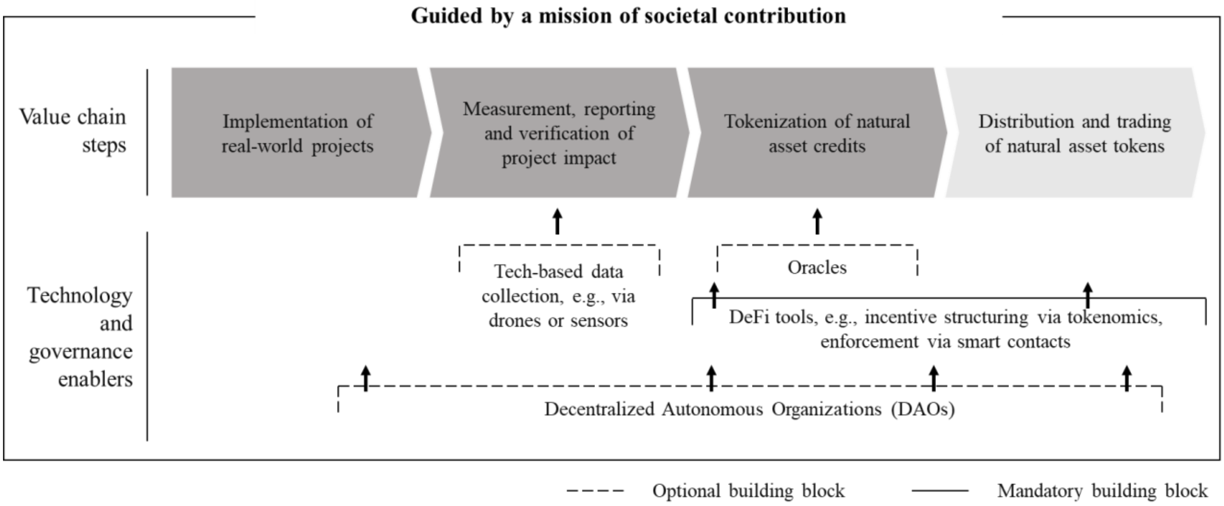

Figure 7. The value chain and technological and governance enablers in Regenerative Finance.

The starting point of the value chain is the **implementation of a real-world project that is positively adding to a societal matter**. No common technological enablers emerged in this step as the nature of the project and hence implementation enablers might differ along with the project's purpose. Currently dominating are carbon credit projects. As a co-founder of a ReFi project explains: "Carbon credits is, I want to call it, almost the low-hanging fruit of ReFi." Their digital nativeness (i.e., existing solely in database entries) and international nature

[19] Quote translated into English.

combined with an illiquid OTC-based market, makes carbon credits a perfect use case for ReFi, so the interviewee.

The second value chain step is the **measurement, reporting, and verification of the projects' impact**. In the carbon credit market, organizations such as Verra or the Gold Standard facilitate this process and present an independent, trusted third party to certify the quality of issued carbon credits. Some ReFi projects relied on these standards and provided a bridge to transfer these off-chain registries on-chain. This step, also called **'tokenization'**, referring to the representation of an off-chain as an on-chain asset, presents the third part of the value chain. However, with the advancements of DeFi, the interviewees propose these steps to be implemented in a technology-based, trustless way. As one interviewee points out, 'the verification process through Verra and Gold Standard is very costly and takes a long time.'[19] As she further outlines, the chance of ReFi is to build a bottom-up approach in which also small projects, e.g., involving any land stewards, can produce carbon credits. Such an approach would not only further scale the carbon credit market but also include a larger community in this matter.

The combination of two technological steps paves the way for such a bottom-up approach. First, advanced tools automatically collect and measure project impact data (e.g., drones or soil sensors). Second, so called 'oracles' provide a technological, trustless bridge to transfer these off-chain information onto a blockchain where DeFi tools can convert a nature-based tokenized asset out of the information. The connection of off-chain and on-chain events through oracles further facilitates a fair participation of contributing off-chain communities on the generated asset value, for example via royalties. Such an interface for mapping real-world assets on-chain functions without costly, time-intensive intermediary processes but requires regulatory clarity.

Once tokenized on a blockchain, the project outcomes with societal impact present a tradeable asset which can now be **distributed to investors**, depicted here as the fourth value chain step. The distribution of tokens may use the full toolbox of DeFi (e.g., incentive structuring via tokenomics and enforcement via smart contacts) such that the same advantages which have been praised in DeFi before, do now also unfold for ReFi assets: data and transaction transparency, retail accessibility, minimized transaction costs, and trustless real-time trading—resulting in system-embedded trust, enhanced liquidity, and 'true' price discovery. To ensure sufficient demand, end-user faced projects such as marketplaces specialize in aggregating ReFi token registries to provide palatable end-user products for both retail and institutional clients. Given the simple composability of tokenized assets, customized ReFi funds can easily be constructed, for example, with varying asset quality or environmental impact requirements. Tokenomics thereby provides the means to construct any economic models to incentive potential investors to contribute to the societal mission.

Moreover, tokenomics enable simply implemented co-ownership models, which not only incentivize investment but also co-creation. The possibility to create such incentive structures for active participation are one of the most often named advantages of organizing ReFi projects via the governance form of DAOs. Leveraging DAO tokenomics, teams can quickly build a global community of supporters for their regenerative mission which is particularly important in consumer facing projects. On the other hand, governance through DAOs also brings some pitfalls. The decentralized nature of DAOs and hence their decision-making processes might hinder effectiveness. This setback becomes especially prevalent in early-stage phases when many important directional decisions are to be taken fast. Referring back to the value chain, DAOs especially reach their limits in the very beginning and end, when it comes to collaborations with non-crypto native entities. As one interviewee explains the issues of implementing real-world projects via DAOs: ‘A DAO is not a legal entity. A DAO cannot sign contracts; a DAO cannot buy a piece of forest; a DAO cannot even sign a loan agreement.’[19] Similarly, for projects with B2B business models, in which a community is less important and the counterpart is a legal entity as well, a non-DAO governance form is better suited.

Having conceptualized the current picture of ReFi, the next section looks forward and outlines ReFi’s future pathway.

5.3.2. The prospects of Regenerative Finance

Considering that legacy systems regularly fail on their climate targets, all interviewees argued in favor of a long-term and impactful perspective of ReFi. To make such a long-term perspective realistic, all of them identified required actions to drive ReFi’s large-scale adaption and impact as well as risks which could threaten this endeavor. A structured overview of the answers is depicted in **Table 13**.

Table 13. Determinants of the future of ReFi.

Conditions and actions to be taken to achieve the overarching goals
• Creation of **more ReFi awareness** through cooperations with prestigious legacy institutions, education on ReFi, and academic research

- **Integration of a broader range of stakeholder interests** in ReFi business models, i.e., regulators, legacy institutions, project suppliers, customers
- **Improvements along the ReFi value chain**, i.e., more on-site involvement in real-world projects, better integration of off-chain and on-chain steps through oracles, enhanced user friendliness of ReFi applications, closer collaboration among projects
- **Regulation of ReFi-related aspects** (DeFi tools, natural assets, DAOs) to provide certainty to all stakeholders
- Attracting **more talent** to the ReFi ecosystem
- **Change of narrative** in projects towards regenerative benefits via ReFi rather than a crypto focus

Overarching goals

- **Increase in supply** of projects with a regenerative impact
- Attainment of a **larger customer base** (institutional and retail demand) for **more investments** and liquidity

Risks to be mitigated

- Reputation issues through bad quality or **scam ReFi projects**
- Reputation issues and market **spillover effects from DeFi space**
- **Regulatory bans** and **resistance** from **legacy institutions**

Two **overarching goals** emerged for the ReFi community. On the one hand, an increase in supply of regenerative projects and thereby in the regenerative impact from the space is desired. On the other hand, an attainment of a larger customer base is required to provide the demand for the assets generated from regenerative projects. An increase in investments would provide more liquidity in the ReFi market and hence make it more efficient. Both retail but especially institutional investments should be targeted to achieve this goal.

Overall, six broad categories of **required conditions and actions** emerged to enable these goals. The first main vehicle to scale ReFi lies in creating more awareness about it. The most often mentioned means to enhance awareness and subsequent adaption of ReFi is to increase the cooperation with, ideally, well-known and impactful legacy stakeholders, such as through, as one interviewee explains, 'collaborations with the federal governments, the U.N., the EU, with some NGOs that are not Web3 native, to begin with, and thus build trust. Identify these 'early adopters,' create this journey with them, and take that as an example for many, many other potential stakeholders.'[19] An important accompanying measure, as with all new technologies, rests on educating people about the purpose and functionalities of ReFi more broadly. The education should thereby translate ReFi aspects into an easy to understand language for non-crypto natives and span the exact spheres that motivated early adopters to start and join the ReFi community in the first place (cf. Figure 1): i) means to support the combat of climate change such as carbon credit markets, ii) flaws in the current, non-ReFi processes for environmental protection, and iii) the functionalities of DeFi mechanisms and how they can build the basis for an efficient ReFi market. Objective research about measurable associated regenerative effects, limitations, and potential improvements of ReFi processes is demanded as academic support from the interviewees.

Second, a common thread emerged around the importance of better integrating various stakeholders in ReFi business models. ReFi solutions and projects should hence not only be developed within and for crypto-native spheres but should be built to be suitable to a wider community, entailing regulators, legacy institutions such as Verra or the Gold Standard, project suppliers and communities, as well as a broad institutional and retail customer base. One interviewee explains ‘as soon as you have this institutional buy-in and this legitimization from the established markets, such as the carbon markets, I believe that this will simply take the topic of ReFi to another level.’[19] Another interviewee concretizes his vision for empowered local communities via ReFi: ‘Because once you give all of this financial tooling and tooling that allows communities to define their own types of green assets, ecological assets or natural capital, they will latch on to that, I think. This means that you will have a network of communities all around the globe that are operating and producing green assets in a sovereign way.’[19]

Third, different aspects were mentioned on how to improve different parts of the value chain (cf. **Figure 7**). Starting with the beginning of the value chain, more on-site involvement from ReFi-related projects is required to ensure a supply of high-quality and equitable regenerative projects. One interviewee explains the strength of the ReFi project *MossDAO* as regionally engaging on-site in the Amazon region and that this on-site involvement marks the point where the possibility for ReFi to scale would need to be proven, that is ‘whether you then bring the manpower onto the street or into the forest is the exciting question.’[19] Further, some interviewees put forward the need for a smooth integration of real-world off-chain components and on-chain token distribution. To do so, reliable oracles are required. Eventually, to ensure an increase in demand, ReFi applications need to become more user friendly. This aspect is especially crucial to attract more non-DeFi native customers. All these improvements of the value chain would be better attained if projects would enter into more partnerships with each other and further realize the composability potential. One interviewee even proposed a consolidation of projects.

A mandatory base for better collaboration among ReFi stakeholders and for an accomplishment of improvements along ReFi's value chain also requires regulatory certainty on ReFi-related aspects as well as ReFi's compliance with existing regulations. As the fourth category of required conditions, regulation is thereby needed regarding the usage of DeFi tools (e.g., smart contract-based platforms or oracles), the rights and obligations coming with the possession and trading of natural assets such as carbon credits, and the legal status of DAOs.

Fifth, to stem these actions, more talent needs to be steered towards the ReFi ecosystem. Developers currently signify the largest bottleneck. Yet founders and other skilled talent such as designers or people familiar with business development are also in demand.

Sixth, ReFi participants should try to change the overall narrative of their space away from a blockchain and crypto focus. The focus should rather lie on the regenerative benefit which ReFi solutions provide compared to other non-crypto solutions. The change in narrative will also help in mitigating some of the crypto-immersing reputation risks as outlined in the following section.

In total, three **main risks** have emerged that might threaten a quick wide-scale adoption of ReFi. Two of these risks concern reputation issues for the space, either stemming from bad quality or scam projects within the ReFi space itself or from spillover effects from DeFi projects. A common example of the former is the project 'KlimaDAO,' in which short-term financial incentives were built upon bad-quality carbon certificates. One interviewee explains the consequences of 'projects that virtually bring the bad guys from DeFi to ReFi'[19] as follows: 'That such things as Terra Luna happen with natural assets and people feel not only this financial loss, but perhaps also an emotional loss, because it is now perhaps links to forests, or to animals, or to people and accordingly communities.'[19] To mitigate this risk of integrity loss and greenwashing accusations, the community needs to make sure that the quality of underlying ReFi assets is high and that long-term benefits instead of short-term financial incentives are set.

The latter, reputation issues from the DeFi space, is accompanied also with potential market spillover effects given the interdependencies between both. One ReFi entrepreneur explains the reputation effects from first-hand experience: 'What we have now felt very strongly, […], in discussions with investors, for example, is the fiasco around Terra Luna. That didn't necessarily help us because it gave the term 'stablecoin' a lot of disrepute.'[8] Apart from reputation issues, risks stemming from the underlying technological structure might spill over from DeFi (e.g., smart contract issues) and some interviewees outline the investment traction to be generally lower in DeFi bear markets. Third, while regulation is appreciated to provide certainty in ReFi-related endeavors, a regulatory ban of any associated building blocks would threaten ReFi's future. Similarly, headwind and non-cooperation from legacy bodies in the space of regenerative economics would impede ReFi's ambitions.

5.4. Discussion and conclusion

Our work shows that the ReFi community is aware of the critique and risks that former scholars have pointed out. In line with concerns by Howson (2020) or Stuit et al. (2022), the interviewees have named falsely designed ReFi projects, which do not positively contribute to societal matters but only benefit its developers, as the main risk of and for ReFi. Similarly, the experts join the call to action of Manski and Bauwens (2020) and Thomason et al. (2018) for a closer collaboration with non-crypto native sustainability stakeholders to jointly design well-rounded and effective regenerative solutions. To ensure an equitable involvement of communities' needs and concerns in project designs, the interviewees argue for more on-site involvement from ReFi contributors. In the collaboration with other non-crypto native legacy stakeholders, however, the interviewees hold all parties responsible to enable a value-adding cooperation and name resistance from possible collaboration partners as a main concern.

By providing an independent consolidation of ReFi pioneers' perspectives, driving forces, visions, and concerns, our paper supports the dialogue between those stakeholders. Further, our paper contributes to creating awareness on ReFi's goals and explains the technological and economic means to attain these goals. The synthesization of our interviewees' views on deficiencies and improvement potential in current processes, as well as risks to be mitigated, present actionable measures to be addressed by the ReFi community and the support from further scholars.

The integration of ReFi-native views, as in our paper, is yet only one side of the story. We agree with Stuit et al. (2022) that to assess the actual impact of ReFi, associated project outcomes should be measured on the ground and in collaboration with the local communities that the project involves. A transparent analysis of both accomplishments as well as limitations and pitfalls would enable an objective record of lessons learned and in turn an improvement in the future design of impactful ReFi business models. While academic support as demanded from the interviewees thus supports educating people about ReFi and facilitating dialogue among all stakeholders, we agree with Manski and Bauwens (2020) that, eventually, it is the responsibility of ReFi entrepreneurs and investors to design true regenerative social and economic systems beyond capitalism.

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6 Conclusion

For many decades, digital advancements have changed how financial services are operated (Gomber et al., 2017). While other technological innovations such as artificial intelligence are rather industry-generic, the unique characteristic of blockchains is that they have been invented to specifically disrupt the financial industry, that is to replace well established intermediaries by decentralized governance mechanisms and smart contracts.

Although, in the meantime, blockchains are implemented and discussed in application areas far beyond financial use cases (e.g., as a basis for a new era of a decentralized internet[20], NFT branding strategies of well-known brands, or decentralized governance mechanisms), the financial industry remains the largest application area. On the one hand, well-established financial institutions are starting to adapt blockchain technology to improve their operations. On the other hand, DeFi entrepreneurs continue to drive their vision of a large-scale, decentralized financial system. That this endeavor is to be taken seriously, is reflected in the overall growth of the total value locked in DeFi smart contracts, the still remarkable market capitalizations of crypto-assets compared to those of traditional banks, and the growing academic interest reflected in many DeFi publications.

Given the many opportunities to still shape the design of the DeFi space, many academic publications are following 'Proof-of Concept' methodologies, that is improving or inventing new ways for i) easy modelling of financial smart contracts, ii) DeFi asset designs, or iii) DeFi applications. Such research is clustered under the 'micro-level'. A second stream of research, i.e., the 'meso-level', leverages the openly accessible transaction data to better understand DeFi

[20] cf. Momtaz (2022)

events or to identify malicious activities such as Ponzi schemes. In the last stream of DeFi research, the 'macro-level', prior studies have comprehensively derived the theoretical advantages, potentials, and risks of DeFi as of today and for the future. Less explored, on the other hand, is the role of different external stakeholders on the DeFi ecosystem and vice versa—a research avenue which is pursued in this thesis.

More concretely, the thesis contributes to two further particular research areas. The first one is how sentiment impacts the blockchain-based financial sector. Yet unexplored is how influencers contribute to the largely sentiment-driven crypto-asset investment field. In line with the hypotheses derived, Essay II finds that the emotions derived from a VADER-based sentiment analysis in the titles and transcripts from crypto vloggers conducting daily Bitcoin market analyses, are indeed positively correlated to the emotions in subsequent viewer comments. The use of sensationalist and on average rather negative title sentiment scores compared to the rather positive and less extreme sentiment scores of the transcripts, indicates that vloggers use emotions to generate more views. While such click bait strategies are not unusual for vloggers, they are problematic if contributing to a sentiment-driven investment behavior in a very volatile asset class. The fact that mostly young people watch vlogs while simultaneously being more susceptible to a vlogger's emotional influence, increases such concerns. And as Essay III shows, aligning one's investments with the market analyses of such vloggers is not a promising investment strategy. The implications mainly concern three stakeholder groups: we call i) crypto vlog viewers to be aware of the emotional influence they are exposed to as well as the low probability of conducting a successful trade following the vloggers' market assessments, ii) regulators to reassess the extent to which such vloggers are regulated, and iii) marketers for caution before collaborating with crypto vloggers as perceived betrayals might affect both the long-term perception of the influencer but also the associated brands (Reinikainen et al., 2021; Tan et al., 2021).

In the meantime, off from the question of how a crypto-asset will financially perform in the short-term, a group of people has gathered to shift the focus around blockchain-based finance innovations back to contributing to societal matters. By conducting semi-structured interviews, Essay IV describes how ReFi entrepreneurs aim to use capitalist incentives and DeFi tools such as smart contracts and blockchain-based assets to build business models which positively contribute to a societal matter such as environmental protection. The motive forces are threefold, namely i) dissatisfaction with the impact of established sustainability endeavors, ii) the shifting focus from many DeFi players towards merely financial gains, as well as iii) the urge to combat climate change. Among the required actions to increase both supply and demand in ReFi projects, also the support of academia has been identified, e.g., to measure and enhance the impact of ReFi projects and to help raising awareness of ReFi's potential, especially in cooperation with established players.

Overall, this thesis has presented two sides of the world which have emerged around blockchain-based digital finance innovations. On the one hand, as with many promising new technologies, people are trying to identify investment opportunities to participate in the technology's success prospects. Given the high volatility in combination with 24/7 trading possibilities and a great breadth for investment opportunities in many new crypto-assets, crypto-asset investing can yield big profits but equally large losses. In absence of fundamental valuation techniques, crypto-asset prices are largely dominated by investor sentiment—a fact on which crypto vloggers established a whole industry and which they further fuel by using emotion-driven vlogging strategies. On the other hand, a group of ReFi entrepreneurs is working to leverage the advantages of DeFi (e.g., transaction transparency, liquidity, and composability) to build solutions which better contribute to societal matters (e.g., environmental protection) than current non-blockchain based projects. One of the largest self-identified risks of the ReFi interviewees matches with that of former scholars (e.g., Howson, 2020; Stuit et al., 2022): that some entrepreneurs use the disguise of ReFi to build business models which ultimately only yield a financial benefit for themselves and which, contrary to their promise, rather increase inequalities between rural communities and developed countries.

Which of both sides will dominate the crypto-assets and DeFi space remains open until now. The potential to build sustainable and beneficial financial business models for society with the help of blockchains is given. Whether such long-term aspirations can prevail against short-term financial speculators, will be seen over the next few years.

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