INVESTMENT IN DIGITAL ASSETS:
DELEGATE TO AI OR NOT

by
Jiasheng (Ray) Zhu
Signature Work Product, in partial fulfilment of the Duke Kunshan University Undergraduate Degree Program

April 25, 2022

Signature Work Program
Duke Kunshan University

APPROVALS

____

Mentor: Luyao Zhang, Assistant Professor of Economics, Social Science Division
Senior Research Scientist, Data Science Research Center

____

Marcia B. France, Dean of Undergraduate Studies

ABSTRACT

Artificial Intelligence (AI) investment is increasingly popular, driven by recent technology advancements in blockchain, machine learning, and various application scenarios. However, little evidence has shown that AI is more reliable than humans in volatile financial markets, especially the emerging digital assets markets. To answer the fundamental question of whether delegating to AI improves investment performance, we conducted economic analysis on two types of digital assets portfolios created by Set Protocol, one executed by AI and the other by human traders. This research project investigates the role of AI in financial investment and finds that human traders have a better investment performance than AI over a shorter investment horizon; but as the investment horizon gets longer, AI tends to perform better in portfolio management and investment results. We further advise investors with more rational choices with token portfolios. The project has created value in multiple disciplines as it integrated knowledge in financial investment, portfolio theory, explainable AI (XAI), augmented AI, data science, behavioral economics, and blockchain. Moreover, this research project has also inspired me to initiate or participate in other relevant projects and contribute to academic papers, and one of my papers has been accepted by two international conferences thus far.

ACKNOWLEDGEMENTS

Throughout the SW project construction, I have received a great deal of support and assistance.

I would first like to thank my mentor and advisor, Professor Luyao Zhang. Prof. Zhang keeps guiding and instructing me patiently and giving me sufficient support. Her courses and insightful feedback have greatly pushed me to sharpen my thinking and brought my work to a higher level.

I also would like to thank Prof. Tim Bollerslev at Duke University, whose excellent lectures in financial investment have inspired me to conduct research in this field and pursue a higher-level degree upon graduation.

I want to thank Duke Kunshan University's Student Experiential Learning Fellowship (SELF), which helped me complete my experiential learning project, a finance research experience at New York University Shanghai, last summer. I also would like to thank the Center of Teaching and Learning's funding, which helped me conduct my research project on active learning techniques in economics education. All the experience has contributed to my research capabilities, interdisciplinary skills, and my signature work product.

I want to thank my friends, classmates, faculty, staff, and everyone at Duke Kunshan University for providing me with such an amazing and immersive college experience, even during the global pandemic. I could not have completed this project without the support of my friends, Austen Li and Ryan He, who provided stimulating discussions and happy distractions to rest my mind outside of my research.

Last but not least, I would like to thank my parents for their consistent support.

TABLE OF CONTENTS

LIST OF TABLES

TABLE OF FIGURES

INTRODUCTION

Artificial Intelligence (AI) investment is increasingly popular, driven by recent technology advancements in blockchain, machine learning, and various application scenarios. First, AI has been widely applied with the Industrial 4.0 revolution. Besides the outstanding performance of AlphaGo, an AI agency that beat the best Go player in the world, AI also exhibits a huge potential in empowering financial investment in digital assets (DeepMind 2016). Second, the invention and expanding applications of blockchain and decentralized finance (DeFi) provide a framework to solve various problems existing in the traditional finance world. Finally, as a combination of AI and blockchain, emerging decentralized applications (dApp) could reinvent the finance world and reveal more possibilities. However, little evidence has shown that AI is more reliable than humans in volatile financial markets, especially the emerging digital assets markets.

The portfolio is one of the most common channels people use to invest in the financial markets. Any mix of financial assets, such as stocks, bonds, and cash, is referred to as a “portfolio” (Markowitz 1952). Individual investors can either create their own portfolios or take paid services. Financial professionals, hedge funds, banks, and other financial institutions, are there to offer portfolios and portfolio management services. It is widely recognized that an investor's risk preference, time horizon, and investing objectives should all be considered while constructing a portfolio. The risk and expected return are two factors that people are most concerned about in a portfolio (Markowitz 1952). Following the spirit of not putting all eggs in the same basket, we value the virtue of portfolio in financial investment. Through portfolio investment, an individual investor can take advantage of diversification to reduce the investment risk, thus attaining a better investment performance.

A portfolio in the traditional sense could include any class of assets with any percentage ranging from zero to one hundred percent. In comparison to the conventional portfolios, which mainly include bonds, stocks, real estate, and other traditional assets, a token portfolio only contains tokens or, in other words, cryptocurrencies. A Set is defined as a token portfolio created on the Set Protocol. Set Protocol is a decentralized finance (DeFi) tool in which users can build, rebalance, and actively manage token portfolios as they wish, like an exchange-traded fund (ETF) in traditional finance ("What Is Set Protocol? Set Tokens and TokenSets," n.d.). The tokens are mainly ERC-20 tokens based on the Ethereum blockchain, and they themselves are tradable on crypto exchanges. On the platform of Set Protocol, users can participate in the crypto market by buying and holding portfolios (in this scenario, sets) created by others and sharing the wisdom of their strategies. Users can also construct their own portfolios or indexes to invest in; they can further make the portfolios public to be bought.

This paper will study the features and investment performance of two different types of token portfolios, Robo Sets, run by hard-coded algorithms, and Social Sets, managed by human traders, in the platform of Set Protocol. AI algorithms follow the pre-determined rules and strategies and accurately and immediately adjust in accordance with the rapidly changing markets without being monitored by humans. This works especially well for the digital assets market because first, all information and trading are online, and second, they are actively traded on a twenty-four-hour basis. However, sometimes codes could be wrong, depending on the specific context and situation. AI algorithms have black-box problems that people may have no idea what is going on behind the strategies, which could be a modern “Ponzi scheme”. Besides, AI algorithms might fail when confronting a new dilemma that has not been programmed before if it is not the problem of bugs in coding. Through this case analysis, we will answer whether delegating to AI would improve the investment performance in digital assets markets. Moreover, we also analyze and advise individual traders to choose the more profitable token portfolios.

LITERATURE REVIEW

Theoretical and practical advancements have boosted the application of Artificial Intelligence (AI) in financial investment in several aspects. In the Industrial 4.0 revolution, AI has empowered agencies like AlphaGo, which beat the best Go player in the world; AI also exhibits a huge potential in empowering financial investment in digital assets (DeepMind 2016). Leading financial firms, such as J.P. Morgan (n.d), have already jumped at the chance to develop AI smart investment services for several reasons. With the equipment of AI, digital asset trading could be automated so that investors would not need to stare at the price all the time and greatly save attention.

The invention and expanding applications of blockchain and decentralized finance (DeFi) provide a framework to solve the third-party trust problem, CeFi privacy issues, Big Tech corruption, and single point failure. In fintech, combining the advantages of AI and blockchain, DeFi (decentralized finance) is reconstructed in the modern world but is more efficient than it first appeared as the barter system thousands of years ago (Harvey 2021). Smart contracts on the blockchain make automated trading much more frictionless than ever before. Enzyme[1] and dHEDGE [2]are such examples of smart contracts developed on the Ethereum blockchain.

[1] https://enzyme.finance/
[2] https://www.dhedge.org/

As a combination of AI and blockchain, emerging decentralized applications (dApp) could reinvent the finance world and reveal more possibilities. dApp is not only a concept but has already existed in real-world scenarios with high technology readiness, such as asset management agents, Set protocol, where investors can participate in the digital asset market with a predefined AI strategy. Set protocol allows for the creation, management, and trading of Sets, ERC20 tokens that represent a portfolio or basket of underlying assets ("Set Protocol | Stats, Charts and Guide | DeFi Pulse" n.d.). Controlled by the codes written in the smart contracts, Sets rebalance the portfolio periodically to optimize investment.

However, at the same time, we still have much to explore in this innovative investment approach. To begin with, AI-based systems, in most cases, still lack transparency and trust and maintain their black-box nature, which has become one major impediment to their development and application (Adadi and Berrada 2018). As a response, recent literature has been discussing Explainable Artificial Intelligence (XAI) to cope with the increasing demands for transparency and trust (Wells and Bednarz 2021). For instance, Cong et al. (2020) applied XAI and cutting-edge deep reinforcement learning to improve portfolio management, increase investment performance, and uncover the key drivers behind it. Our research does not only reconfirm the importance of transparency and trust but goes a step further: it explores how AI strategies and machine learning techniques could augment human choices.

Moreover, whether or not delegating to AI improves investment performance is largely unknown. Specifically, little empirical evidence has supported the positive role that AI could play in digital asset investment. Existing research is mainly concerned with choosing different automated algorithmic trading strategies. For example, Chen, Mak Kaboudan, and Du (2018) have discussed various algorithmic trading strategies in different contexts. Unlike the previous literature, our paper will compare hard-coded AI strategies in general with human traders.

Furthermore, fintech, cryptocurrency, and blockchain development bring new possibilities to AI investment. Goldstein, Jiang, and Karolyi (2019) recognized fintech's application prospect in shaping algorithmic trading more effectively and trustworthy way. In modern finance, the arbitrage pricing model (APT) is based on the absence of arbitrage. With the help of decomposing the price deviation into two parts, the common part and the idiosyncratic part, as modern finance does, Makarov and Schoar (2019) explained cryptocurrency's return movement through discussions about arbitrage. Liu, Tsyvinski, and Wu (2019) provide ten characteristics that help price cryptocurrencies. To construct AI investment tools in our research, we will rely on existing digital asset pricing research. Moreover, our test results might also inform whether these pricing models are accurate or not.

Last, our research also contributes to the economics literature about delegation choice. Previous literature has discussed delegation choices in economics, including delegation of experimentation and delegation of wage decisions (Charness 1998; Charness et al. 2012; Guo 2016). This proposed research also investigates the delegation problem but in a different way: we study delegation to AI or not in the algorithmic trading and DeFi application context. One thing we share in common with Charness (1998) is that we also assume that there is a responsibility-alleviation effect in digital asset investment, and we introduce the locus of control test to testify to this hypothesis. This research also relates to experimental economics and behavioral finance. According to Fréchette and A Schotter (2015), economic experiments could mimic real-world incentives, test the validity of economic theories, and help understand individuals' behaviors. We conduct randomized controlled trials to reveal the causal relationships and answer fundamental economic questions through carefully designed experiments (Banerjee and Duflo 2009).

This research will integrate interdisciplinary methods, including economics, finance, data science, and economic experiments in the future to answer two important questions. First, whether delegating to AI improves performance in digital asset investment? Second, how do we suggest investors in choosing their choice about portfolios in the digital asset markets?

METHODOLOGY

Set Protocol assets are comparable to exchange-traded funds (ETFs), which are derivative assets that provide exposure to a portfolio of securities and trade like stocks ("What Is Set Protocol? Set Tokens and TokenSets," n.d.). Users can assemble baskets of crypto tokens into Sets, which they can then buy, sell, or trade on exchanges. Collection Protocol allows users to create sophisticated asset-management strategies by determining the exact allocation of individual tokens, automating rebalancing settings, and interacting with a growing set of functions. Each Set is converted into an ERC-20 token using its own smart contract, allowing each token to be fine-tuned and tailored to the creator's preferences.

Our research question is whether delegating to AI improves investment performance in digital assets markets. To get the answer, I conducted data analysis on two types of digital assets portfolios created by Set Protocol, Robo Sets and Token Sets. Typically, for those who invest through Set Protocols, there are three ways they can participate in the investment. First, they can choose to buy a Robo Set, the token portfolio executed by AI algorithms based on pre-determined rules. Second, they can choose to buy a Social Set, which one or more human traders manage. An entire community of investors can even run it through blockchain. Finally, an investor could also create and design its own token portfolio.

We illustrate relationships among different portfolios in Figure 1.

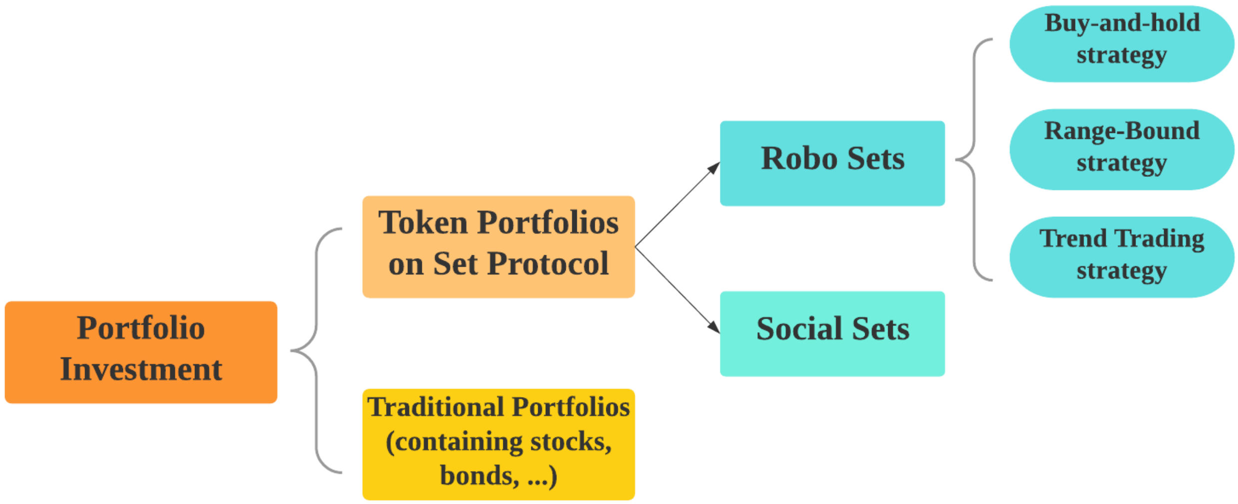

Figure 1. Logical Chart of different types of Portfolios (Created in LucidChart)

Robo Sets are hard-coded Portfolios, including mainly three strategies, buy-and-hold, Range-Bound, and trend trading (Richard 2022). These techniques are hardcoded, and algorithms, not humans, make the buying and selling decisions.

First, the buy-and-hold strategy is the simplest one, focusing on a combination of different assets and long-term investments. The "Buy and Hold" strategy is a classic investment strategy that never goes out of vogue. Buy and Hold Sets may be right for you if you're bullish but want more diversification than a single token.

The second is the Range-Bound Strategy. If you believe the price of an asset will move sideways for a while, you should use a Range Bound strategy. This technique automatically switches between a volatile (ETH) and a stable token (like DAI). As a result, when the volatile asset's price reaches the top of the range, the Set will sell it automatically. The Set will buy it when it reaches the bottom of the price range. In this situation, the Set would keep DAI in order to buy ETH on dips.

The last one is trend trading strategy, which echoes the idea of technical analysis, including indicators such as moving averages in traditional financial investment. Traditional technical analysis, which takes the form of a variety of trading rules, aims to find trend peaks and bottoms and is frequently utilized in the stock market (Lin, Yang, and Song 2011). Unfortunately, applying technical analysis directly is not practical because selecting acceptable rules for each share relies on a person's experience. However, the trend trading strategy in Set Protocol could be enhanced through machine learning and other hard-coded AI algorithms. Besides, according to Lento and Gradojevic (2022), technical analysis is proven more profitable than simple buy-and-hold strategies under specific conditions during COVID-19. As for trend trading Robo Sets, trading entry and technical analysis indicators will automatically trigger exit positions. As a result of using this method, the Set will always include 100% of the target asset at any given time. The Set would automatically rebalance itself to 100 percent DAI whenever a technical analysis indicator indicated a downward trend reversal in ETH, for example.

In terms of Social Sets, human traders or off-chain algorithms provide signals for Social Trading Sets to trade. Traders can use any method, such as technical analysis, on supported trading pairs, for instance, BTCUSDC, ETHUSDC, ETHBTC, or ETHDAI.

Your assets are never in the hands of traders or the Social Set. When a Set is not rebalancing, you can leave a Social Trading at any time.

For the purpose of our research question, we are to compare the first and second investment ways mentioned above, which is investing through either a Robo Set or a Social Set. We want first to select a group of token portfolios and then collect their historical price information and relevant data. Then, we compare the average return (return of investment, abbreviated as ROI) of Robo Sets and Social Sets. If the Robo Sets among our selected pool have a higher average return, we can conclude AI has a better investment performance than human traders. If the Social Sets among our selected pool have a higher average return, then we can conclude human traders have a better investment performance than AI algorithms.

DATA DESCRIPTOR

As mentioned above, Set Protocol is a decentralized platform where investors can buy and create portfolios of ERC-20 tokens and participate in the digital assets markets. Set Protocol mainly offers two types of Sets: Social Sets and Robo Sets.

We rank the featured Sets on Set Protocol's official website by the market capitalizations of Sets. Then we pick the top 15 featured sets to study for our research questions, as shown in Figure 2.

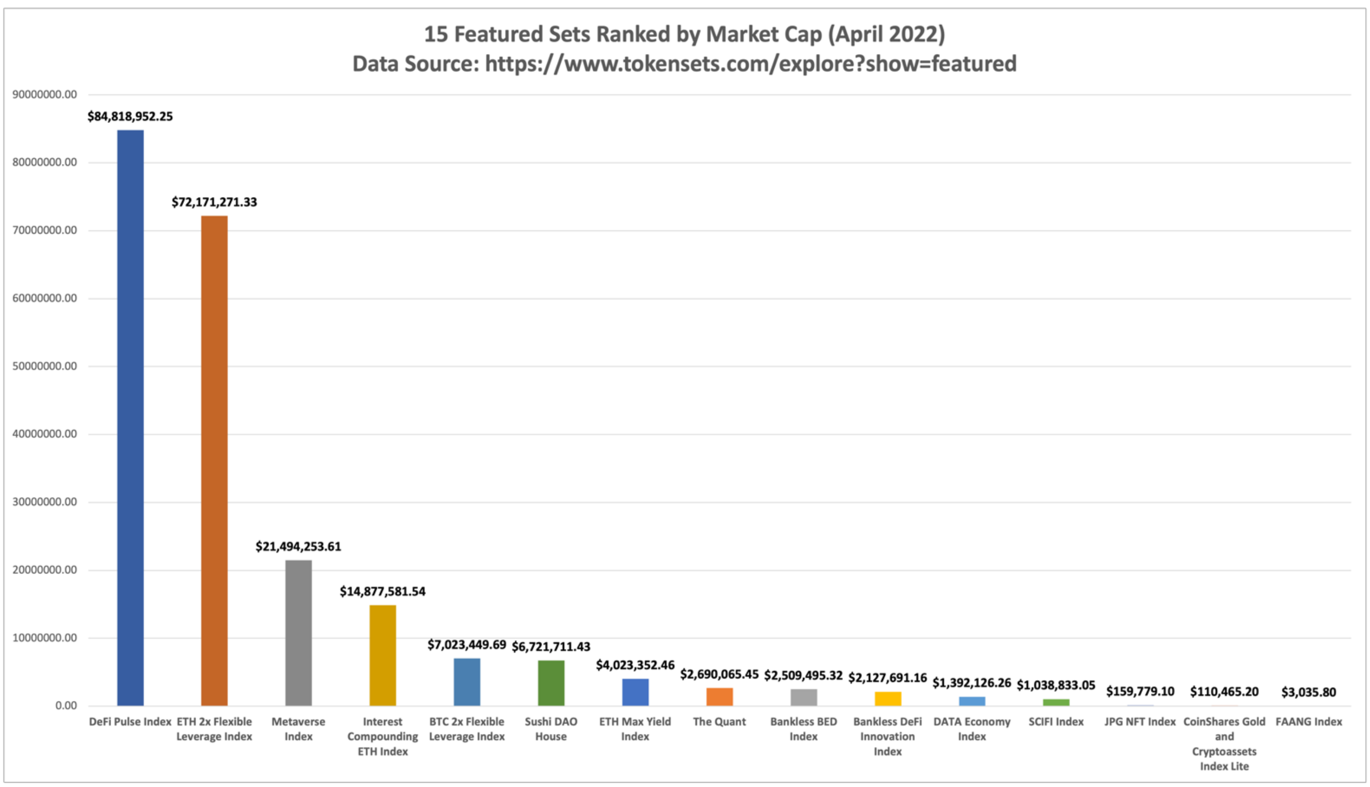

Figure 2. Fifteen Featured Sets Ranked by Market Capitalization (April 2022)

We then visualize the top fifteen market-cap Sets' holder numbers in Figure 3. Although DeFi Pulse Index, the largest Set, has the largest number of holders and the third-largest Set, Metaverse Index, has the second largest number of holders, we cannot generalize this observation to positive correlations between market capitalization and hold numbers.

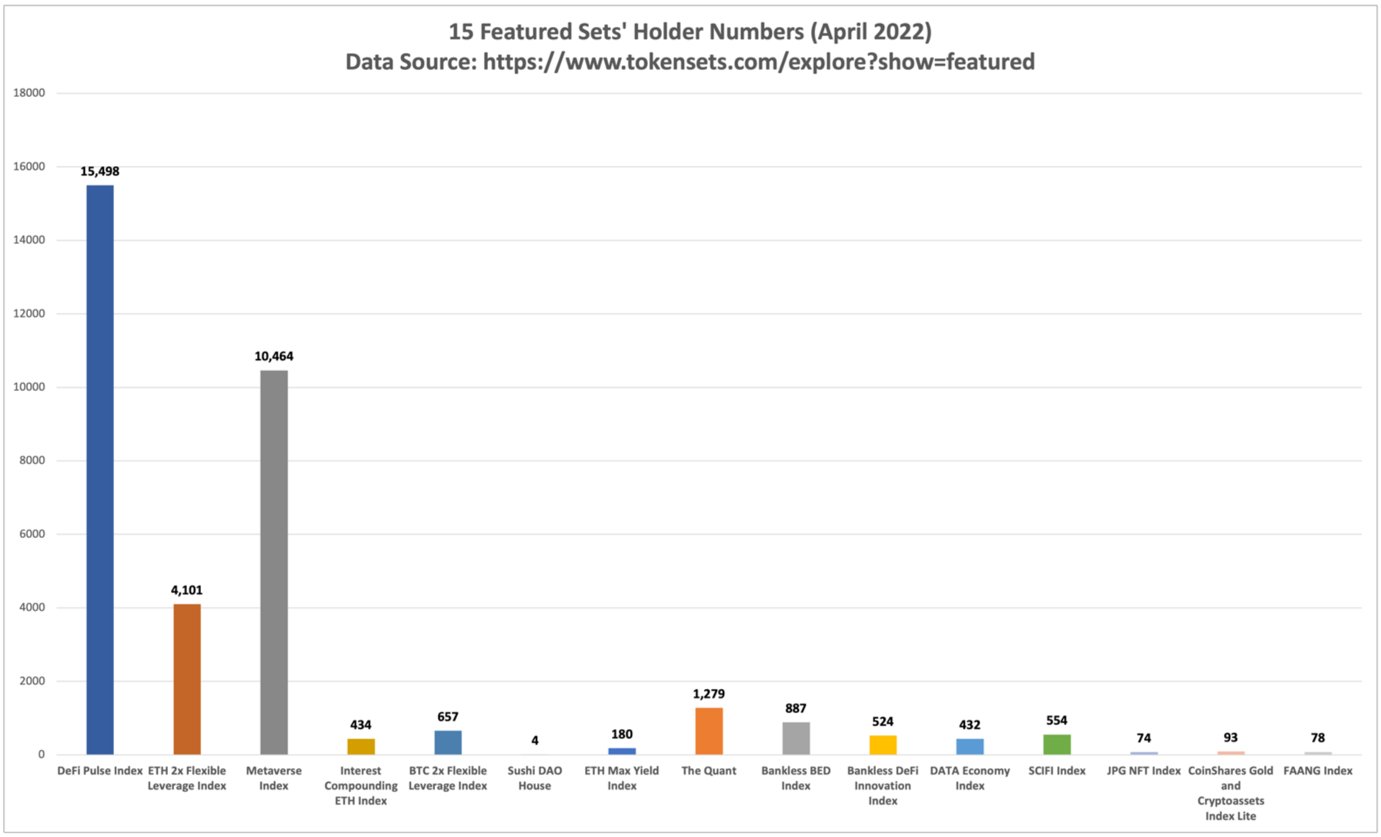

Figure 3. Top Fifteen Market-Cap Sets and Corresponding Holder Numbers (April 2022)

In addition to market capitalization and hold numbers, streaming fee, leverage ratio, and max drawdown are also critical features that investors usually take into their account. The streaming fee is a yearly fee that the Set Creator may accrue through time based on the Set's overall market cap. A Set, for example, is produced with a 2% streaming cost. After six months, the Set Creator is entitled to 1% of the Set's total market cap as fees. Leverage ratio measure how much a portfolio borrows compared to its holdings. However, some Sets do not clearly indicate a streaming fee, and many of the portfolios also do not engage leverage in their strategies and thus have no leverage ratio. Therefore, we do not consider these two features in our research.

We then plot the max drawdown, the largest decline in a Set's value from peak to trough over the lifetime of a Set, of the top fifteen market-cap Sets in Figure 4. Although an apply-to-all pattern has not been identified, we can find that those Sets with high market value and a large number of holders are not necessarily and absolutely better than the rest of the Sets because of their relatively larger size of the max drawdown. Max drawdown, mapping onto the 5% rate in traditional stock investment analysis, is an essential measure of an asset's risk. We should be cautious and pay additional attention to this risk measurement as crypto assets are more volatile and inclined to confront "black swan" incidents, thus being more likely to face a severe trap.

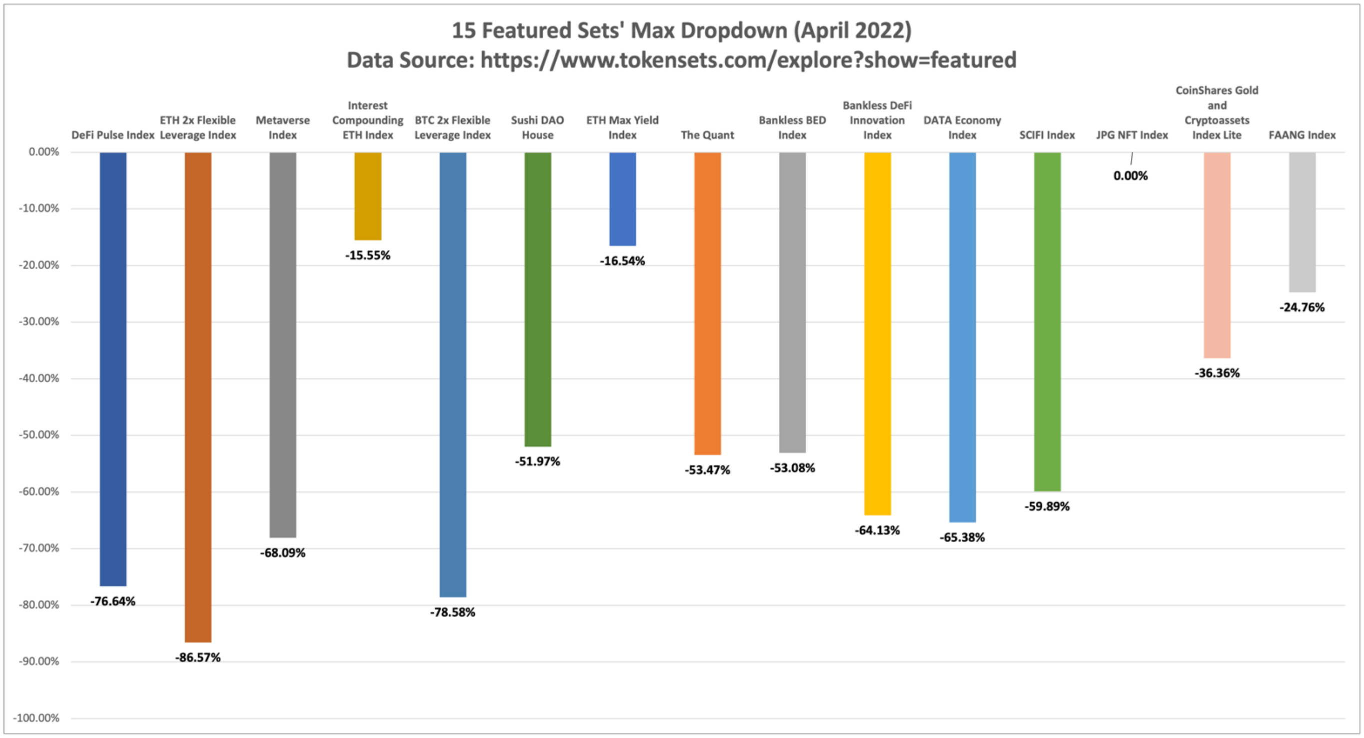

Figure 4. Top Fifteen Market-Cap Sets and Corresponding Max Drawdown (April 2022)

Figure 5 shows the Robo Sets in the top fifteen market-cap Sets, ranging from high market value to low. The average market capitalization of these eight Sets is $23,477,611.43. The average holder number is 4073. The mean of max drawdown is -0.52%.

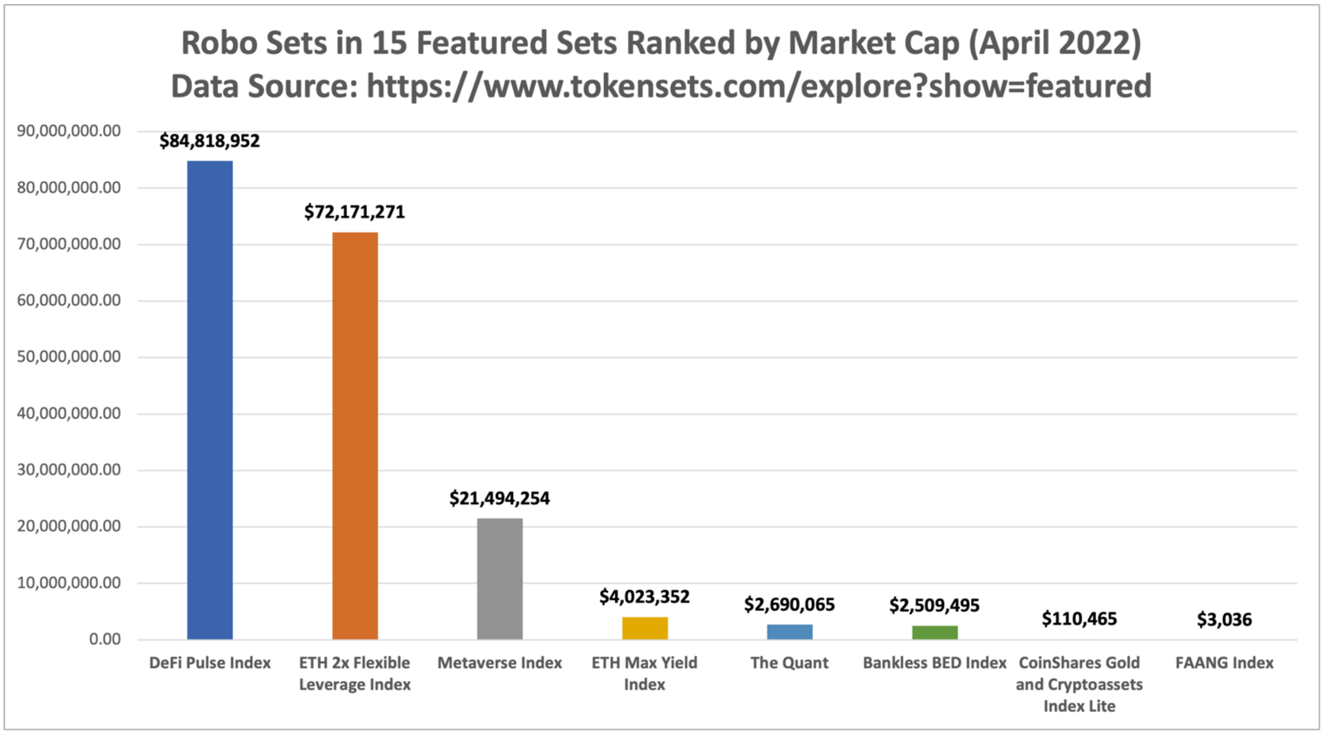

Figure 5. Robo Sets in Top Fifteen Market-Cap Sets Ranked by Market Capitalization (April 2022)

Figure 6 shows the Social Sets in the top fifteen market-cap Sets ranging from high market value to low. The average market capitalization of these eight Sets is $4,763,024.60. The average holder number is 383. The mean of max drawdown is -0.48%.

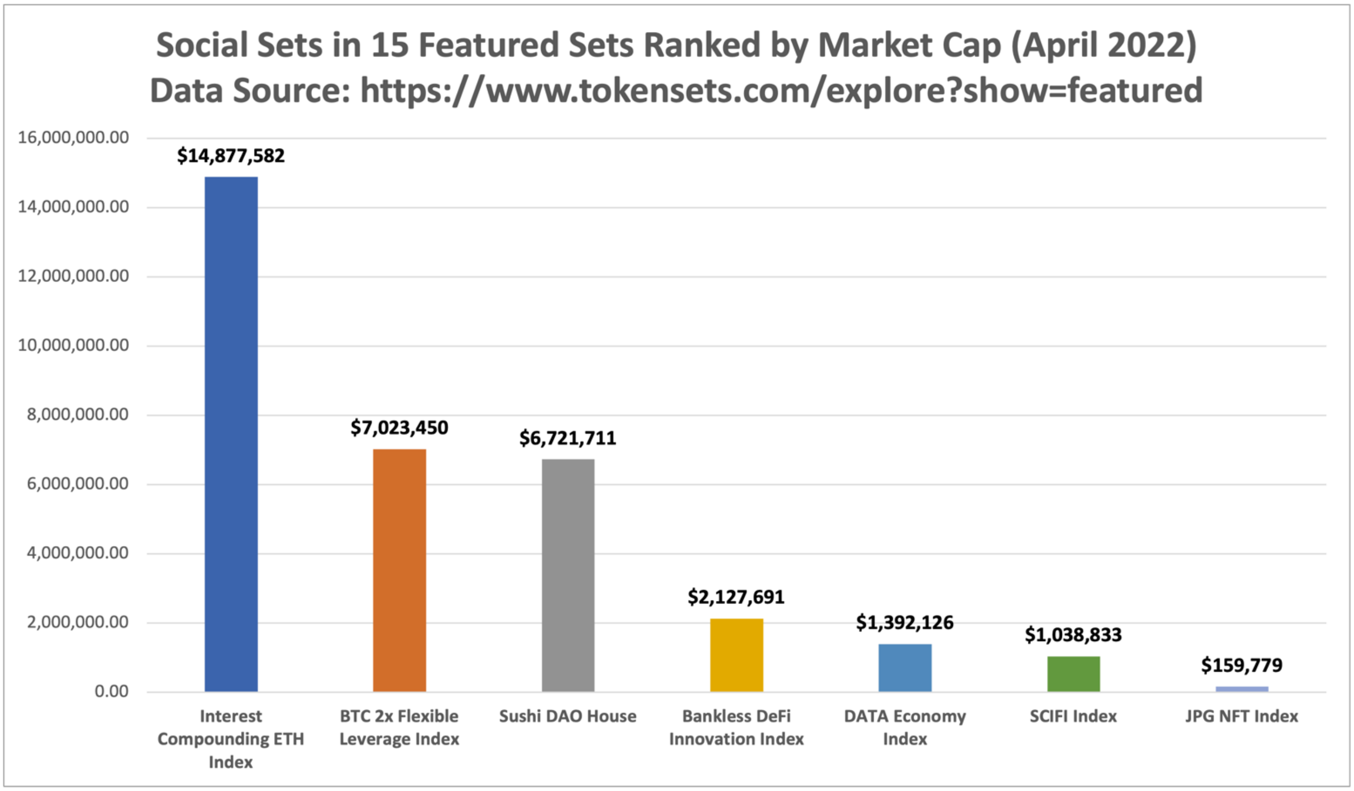

Figure 6. Social Sets in Top Fifteen Market-Cap Sets Ranked by Market Capitalization (April 2022)

To acquire the data on average returns and volatility of selected token portfolios, we first collect the historical trading price of the portfolios from the official website of Set Protocol. For instance, Figure 7 shows the historical data of the DeFi Pulse Index. Then, we calculate the means, stand deviations, and other data features on a weekly, monthly, and 3-month basis, respectively, to compare the investment performance of Robo Sets and Social Sets.

Figure 7. Historical Trading Price of DeFi Pulse Index, A Token Portfolio (Data Source: https://www.tokensets.com/portfolio/dpi)

RESULTS AND DISCUSSIONS

Since we are comparing the returns of Robo Sets and Social Sets over the same period and on the same frequency, we can assume all other conditions hold the same, and the only variation is the agent that manages the portfolio. Then, the difference in the investment results could, to some extent, be explained by whether the portfolio management is delegated to humans or AI. The main results are presented in Table 1 and Figure 8.

Table 1. Means and Standard Deviations of Selected Robo Sets and Social Sets' Max Drawdown, Weekly Returns, Monthly Returns, and 3-month Returns

		Drawdown	Weekly Average	Monthly Average	3-month Average
Robo Sets	Mean	-51.94%	-4.81%	-11.20%	-3.55%
	STD	24.81%	1.86%	7.84%	12.57%
Social Sets	Mean	-47.93%	-3.41%	-13.94%	-9.27%
	STD	28.90%	1.25%	7.95%	12.13%

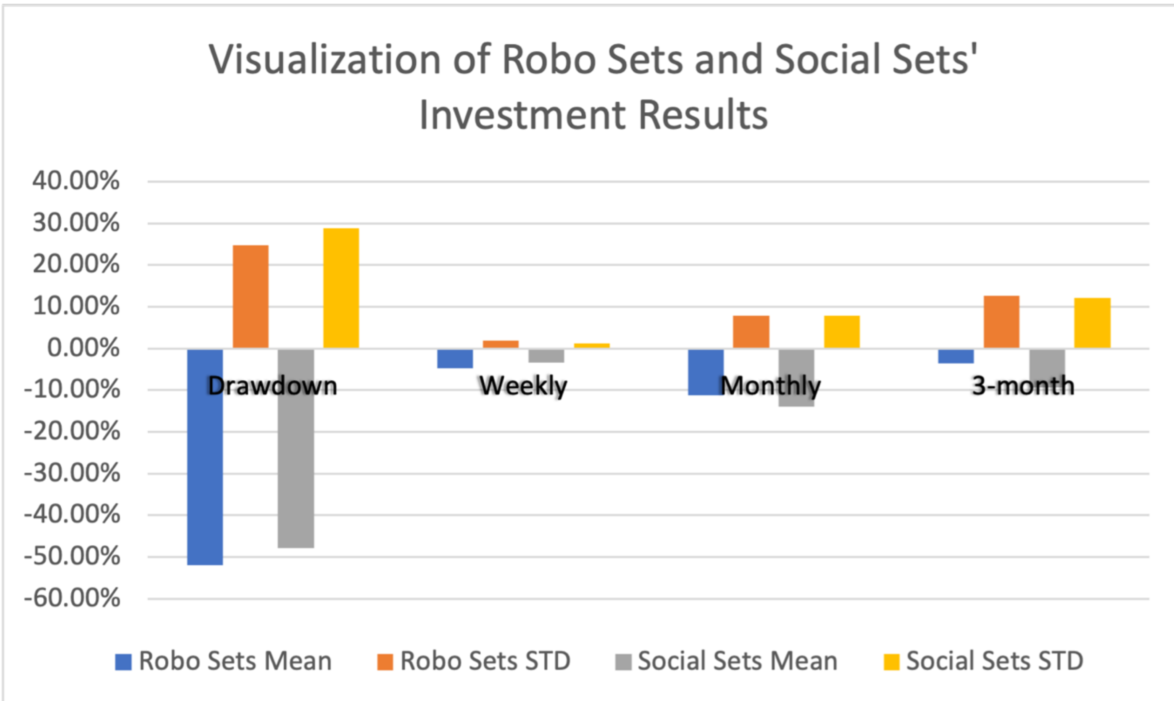

Figure 8. Visualization of Robo Set and Social Sets' Investment Results

Table 1 shows the weekly average return of Social Sets is higher than that of Robo Sets. Besides, the standard deviation of Social Sets is less than Robo Sets. In other words, the selected Social Sets are less risky in general than Robo Sets. Then, we can tell that human traders show a better investment performance than AI algorithms on a weekly measure.

However, if we look at the monthly average, Robo Sets generates a higher average return with a lower standard deviation; that is to say, selected Robo Sets to produce a better investment result with a relatively lower risk level. We find that, in this case, AI has a better investment performance than human traders.

When we look at the 3-month time scale, Robo Sets give out a significantly higher average return. Although the standard deviation of Robo Sets is higher than that of Social Sets, the difference is only 0.44%, taking only 3.63% of the average risk shared by a single Social Set in our pool. Considering the negligible difference between the standard deviations, we still think AI has a better investment performance than humans over a 3-month investment period.

Combining our observations, we conclude that human investors have a better performance over shorter investment periods, for instance, weekly. But from a monthly or quarterly perspective, AI shows a better investment capability than humans in digital assets markets. Moreover, it seems that the longer the investment horizon is, the wider the gap between AI and humans' investment performance may hold. But this observation is to be tested with a larger amount of data and a longer time horizon, which is implausible by now as most of the crypto markets are still emerging and most of the financial assets available have a relatively short history. We may have to wait until further later to trace back the validity of this conclusion.

In addition to the features of Robo Sets and Social Sets' returns, we also compare the average market capitalization, holder number, and max drawdown of these two categories of token portfolios.

The average market capitalization of our selected Robo Sets is $ 23,477,611.43, much higher than that of Social Sets, $ 4,763,024.60. In traditional finance, the total value of all a company's shares of stock is referred to as market capitalization ("What Is Market

Cap? - Fidelity," n.d.). Market capitalization is usually treated as an indicator of a company's size and a measure of a company's overall value. The common understanding of market capitalization also applies to the crypto markets. So, on average, we can say that AI-managed Sets have a much larger market or market value than human-managed Sets.

Similarly, the average holder number of Robo Sets is 4073, much greater than that of Social Sets, which is 383. This tells the similar story that market capitalization tells. However, we are unsure about the reasons behind it. It could be caused because people in general trust more AI in digital assets investment. It could be possible that people have no time or energy to closely monitor and actively trade the assets and choose to delegate them to AI agents. Maybe this is because AI has a more powerful and rigorous investment capability so that AI is more likely to manage more clients and money in digital assets markets.

Drawdown is another data we want to analyze. In traditional financial investment, we analyze returns and risks as the two most important data, and all modern portfolio theories are based on this mean-variance analysis. However, in many cases, mean-variance analysis cannot accurately represent the comprehensive picture as it misses information when simplifying the complex financial problems into a two-dimension mean-variance problem. Considering "black swan" incidents, time-varying volatility, extreme return clustering, and skewness and fat tails of some return distributions, we might turn to loss possibility, value at risk, and other signals to fairly assess an asset or a portfolio in traditional finance. Max drawdown in Set Protocol shares this spirit, and it measures the largest decline in a Set's value from peak to trough over the lifetime of a Set. Although both max drawdowns for Social Sets and Robo Sets are large, due to the nature of volatile crypto assets, Social Sets have a smaller max drawdown than Robo Sets. Based on this finding, we may conclude that Social Sets are more risk resistible. It could be rationalized as human traders keep the full discretion and could flexibly adjust strategies in front of risks or disastrous events. However, AI may stick to pre-determined rules and is more likely to be caught by traps in the market.

CONCLUSIONS AND IMPACTS

In today's world, AI has been playing an increasingly important role in many aspects. AI could also facilitate portfolio management and investment in the digital assets market. Set Protocol is a novel way of providing broad market exposure through baskets of Ethereum-based tokens. It also allows creators to tokenize and share their asset-management ideas with a larger audience while also earning streaming fees. Set Protocol can even be used to group objects together in games. The protocol's basket approach to tokenized assets also allows users to manage and transfer batches of assets while saving money on transaction fees because there are fewer individual transactions. The basket model of tokenized asset management offers a wide range of applications and benefits, and Set has established itself as a market leader.

On the platform of Set Protocol, we compared the investment results of two categories of token portfolios, one is Robo Set, executed by pre-determined AI algorithms, and the other is Social Set, under the management of human traders. The results show that humans have a better investment performance over the weekly horizon. However, AI could generate higher investment returns with a similar or even lower risk on a longer time horizon, such as a monthly or quarterly measure. Therefore, we would recommend investors delegate to human traders for a short-term investment. We suggest investors delegate to AI for long-term investment in digital assets markets. Long-term investors should further be cautious about the streaming fee a portfolio requires as it accumulates as time goes by. Besides, the market capitalization of portfolios executed by AI algorithms is much larger than those under human traders' management. However, it is notable that AI-managed portfolios have a larger max drawdown than human-managed portfolios. Based on this finding, we would suggest more risk-averse investors choose Social Sets.

Admittedly, this research project has some limitations. First, due to the emerging nature of the digital assets market, there are not enough market participants, and thus, this is certainly not a perfectly competitive market. Second, we are also greatly limited by the data we can collect from the official website as we do not have a comprehensive database of these assets and their trading data, nor can we directly crawl data. We also could not find well-sorted data available in an online open-source community like GitHub. All the data in this research project is collected manually and is thus time-consuming and inefficient. Third, although the featured portfolios that we evaluate in this project are from the official website and were chosen because they are representative, we cannot find the detailed rules about how they are designated as featured Sets. Last but not least, in terms of the categorization of Social Sets and Robo Sets, we divide the token portfolios by reading the introduction and management manuals and following the definition of Social Sets and Robo Sets. In the future, if each registered Set could notify whether it is Social or Robo, the categorization would be more accurate and efficient, avoiding unnecessary misunderstanding.

This Signature Work project aims at conducting interdisciplinary research at the frontier of FinTech and financial investment. The project has created academic value in multiple disciplines as it integrated knowledge in economics, algorithmic trading, explainable AI (XAI), augmented AI, delegation choice, and the emerging digital assets markets. All the interdisciplinary knowledge helps answer fundamental economic questions and create commercial value.

Furthermore, this signature work project also has a variety of practical impacts. First, people unfamiliar with digital asset investment could learn how to participate in the market through token portfolios. Reading this paper, they can learn about the detailed differences and similarities between traditional and token portfolios. Second, this paper evaluates whether delegating to AI is a wise decision over a certain time horizon and advises investors to choose a more suitable token portfolio based on the time scale of investment and their risk profiles.

In addition to the data analysis we conduct in this paper, we would like to answer whether delegating to AI improves investment performance again through behavioral economics experiments in the future when we secure funding and a group of subjects. We have already had a complete design of the experiment. This innovative project could transform academic results into industrial products and even generate significant educational values. We conducted a pilot experiment with 32 economics students. We plan to transform the experiment design into a web-based application with a team with an interdisciplinary background in software engineering and user interface (UI) and user experience (UX) design. This multidisciplinary collaboration greatly facilitates technology transfer for scientific results. Moreover, this web-based application can play its unique role in investment whilst providing rare perspectives to academic research. We could further wrap the experience up as a public education resource.

In the future, we would like to further develop a model to predict whether human traders outperform hard-coded algorithmic strategies in digital asset investment over a certain time horizon. We may also use the prediction result to advise investors with a more accurate choice with investment.

We also plan to propose a series of concrete strategies that individual traders can adopt to construct a token portfolio from scratch. We plan to investigate the relationships between several features of a Set and its return on investment. Then we can construct a model based on portfolio features to help predict its performance in the recent future. We will run various regressions on returns over different Set features, including asset categories, the past return on investment, total volume, and other typical trading signals. We will generate more supportive advice in digital asset investment by borrowing some insights from traditional finance.

REFERENCES

Adadi, Amina, and Mohammed Berrada. 2018. “Peeking inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI).” *IEEE Access* 6: 52138–60. https://doi.org/10.1109/access.2018.2870052.

“Artificial Intelligence.” n.d. Www.jpmorgan.com. https://www.jpmorgan.com/technology/artificial-intelligence.

Banerjee, Abhijit V., and Esther Duflo. 2009. “The Experimental Approach to Development Economics.” *Annual Review of Economics* 1 (1): 151–78. https://doi.org/10.1146/annurev.economics.050708.143235.

Charness, Gary. 1998. “Responsibility and Effort in an Experimental Labor Market.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.139676.

Charness, Gary, Ramón Cobo-Reyes, Natalia Jiménez, Juan A Lacomba, and Francisco Lagos. 2012. “The Hidden Advantage of Delegation: Pareto Improvements in a Gift Exchange Game.” *American Economic Review* 102 (5): 2358–79. https://doi.org/10.1257/aer.102.5.2358.

Chen, Shu-Heng, Mak Kaboudan, and Ye-Rong Du. 2018. *The Oxford Handbook of Computational Economics and Finance*. New York, Ny: Oxford University Press.

Cong, Lin, Ke Tang, Jingyuan Wang, and Yang Zhang. 2020. “AlphaPortfolio for Investment and Economically Interpretable AI.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3554486.

DeepMind. 2016. “AlphaGo: The Story so Far.” Deepmind. 2016. https://deepmind.com/research/case-studies/alphago-the-story-so-far.

FréchetteGuillaume R, and A Schotter. 2015. *Handbook of Experimental Economic Methodology*. New York, Ny: Oxford University Press.

Goldstein, Itay, Wei Jiang, and George Andrew Karolyi. 2019. “To FinTech and Beyond.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3328172.

Guo, Yingni. 2016. “Dynamic Delegation of Experimentation.” *American Economic Review* 106 (8): 1969–2008. https://doi.org/10.1257/aer.20141215.

Harvey, Campbell R. 2021. *Defi and the Future of Finance.* S.L.: John Wiley.

Lento, Camillo, and Nikola Gradojevic. 2022. “The Profitability of Technical Analysis during the COVID-19 Market Meltdown.” *Journal of Risk and Financial Management* 15 (5): 192. https://doi.org/10.3390/jrfm15050192.

Lin, Xiaowei, Zehong Yang, and Yixu Song. 2011. “Intelligent Stock Trading System Based on Improved Technical Analysis and Echo State Network.” *Expert Systems with Applications* 38 (9): 11347–54. https://doi.org/10.1016/j.eswa.2011.03.001.

Liu, Yukun, Aleh Tsyvinski, and Xi Wu. 2019. “Common Risk Factors in Cryptocurrency.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3379131.

Makarov, Igor, and Antoinette Schoar. 2019. “Trading and Arbitrage in Cryptocurrency Markets.” *Journal of Financial Economics* 135 (2). https://doi.org/10.1016/j.jfineco.2019.07.001.

Markowitz, Harry. 1952. “Portfolio Selection.” *The Journal of Finance* 7 (1): 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x.

Richard. 2022. “What Is the Difference between Social Trading and Robo Sets?” Help.tokensets.com. April 1, 2022.

https://help.tokensets.com/en/articles/3637028-what-is-the-difference-between-social-trading-and-robo-sets.

“Set Protocol | Stats, Charts and Guide | DeFi Pulse.” n.d. Defipulse.com. Accessed December 28, 2021. https://defipulse.com/set-protocol.

Wells, Lindsay, and Tomasz Bednarz. 2021. “Explainable AI and Reinforcement Learning—a Systematic Review of Current Approaches and Trends.” *Frontiers in Artificial Intelligence* 4 (May). https://doi.org/10.3389/frai.2021.550030.

“What Is Market Cap? - Fidelity.” n.d. Www.fidelity.com. https://www.fidelity.com/learning-center/trading-investing/fundamental-analysis/understanding-market-capitalization#:~:text=Market%20cap%E2%80%94or%20market%20capitalization.

“What Is Set Protocol? Set Tokens and TokenSets.” n.d. Gemini. https://www.gemini.com/cryptopedia/set-protocol-erc20-set-token-tokensets-asset-tokenization#section-what-is-set-protocol.

Appendix A: Submitted Paper

(a) Title: “Educational Game on Cryptocurrency Investment: Gamification for Understanding Macroeconomics in Micro Human-Computer Interaction”

(b) Authors: Jiasheng Zhu and Luyao Zhang

(c) Abstract: Classroom games are an effective experiential learning activity because students are engaged in decisions of economic relevance. We present a design of experiential education in classroom games that effectively cultivates independent research capability. We also introduce a qualitative and quantitative methodology to test the effectiveness of classroom games on various learning objectives. Both games we present are activities in macroeconomic courses at Duke Kunshan University in Fall 2020 and Spring 2021 and are about investment in the emerging market of cryptocurrency. Reflecting on the games, students can understand economics better by comparing what the theory dictates and what their instinct advises. Furthermore, viewing the games as research in experimental economics, students develop the skill of systematic scientific inquiry in experiential education.

(d) Keywords: Classroom Games, Economics Education, Experiential Learning, Independent Student Research, Investment in Cryptocurrencies

(e) JEL code: A20; C90; D90

Appendix B: Paper Accepted by Conferences

(a) Title: "The Right Tool for the Job: Matching Active Learning Techniques to Learning Objectives"

(b) Authors: Sarah A. Jacobson, Luyao Zhang, Jiasheng Zhu

(c) Abstract: Active learning techniques have been shown to be productive additions to classes at the university level (e.g., Freeman et al., 2014; Prince, 2004). However, in economics, many instructors still make little or no use of active learning (Sheridan and Smith, 2020). Further, these techniques may vary in their effectiveness at achieving different goals (Prince, 2004). In this paper, we assess a variety of active learning techniques, comparatively to each other and to a set of traditional teaching elements, as implemented in an intermediate macroeconomics course, with a particular focus on building skills for independent research.

(d) Keywords: active learning techniques, student engagement, student perceptions, learning objectives

(e) JEL code: A20, A22, I21

Appendix C: SciEcon Research Seminar Presentation

[Wapwire]
[Slides URL]
[PDF URL: Conversation documents]

Appendix D: Econ 211 Presentation

[Video Recording]
[2021 Spring Presentation Slides]
[PDF URL: Research Proposal]
[PDF URL: Conversation documents]
[2021 Fall Presentation Slides]

Appendix E: SciEcon AMA Interview Series

I launched the SciEcon AMA Interview Series and I am now Chair of SciEcon AMA. “On the Internet Computer: SciEcon AMA (Ask Me Anything) Interview Series” is an intellectual conversation among professors, entrepreneurs, developers, and students on the topics of fintech, blockchain, and beyond. We together are contributing to the great purpose of open-source documentation about the leading-edge fintech technologies. More importantly, we are pioneering a deep connection between academia and industry that can generate profound insights and practical impacts for generations to come. We build a greatly interdisciplinary and intercultural team with 20+ young scholars from around the globe. By now, we have interviewed 30+ distinguished scholars and entrepreneurs from various top institutions and published the conversations on Medium and WeChat.
[Presentation Slides]

The following are the articles that I am either an interviewer, editor, or participant:
1. Prof. Campbell Harvey [WeChat][Medium] – How will DeFi Reshape the Future of Finance?
2. Prof. Jimmie Lenz [WeChat][Medium] – DeFi: Reinventing Finance and Expanding the Possibilities
3. Prof. Yu Xiong [WeChat][Medium] – Calls for the Internet Computer to Integrate the Spirit of Magna Carta
4. Prof. Justin Cappos [WeChat][Medium] – Calls for the Internet Computer to Integrate the Spirit of Magna Carta
5. CEO Charles Du [WeChat][Medium] – The Future of Cryptocurrency
6. Prof. Olivier Marin [WeChat][Medium] – The Future of Consensus: Algorithm on Blockchain
7. CEO Bill Russo [Medium] – The Future of Mobility
8. Dr. Diana Gamborino-Schweizer [WeChat][Medium] – How to Realize Options Trading in Decentralized Finance

Appendix F: SciEcon Research

SciEcon Research is a series of research labs focusing on interdisciplinary research in economics and data science. There are currently six research labs working on game theory, machine learning, non-fungible token, sustainable finance, mechanism design, and TEA taskforce. The labs work with the top scholars and industry practitioners around the world to contribute to the real-world challenges. We hold workshops and symposiums to encourage communication of ideas.

(a) **Research Article Title**: How Blockchain Empowers Social Media: on the mechanics of token economy and decentralization?

(b) Abstract: Nowadays, users have an increasing demand for decentralized platforms when censorship, privacy disclosure, and security of personal data are severely concerned in traditional social media. The innovative blockchain technology perfectly solves this dilemma by reducing the trust cost, protecting users' freedom of expression, and serving as a reliable peer-to-peer (P2P) network framework.

Taking a further step, a few social media companies have introduced the token system into their platforms. Tokens, in other words, are the digital currencies distributed through the blockchain network. Tokenized social media connects the platform and users by consensus on the token value. Moreover, token's financial and economic mechanisms incentivize users to contribute their intelligence to the virtual community and actively participate in on-chain governance. This article will introduce three typical tokenized social media, Steemit, Bihu, and Voice, in facets of business background, business models, SWOT (strengths, weaknesses, opportunities, and threats) analysis, and finance and economics in the token system.

This comprehensive analysis about three tokenized social media firms not only presents the revolutions in the online social network, but also reveals new investment opportunities and the future of diversity and inclusion.

(c) Medium Publications:

[Part 1: Background Review URL]

[Part 2: Business Model Analysis URL]

[Part 3: Token Economics URL]

Appendix G: SELF Summer Research

Supported by the DKU SELF Research Fellowship, I had an invaluable experiential learning experience at NYU Shanghai as a research assistant of Prof. Ye Jin and Prof. Guodong during the summer. I cultivate my research skills and broaden my academic horizons through mainly three research projects. I participated in Prof. Jin's research about the "cheap talk" by discussing the experimental design and analyzing the data. Then, we researched the market bubble, reviewed 19 papers on asset markets together, and addressed the experiment design for further studies. We also shared our experience in managing the behavioral lab. Besides, I also conducted research about how the COVID-19 affects collective decision making in listed companies [Handbooks] [Literature].
[NYU RA Internship Certificate]
[SELF Abstract]
[SELF Report]
[SELF Poster]

Appendix H: Build A Virtual Behavioral Lab at DKU

Under supervision and instruction of Prof. Luyao Zhang, I built a Virtual Behavioral Economics Lab at DKU from scratch, and participated in several research projects as a lab manager and research assistant. My main contributions are in three aspects. First, I formulated the terms of use, interactive guidelines, and privacy policies through communications with lab managers from other institutions [GitHub]. Second, I initiated the official website, managed the process of lab projects, and published the research results on the website. Moreover, I also designed and implemented a stablecoin investment experiment to quantitatively study irrationality and price misperception.