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by

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Abstract:

Should cryptocurrencies be viewed as a gambling tool or a risky investment instrument? While their unpredictable returns resemble gambling, recent studies show their prices having a time-varying correlation with traditional risky assets like the S&P 500. Many institutional investors have, thus, included cryptocurrencies in their portfolios for diversification. This paper examines the behavior of cryptocurrency market participants and investigates whether they behave like gamblers or investors. Literature shows that gamblers often engage in loss-chasing behavior, escalating risk-taking after losses that may go on indefinitely. In contrast, investors typically exhibit risk aversion after losses, though some might increase risk-taking after "paper losses," a phenomenon called the "realization effect." Our study found high-risk individuals exhibit gambling-like behavior, chasing both realized and paper losses. In contrast, we found limited evidence that low-risk individuals engage in risk aversion and realization effect, similar to investors. These insights are crucial for policymakers, as loss-chasing can lead to the siutation where people taking on more risk than they can afford, potentially resulting in bankruptcy.

JEL Codes: D81, G11, G41

Keywords: Cryptocurrency, Realization Effect, Loss-Chasing, Behavioral Finance

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1. Introduction

There has been a debate on whether cryptocurrencies should be viewed as a gambling tool or a risky investment instrument. Several studies highlight the unpredictability of their returns, noting that fluctuations in cryptocurrency prices often do not appear to be explainable by fundamental factors. Rather, prices tend to be influenced by news and social media sentiments (Kraaijeveld and De Smedt, 2020; Critien et al., 2022). As a result, their outcomes can resemble those of gambling. However, recent studies have indicated that cryptocurrency price fluctuations have become more correlated with traditional risky assets, such as the S&P 500 (Iyer, 2022). Moreover, many institutional investors have incorporated them into their portfolios to improve their efficient frontiers. Consequently, some consider cryptocurrencies as a risky investment asset.

One way to contribute to the debate is to look at people's behavior in the cryptocurrency market. Do they behave as if they are engaging in gambling or act as though they are making investments?

In observing casino gamblers, the literature discovers that gamblers often engage in loss-chasing behavior, betting increasing amounts of money (i.e., escalating risk-taking) after losses in hopes of recouping their original funds. They might chase their losses indefinitely until "the bitter end" (Ebert and Strack, 2015; Gainsbury et al., 2014). The literature identified loss-chasing behavior as an impulse-control disorder. It is also known as compulsive gambling, pathological gambling, or problem gambling, and it requires treatment (American Psychiatric Association, 2013; Gainsbury et al., 2014; Zhang and Clark, 2020). Moreover, research has demonstrated that brain scan images of individuals diagnosed with compulsive gambling bear similarities to those of people with substance or drug addictions (Bowden-Jones & Clark, 2011; Romanczuk-Seiferth et al., 2014).

On the other hand, risk aversion can often be observed in people making investment decisions as they avoid risk-taking after incurring losses. To delve further into the nuances of losses, Imas (2016) observed that people tend to avoid risk-taking after experiencing "realized losses" (i.e., when money has been transferred). However, they might increase their risk-taking following "paper losses" (i.e., when money has not yet been transferred). Imas (2016) termed this phenomenon the "realization effect." He explained that escalating risk-taking after experiencing losses can be viewed as a response to recoup those losses while the current investment session is ongoing. He further explained that people "bracket" paper losses with subsequent risk-taking decisions and evaluate them together. However, they do not apply the same bracketing for realized losses (Tversky & Kahneman, 1992; Rabin & Weizsäcker, 2009; Read et al., 1999).

This paper aims to contribute to the debate on whether cryptocurrencies are perceived as a gambling tool or a risky investment instrument. We investigate the behavior of cryptocurrency market participants to determine if they act more like casino gamblers or investors making risky investments. While this research question has been broached in theoretical discussions, empirical exploration using transaction-level data remains scant. To the best of our knowledge, this research question has not yet been explored empirically using transaction-level data. This paper seeks to bridge this gap by presenting empirical evidence from Thailand's cryptocurrency market, which has a high enthusiasm for cryptocurrencies with widespread adoption. According to Chainalysis, Thailand ranked eighth globally in the crypto adoption index in 2022 and third in the DeFi adoption index in 2021.[1,2] In essence, while our empirical evidence is rooted in Thailand's market, the

[1] https://blog.chainalysis.com/reports/2022-global-crypto-adoption-index/
[2] https://blog.chainalysis.com/reports/2021-global-defi-adoption-index/

patterns, behaviors, and insights gleaned are applicable and valuable to the understanding in the broader global cryptocurrency landscape.

We utilized transaction-level data of market participants who traded cryptocurrencies in Thailand via licensed digital asset exchanges regulated under Thai laws.[3] Per the Notification of the Securities and Exchange Commission No. GorThor. 26/2562, the Securities and Exchange Commission of Thailand (SEC) requires digital asset exchanges operating in Thailand to provide detailed information on their customers' trading activities. Accordingly, the transaction-level data has been regularly submitted to the SEC since November 2020. These transaction-level observations allow us to construct panel data of individuals' implied holdings with the market values and the costs of their holding (calculation details will be provided in the data section). This information is central to our understanding of individuals' risk-taking behavior. Our sample period is from December 2020 to December 2022, as illustrated in Figure 1, along with the bitcoin price.

Our results revealed that participants in the cryptocurrency market treat cryptocurrencies as both gambling tools and investment instruments. High-risk individuals, determined by their portfolio volatility equal to or above the median in each month, exhibit loss-chasing behavior. They tend to increase risk-taking after losses, regardless of whether their losses are realized or not. This behavior mirrors that of gamblers. Conversely, low-risk individuals, determined by their portfolio volatility below the median, behave differently. We found limited evidence that low-risk individuals engage in risk aversion or behave according to the realization effect. We consequently conclude that they behave more like investors.

[3] The data is acquired by Thailand's Securities and Exchange Commission (SEC). The sensitive/protected information has been removed prior to our research use. The data is managed and handled by the authors who work at the SEC according to the SEC's data protection protocol.

Figure 2 presents the portfolio composition of high-risk vs. low-risk groups as of December 2021 to provide a clearer picture of how the two groups differ. The low-risk group holds a large portion of Bitcoin (41.60%) and stablecoins such as Tether (17.44%). In contrast, the high-risk group holds a significantly smaller share of Bitcoin (only 7.22%) and stablecoins (none of the stablecoins made it on the top 10 list). In addition, the high-risk group also holds a sizable portion of non-traditional cryptocurrencies issued by Thai operators, such as Bitkub coin (19.14%) and JFin coin (12.01%).

The results of our study are useful for policy recommendations, as loss-chasing behavior may result in people taking on more risk than they can afford. Theory predicts that people may chase their losses indefinitely until they go bankrupt (Ebert and Strack, 2015; Gainsbury, et al., 2014). With more people being exposed to cryptocurrencies over the years, such behavior may have a broader impact on the overall financial market and society.

The rest of this paper is organized as follows. Section 2 discusses the relevant literature. Section 3 explains the data. Section 4 outlines the methodology. Section 5 discusses the results. Section 6 reveals the robustness tests. Finally, Section 7 concludes the paper.

2. Literature Review

Two branches of literature are relevant for this study. The first branch of literature focuses on loss-chasing behavior observed in casino gambling. The other branch of literature focuses on the realization effect, which explains how realized and unrealized (i.e., paper) outcomes may impact an individual's risk-taking behavior.

Loss-chasing behavior happens when gamblers bet an increasing amount of money (i.e., increased risk-taking) after losses, hoping to win back their original funds. They may chase their losses indefinitely until "the bitter end" (Ebert and Strack, 2015; Gainsbury, et al., 2014). The literature regarded this behavior as an indicator of compulsive gambling or gambling addiction (American Psychiatric Association, 2013; Zhang and Clark, 2020). Theoretically, the loss-chasing behavior can be modeled using the Cumulative Prospect Theory (CPT), a modified version of the prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman; 1992). Under the prospect theory, individuals are considered loss-averse. With an equal dollar amount, they would despise the loss more than they would appreciate the gain. CPT modified the original theory by adding a weighing feature to overweigh the tails of the cumulative probability distribution function. Barberis (2012) used CPT to explain loss-chasing behavior in casino gambling. He showed that an agent entering a casino may have originally planned to stop when losing but could eventually change his mind and continue playing. Such an agent would take on more risk than originally planned and more than optimal. Ebert and Strack (2015) explored CPT in a dynamic setting and showed that individuals could continue to chase their losses and never stop gambling.

Some studies have highlighted the similarities between gamblers and cryptocurrency traders. Delfabbro et al. (2021) showed that people who enjoy gambling are more likely to engage in cryptocurrency trading. Johnson, et al. (2022) found that cryptocurrency traders and problem gamblers share similar demographic and personality characteristics.

Another branch of the literature seeks to explain how prior investment outcomes can influence people's risk attitudes and behaviors. While individuals often exhibit risk aversion, leading them to avoid risk-taking after losses, there are circumstances when they increase risk-taking following losses. Imas (2016) observed that people tend to avoid risk-taking after "realized losses" (i.e., when money has been transferred) but might escalate their risk-taking after "paper losses" (i.e., when money has not been transferred). He termed this phenomenon the "realization effect." Building on CPT, Imas (2016) introduced an assumption about how paper losses are "bracketed" with an individual's subsequent risk-taking decision. Bracketing explains why people are more willing to assume greater risk if there is a chance to offset their existing paper losses. Conversely, once internalized, realized losses do not exert the same influence, leading people to reduce risk-taking.

This bracketing of mind is sometimes referred to as "mental accounting" (Thaler, 1985). Merkle et al. (2021) expanded on Imas' (2016) model to investigate scenarios where the experienced outcomes were positive. He demonstrated that paper gains can also amplify people's risk-taking behavior.

In the context of individual investment behavior, Shefrin and Statman (1985) introduced the concept of "disposition effect," another prominent application of Kahneman and Tversky's (1979) prospect theory. The disposition effect literature seeks to explain why individuals might want to hold on to losing investments and be inclined to sell winning investments prematurely. While both the "realization effect" and the "disposition effect" have their roots in prospect theory and share some overlapping components, they differ in their primary focus. The "realization effect" focuses on risk-taking behavior following unrealized (i.e., paper) versus realized losses. In contrast, the "disposition effect" looks into why individuals might be hesitant to acknowledge losses but eager to recognize gains.

3. Data

Our study utilized anonymized, transaction-level data of market participants who traded cryptocurrencies in Thailand's licensed digital asset exchanges regulated under Thai laws.[4] Per the Notification of the Securities and Exchange Commission No. GorThor. 26/2562, digital asset exchanges operating in Thailand must submit information on customers' trading activities to the SEC starting November 2020. Our sample period is from December 2020 to December 2022. The original data is retrieved daily and processed into monthly data for our empirical analysis. The authors who work at the SEC manage and handle the data according to the SEC's data protection protocol.[5]

The dataset contains relevant information on the buy and sell transactions, such as the date and time of the trade execution, the type of cryptocurrency, the amount bought and sold, the execution price, and the pseudonymized customer key. We generate each account's implied portfolio by constructing the daily portfolio holdings from all recorded transactions. When an asset is bought, its nominal value (amount and execution price) is added to the individual's portfolio. When an asset is sold, a realized gain or a realized loss is computed from the asset's average-cost basis. With daily asset prices, other information, such as the daily portfolio returns and the paper (unrealized) gains or losses (computed from cost basis), can be calculated as intermediate variables for the final calculation.[6]

[4] The data is acquired by Thailand's Securities and Exchange Commission (SEC). The sensitive/protected information has been removed prior to our research use.
[5] Our research use has been approved by the SEC data governance committee.
[6] To adjust for any round-trip buy-sell transactions within one day, in the daily return formula, the portfolio value at day t (end of day) needs to be adjusted (added) by the asset value already sold on day t. Also, the portfolio value at day (t-1) needs to be adjusted (added) by the asset value bought on day t.

Our primary variable used as a proxy for risk-taking is the individual's monthly portfolio volatility, computed from the daily portfolio returns over 30 days. The final dataset is monthly with the end-of-month portfolio volatility, end-of-month paper gains or losses, and the cumulative realized gains or losses over the entire month.[7]

Since we would like to focus on individuals, we excluded accounts identified as institutional investors, brokers/dealers, and market makers from our dataset. We also removed accounts that started with non-zero position as of December 2020 and accounts that did not trade at least once during our sample period. As a result, we started with 1,168,368 unique accounts and ended up with 832,050 unique accounts (or 13,017,370 account-month observations) after the cleaning.

Table 1 provides the summary statistics of the data. During the period, the portfolio volatility ranged from 0% to 59.43%, with a mean of 3.95%.[8] On average, people held 4.11 different types of cryptocurrencies. They executed 1.92 buy transactions and 1.62 sell transactions per month. The average purchase amount is THB 18,327, and the average sale amount is THB 16,211. In an average month, the average paper gain is THB 3,884, and the average paper loss is THB 14,807. The average realized gain is THB 676 and the average realized loss is THB 627.

As previously mentioned, we categorize cryptocurrency market participants into two groups: low-risk and high-risk groups. The distinction between low-risk and high-risk is determined by whether their portfolio volatility is below or above the median. However, since portfolio volatility will be used as our dependent variable in our empirical analyses, using this variable directly to segment the sample might not be appropriate because we would sort the sample

[7] The paper gain/loss and the realized gain/loss are normalized by the portfolio cost at month (t-1) plus the total amount purchased during month t.
[8] We winsorize the portfolio volatility variable at thresholds of 0.1% and 99.9% to limit the influence of outliers.

based on the dependent variable. To circumvent this issue, we use the portfolio volatility median from the previous period (i.e., period t-1) to segment the current period's sample (i.e., period t).

Tables 2 and 3 provide the summary statistics of the low-risk and high-risk groups. By construction, the average portfolio volatility of the high-risk group (5.90%) is higher than that of the low-risk group (2.23%). On average, the high-risk group appears to hold more cryptocurrency types than the low-risk group (4.34 vs. 3.99). As shown in Figure 2, the low-risk group tends to hold many traditional cryptocurrencies, such as Bitcoin and Tether. In contrast, the high-risk group tends to hold a sizable portion of non-traditional cryptocurrencies issued by Thai operators, such as Bitkub coin and JFin coin.

Considering the time dimension, Figure 3 illustrates how our sample is divided further into four sub-periods for in-depth analysis. We define a bear market as starting from a new high and continuing until a reflection point.[9] Based on this, we segment the sample into:

(i) Bull Market #1 (Dec 2020 – Mar 2021),

(ii) Bear Market #1 (Apr 2021 – Jul 2021),

(iii) Bull Market #2 (Aug 2021 – Oct 2021), and

(iv) Bear Market #2 (Nov 2021 – Dec 2022).

Figure 4 displays the number of active accounts during our focus period. It is apparent that the number of active accounts increased during the bull markets. Figure 5 displays the mean and median portfolio volatility (standard deviation of daily returns) of these accounts over the period. While there does not appear to be a specific relationship between volatility and the distinction between bull and bear markets, the volatility seems to coincide with the CVI (Crypto Volatility

[9] The minimum between the two new highs.

Index).[10] Figure 6 depicts the mean and the median of individual accounts' unrealized Profit/Loss (unrealized P/L). We can see that, although the average unrealized P/L was positive during upturns, most accounts still did not have positive unrealized P/L. During downturns, the mean and the median fell into the negative territories. Thus, it is likely that the majority of market participants are not performing well in the cryptocurrency market.

4. Methodology

To test our hypothesis, we utilize the monthly portfolio volatility as our risk measure. We estimate the following first-differenced model.

$$\Delta y_{i,t} = \beta_0 + \beta_1 \cdot \Delta g_{i,t-1} + \beta_2 \cdot \Delta l_{i,t-1} + \beta_3 \cdot \Delta G_{i,t-1} + \beta_4 \cdot \Delta L_{i,t-1} + \gamma_t + \varepsilon_{i,t}$$

$y_{i,t}$ is the log of portfolio volatility.[11] i represents each individual. t represents each month. $g_{i,t-1}$ and $l_{i,t-1}$ are individual i's paper gain and paper loss of the previous month. $G_{i,t-1}$ and $L_{i,t-1}$ are individual i's realized gain and realized loss of the previous month. The gains and losses are normalized by portfolio value for comparability. γ_t's are time (monthly) fixed effects. $\varepsilon_{i,t}$'s are error terms. Standard errors are clustered by individual account.

The time fixed effects are important as they capture time-specific events, such as major crypto market crashes and other economy-wide events that could affect the calculated portfolio volatility. Thus, the time-fixed effects allow relative changes in portfolio volatility following realized/unrealized gains and losses in previous months to be interpreted as changes in risk-taking.

[10] https://www.investing.com/indices/crypto-volatility-index; https://docs.cvi.finance/cvi-index/index-calculation

[11] To account for the possibility that more volatile assets might experience a larger increase in volatility (in absolute terms) during turbulent markets compared to less volatile assets, we scale the dependent variable by taking its logarithm.

The inclusion of time fixed effects does preclude the possibility that there exists a systematic relationship between past crypto asset returns (which affects portfolio gains and losses as well) and future volatility, and our identificiation strategy would require an assumption that investors are aware of this relationship and adjust their portfolio accordingly. To verify whether such relationship exists, we compute the correlation between the monthly lagged return of the Crypto Market Index (the Bloomberg Galaxy Crypto Index[12]) and the monthly volatility. The correleation is 0.045 and statistically insignificant, so such assumption is not required.

The coefficients β_1, β_2, β_3, and β_4 as they reveal how prior outcomes (i.e., changes in paper gain, paper loss, realized gain, and realized loss) may have an impact on an individual's risk-taking behavior. Since we are interested in how individuals react to losses (both realized and unrealized), we are particularly interested in β_2 which is the coefficient of $\Delta l_{i,t-1}$ and β_4 which is the coefficient of $\Delta L_{i,t-1}$. As the left-hand-side variable is presented in logarithmic form, the coefficient can be interpreted as percentage change in portfolio volatility.

5. Results

Table 4 presents our baseline results. Column 1 displays the regression results where all observations are included. Columns 2 and 3 segregate the observations into low-risk and high-risk groups.

While an examination of the full sample (Column 1) reveals that the coefficients of $\Delta l_{i,t-1}$ (change in paper loss) and $\Delta L_{i,t-1}$ (change in realized loss) are positive and significant —

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[12] The Bloomberg Galaxy Crypto Index (BGCI) is the index administered by Bloomberg. The index is in collaboration with Galaxy Digital Capital Management with the main objective of being a benchmark index reflecting the performance prominent cryptocurrencies traded in USD.

indicating that, on average, people seem to exhibit loss-chasing behavior—a closer look at the low-risk group (Column 2) and high-risk group (Column 3) suggests that behavior differs. The high-risk group displays loss-chasing behavior, but the low-risk group's behavior aligns with the realization effect, as the coefficient of $\Delta l_{i,t-1}$ for this group is positive and significant, while the coefficient of $\Delta L_{i,t-1}$ is negative and significant.

Interpreting the results in terms of magnitude requires additional work as follows. From Table 1, one standard deviation of (normalized) paper loss is 0.30. For the low-risk group, from Table 4 Column 2, the coefficient of $\Delta l_{i,t-1}$ is 0.111. Therefore, a one-standard-deviation increase in change in paper loss would increase their portfolio volatility (i.e., increase risk-taking) by 3.29% (0.30 times 0.111). Similarly, a one-standard-deviation increase in change in realized loss would decrease their portfolio volatility by 0.27%. For the high-risk group, a one-standard-deviation increase in change in paper loss and realized loss would increase their portfolio volatility by 18.34% and 3.09%, respectively.

Table 5 displays the results when segregating the data based on bull and bear periods. Columns 1, 2, and 3 represent the bull market results for all individuals, low-risk individuals, and high-risk individuals, respectively. Similarly, Columns 4, 5, and 6 show the bear market results for all individuals, low-risk individuals, and high-risk individuals, respectively.

Loss-chasing behavior is evident for high-risk individuals in both bull and bear markets. This is indicated by the positive and significant coefficients of $\Delta l_{i,t-1}$ and $\Delta L_{i,t-1}$. Specifically, during the bull market, a one-standard-deviation increase in change in paper loss and realized loss increases their portfolio volatility by 27.07% and 3.67%, respectively. These values are 17.78% and 3.03% during the bear market, respectively.

For low-risk individuals, we observe realization effects during oth bull and bear markets. During the bull market, a one-standard-deviation increase in change in paper loss increases their portfolio volatility by 5.88%. In comparison, a one-standard-deviation increase in change in realized loss decreases their portfolio volatility by 1.24%. During the bear market, the magnitudes are 3.15% and 0.17%, respectively.

Table 6 presents the results for both bull and bear market sub-periods: (i) Bull Market #1 (Dec 2020 – Mar 2021), (ii) Bear Market #1 (Apr 2021 – Jul 2021), (iii) Bull Market #2 (Aug 2021 – Oct 2021), and (iv) Bear Market #2 (Nov 2021 – Dec 2022).

Across all periods, except for Bull Market #1, it is evident that the high-risk group exhibits loss-chasing behavior, as the coefficients of $\Delta l_{i,t-1}$ and $\Delta L_{i,t-1}$ are positive and significant. During Bear Market #1, a one-standard deviation increase in the change in paper loss and realized loss results in an increase in portfolio volatility by 27.99% and 1.42%, respectively. In Bull Market #2, these values are 27.13% and 3.71%, and in Bear Market #2, they are 17.63% and 3.03%, respectively.

For low-risk individuals, we observe behavior indicative of realization effects during Bull Market #2 and Bear Market #2. However, they display loss-chasing during Bear Market #1. With these findings, the results for low-risk individuals remain inconclusive.

As mentioned, this paper seeks to contribute to the ongoing debate on whether individuals perceive cryptocurrencies as a form of gambling or a risky investment. Our results confirm that high-risk individuals in the cryptocurrency market exhibit loss-chasing behavior, similar to those who engage in gambling. Given that the price fluctuations of cryptocurrencies often do not seem to be grounded by fundamental factors (Kraaijeveld and De Smedt, 2020; Critien et al., 2022), the investment return characteristics resemble gambling. Thus, it is understandable that cryptocurrencies would attract individuals with a gambling mindset.

Delfabbro et al. (2021) illustrated that individuals who enjoy gambling are more inclined to engage in cryptocurrency trading. Johnson et al. (2022) discovered that cryptocurrency traders and problem gamblers share similar demographic and personality traits. Our evidence suggests that gambling individuals belong to the high-risk group, not the low-risk group, and their cryptocurrency holdings differ greatly.

While low-risk individuals display realization effects under most specifications, the results are not robust. However, because low-risk individuals do not significantly exhibit loss chasing behavior, we can partly infer that they behave more like investors. We conclude that there is limited evidence that low-risk individuals behave like investors. Drawing parallels with stock market literature might provide more insights into the behavior of traditional investors. For example, Hoffmann et al. (2015) found that changes in investors' perceptions played a crucial role in shaping their actual trading and risk-taking behaviors among Dutch investors. Additionally, Andersen and Nielsen (2019) highlighted that experiences of market downturns could make an individual more risk-averse. In another study, Arnold and Subrahmanyam (2022) analyzed British investors and discovered that specific attention triggers could amplify their risk-taking tendencies.

6. Robustness Tests

Table 7 presents the results of our robustness tests. Specifically, we carried out three distinct sets of robustness tests. The details are provided below.

During our observation period, some individuals received airdrop tokens, which are complimentary tokens given to those who meet certain criteria. In our main analyses, we excluded these tokens due to the absence of cost information but retained the associated accounts. However, it remains uncertain whether the presence of such tokens might influence individuals' trading patterns and, consequently, their risk-taking behavior. As a result, in our first robustness test, we entirely excluded the accounts of those who had received airdrop tokens. Columns 1, 2, and 3 display the results for all individuals, low-risk individuals, and high-risk individuals, respectively, after omitting those who had received airdrop tokens. The results confirm that high-risk individuals exhibit loss-chasing behavior, escalating their risk-taking following both realized and unrealized losses. On the other hand, low-risk individuals appeared to demonstrate realization effect, diminishing their risk-taking after realized loss but increasing it after unrealized losses.

The second set of robustness tests is associated with individuals who might have emptied their portfolios after realizing gains or losses. Consequently, these individuals would have zero portfolio volatility following the prior month's realized gain or loss. Columns 4, 5, and 6 present the results after excluding these individuals from our analysis. The findings again confirm that high-risk individuals display loss-chasing behavior, increasing their risk-taking in response to both realized and unrealized losses. Conversely, low-risk individuals no longer demonstrate realization effect; they, too, seem to engage in loss-chasing.

The last set of robustness tests is associated with changing the time of reference. In our main analyses, we use the previous month as the reference point for experiencing gain or loss. In this set of robustness tests, we examine whether the results still hold when the reference point is further away (i.e., the month before the previous month). Columns 7, 8, and 9 are the results when $\Delta g_{i,t-1}$, $\Delta l_{i,t-1}$, $\Delta G_{i,t-1}$, and $\Delta L_{i,t-1}$ are replaced with $\Delta g_{i,t-2}$, $\Delta l_{i,t-2}$, $\Delta G_{i,t-2}$, and $\Delta L_{i,t-2}$, respectively. The results revealed that we can still confirm the loss-chasing behavior for high-risk individuals. However, low-risk individuals appeared to exhibit risk aversion by avoiding risks after both realized and unrealized losses.

Based on our three sets of robustness tests, we can affirm that high-risk individuals engage in loss-chasing behavior similar to gamblers. This is true across all specifications. However, while low-risk individuals exhibit realization effect and risk aversion in most scenarios, they also show signs of loss-chasing in certain situations. Consequently, our findings for low-risk individuals remain limited but partly infer that they tend to consider cryptocurrencies as a risky investment class.

7. Conclusion and Discussion

One way to contribute to the discussion on whether cryptocurrencies should be perceived as tools for gambling or risky investment instruments is to examine the behavior of cryptocurrency market participants. We aim to ask whether they act more like casino gamblers or investors making investment decisions.

This paper contributes to the literature by utilizing transaction-level data to explore people's risk-taking behavior in Thailand's cryptocurrency market. To the best of our knowledge, this research question has not yet been explored empirically using transaction-level data. Thailand makes an interesting case study due to the country's high level of enthusiasm for cryptocurrencies and their widespread adoption.

Existing literature indicates that gamblers frequently engage in loss-chasing behavior, amplifying risk-taking after losses that may go on indefinitely. Investors, on the other hand, generally display risk aversion following losses. However, some might increase risk-taking after "paper losses," a phenomenon termed the "realization effect."

Our findings suggest that cryptocurrency market participants perceive cryptocurrencies as both gambling tools and investment instruments, and the behavior is different across groups. High-risk individuals, defined by portfolio volatility at or above the median each month, behave like gamblers. They tend to amplify risk-taking following both realized and unrealized losses. In contrast, low-risk individuals, with portfolio volatility below the median, exhibit patterns similar to traditional investors. However, our evidence for the behavior of low-risk individuals remains somewhat limited.

The implications of our study are significant for both monitoring and policy formulation. The findings of Ebert and Strack (2015) suggest that individuals engaged in loss-chasing might continue until they face bankruptcy. As the exposure to cryptocurrencies has expanded over the years, such behavior could profoundly impact the broader financial market and society. Recognizing these patterns is vital for policy recommendations, especially since unchecked loss-chasing can lead individuals to assume risks beyond their means. This gambling-like behavior among high-risk individuals could have far-reaching consequences for the financial ecosystem and the wider community. As a consequence, policymakers may be motivated to act on our evidence.

8. References

American Psychiatric Association (2013). *Diagnostic and Statistical Manual of Mental Disorders*, 5th ed. American Psychiatric Publishing, Arlington, VA.

Andersen, S., Hanspal, T., & Nielsen, K. M. (2019). Once bitten, twice shy: The power of personal experiences in risk taking. *Journal of Financial Economics*, *132*(3), 97-117.

Arnold, M., Pelster, M., & Subrahmanyam, M. G. (2022). Attention triggers and investors' risk-taking. *Journal of Financial Economics*, *143*(2), 846-875.

Barberis, N. (2012). A model of casino gambling. *Management Science*, *58*(1), 35-51.

Bowden-Jones, H., & Clark, L. (2011). Pathological gambling: a neurobiological and clinical update. *The British Journal of Psychiatry*, *199*(2), 87-89.

Critien, J. V., Gatt, A., & Ellul, J. (2022). Bitcoin price change and trend prediction through twitter sentiment and data volume. *Financial Innovation*, *8*(1), 1-20.

Delfabbro, P., King, D., Williams, J., & Georgiou, N. (2021). Cryptocurrency trading, gambling and problem gambling. *Addictive Behaviors*, *122*, 107021.

Ebert, S., & Strack, P. (2015). Until the bitter end: On prospect theory in a dynamic context. *American Economic Review*, *105*(4), 1618-1633.

Gainsbury, S. M., Suhonen, N., & Saastamoinen, J. (2014). Chasing losses in online poker and casino games: Characteristics and game play of Internet gamblers at risk of disordered gambling. *Psychiatry Research*, *217*(3), 220-225.

Hoffmann, A. O., Post, T., & Pennings, J. M. (2015). How investor perceptions drive actual trading and risk-taking behavior. *Journal of Behavioral Finance*, *16*(1), 94-103.

Imas, A. (2016). The realization effect: Risk-taking after realized versus paper losses. *American Economic Review*, *106*(8), 2086-2109.

Iyer, T. (2022). *Cryptic connections: spillovers between crypto and equity markets*. International Monetary Fund.

Johnson, B., Co, S., Sun, T., Lim, C. C., Stjepanović, D., Leung, J., Saunders, J.B., & Chan, G. C. (2022). Cryptocurrency trading and its associations with gambling and mental health: A scoping review. *Addictive Behaviors*, *136*, 107504.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263-292.

Kraaijeveld, O., & De Smedt, J. (2020). The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. *Journal of International Financial Markets, Institutions and Money*, *65*, 101188.

Merkle, C., Müller-Dethard, J., & Weber, M. (2021). Closing a mental account: The realization effect for gains and losses. *Experimental Economics*, *24*(1), 303-329.

Rabin, M., & Weizsäcker, G. (2009). Narrow bracketing and dominated choices. *American Economic Review*, *99*(4), 1508-1543.

Read, D., Loewenstein, G., & Rabin, M. (1999). Choice Bracketing. *Journal of Risk and Uncertainty*, *19*(1-3), 171-197.

Romanczuk-Seiferth, N., Van Den Brink, W., & Goudriaan, A. E. (2014). From symptoms to neurobiology: pathological gambling in the light of the new classification in DSM-5. *Neuropsychobiology*, *70*(2), 95-102.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, *40*(3), 777-790.

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing Science*, *4*(3), 199-214.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297-323.

Zhang, K., & Clark, L. (2020). Loss-chasing in gambling behaviour: Neurocognitive and behavioural economic perspectives. *Current Opinion in Behavioral Sciences*, *31*, 1-7.

Table 1: Summary Statistics (All Observations)

Obs. Unit: Account-Month

Variable	Obs.	Mean	Std. Dev.	Min	Max
Portfolio Volatility	13,017,370	3.95	4.05	0.00	59.43
Log of Portfolio Volatility	11,834,353	1.23	0.72	0.00	4.08
No. of Assets	13,017,370	4.11	4.48	0.00	86.00
No. of Buy	13,017,370	1.92	20.94	0.00	21,010.00
No. of Sell	13,017,370	1.62	26.34	0.00	24,045.00
Amount Buy	13,017,370	18,326.78	667,310.60	0.00	411,000,000.00
Amount Sell	13,017,370	16,211.18	613,134.60	0.00	395,000,000.00
Paper Gain	13,017,370	3,884.18	183,153.80	0.00	128,000,000.00
Paper Loss	13,017,370	14,807.47	173,419.90	0.00	87,300,000.00
Paper Gain (Normalized)	11,210,662	0.20	1.27	0.00	600.71
Paper Loss (Normalized)	11,210,662	0.33	0.30	0.00	1.00
Realized Gain	13,017,370	675.93	72,905.62	0.00	182,000,000.00
Realized Loss	13,017,370	627.14	23,850.29	0.00	25,100,000.00
Realized Gain (Normalized)	11,210,662	0.01	0.26	0.00	400.77
Realized Loss (Normalized)	11,210,662	0.01	0.06	0.00	1.00

Source: SEC; Only accounts owned by individuals are included

Table 2: Summary Statistics (Low-Risk Group)

Obs. Unit: Account-Month

Variable	Obs.	Mean	Std. Dev.	Min	Max
Portfolio Volatility (t-1)	6,059,792	2.23	1.54	0.00	7.60
Log of Portfolio Volatility (t-1)	4,978,085	0.84	0.69	0.00	2.03
No. of Assets	6,059,792	3.99	4.80	0.00	86.00
No. of Buy	6,059,792	1.71	24.04	0.00	21,010.00
No. of Sell	6,059,792	1.47	30.07	0.00	24,045.00
Amount Buy	6,059,792	22,787.20	906,713.30	0.00	411,000,000.00
Amount Sell	6,059,792	19,808.01	825,157.80	0.00	395,000,000.00
Paper Gain	6,059,792	4,408.56	171,697.80	0.00	90,500,000.00
Paper Loss	6,059,792	15,938.92	188,508.80	0.00	87,300,000.00
Paper Gain (Normalized)	5,132,744	0.09	0.63	0.00	159.80
Paper Loss (Normalized)	5,132,744	0.29	0.27	0.00	1.00
Realized Gain	6,059,792	588.28	54,807.61	0.00	111,000,000.00
Realized Loss	6,059,792	601.64	25,195.41	0.00	25,100,000.00
Realized Gain (Normalized)	5,132,744	0.01	0.12	0.00	31.37
Realized Loss (Normalized)	5,132,744	0.01	0.05	0.00	1.00

Source: SEC; Only accounts owned by individuals are included

Table 3: Summary Statistics (High-Risk Group)

Obs. Unit: Account-Month

Variable	Obs.	Mean	Std. Dev.	Min	Max
Portfolio Volatility (t-1)	6,125,528	5.90	4.99	1.95	59.43
Log of Portfolio Volatility (t-1)	6,125,528	1.61	0.51	0.67	4.08
No. of Assets	6,125,528	4.34	4.26	0.00	86.00
No. of Buy	6,125,528	1.88	14.84	0.00	16,798.00
No. of Sell	6,125,528	1.60	19.68	0.00	22,303.00
Amount Buy	6,125,528	12,390.90	262,689.40	0.00	222,000,000.00
Amount Sell	6,125,528	11,366.86	258,784.00	0.00	225,000,000.00
Paper Gain	6,125,528	3,533.44	194,597.10	0.00	128,000,000.00
Paper Loss	6,125,528	15,188.89	168,417.00	0.00	78,700,000.00
Paper Gain (Normalized)	6,077,918	0.30	1.62	0.00	600.71
Paper Loss (Normalized)	6,077,918	0.37	0.31	0.00	1.00
Realized Gain	6,125,528	735.98	84,798.12	0.00	182,000,000.00
Realized Loss	6,125,528	673.43	23,712.53	0.00	24,000,000.00
Realized Gain (Normalized)	6,077,918	0.02	0.33	0.00	400.77
Realized Loss (Normalized)	6,077,918	0.01	0.07	0.00	1.00

Source: SEC; Only accounts owned by individuals are included

Table 4: Regression Results (Overall)

VARIABLES	(1) Volatility	(2) Volatility	(3) Volatility
l_paper_gain_pc = D,	-0.0468***	-0.00942***	-0.0393***
	(0.000180)	(0.000704)	(0.000188)
l_paper_loss_pc = D,	0.511***	0.111***	0.618***
	(0.00142)	(0.00238)	(0.00170)
l_realized_gain_pc = D,	-0.0652***	-0.0224***	-0.0581***
	(0.000529)	(0.00107)	(0.000592)
l_realized_loss_pc = D,	0.336***	-0.0426***	0.492***
	(0.00246)	(0.00383)	(0.00301)
Constant	-0.597***	-0.328***	-0.801***
	(0.00468)	(0.00646)	(0.00614)
Observations	9,273,833	4,128,865	5,144,968
R-squared	0.428	0.508	0.428
Time Dummies	Yes	Yes	Yes
Obs	All	Low-Risk	High-Risk
Period	All	All	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regression Results (Bull vs. Bear Markets)

VARIABLES	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility	(5) Volatility	(6) Volatility
l_paper_gain_pc = D,	-0.00437***	0.00386*	-0.00709***	-0.0481***	-0.0111***	-0.0402***
	(0.000997)	(0.00218)	(0.00102)	(0.000183)	(0.000744)	(0.000192)
l_paper_loss_pc = D,	0.827***	0.198***	0.912***	0.490***	0.106***	0.599***
	(0.00543)	(0.00920)	(0.00612)	(0.00148)	(0.00247)	(0.00177)
l_realized_gain_pc = D,	-0.113***	-0.195***	-0.0462***	-0.0647***	-0.0208***	-0.0581***
	(0.00554)	(0.00955)	(0.00605)	(0.000533)	(0.00108)	(0.000599)
l_realized_loss_pc = D,	0.359***	-0.198***	0.585***	0.332***	-0.0278***	0.483***
	(0.00907)	(0.0126)	(0.0112)	(0.00255)	(0.00402)	(0.00313)
Constant	-0.605***	-0.334***	-0.809***	0.500***	0.605***	0.423***
	(0.00448)	(0.00624)	(0.00547)	(0.00329)	(0.00468)	(0.00426)
Observations	755,993	334,736	421,257	8,517,840	3,794,129	4,723,711
R-squared	0.049	0.085	0.083	0.443	0.525	0.437
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs	All	Low-Risk	High-Risk	All	Low-Risk	High-Risk
Period	Bull1+Bull2	Bull1+Bull2	Bull1+Bull2	Bear1+Bear2	Bear1+Bear2	Bear1+Bear2

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regression Results (Bull vs. Bear Markets (Sub-periods))

VARIABLES	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility	(5) Volatility	(6) Volatility	(7) Volatility	(8) Volatility	(9) Volatility	(10) Volatility	(11) Volatility	(12) Volatility
l_paper_gain_pc = D,	-0.0282***	-0.0696***	-0.0249***	-0.00748***	-0.00382	-0.00557***	-0.00378***	0.00559**	-0.00659***	-0.0638***	-0.0138***	-0.0556***
	(0.00705)	(0.0180)	(0.00717)	(0.000523)	(0.00350)	(0.000476)	(0.00101)	(0.00219)	(0.00103)	(0.000206)	(0.000763)	(0.000220)
l_paper_loss_pc = D,	0.0741	0.601**	0.555***	1.019***	1.319***	0.943***	0.829***	0.197***	0.914***	0.476***	0.0477***	0.594***
	(0.117)	(0.246)	(0.124)	(0.0103)	(0.0155)	(0.0126)	(0.00542)	(0.00919)	(0.00610)	(0.00148)	(0.00249)	(0.00178)
l_realized_gain_pc = D,	-0.0919***	-0.149***	-0.0374**	0.00249*	0.0215***	0.00325***	-0.121***	-0.206***	-0.0509***	-0.113***	-0.0226***	-0.118***
	(0.0170)	(0.0328)	(0.0183)	(0.00129)	(0.00748)	(0.00118)	(0.00604)	(0.0102)	(0.00665)	(0.000633)	(0.00108)	(0.000753)
l_realized_loss_pc = D,	-0.307*	-0.230	-0.304*	0.240***	0.498***	0.226***	0.363***	-0.199***	0.591***	0.324***	-0.0676***	0.483***
	(0.159)	(0.280)	(0.175)	(0.0226)	(0.0339)	(0.0270)	(0.00906)	(0.0126)	(0.0112)	(0.00255)	(0.00401)	(0.00314)
Constant	-0.597***	-0.322***	-0.805***	0.500***	0.620***	0.419***	-0.140***	0.148***	-0.403***	0.744***	0.990***	0.574***
	(0.00566)	(0.00779)	(0.00716)	(0.00408)	(0.00631)	(0.00473)	(0.00128)	(0.00173)	(0.00162)	(0.000879)	(0.00125)	(0.00114)
Observations	11,548	4,910	6,638	293,586	139,454	154,132	744,445	329,826	414,619	8,224,254	3,654,675	4,569,579
R-squared	0.004	0.008	0.006	0.236	0.351	0.238	0.041	0.080	0.072	0.453	0.536	0.447
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	All	Low-Risk	High-Risk	All	Low-Risk	High-Risk	All	Low-Risk	High-Risk	All	Low-Risk	High-Risk
Period	Bull1	Bull1	Bull1	Bear1	Bear1	Bear1	Bull2	Bull2	Bull2	Bear2	Bear2	Bear2

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Regression Results (Robustness)

VARIABLES	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility	(5) Volatility	(6) Volatility	(7) Volatility	(8) Volatility	(9) Volatility
l_paper_gain_pc = D,*^	-0.0373***	-0.00539***	-0.0321***	-0.0463***	-0.0123***	-0.0395***	-0.0204***	-0.0142***	-0.0165***
	(0.000275)	(0.000918)	(0.000290)	(0.000179)	(0.000680)	(0.000189)	(0.000182)	(0.000351)	(0.000212)
l_paper_loss_pc = D,*^	0.480***	0.0797***	0.624***	0.516***	0.131***	0.624***	0.00789***	-0.129***	0.114***
	(0.00148)	(0.00251)	(0.00178)	(0.00141)	(0.00229)	(0.00171)	(0.00149)	(0.00237)	(0.00182)
l_realized_gain_pc = D,*^	-0.0487***	-0.0330***	-0.0389***	-0.0551***	-0.0187***	-0.0484***	-0.00299***	0.00598***	-0.0132***
	(0.000750)	(0.00179)	(0.000818)	(0.000526)	(0.00104)	(0.000592)	(0.000538)	(0.000640)	(0.000825)
l_realized_loss_pc = D,*^	0.340***	-0.0378***	0.522***	0.364***	0.0130***	0.511***	-0.0489***	-0.0851***	0.0116***
	(0.00254)	(0.00404)	(0.00311)	(0.00242)	(0.00371)	(0.00299)	(0.00257)	(0.00381)	(0.00323)
Constant	-0.600***	-0.360***	-0.814***	-0.577***	-0.316***	-0.774***	0.485***	0.582***	0.414***
	(0.0160)	(0.0212)	(0.0220)	(0.00459)	(0.00625)	(0.00606)	(0.00472)	(0.00643)	(0.00623)
Observations	7,395,674	3,293,485	4,102,189	8,622,338	3,888,946	4,733,392	8,465,485	3,775,261	4,690,224
R-squared	0.444	0.522	0.435	0.457	0.547	0.452	0.428	0.527	0.419
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	No Airdrop	NA Low-Risk	NA High-Risk	No Zero	NZ Low-Risk	NZ High-Risk	All	Low-Risk	High-Risk
Period	All	All	All	All	All	All	All	All	All

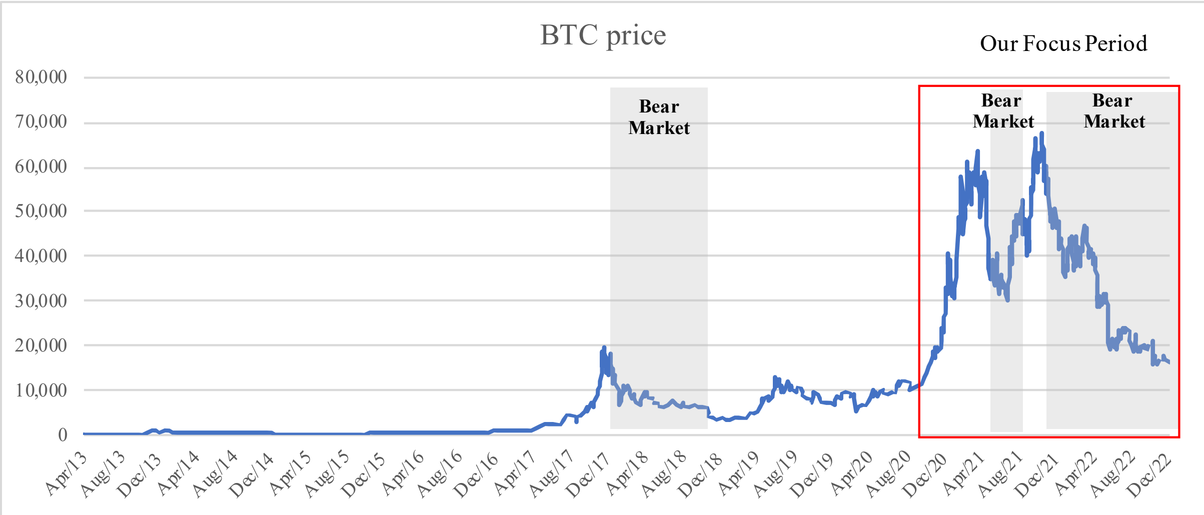
Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

*^ represents lag(1) for models 1 to 6 and represents lag(2) for models 7 to 9

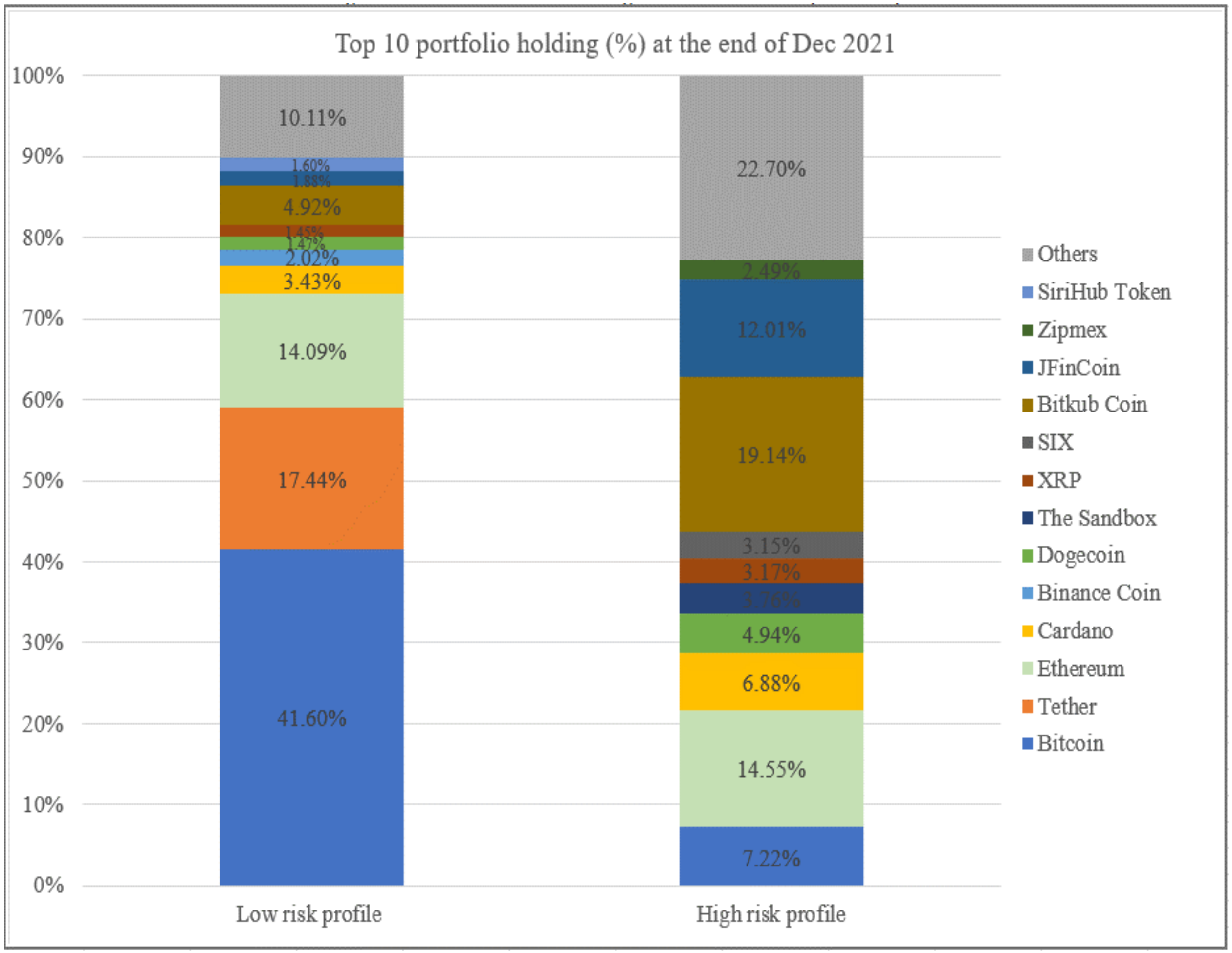
Figure 1: Historical Bitcoin Price

Unit: USD



Source: CoinGecko

Figure 2: Portfolio Breakdown for High-Risk vs. Low-Risk (Dec 2021)



Source: SEC; Only accounts owned by individuals are included

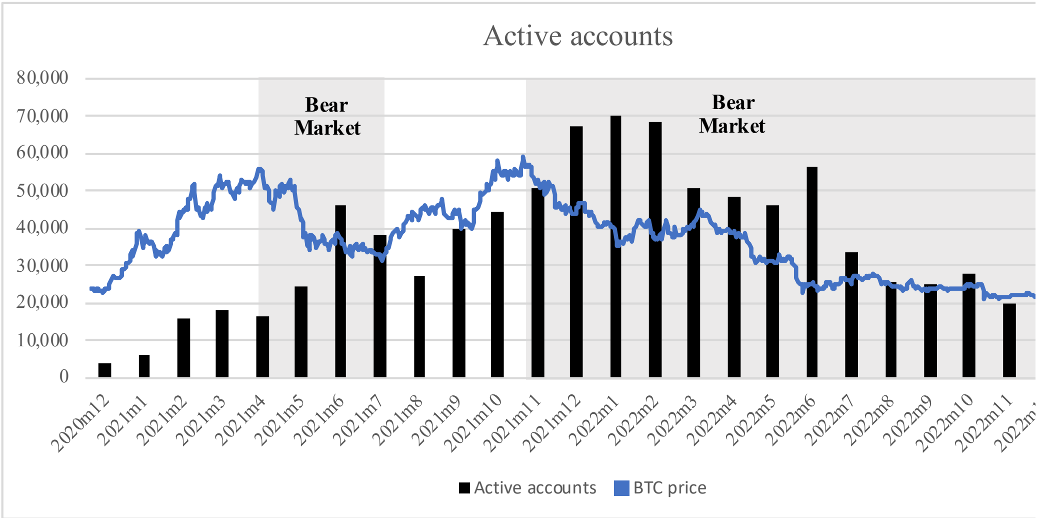
Figure 3: Historical Bitcoin Price (Dec 2020 -Dec 2022)

Unit: USD

Source: CoinGecko

Figure 4: Active Accounts (Dec 2020 - Dec 2022)

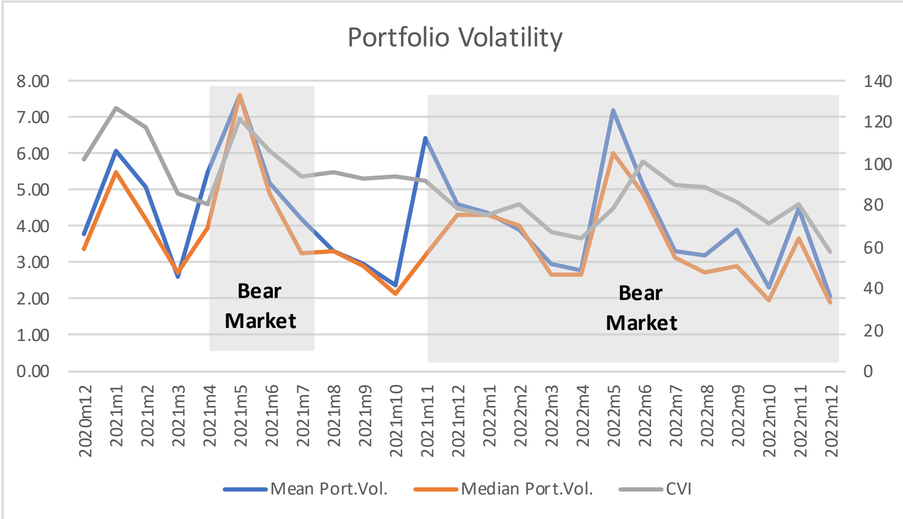
Unit: USD, Account



Source: SEC; Only accounts owned by individuals are included

Figure 5: Portfolio Volatility (Dec 2020 - Dec 2022)

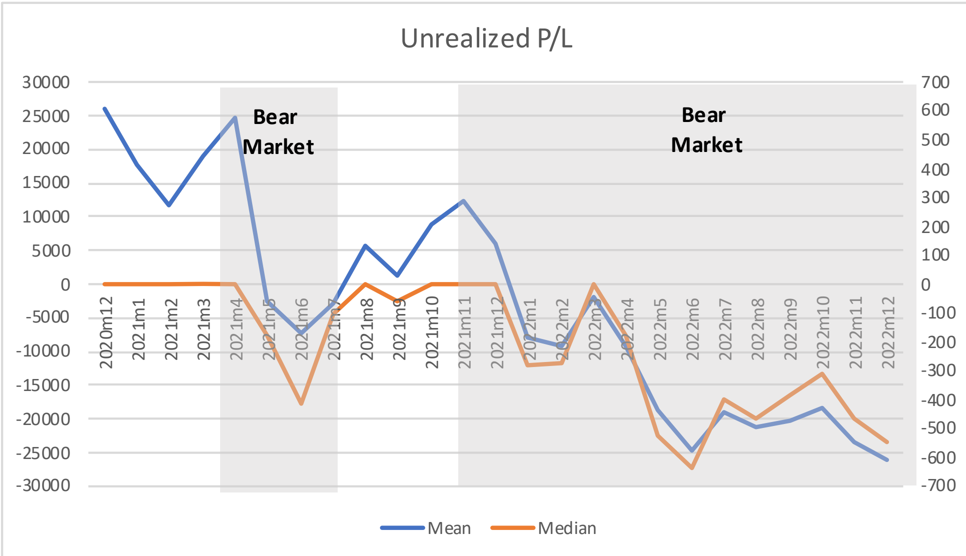
Unit: %, index



Source: SEC; Only accounts owned by individuals are included

Figure 6: Portfolio Unrealized Profit/Loss (Dec 2020 - Dec 2022)

Unit: THB



Source: SEC; Only accounts owned by individuals are included