Gambling for Goals*

Costas Arkolakis† Spencer Y. Kwon‡ Dominic Russel§ Claire Shi¶
Hyunjoo Yang‖

March 2026

Abstract

As young adults in advanced economies grow more pessimistic about their economic prospects, high-risk, gambling-like financial activities have proliferated. We propose a theory that links these trends through a Friedman-Savage (1948) motive: when traditional goals, such as homeownership or marriage, seem unattainable through conventional means, individuals turn to financial gambles. We test the theory using an original survey combined with millions of linked records from Korea's leading credit bureau, telecom provider, and credit card issuer. Consistent with our model, individuals who place greater importance on hard-to-reach financial goals are more likely to engage in high-risk investment. When goals are further out of reach, demand for risk increases: cryptocurrency usage rises following unemployment and lower-income households prefer more skewed assets. By contrast, when goals become attainable, risk-taking declines. Exploiting Korea's housing lottery, which quasi-randomly allocates subsidies for home purchase, we show that attaining homeownership reduces cryptocurrency interest. We conclude with a stylized calibration showing that Friedman-Savage motives can amplify the welfare costs of overoptimism.

*We thank John Campbell, Raj Chetty, Toren Fronsdal, Ed Glaeser, Sam Hanson, Nathan Hendren, Rafael La Porta, Yueran Ma, Cameron Peng, Emily Oster, Andrei Shleifer, Jeremy Stein, Adi Sunderam, and Jaemin Woo for helpful comments and feedback. We thank Taewoong Jo, Dahye Kim, and especially Sungeun Park, for outstanding research assistance. We also thank the SKT Survey Team, including Jason Baek, for help administering the survey. This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2024S1A5A2A03040147). The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. The data used in the paper were accessed according to a data-purchase agreement. The provider did not restrict our research or review our results prior to this draft.

†costas.arkolakis@gmail.com. Yale University.
‡spencer_kwon@brown.edu. Brown University.
§drussel@g.harvard.edu. Harvard University.
¶cshi@g.harvard.edu. Harvard University.
‖hyang@sogang.ac.kr. Sogang University.

"[An unskilled worker] may jump at an actuarially fair gamble that offers a small chance of lifting him out of the class of unskilled workers and into the 'middle' or 'upper' class, even though it is far more likely than the preceding gamble to make him one of the least prosperous unskilled workers. Men will and do take great risks to distinguish themselves, even when they know what the risks are."

— Milton Friedman & L. J. Savage (1948)

"I invest all my money in crypto and I am aware of that. But it is my only way to ever achieve my dreams and financial independence. Fortune favors the brave."

— Reddit user (2022)

1 Introduction

A growing body of evidence documents rising economic dissatisfaction in many advanced economies, particularly among younger cohorts, as housing affordability and economic mobility have declined.[1] In a 2025 survey, only 25% of Americans believed they had a good chance of improving their standard of living—the lowest since the survey began in 1987, when the corresponding figure was nearly 75% (Ellis and Zitner, 2025). In Korea and Japan, the terms *Sampo* and *Satori* generations have emerged to describe younger individuals who have given up on achieving conventional life goals.

At the same time, there has been growing concern about the proliferation of high-risk financial behavior, particularly among young adults. Retail speculation appears widespread in stocks (Barber et al., 2022), options (de Silva et al., 2023; Bryzgalova et al., 2023; SEBI, 2025), and cryptocurrency markets (Wheat and Eckerd, 2022; Weber et al., 2023; Auer et al., 2025), both in the U.S. and abroad. Sports gambling and prediction markets have grown in popularity (Siena College Research Institute, 2024; Lanz, 2026).

Can economic frustration help explain high-risk financial behavior? A common explanation for the rise in risky financial behavior emphasizes supply-side forces: trading has become easier, cheaper, and more gamified (Asness, 2024), and certain forms of gambling have been legalized. While this view may help explain why speculative opportunities have increased, it does not explain why participation varies systematically across individuals. If access has expanded for everyone, why are some households far more drawn to high-risk financial activities than others?

[1] See for example, Blanchflower et al. (2025); Twenge and Blanchflower (2025); VanderWeele et al. (2025); Helliwell et al. (2024); Knoll et al. (2017); Berman (2022); Manduca et al. (2024); Chetty et al. (2017).

In this paper, we develop and test a demand-side theory of high-risk financial behavior rooted in Friedman and Savage (1948). Individuals take financial gambles when salient goals, such as homeownership or marriage, are perceived to be attainable only through high-risk bets. We test our theory with an original survey combined with millions of linked records from Korea's credit bureau, credit card spending data, and mobile app usage. Consistent with the theory's predictions, those who view high-risk investment as necessary to achieve their financial goals are substantially more likely to hold cryptocurrency and choose more right-skewed lottery choices, even conditional on return beliefs. We show that cryptocurrency usage rises following adverse unemployment shocks, and declines after individuals win the right to purchase price-regulated housing through a lottery and attain homeownership. Our findings suggest economic frustration is an important driver of high-risk financial behavior.

We begin with a theory that formalizes how hard-to-reach goals generate demand for high-risk investment in the spirit of Friedman and Savage (1948). Friedman and Savage (1948) rationalize gambling by allowing utility to be locally convex over intermediate wealth levels, so that some individuals prefer a fair gamble with a small chance of a large, status-altering gain. In our model, individuals derive utility from achieving a salient, discrete goal, such as homeownership, that cannot be smoothly scaled. When this goal is out of reach through conventional saving but attainable with some probability through risky investment, the agent optimally takes a gamble, generating a local convexity in utility over wealth. This mechanism formalizes what popular commentators have called "financial nihilism", the belief, particularly among young adults, that only high-risk bets offer a realistic path to one's goals (Scanlon, 2025; Harring, 2025).[2]

The model yields a set of empirical predictions. First, demand for high-risk investment is concentrated among individuals who aspire to goals that are unattainable through safe saving but remain within reach through risk. Second, distance to the goal shapes not only demand for risk, but also its type: individuals farther from their goals choose more right-skewed, low-probability, high-payoff gambles. Third, conditional on goals and wealth, those who gamble reallocate resources toward current consumption. Fourth, negative shocks that push individuals further from their goals increase demand for risk. Fifth, achieving a salient goal reduces demand for risk. We contrast these predictions with alternative explanations based on intrinsic enjoyment or optimistic beliefs, which generate different patterns across individuals and over time.

[2]In a survey of Americans, nearly two-thirds of Gen Z and millennial respondents report that building significant wealth today requires "alternative methods," including cryptocurrency and gambling (The Harris Poll, 2025). In a survey of Koreans, almost 80% of respondents attributed cryptocurrency's rise at least partly to limited upward mobility (Embrain, 2021).

Testing these predictions is challenging because it requires jointly observing financial goals, beliefs, and high-risk behavior, which are rarely available in a single dataset. We address this challenge by combining a new targeted survey with unique large-scale administrative data linked across three major South Korean companies: the leading credit bureau, the largest telecom provider, and the largest credit card company. The data include mobile app activity, allowing us to measure engagement with cryptocurrency platforms and relate it to administrative measures of spending, borrowing, and assets. Korea offers an especially compelling context for studying high-risk financial activities: its households are among the most active participants in cryptocurrency markets, and its evolving demographic structure, declining housing affordability, and rising life dissatisfaction make it a potential bellwether for trends in other advanced economies.

We begin with survey evidence that directly measures individuals' financial goals, beliefs, and risk preferences. Respondents report the importance of a range of goals—including homeownership, retirement, and broader status-oriented objectives such as increasing their attractiveness as a romantic partner. We show that cryptocurrency holders are more likely to report both stronger aspirations and a greater perceived need for high-risk investment to achieve their goals, even after controlling for expected returns and risk preferences. In lottery choice tasks, those who place greater importance on hard-to-reach financial goals are more likely to choose risk-seeking options. Participation across lottery, crypto, and stock markets also varies with income, with lower-income households preferring more right-skewed assets. Together, these results support Friedman–Savage motives beyond explanations based solely on beliefs or entertainment.

We then turn to administrative data that allow us to examine these patterns at scale and link them to economic outcomes. We first document patterns of cryptocurrency app usage, our primary measure of interest in high-risk financial assets.[3] Usage is widespread, particularly among men: almost a quarter use a cryptocurrency app in a given month, and nearly 10% are "heavy users," logging on at least 30 times. Usage is higher among those who spend more time on social media, real-estate, and video apps, even controlling for total app usage.[4] Consistent with our model, cryptocurrency usage is lowest among high-asset individuals, in sharp contrast to stock app usage, which rises with wealth. Furthermore, consistent with the third prediction, usage is higher among households with higher levels of spending-to-assets and unsecured debt. Inconsistent

[3]Unlike stock-related app usage, which may reflect investment in a wide variety of assets, cryptocurrency app usage more directly captures engagement with high-risk investment. Section 4 shows that cryptocurrency app usage is a strong predictor of actual holdings in linked survey data.

[4]Social media apps include Instagram and Facebook; real-estate apps include Naver, Hogangnono, and Zigbang (similar to services like Zillow); video apps include YouTube and TikTok.

with crypto interest reflecting small "entertainment" bets, usage is tied to meaningful economic outcomes: heavy users' spending responds to price fluctuations, and they are more likely to purchase a home after price booms and to enter delinquency after crashes.

Next, we exploit within-individual variation to test how risk-taking responds to changes in economic circumstances. We first test whether demand for high-risk investment increases when goals become harder to attain through saving. We focus primarily on unemployment episodes. Cryptocurrency app usage rises by 6% (relative to the pre-period) in the year of an unemployment episode relative to observably similar individuals who remain employed. This increase does not reflect a general rise in mobile activity; placebo tests show no comparable increase in other app categories. A similar pattern emerges when individuals take on new unsecured debt, consistent with a response to expense shocks that push goals out of reach.

We then test whether individuals reduce high-risk investment after achieving a financial goal. We focus on homeownership, a particularly salient goal in Korea given declining housing affordability, as in many other advanced economies. Cryptocurrency app usage falls significantly in the year after a home purchase, a larger decline than for any other app category except real estate. While suggestive, homeownership is inherently related to past financial outcomes and expectations about the future. To address these endogeneity concerns, we exploit Korea's housing lottery, which quasi-randomly allocates rights to purchase price-regulated housing. We identify 1,347 winners and compare them to not-yet-treated future winners in a difference-in-differences design, similar to Arkolakis et al. (2026).[5] Following the announcement, cryptocurrency app interactions decline by 31% for winners relative to the pre-win month. These results provide direct evidence that attaining homeownership reduces demand for cryptocurrency.

In the final section of the paper, we examine the welfare implications of our theory. If investors hold rational expectations and aspire to difficult-to-reach goals, gambling could, in principle, enhance welfare by enabling the pursuit of high-risk, high-reward opportunities. However, when individuals are overoptimistic, Friedman-Savage preferences can amplify belief distortions, generating substantial welfare losses relative to a rational expectations benchmark. In a stylized calibration, some overly optimistic households make risky investments in pursuit of unlikely gains, effectively engaging in costly gambles that leave them worse off on average. Additionally, restricting access to one form of high-risk investment can lead individuals to substitute toward alternative gambles in pursuit of the same goals, making the welfare effects of these interventions ambiguous.

[5]These lottery wins provide a large subsidy: Arkolakis et al. (2026) show that for comparable projects, the median discount is 20 percent.

Literature Our paper relates to several strands of work. First, it speaks to a growing literature documenting rising dissatisfaction, economic frustration, and declines in well-being, especially among younger cohorts (e.g., Blanchflower et al., 2025; Twenge and Blanchflower, 2025; VanderWeele et al., 2025). Related work shows that intergenerational mobility has declined substantially over time (Chetty et al., 2017; Manduca et al., 2024), while other studies highlight how inequality and social conditions shape perceptions of opportunity and life satisfaction (Helliwell et al., 2024; Knoll et al., 2017; Berman, 2022). Relative to this literature, we focus on the financial consequences of rising dissatisfaction: when discontent stems from difficulty attaining a salient, discrete goal, it can reshape risk appetite and portfolio choices. Closest to our work, Lee and Yoo (2025) show how declining housing affordability can lead households to increase spending and take on greater financial risk. Relative to their work, we provide direct evidence on high-risk financial behavior using granular administrative data, study a broader set of goals (including housing, social status, and starting a business), and test the theory by leveraging survey evidence and within-person variation in distance to goals.

Our paper also contributes to a literature explaining preferences for high-risk assets and gambling. Friedman and Savage (1948) posit a reduced-form utility function that generates both local risk aversion and a taste for lotteries, while Kwang (1965) derives similar preferences from indivisible consumption. Other approaches model gambling as directly entering utility (Conlisk, 1993; Asness, 2024), or emphasize behavioral distortions such as probability weighting (Barberis, 2013; Barberis and Huang, 2008), salience (Bordalo et al., 2022), and non-pecuniary motives like anticipation or sensation-seeking (Loewenstein, 1987; Grinblatt and Keloharju, 2009). Closely related to our framework are consumption commitments, where discrete fixed costs generate convexities in utility (e.g., Chetty and Szeidl, 2007). We build on this insight and emphasize that the key ingredient is the presence of salient, discrete goals that generate local convexity in perceived utility. We also discuss alternative microfoundations such as categorical thinking (Mullainathan et al., 2008; Conlon and Kwon, 2025; Bordalo et al., 2025), which can make even nominally continuous goals behave as if they were discrete. This perspective broadens the scope of when Friedman–Savage-type motives may arise.

Finally, our paper contributes to the large literature on retail investor behavior. This literature has shown that retail attention is often drawn to "flashy" or salient assets (Barber and Odean, 2008), lottery-like stocks (e.g., Bali et al., 2019; Kumar, 2009; Barberis and Huang, 2008), and cryptocurrency (e.g., Kogan et al., 2024; Aiello et al., 2023b; Weber et al., 2023; Auer and Tercero-Lucas, 2022; Pursiainen and Toczynski, 2022). Instead of focusing on which asset classes disproportionately attract retail investors, we study in-

vestor heterogeneity in the cross-section. In this sense, our work is closer in spirit to Liu et al. (2022a) and Jiang et al. (2024). Relative to these findings, which emphasize fixed individual characteristics, we provide a framework in which such motives arise endogenously from households' economic circumstances. Our framework also yields sharp predictions not only for overall risk-taking, but for the types of gambles individuals choose.

2 Gambling for Goals: A Theory

This section motivates and introduces a model that formalizes the Friedman and Savage (1948) connection between difficult-to-attain financial goals and risk-taking. The model's predictions guide our empirical analysis.

2.1 Motivation: Difficult-to-Attain Financial Goals

Our model is motivated by rising economic dissatisfaction in many advanced economies, particularly among younger cohorts.[6] We highlight two potential drivers. First, by many measures, traditional financial milestones—including home ownership, upward mobility, and a secure retirement—have become materially harder to achieve through conventional career paths. Second, social media and broader cultural shifts may have raised perceived benchmarks for "success." Together, these forces suggest that some individuals may hold financial goals that are unattainable with traditional savings alone.

Increasing Difficulty of Traditional Goals. Some traditional economic milestones appear to have become harder to achieve for young adults. In many developed countries, housing affordability has fallen (Knoll et al., 2017; Igan, 2024), becoming a central social concern in countries such as Korea (Yoon, 2025). In the U.S., median home prices have risen faster than median incomes, with some suggesting that 65-85% of households are "priced out" of the housing market (JCHS, 2025; NAHB, 2026).[7] Upward mobility has also declined: while 90% of American children born in 1940 made more than their parents by age 30, only 50% of those born in the 1980s did so (Chetty et al., 2017). Similar trends have been documented in many advanced economies (Berman, 2022). Many working-age adults also report concerns about retirement preparedness; for example, more than 40% of Americans under age 60 lack confidence that their wealth will last through retirement (Lin and Menasce Horowitz, 2025).

[6] See footnote 1.

[7] Consistent with this, in 2025, the median age of a first-time home buyer reached 40 for the first time (National Association of Realtors, 2025).

Rising Salience of Difficult-to-Attain Goals. Social media and broader cultural shifts may have also changed milestones of "success." In one survey, more than 40% of Generation Z (born after 1997) respondents reported perceiving themselves as financially behind due to unfavorable social comparisons rather than objective indicators (Intuit Credit Karma, 2024).[8] These responses align with recent psychology studies suggesting that social media use can lead to increased upward social-comparisons and lower self-esteem (Vogel et al., 2014; Verduyn et al., 2020; McComb et al., 2023). In another survey, Generation Z respondents reported believing, on average, that financial "success" requires a $588,000 annual salary and $9.5 million in net worth (Kelly, 2024). For many, these outcomes are difficult to attain through conventional wealth accumulation.

2.2 Model

To formalize how difficult-to-attain financial goals shape risk-taking, we introduce a model of "gambling for goals" that builds on Friedman and Savage (1948) and generates testable empirical predictions. Proofs are in Appendix A.1.

Setup Consider a two-period model in which an agent is endowed with initial wealth W_0, has concave utility over consumption $u(c)$, and can attain a financial goal $g \in \{0,1\}$ in period two at cost G. If attained, the goal delivers a discrete utility boost θ. The goal can reflect a purchase of a large durable good or investment (e.g., buying a home, starting a new business), or other broader material objectives (e.g., attaining a different social class). The goal is discrete: the agent cannot continuously "scale down" the goal and substitute it for a cheaper alternative. We discuss this discreteness in more detail below. The agent can save at the riskless rate $R_0 = 1$ or invest in a "risky gamble" which returns R_H or R_L with probabilities p_H or p_L, respectively, and where $p_H R_H + p_L R_L = 1$. For simplicity the agent's discount rate is 1. The agent therefore solves:

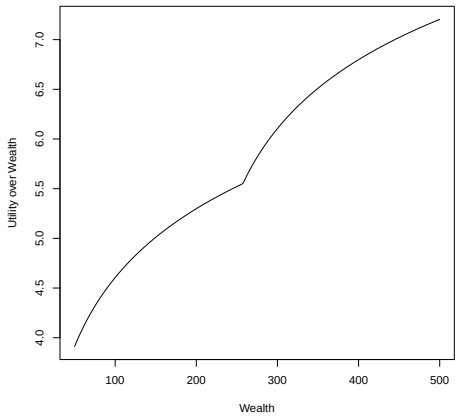
$$\max u(c_1) + E\left[u(c_2) + \theta \cdot g\right], \text{ s.t. } c_2 + G \cdot g = R \cdot (W - c_1). \tag{1}$$

Implications Figure 1 illustrates how the goal locally convexifies the agent's utility over wealth, endogenously generating a utility curve of the form hypothesized by Friedman and Savage (1948). Intuitively, the convexity is centered at the point at which the agent is indifferent between spending G to attain the goal or to increase consumption. Proposition

[8] In the same survey, almost half reported being "obsessed" with being wealthy.

Figure 1: Goals generating convexity

(a) Utility over Wealth Given Goals



(b) Friedman-Savage Utility (JPE)

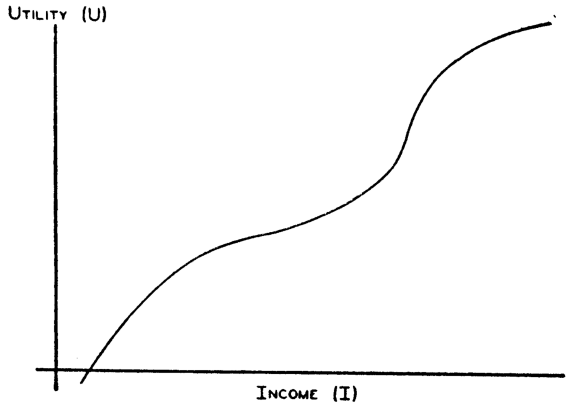


FIG. 3.—Illustration of typical shape of utility curve.

Notes: Figure shows the implied utility over wealth for $u(c) = \log c$, $G = 200$, and $\theta = 1$. Panel (b) displays the third figure in Friedman and Savage (1948).

1 characterizes the agent's investment, goal attainment outcomes, and consumption in different regions around this local convexity.

Proposition 1. *There exists an interval* $[W_L^*, W_H^*]$ *with the following properties:*

(a) ***Gambling:*** *If* $W \in [W_L^*, W_H^*]$*, the individual prefers to gamble (i.e. chooses the risky asset). Otherwise, she prefers the safe asset.*

(b) ***Goal Attainment:*** *If* $W \in [W_L^*, W_H^*]$*, the agent attains her goals only when the gamble pays off. If* $W < W_L^*$*, the agent gives up on her goals. If* $W > W_H^*$*, the agent risklessly attains her goals.*

(c) ***Consumption:*** *If* $W \in [W_L^*, W_H^*]$*, the agent's consumption,* $c(W)$*, satisfies:*

$$u'(c) = p_H R_H \cdot u'(R_H(W-c) - H) + p_L R_L \cdot u'(R_L(W-c)). \tag{2}$$

If $W < W_L^*$*, consumption is* $c(W) = \frac{W}{2}$*. If* $W > W_H^*$*, consumption is* $c(W) = \frac{W-G}{2}$*. As a result, for* $\epsilon > 0$*,* $c(W_H^* - \epsilon)$ *is discretely higher (relative to net worth) than* $c(W_H^* + \epsilon)$*.*

Propositions 1(a) and 1(b) describe the set of individuals who will prefer to gamble and when they will attain their goals. In particular, goal-driven gambling will be strongest among individuals who aspire to goals that would not be within reach with riskless savings, but is attainable if the risky gamble pays off. In contrast, gambling does

not appeal to those who can achieve their goals without risk, nor to those who cannot achieve them even with risk.

Proposition 1(c) shows that goals also affect intertemporal consumption. Relative to their wealthier peers, gamblers consume more in the present. Intuitively, saving and risk-taking are substitutes: individuals confident about reaching their goals through saving must defer consumption, whereas those who gamble "partially give up" and reallocate resources toward current consumption. Empirically, conditional on the goal, those who choose the risky asset should have lower savings and higher consumption.

Optimal gamble So far, we have assumed that the agent is choosing between riskless savings and an exogenously given risky asset. In practice, however, individuals can often choose among a wide range of risky opportunities, from lottery tickets to cryptocurrencies, speculative stocks, or option strategies, each with different payoff profiles. To capture this flexibility, Appendix A.2 considers a generalization in which the agent can optimally design an actuarially fair gamble. Formally, suppose the agent can choose p_H, p_L, r_H, r_L subject to the fact that the asset is an actuarially fair gamble: $p_H \cdot r_H + p_L \cdot r_L = 1$. The following proposition characterizes the optimal gamble as a function of agent wealth.

Proposition 2. *As before, there exists W_L^{**} and W_H^{**} such that the agent chooses to gamble if and only if $W \in [W_L^{**}, W_H^{**}]$. In this region, poorer agents optimally choose more right-skewed gambles: as wealth decreases, the probability of a high payoff falls while its size increases: $\frac{\partial p_H^*}{\partial W} > 0$, $\frac{\partial r_H^*}{\partial W} < 0$.*

Proposition 2 highlights that the Friedman–Savage motive not only predicts whether individuals gamble, but also which types of gambles they prefer. Individuals who are far from their goals (but not so far as to give up entirely) optimally choose highly skewed bets – low-probability, high-payoff "lottery-like" outcomes. Intuitively, agents benefit from risk-taking only if success allows them to reach their goals. For agents far from their goals, this requires a large payoff, which under the fair-odds constraint requires a lower probability of success to limit downside risk. As agents move closer to their goals, the required payoff shrinks, and they optimally shift toward less extreme gambles that deliver success with higher probability. In this sense, distance to the goal shapes not only the demand for risk, but also the form of risk-taking.[9]

[9] Appendix A.2 also shows that with full flexibility over lotteries, consumption c is constant over $W \in [W_L^{**}, W_H^{**}]$, in contrast to Proposition 1(c). The intuition is that the agent allocates marginal wealth toward improving the lottery rather than increasing consumption. In a more realistic setting where the agent chooses from a limited menu of gambles, a version of Proposition 1(c) is restored: relative to an agent choosing a safer gamble, a slightly poorer agent selecting a riskier gamble consumes more.

Empirical Predictions Corollary 1 describes how our propositions translate into a set of empirical predictions that we bring to the data.

Corollary 1. *Our model predicts the following:*

1. ***Distance to Goal:*** *Gambling appeals most to individuals who have goals that are difficult to attain risklessly, but not so far as to always be out of reach.*

2. ***Choice of Gambles:*** *As individuals move farther from their goals, they prefer more right-skewed gambles. For a given gamble, demand is highest among individuals for whom the upside payoff is large enough to make the goal attainable, but not so small that a safer gamble would suffice.*

3. ***Effect of Goals on Consumption:*** *Conditional on the goal and a similar level of wealth, individuals who gamble have higher consumption.*

4. ***Desperation Shocks:*** *A negative shock to net worth can induce gambling, especially for those who were previously able to achieve their goals risklessly.*

5. ***Post Goals:*** *Gambling decreases once the individual attains their goals.*

Before testing these predictions, we discuss the role of goal discreteness and how our predictions differ from alternative models of gambling.

2.3 Why Discrete Goals?

The key nonstandard feature of our model that generates a gambling motive is the discreteness of goals: an individual either achieves their goal or does not, they cannot scale it downward. Appendix Figure G.2a shows that when the agent can instead choose a continuous expenditure $G_c \in \mathbb{R}_0^+$ in return for utility $\theta(G_c)$, the local convexity that drives gambling disappears. Proposition 3 formalizes this result.

Proposition 3. *If $\theta(G_c)$ is weakly concave in G_c, the agent does not gamble: she achieves an optimum by choosing the safe portfolio and scaling back G_c.*

As in Friedman and Savage (1948), gambling is attractive only when something *categorically* different is at stake. People gamble to enter a new class, reach a sharply defined benchmark, or hit some other indivisible goal. We briefly discuss two microfoundations that generate this convexity: one neoclassical, rooted in fixed costs, and one behavioral, rooted in categorical perception and psychological rigidity.

Fixed costs Convexity arises naturally from indivisibilities or fixed adjustment costs. As emphasized by Chetty and Szeidl (2007), durable consumption, housing upgrades, and other lumpy investments with fixed costs generate regions of inaction.[10] A sufficiently large positive shock thus permits a discrete jump in utility, which generates risk-seeking motives. A lottery payoff finances a new house; small increments do not.[11]

Psychological frictions and categorical reasoning In our survey (Section 4), many participants report needing high-risk investments to reach goals that are not naturally indivisible. For example, "having enough for retirement" and "improving my social standing" are, in principle, scalable. Why do individuals appear to *not* scale down these goals? One possibility, consistent with several existing works (e.g., Mullainathan, 2002; Mullainathan et al., 2008; Bordalo et al., 2025), is that people reason in discrete categories or classes—e.g., rich vs poor, successful vs ordinary—as implied by Friedman and Savage (1948).[12] In Appendix A.4, we formalize this insight by drawing on the model of Bordalo et al. (2025) and Conlon and Kwon (2025). The results are shown in Appendix Figure G.2b: even with the option of continuous scaling $\theta(G_c)$, if individuals perceive utility gains in a categorical manner, we recover Friedman-Savage utility.

Both microfoundations produce similar reduced-form predictions: gambling requires goals that cannot be smoothly revised. If agents can continuously scale down ambition, they will do so. If they cannot—or believe they cannot—they gamble.

2.4 Alternative Explanations for Gambling

There are, of course, alternative explanations for gambling behavior. We discuss two alternative mechanisms, intrinsic enjoyment and optimistic beliefs, and distinguish the implications of these alternatives from those of our Friedman-Savage framework.

Intrinsic Enjoyment Gambling may confer direct utility beyond its expected effect on wealth, a classic explanation for why risk-averse individuals gamble. For example, individuals may derive utility from sensation-seeking (Grinblatt and Keloharju, 2009) or

[10] In Chetty and Szeidl (2007), they refer to this region of inaction as a (S-s) band. Our $[W_L^*, W_H^*]$ band is a region where individuals take high-risk gambles and hope to land in an action region outside of S.

[11] In related work, Lee and Yoo (2025) generate a gambling motive by implicitly assuming that the fixed cost of a housing downpayment generates discreteness.

[12] This is also highly consistent with recent work in cognitive psychology studying persistent and stable goals (Holton et al., 2025).

anticipating large gains (Loewenstein, 1987), motives often discussed in demand for lotteries and slot machines (Kallick-Kaufmann, 1976). In Appendix A.3, we follow Conlisk (1993) in modeling agents who trade off entertainment with the disutility of risk. On the extensive margin everyone gambles, as risk is second-order relative to entertainment. On the intensive margin, wealthier people gamble more, as they can accept greater volatility in net worth than individuals with less wealth.[13] Another way in which gambling can be intrinsically enjoyable is that it offers a form of escapism or "self-medication," particularly for individuals facing economic stress or limited opportunities, which can explain why gambling can be more ubiquitous among the poor. Even then, these explanations do not have an obvious implication regarding *which* types of gambles are preferred by an agent, in contrast to Proposition 2.

Many of these gambling motives can also be reinforced by features that make them habit-forming or difficult to quit (Becker and Murphy, 1988; Gruber and Köszegi, 2001). While these forces are likely important, especially in environments such as casinos or online betting platforms designed to maximize engagement, they are conceptually distinct from the mechanism we study. In our framework, risk-taking is instrumental and state-dependent: agents demand risk because it offers a (perceived) path toward salient financial goals: in particular, when these goals are attained, the demand should dissipate. By contrast, intrinsic enjoyment or addiction implies demand for risk even in the absence of such goals, and even when gambling may jeopardize already attained goals.

Optimistic Beliefs If individuals perceive high-risk assets not as pure gambles but as offering high expected returns, this can generate participation. For example, individuals may extrapolate recent booms (Barberis et al., 2018; Weber et al., 2023), be overconfident (Barber and Odean, 2001; Liu et al., 2022a), or overweight small probabilities (Kahneman and Tversky, 1979) or salient outcomes (Bordalo et al., 2022; Barber and Odean, 2008). However, for beliefs to account for *cross-sectional variation* in risky investment, a theory for why certain individuals are more optimistic about high-risk returns than others is required, an issue on which there is no single prediction.[14]

Corollary 2. *Alternative models of gambling predict:*

[13] While obtaining precise estimates of relative risk aversion can be challenging, there is suggestive evidence that relative risk aversion declines with wealth (Guiso and Sodini, 2013).

[14] For example, if general optimism drives participation, high-risk investment should be associated with greater reported well-being. If optimism instead reflects differential exposure to hype or informal information channels, poorer individuals may hold more optimistic beliefs and invest more in risky assets. By contrast, if beliefs are shaped by personal experience, poorer households—having experienced more adverse shocks—may be more pessimistic about risky prospects (Bordalo et al., 2018; Malmendier and Nagel, 2011; Kuhnen and Miu, 2017).

1. ***Intrinsic Enjoyment:*** *Small-stakes gambling may be ubiquitous across the wealth distribution, but large-stakes gambling should be concentrated among wealthier individuals.*

2. ***Addiction:*** *Gambling behavior is highly persistent and potentially compounds over time.*

3. ***Overoptimism:*** *Individuals who gamble should be more optimistic about the gamble. Overoptimism has ambiguous predictions for cross-sectional patterns.*

While each of these alternatives likely contributes to gambling behavior for some individuals, Corollary 2 outlines their testable predictions for the cross-section and for beliefs. We examine these predictions to assess whether they can account for the observed patterns. In the remainder of the paper, we test the predictions of our Friedman-Savage framework, highlighted in Corollary 1, and the predictions of alternative models, highlighted in Corollary 2.

3 Data: GranData and Linked Survey

Testing whether Friedman-Savage motives contribute to the rise of high-risk investment is challenging because it requires data that jointly capture household wealth, consumption, and high-risk financial behavior. We overcome this challenge by using a unique linked dataset combining credit bureau, credit card, and mobile app usage records in Korea. Our primary measure of high-risk financial activity is cryptocurrency mobile app usage, which, unlike stock trading applications that may be used for a variety of investments, serves as a comparatively clean proxy for high-risk investment. Furthermore, Korea provides a particularly informative setting given its declining housing affordability, evolving demographic structure, and widespread popularity of cryptocurrency, making it a potential bellwether for broader trends in advanced economies.[15]

3.1 GranData

GranData consists of a linked individual-level panel combining information from Korea's dominant credit bureau, largest telecommunications company, and largest credit

[15]While cryptocurrency can also be used as a means of exchange, in survey responses only 13.7% of Korean crypto holders say that they use it as a substitute for currency in transactions (Korean Financial Consumer Protection Foundation, 2024). Additionally, Auer and Tercero-Lucas (2022) show that crypto investors in the U.S. are not differentially mistrustful of the financial system, consistent with crypto being primarily used for speculation.

card company. Together, these data provide broad, representative coverage of many aspects of the working-age population in Korea. Table 1 summarizes coverage. This section describes key variables and our analysis sample. (Appendix B provides more details.)

Table 1: Basic Structure of Data

Data Source	Sample Period	# of Variables	# of Individuals
KCB	2015Q4 - 2019Q2 (Quarterly)	140	43,036,550
	2019M7 - 2024M5 (Monthly)	140	47,568,784
SKT	2021M1 - 2023M12 (Monthly)	215	18,040,463
Shinhan Card	2019M6 - 2024M5 (Monthly)	119	21,378,211
SKT Survey	March 2026 (Cross Section)	58	2,301

Notes: Table provides an overview of the KCB, SKT, and Shinhan Card datasets in GranData.

Credit Bureau Records Credit bureau records come from the Korean Credit Bureau (KCB), covering 90% of the Korean population over age 15. For each individual by month, the KCB data report information about borrowing (e.g., debt balances, delinquencies, and credit scores), total card spending, assets, and income. Information on debt and spending are provided to KCB from financial institutions. Income and assets are estimated using information from loan applications, contract details, and card usage patterns.

Mobile App Usage Activity Mobile phone activity comes from SK Telecom (SKT), which held 40% market share in December 2023. For each individual and month, the SKT data report application and website usage by category. These categories include many different online services, including cryptocurrency exchanges, real estate platforms, social media, video platforms, and education services. For each category, we observe the number of usage instances (e.g., app sessions or website visits) recorded by the provider. Real estate platforms include Naver, Hogangnono, and Zigbang, services similar to Zillow or Redfin in the United States.

Credit Card Transactions Credit card transactions come from Shinhan Card, which accounted for 21% of transactions in 2023. For each individual and month, the data provide spending across 19 non-overlapping categories (e.g., food, luxury goods, medical expenses, clothing, and travel).

Analysis Sample For our primary empirical analysis, we construct a sample of individuals for whom information from all three providers is available between January 2021 and December 2023. To ensure our sample includes individuals who primarily use their Shinhan Card, we drop individuals whose total Shinhan Card expenditures account for less than half of their total KCB expenditures. We merge this sample to local data on median apartment prices from the Korea Real Estate Board and exclude a small number of observations for whom this information is not available. After applying these restrictions, the final sample comprises 1,427,629 individuals. The panel is unbalanced, but includes a balanced panel of 987,571 individuals jointly observed in every period (see Appendix Table B.1 for coverage by month). For most analyses we further restrict to those who have consented to sharing detailed data with SKT, around 70% of the sample.

Sample Representativeness To better understand our final sample, we compare it with administrative data from the Korea Statistical Information Service (KOSIS). Appendix Table H.1 shows that our sample is broadly representative of Korea's working-age population, with similar employment rates, and median and mean annual incomes. Our sample is somewhat more likely to live in the Seoul metropolitan area (27.6% versus 15.8%) and includes a relatively larger share of individuals under age 50.

Primary Measures of High-Risk Financial Activity We construct two main individual-by-month measures of cryptocurrency usage.[16] First, we say an individual is a "crypto user" if they open a cryptocurrency trading app or website during the month. Second, we say an individual is a "heavy crypto user" if they do so at least 30 times. In some analyses, we also construct analogous measures for stock app usage.

3.2 Linked Survey

We partnered with the telecommunications provider SKT to conduct a targeted survey of individuals in the GranData, stratified by cryptocurrency app usage. It supplements the administrative data with information about beliefs, financial goals, and lottery participation, allowing us to provide additional tests of our framework's predictions. The survey also enables us to validate our app-based measures against self-reported holdings. Appendix C contains more details.

[16] This includes major Korean cryptocurrency trading platforms, such as Upbit and Bithumb, but excludes general stock trading platforms, which do not typically list cryptocurrencies. Appendix Figure G.3 shows a strong relationship between interest in cryptocurrency and Bitcoin returns, consistent with other contexts (Wheat and Eckerd, 2022; Weber et al., 2023; Auer et al., 2025)

Sample Details The survey was administered by phone over a 24-hour period from March 19-March 20, 2026 and yielded 2,301 complete responses. Participants were sampled from three groups based on their cryptocurrency app usage: heavy users (500), middle users (700), and non-users (1,101). The definition of these groups is intended to align with the definitions we use in the GranData, though the exact criteria differ slightly due to data provider constraints.[17] Appendix Table C.1 provides sample summary statistics.

Crypto App Usage and Holdings Appendix Table C.1 shows that app usage tracks actual holdings: 25%, 45%, and 75% of non-users, middle users, and heavy users, respectively, currently hold cryptocurrency. Heavy users also hold substantially more cryptocurrency on average: 22.2 million KRW ($15,540 USD) compared to 5.5 million KRW ($3,850 USD) for middle users. Consistent with this, Figure C.1 shows the CDF of holdings is shifted markedly rightward for heavy users relative to middle users and non-users.

4 Survey Evidence on Goals, Beliefs, and Preferences

This section presents evidence from our survey, which allows us to directly observe goals, beliefs, and preferences. We show that cryptocurrency holders are more likely to both report strongly aspiring to financial goals and to perceive high-risk investment as necessary to achieve those goals, even after controlling for expected returns and risk preferences. Participation across lottery, crypto, and stock markets also varies with income, with lower income households preferring more right-skewed investments. Together, these results provide support for Friedman-Savage motives, above and beyond alternative explanations based solely on beliefs or entertainment motives.

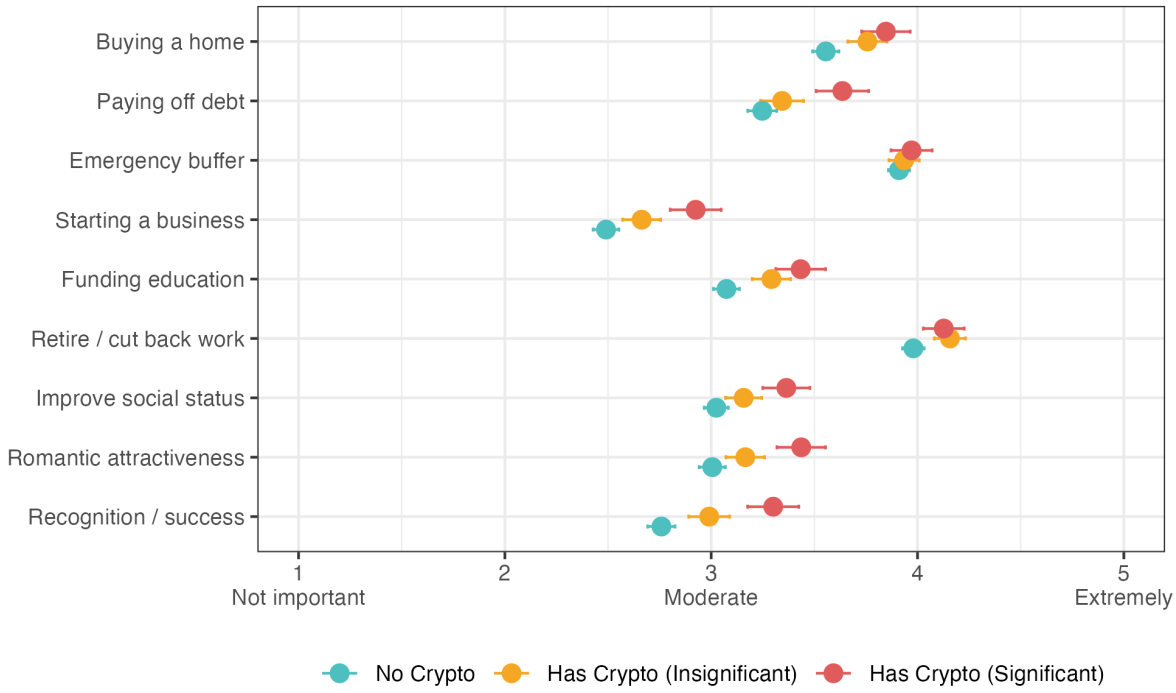
4.1 Testing Prediction 1: Goals and Gambling

Goals Predict High-Risk Investment We begin by examining self-reported financial goals. Respondents rated the importance of nine goals, including buying a home, paying off debt, building an emergency buffer, starting a business, funding education, retirement, and improving social status, romantic attractiveness, and recognition. Respondents were also asked to consider their most important goal and report whether they view high-risk investments as necessary to achieve it. We classify respondents as having

[17] In particular, heavy users were defined as individuals who used a cryptocurrency application on at least 50 of the past 60 days, while middle users are those with 10 to 40 days of usage over the same period. Non-users are individuals who do not use any cryptocurrency application on their phones. The set of applications align with those in the administrative data.

no crypto, insignificant crypto, or significant crypto based on whether losing all holdings would materially affect their financial well-being.[18]

Figure 2: Importance of Financial Goals by Crypto Holdings



Notes: Figure plots mean importance scores for nine financial goals (where 1 = not at all important and 5 = extremely important), separately for respondents with no crypto holdings, insignificant crypto holdings, and significant crypto holdings. Horizontal bars show 95% confidence intervals. Source: SKT survey.

Figure 2 reports mean importance ratings by crypto holdings. Respondents rate most goals highly, with the most salient being those associated with economic frustration—buying a home, preparing for retirement, building emergency savings, and repaying debt. Consistent with Prediction 1 of Corollary 1, respondents with greater crypto exposure report consistently higher goal salience. The differences are not confined to purely financial goals such as housing or retirement; they also extend to broader status-oriented goals such as recognition, social standing, and romantic attractiveness. Consistent with the prediction that *distance* to goals matters, Appendix Figure C.2 shows that the share reporting a need for high-risk investment to achieve their goal rises with crypto holdings.

Goals Predict Gambling in a Lottery Choice Task To provide additional evidence on gambling preferences, we elicit risk-taking preferences in a lottery choice task. Respondents choose between a guaranteed gain and lotteries with a higher payoff but lower

[18]Specifically, respondents were asked: "Hypothetically, if all of your crypto holdings went to zero tomorrow, would this have a significant negative impact on your financial well-being?"

Table 2: Goals Predict Risk Preferences

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk Seeking					
Average Goal Importance	0.064***		0.061***	0.062***		0.059***
	(0.014)		(0.013)	(0.014)		(0.014)
Needs High Risk		0.23***	0.22***		0.21***	0.21***
		(0.020)	(0.020)		(0.021)	(0.021)
Demographic Controls				✓	✓	✓
Observations	2301	2301	2301	2301	2301	2301
Adjusted R^2	0.0085	0.047	0.055	0.030	0.060	0.067

Notes: Table shows a regression of risk-seeking preferences on goals. "Risk-Seeking" is an indicator for whether an individual's preferred hypothetical gamble is not the sure gain when presented with options that have the same expected value. "Average Goal Importance" is the average likert response to goals in Figure 2. "Needs High Risk" is whether a respondent reports that high-risk investments are realistic to achieve their most important financial goals. Demographic controls include sex, income, education, age, marital status, home ownership, employment, and assets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses. Source: SKT survey.

probabilities, holding expected values constant.[19] Respondents who choose a risky option are classified as risk-seeking, as they prefer a fair gamble to a certain payoff.

Table 2 shows that this measure is strongly predicted by both goal salience and the perceived necessity of high-risk investment (columns 1–2). The coefficients change little when both are included simultaneously (column 3), suggesting they capture distinct sources of variation. Both effects remain robust when controlling for sex, income, education, age, marital status, home ownership, employment, and assets (columns 4–6). While risk preferences are often treated as primitives, these results suggest that they may be shaped, at least in part, by underlying goals.

Goals Matter Beyond Beliefs and Preferences We next directly examine the relationship between cryptocurrency holdings and beliefs, risk preferences, and goals. Table 3 presents our results. All specifications include the demographic controls described above.

Goal-related measures predict crypto participation beyond beliefs and risk preferences. Columns 1-2 confirm that expected cryptocurrency returns[20] and risk-seeking preferences are each significant predictors, consistent with prior work. Columns 3-4 show that goal salience and the perceived necessity of high-risk investment to achieve one's goals are also important predictors. When all variables are included simultaneously

[19] Appendix C.1 shows the full question and response options.

[20] Directionally, this pattern is consistent with Weber et al. (2023), who find a 12 percentage-point gap between holders and non-holders among U.S. households.

(column 5), goal-related measures remain large and significant, suggesting that goals capture variation distinct from beliefs and risk preferences. The coefficient on risk-seeking attenuates, consistent with the notion that goals help shape preferences toward risk.

Table 3: Cryptocurrency Ownership on Expectations, Risk Preferences, and Goals

	(1)	(2)	(3)	(4)	(5)
	Currently Owns Crypto				
Expected 1Yr Bitcoin Returns	0.052***				0.045***
	(0.011)				(0.011)
Risk Seeking		0.075***			0.041*
		(0.021)			(0.022)
Average Goal Importance			0.096***		0.089***
			(0.015)		(0.015)
Needs High Risk				0.12***	0.11***
				(0.023)	(0.023)
Demographic Controls	✓	✓	✓	✓	✓
Observations	2139	2139	2139	2139	2139
Adjusted R^2	0.058	0.053	0.067	0.061	0.088

Notes: Table shows a regression of crypto ownership on returns, risk preferences, and goals. "Currently Owns Crypto" is an indicator for whether the respondent reports owning cryptocurrencies. "Expected 1Yr Bitcoin Returns" are expected Bitcoin returns over 1 year, winsorized at 400%. "Risk-Seeking", "Average Goal Importance", "Needs High Risk" and demographic controls are the same as in Table 2. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses. Source: SKT survey.

4.2 Testing Prediction 2: Optimal Gambles

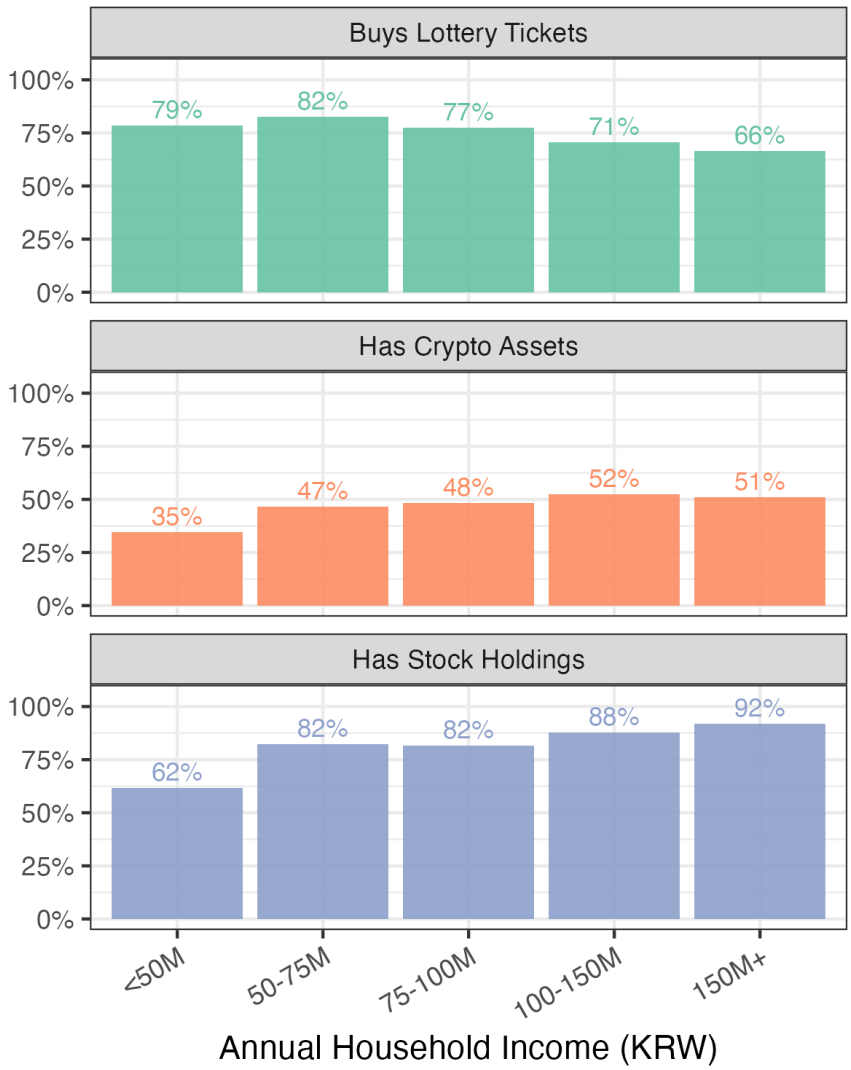
Our model delivers predictions not only on who gambles, but also on the types of gambles individuals choose. When individuals are farther from their goals, they should prefer more right-skewed bets (low-probability, high-payoff opportunities), while those closer to their goals tilt toward safer assets.

Figure 3 provides descriptive evidence consistent with this prediction. The figure plots the share of respondents who buy lottery tickets, hold crypto assets, and have stock holdings of at least 1 million KRW, separately by household income.[21] Broadly, the pattern aligns with Prediction 2 of Corollary 1. Lower-income households, who are plausibly farther from their financial goals, are most likely to buy lottery tickets—the most right-skewed of the three—while stock ownership, the least skewed, rises steeply with income.

[21] Appendix Figure C.3 also shows a similar pattern when one sorts by assets.

Crypto ownership lies between the two, peaking in the upper-middle of the income distribution. This ordering mirrors the model's prediction that as wealth falls, individuals shift toward lower-probability, higher-payoff gambles.

Figure 3: Lottery, Crypto, and Stock Participation by Income



Notes: Figure shows the share of survey respondents who buy lottery tickets, hold crypto assets, and have stock holdings of at least 1 million KRW, by annual household income. Source: SKT survey.

5 Primary Empirical Results

Building on our survey evidence, in this section we use linked credit bureau, credit card spending, and mobile app usage records to provide a large-scale test of the Friedman–Savage framework. Crypto app usage is higher among households with higher

spending-to-asset ratios and unsecured debt, and rises following unemployment. By contrast, individuals who quasi-randomly win the right to purchase price-regulated housing in a housing lottery reduce their interest in cryptocurrency. These results are consistent with Friedman–Savage motives as a driver of demand for high-risk investment.

5.1 Cryptocurrency Participation in Administrative Data

Table 4 summarizes the primary sample in July 2021 by cryptocurrency app usage. Cryptocurrency interest is widespread in Korea: 17% of the full sample and nearly a quarter of men used a crypto app at least once that month. Around 7% of individuals used a crypto app more than 30 times ("heavy" usage) a month.[22] Appendix Figures G.4 and G.5 show how heavy crypto usage varies by assets and age. Approximately 15% of men in their 30s and 40s are heavy users, compared to 4% of women in the same age group. Across the wealth distribution, crypto participation is relatively flat (and if anything slightly declining), in contrast to interest in stocks, which rises with wealth.[23]

Relationship with Other Apps Figure 4 shows how cryptocurrency app usage relates to other app usage. The figure reports coefficients from regressions of an indicator for heavy cryptocurrency use on standardized usage of other app categories, controlling for age, gender, income, assets, and total phone usage. Cryptocurrency engagement is most strongly associated with social media, real estate, and video entertainment app usage.[24] A one standard deviation increase in real estate app usage is associated with about a 20 percentage point increase in the probability of heavy cryptocurrency use. This aligns with the survey evidence in Section 4, where housing is among the most salient goals for cryptocurrency investors. The association with social media usage is also consistent with a role for salient social comparisons as a source of financial goals (McComb et al., 2023).

Economic Effects To understand the economic consequences of cryptocurrency investments, we next examine how consumption, home-ownership, and delinquency respond to fluctuations in cryptocurrency prices (Mankiw and Zeldes (1991) conduct a similar

[22] Our results are consistent with high rates of holding reported in external survey data. For example, a 2021 survey of approximately 1,800 office workers found that almost 50% of office workers in their 30s were investing in crypto (Saramin, 2021). In a 2024 survey of 2,500 adults aged 19 to 69, 34% reported holding some virtual asset (Korean Financial Consumer Protection Foundation, 2024).

[23] This pattern is consistent with Prediction 2 and Section 4.2: stock participation peaks among the wealthy, while cryptocurrency is more prevalent in the middle. Our results are also consistent with Campbell (2006), who shows that stock market participation increases in wealth.

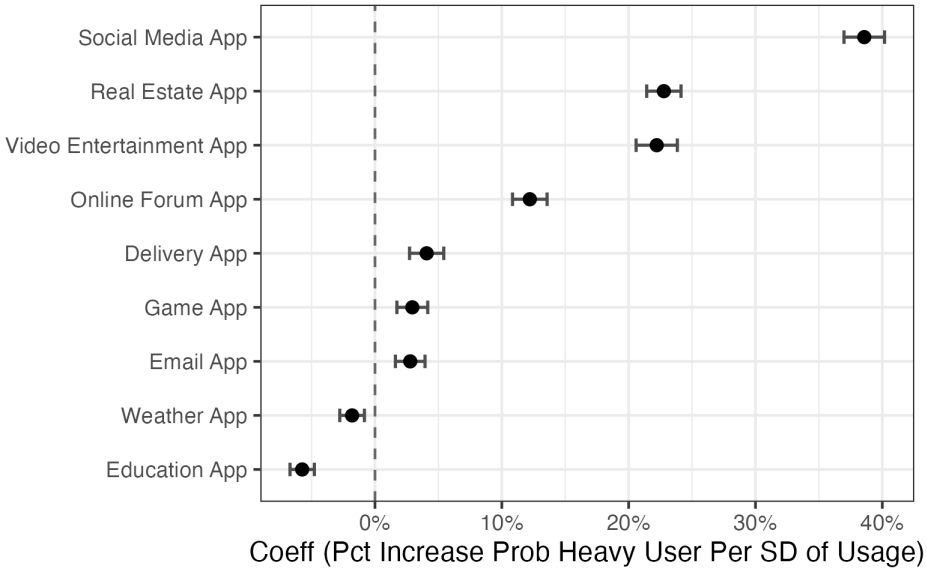
[24] As noted in Section 3, real estate apps allow users to browse for real estate listings, similar to Zillow and RedFin in the US. Video entertainment apps include YouTube and TikTok.

Table 4: Sample Summary Statistics (July 2021)

	Non-Crypto Users	All Crypto Users	Heavy Crypto Users
KCB: Share with Loan by Type			
Credit loan	0.21	0.34	0.41
House loan	0.12	0.14	0.16
Auto loan	0.06	0.08	0.10
KCB: Median Loan Balance Among Non-Zero			
Credit loan (1,000 KRW)	16,210	24,540	27,200
House loan (1,000 KRW)	88,090	104,815	106,700
Auto loan (1,000 KRW)	11,430	12,390	12,670
KCB: Other			
Average Annual Income (1,000 KRW)	37,505.24	42,465.70	44,625.16
	(20,626.57)	(23,619.69)	(23,168.27)
Median Annual Income (1,000 KRW)	33,000.00	37,000.00	39,000.00
Average Net Assets (1,000 KRW)	286,387.53	259,703.32	243,361.35
	(319,794.78)	(277,901.79)	(256,296.51)
Average Monthly Card Spending (1,000 KRW)	1,519.80	1,943.59	2,086.62
	(2,345.45)	(2,587.97)	(2,656.22)
Share Unemployed	0.37	0.27	0.22
Share Owns Home	0.34	0.30	0.32
Share Owns Foreign Car	0.01	0.02	0.03
Share with Delinquency	0.0020	0.0024	0.0023
Share Male	0.47	0.69	0.77
Share under 40	0.33	0.56	0.56
SKT: Usage			
Share Using Stock App	0.35	0.74	0.83
Share Using Game App	0.23	0.41	0.43
Share Using Online Forum App	0.26	0.55	0.56
Share Using Education App	0.30	0.47	0.49
Shinhan Card: Average Monthly Spending by Category			
Luxury Spending (1,000 KRW)	89.00	127.50	135.94
	(413.19)	(496.59)	(500.80)
Total Spending (1,000 KRW)	1,108.54	1,395.44	1,488.55
	(2,026.29)	(2,236.44)	(2,207.85)
Food Spending (1,000 KRW)	124.82	190.21	211.27
	(191.39)	(232.04)	(243.94)
Department Store Spending (1,000 KRW)	33.41	46.56	48.28
	(345.50)	(424.86)	(428.65)
Medical Spending (1,000 KRW)	94.87	97.78	100.91
	(376.00)	(388.60)	(393.34)
Observations	670,929	134,110	52,620

Notes: Table provides summary statistics for the analysis sample in July 2021. Unless otherwise noted, means are reported with standard deviations in parentheses. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times in the month. Source: KCB, SKT, and Shinhan Card.

Figure 4: Other Apps as Predictors of Heavy Crypto Usage



Notes: Figure shows coefficients from a multivariate regression of an indicator for heavy crypto app usage on usage of other app categories. Usage of other apps is standardized by subtracting the mean and dividing by the standard deviation. The regression also includes controls for total data usage, sex, log income, log spending, age, and indicators for whether the individual lives alone, owns a house, has a job, has secured debt, and has unsecured debt. All variables are measured as of July 2021. Bars show 95% confidence intervals. Source: KCB and SKT.

analysis for stocks). We first estimate regressions of the form:

$$\Delta Y_{it} = \beta_1 \Delta P_t \times I^c_{it} + \beta_2 I^c_{it} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{3}$$

where ΔY_{it} is the change in individual i's daily spending[25] from month $t-1$ to t, and ΔP_t is the contemporaneous change in Bitcoin prices.[26] The indicator I^c_{it} denotes whether individual i is a crypto app user, a heavy user, or a "super heavy user" (uses crypto apps > 83 times per month, the 90th percentile among users), depending on the specification.[27] Individual fixed effects, α_i, absorb persistent differences in consumption trends across individuals (e.g., differences due to income growth, or underlying risk preferences), while

[25] We use KCB spending, which captures card spending across all institutions (not only Shinhan Card).

[26] We are implicitly using the price of Bitcoin as a proxy for cryptocurrency asset prices throughout our analysis. Our approach is similar to Aiello et al. (2023a) who assume that investors purchase a market-weighted portfolio of Bitcoin and Ethereum. While we do not observe the specific cryptocurrencies individuals hold in our data, survey data show that 76% of Korean crypto investors held Bitcoin (Korean Financial Consumer Protection Foundation, 2024), and the returns of the two next most commonly held cryptocurrencies—Ethereum and Ripple— as well as the value-weighted return of the entire crypto market co-move strongly with Bitcoin (Liu et al., 2022b). Lastly, mismeasurement of holdings would likely attenuate our estimated effects of price changes on outcomes toward zero.

[27] We also present results from intensive margin specifications where I^c_{it} is instead a continuous measure of the number of times individual i logs into a cryptocurrency app per day during month t.

time fixed effects, γ_t, absorb aggregate changes in consumption (e.g., due to seasonality).

Table 5: Changes in Consumption versus Changes in Cryptocurrency Prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crypto User		Heavy User		Super Heavy User		Crypto Usage per day	
$\Delta P_t \times I^c_{it}$	0.0266*	0.0271*	0.0507**	0.0520**	0.0662**	0.0655*	0.0233***	0.0227***
	(0.0138)	(0.0139)	(0.0209)	(0.0219)	(0.0324)	(0.0332)	(0.0062)	(0.0068)
I^c_{it}		0.3524***		0.5525***		0.2187		0.3031***
		(0.0784)		(0.1582)		(0.2585)		(0.0750)
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.006	0.006	0.006	0.006	0.006	0.0047	0.0472	0.0472
Observations	30,497,369	30,497,369	30,497,369	30,497,369	30,497,369	30,497,369	4,494,656	4,494,656

Notes: Table shows results from the regression in Equation 3. The dependent variable, ΔY_{it}, is the change in individual i's average daily consumption (thousand KRW) from month $t-1$ to t. The variable ΔP_t is the change in the average monthly Bitcoin price (million KRW). I^c_{it} is whether an individual is a crypto app user, as defined in each column label. Standard errors are clustered at the time level. *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses. Source: KCB and SKT.

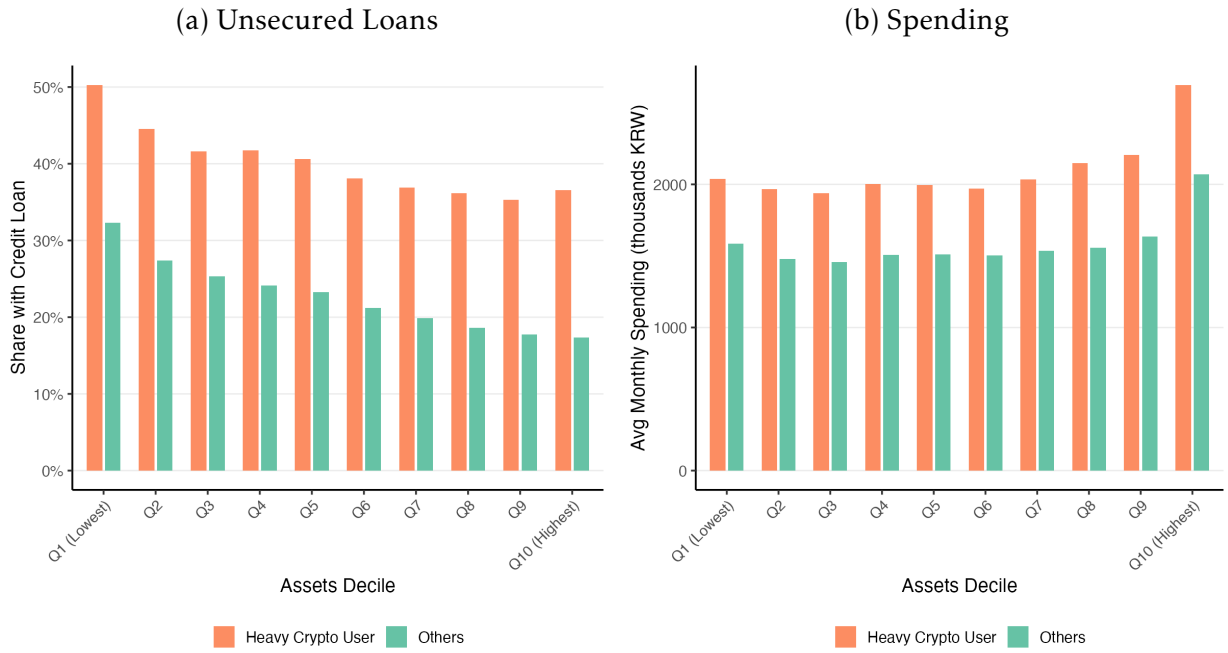
Table 5 shows that the spending of cryptocurrency app users responds differentially to changes in cryptocurrency prices. Our estimates imply that a doubling of Bitcoin prices (relative to the sample mean) corresponds to a 2.1 percent increase in daily spending among all crypto app users, 4.1 percent among heavy users, and 5.1 percent among super heavy users. [28] In Appendix D, we examine responses to Bitcoin price boom and bust episodes. A 2021 price boom is associated with a 6% increase in the likelihood of homeownership among heavy crypto app users. In contrast, a 2022 bust is associated with a 20% increase in delinquency (from a low baseline rate of 0.23 percent).

5.2 Testing Prediction 3: Gambling and Consumption

We next test the third prediction in Corollary 1: individuals who gamble toward aspirational goals "partially give up" on traditional saving and, conditional on wealth and goals, reallocate resources toward current consumption. Table 4 provides suggestive evidence consistent with this: while heavy crypto users have incomes that are roughly 30% higher, they spend around 50% more on food, luxury goods, and department stores.

[28] The response is stronger for those who use cryptocurrency apps more frequently is consistent with heavier users holding larger investments. Assuming a quarterly marginal propensity to consume out of crypto returns of 9.7% (as estimated for US households in Aiello et al., 2023a), this implies that on average crypto users, heavy users, and super heavy users, hold 1.4 million KRW ($980 USD), 2.7 million KRW ($1,900 USD), and 3.4 million KRW ($2,400 USD) in crypto, respectively. These estimates for heavy-users are somewhat lower than average crypto holdings in our linked-survey (Table C.1), which is consistent with attenuation (and skew in the distribution of holdings).

Figure 5: Crypto Heavy Users vs Others: Unsecured Debt and Spending by Assets



Notes: Figure shows the share of individuals with unsecured loans (Panel a) and average monthly spending (Panel b) by asset decile, separately for heavy crypto users and others. Net assets are in deciles. Spending is measured in thousands of KRW. All variables are measured as of July 2021. Source: KCB and SKT.

Figure 5 shows that, across the asset distribution, both unsecured debt and average spending are substantially higher for heavy crypto users. Panel (a) shows that heavy crypto users are more likely to carry unsecured debt at every asset level: in the fifth asset decile, 41% of heavy crypto users hold unsecured loans, compared to 23% of others. Panel (b) shows that heavy crypto users also spend more at every asset level; in the fifth asset decile, heavy users spend an average of 1,997 thousand KRW per month versus 1,510 thousand KRW for others. Appendix Figures G.6 and G.7 show these patterns hold across age groups. Appendix F shows they persist in multivariate regressions controlling for gender, age, income, and other individual characteristics.

Taken together, these results are consistent with Prediction 3. In the model, individuals who view their goals as attainable only through high-risk investment optimally reduce saving and shift toward current consumption, as saving and gambling act as substitutes. The higher spending and greater use of unsecured debt among crypto users, conditional on assets, are consistent with this mechanism. While these patterns could also reflect underlying preferences, for example if more risk-seeking individuals have a stronger preference for present consumption, the survey evidence linking goals to risk-taking suggests that goal-driven motives play an important role in shaping this behavior.

5.3 Testing Prediction 4: Desperation Shocks

We next turn to the fourth prediction in Corollary 1, which concerns how changes in economic circumstances affect demand for high-risk investment. The model predicts that negative shocks that move individuals farther from their financial goals should increase their demand for gambling, as conventional saving becomes less effective as a path to goal attainment. We therefore focus on shocks to employment and household finances that plausibly reduce the feasibility of achieving goals through traditional means. In ongoing work, we also study changes in housing affordability.

Unemployment Events: Design & Specification To examine changes in cryptocurrency interest around unemployment, we first restrict the sample to individuals who were employed during the pre-period (January–June 2021). In our sample, 474,227 individuals were continuously employed in the pre-period. Next, we test whether those who experienced unemployment in the next year (July 2021-June 2022) increased their cryptocurrency interest. Formally, our regression specification is:

$$\Delta Y_i = \beta_0 + \beta_{unemp} \cdot \text{BecameUnemployed}_{post,i} + \gamma \cdot W_{pre,i} + \epsilon_i. \tag{4}$$

$\Delta Y_i \equiv \overline{Y}_{post,i} - \overline{Y}_{pre,i}$ captures the change in individual i's cryptocurrency interest between the pre-period and the post-period. Across specifications, this can be indicators for crypto app use or heavy use, as well as changes in average monthly app usage. On the right-hand side, we include a vector of controls $W_{pre,i}$, including age, gender, spending, and income, as measured at the beginning of the pre-period. Our main coefficient of interest is β_{unemp}, which captures the difference in cryptocurrency engagement between individuals who experienced unemployment relative to not.

Table 6 shows the results of Equation 4. Columns (2) and (4) suggest that, with controls, becoming unemployed corresponds to a 1.7 and 0.86 percentage point increase in the probability of being a crypto user and heavy user, respectively, in the post-period (relative to the pre-period). This corresponds to approximately a 6% and 8% increase relative to the pre-period. Column (6) suggests that, on average, cryptocurrency app usage increases by 0.2 (6%) interactions per month.

Our results are not driven by a general increase in phone usage following unemployment. We can use SKT's granular measures of application usage across categories to test for similar effects in other types of apps, such as online forums and real estate apps. Figure 6 shows that, following unemployment, there is a marked rise in cryptocurrency application usage relative to other categories, a smaller increase in stock trading applica-

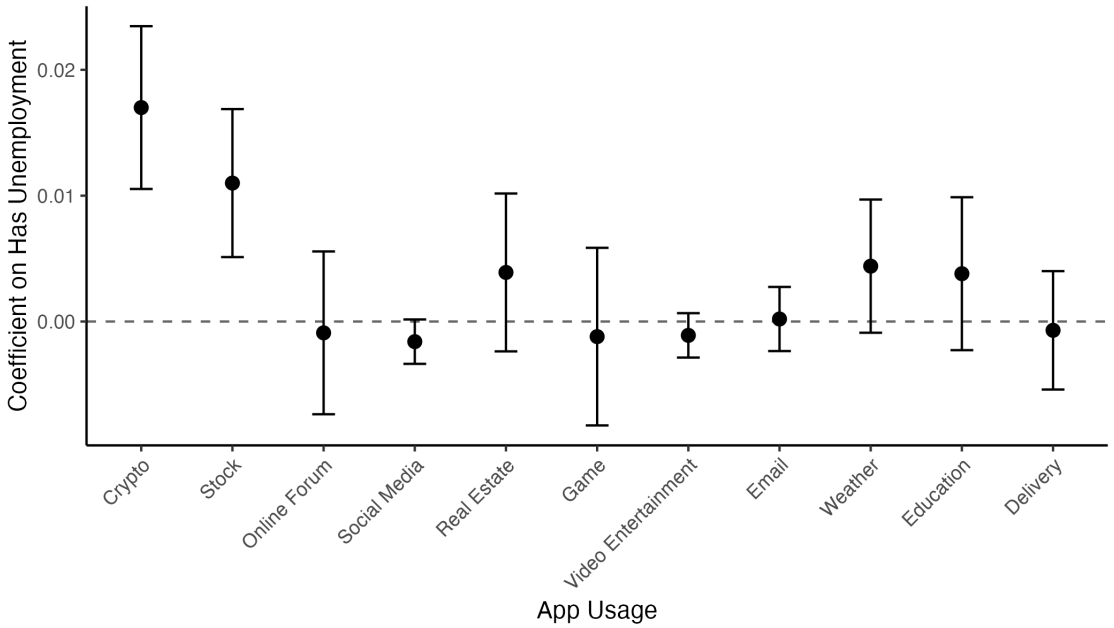
Table 6: Unemployment and Changes in Cryptocurrency Interest

	Δ Crypto Usage		Δ Crypto Heavy Usage		Δ Avg Crypto Usage	
	(1)	(2)	(3)	(4)	(5)	(6)
HasUnemploy	0.0202***	0.0170***	0.0117***	0.0086***	0.5979***	0.2052*
	(0.0032)	(0.0033)	(0.0019)	(0.0020)	(0.1070)	(0.1074)
All Controls		✓		✓		✓
R^2	0.0001	0.0024	0.0001	0.0054	0.0001	0.0388
Observations	474,227	450,990	474,227	450,990	474,227	450,990

Notes: Table shows results from Equation 4. The sample includes all individuals who were continuously employed in the pre-period (January-June 2021). The outcome in columns 1-2 is the difference in indicators (-1, 0, or 1) for whether individual i used a crypto app in any month in the pre- vs. post-period (July 2021-June 2022). The outcome in columns 3–4 is analogous but for "heavy usage", defined as using cryptocurrency apps more than 30 distinct times within the month. The outcome in columns 5-6 is the average monthly crypto usage. "All controls" are those in Figure F.1 (see Appendix F). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses.

tions, and no significant increase for the remaining categories. This is consistent with our hypothesis that unemployment episodes are uniquely tied to high-risk assets, relative to other applications.

Figure 6: Effects of Unemployment Experience by App Types



Notes: Figure shows coefficients from the regression in Equation 4. We report results from regressions analogous to column (2) in Table 6. Each coefficient corresponds to a separate regression using a different type of application usage as the outcome. Bars show 95% confidence intervals.

Crypto Interest around New Unsecured Loans We find similar patterns around episodes of increased unsecured borrowing. Using the same timing and design as the unemployment analysis, Appendix Table E.1 shows that individuals who take on new unsecured debt exhibit a subsequent rise in cryptocurrency usage, with a timing closely mirroring the response to unemployment shocks. These dynamics complement the consumption results in Section 5.2. While the earlier evidence shows that cryptocurrency users have higher consumption on average, the results here track within-individual changes, showing that cryptocurrency engagement increases following adverse financial events. This timing makes it less likely that the patterns are driven solely by fixed differences across individuals.

One interpretation is that these events reflect expense shocks or tightening financial constraints that push individuals further from their goals, increasing the appeal of high-risk investment. At the same time, these results should be interpreted with caution. Changes in unsecured borrowing are not exogenous and may reflect underlying differences in financial behavior or risk tolerance that are also correlated with cryptocurrency participation. We therefore view these findings as suggestive.

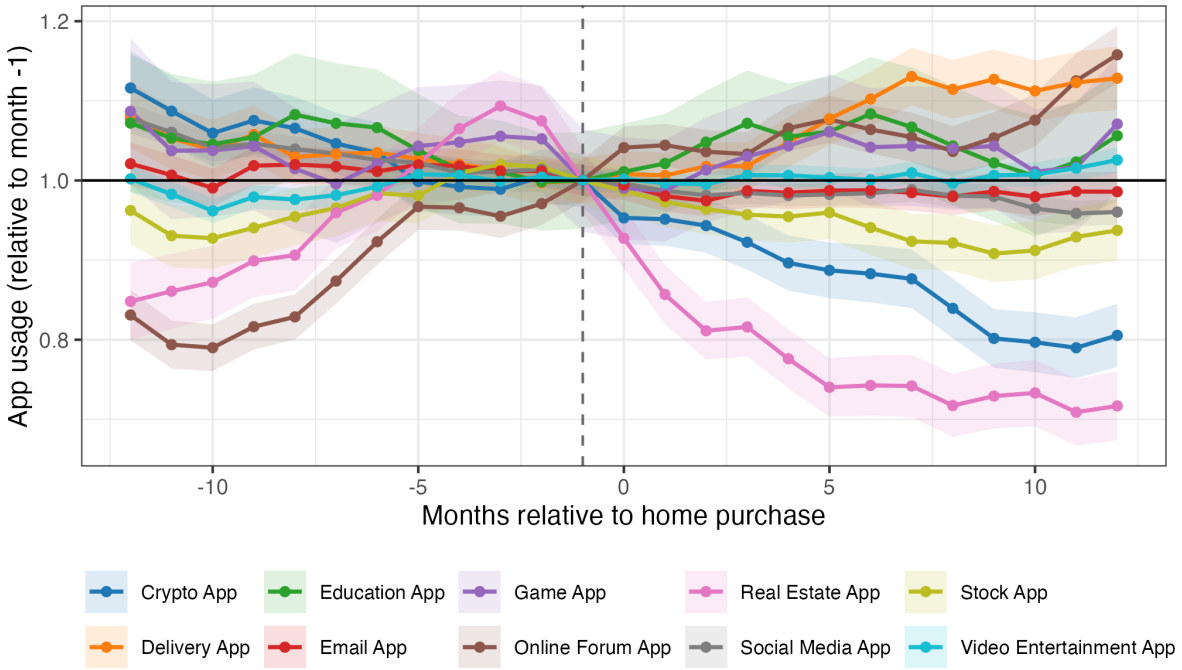
5.4 Testing Prediction 5: Goal Attainment

We next test Prediction 5: if individuals attain a salient financial goal, demand for high-risk investment should decline. We focus on homeownership, which is one of the most commonly cited goals in our survey and in related work. If cryptocurrency investment is used, at least in part, as a means of achieving such goals, then attaining homeownership should reduce its appeal. This prediction distinguishes our mechanism from other potential gambling motives. In particular, it isolates whether high-risk investment is used instrumentally, as a way of reaching a specific financial objective, rather than something that individuals enjoy on its own. Explanations based on intrinsic enjoyment, habit formation, or extrapolative beliefs do not naturally predict a discrete change in behavior tied to goal attainment.

Motivating Evidence Figure 7 plots mean app usage by category in the months surrounding a home purchase, normalized to usage in month −1. Consistent with our model's prediction, crypto app usage falls sharply around the time of purchase (by 20% one year later relative to one month before purchase), a larger decline than for any other app category except real estate. Other app categories show little systematic change, suggesting the drop is specific to high-risk investment rather than a general reduction in phone usage. Since home purchases are endogenous, these patterns are only suggestive:

they reflect both past financial outcomes and expectations about the future, which may also affect demand for high-risk investment.

Figure 7: App Usage Around a Home Purchase



Notes: Figure plots mean app usage by category in the months before and after a home purchase, normalized to usage in the month prior to purchase (month −1 = 1). The dashed vertical line marks month −1. Shaded bands show 95% confidence intervals. Source: KCB and SKT.

Quasi-Random Effects from Homeownership Lottery To address endogeneity concerns, we exploit quasi-random variation in home-ownership introduced by a popular housing lottery in South Korea (*cheongyak*), similar to Arkolakis et al. (2026). Many newly built apartments are offered in the lottery, and eligible households can apply for the right to purchase units prior to construction. To be eligible, applicants must be non-homeowners, satisfy income and asset thresholds, and contribute into a designated savings account. Within each apartment project, applicants are ranked by a priority score based on family composition, savings history, and age. When a project is oversubscribed, as is typical in the capital region, random lottery is implemented, which generates quasi-random assignment in winners. Winning the lottery grants the winner the right to purchase an apartment at a regulated pre-sale price that is often substantially below market value. Arkolakis et al. (2026) estimate that the median discount offered is approximately

20%, which translates to a discount of 160 million KRW ($120,000 USD).[29] As a result, lottery assignment induces a discrete change in distance to homeownership.

For each lottery winner, we define the event date as the announcement/contract date rather than the move-in date.[30] The contract date is the date by which the winner must decide whether to enter into a purchase agreement and initiate financing arrangements. The move-in date usually occurs two to three years after the contract date.

Sample Construction and Specification Since applicant rosters for the housing lottery are not publicly available, we use the sample construction developed in Arkolakis et al. (2026) to identify winners in our administrative data.[31] We identify 1,347 lottery winners who won during a 36 month period between January 2021 and December 2023. The key idea is to match lottery projects to geographic locations in the credit bureau data and identify households that first appear at these locations around the project's move-in date. We then impose additional filters that are as close as possible to institutional eligibility rules to identify winners. First, we require that no member of the household owned residential property prior to the application date, consistent with the lottery's non-homeownership requirement. Second, we require that at least one household member transitions into homeownership after the lottery announcement, ensuring that the household is a purchaser rather than a renter or secondary occupant. We also restrict our sample to oversubscribed projects to focus on lottery winners that were likely not able to buy a comparable house otherwise. We then compare winners with a control group constructed of not-yet-treated future winners.

Our differences-in-differences specification for lottery winner i and calendar time t is:

$$Y_{i,t} = \sum_{k} \beta_k \mathbb{I}(k = t - G_i) + \alpha_t + \delta_i + \epsilon_{i,t} \tag{5}$$

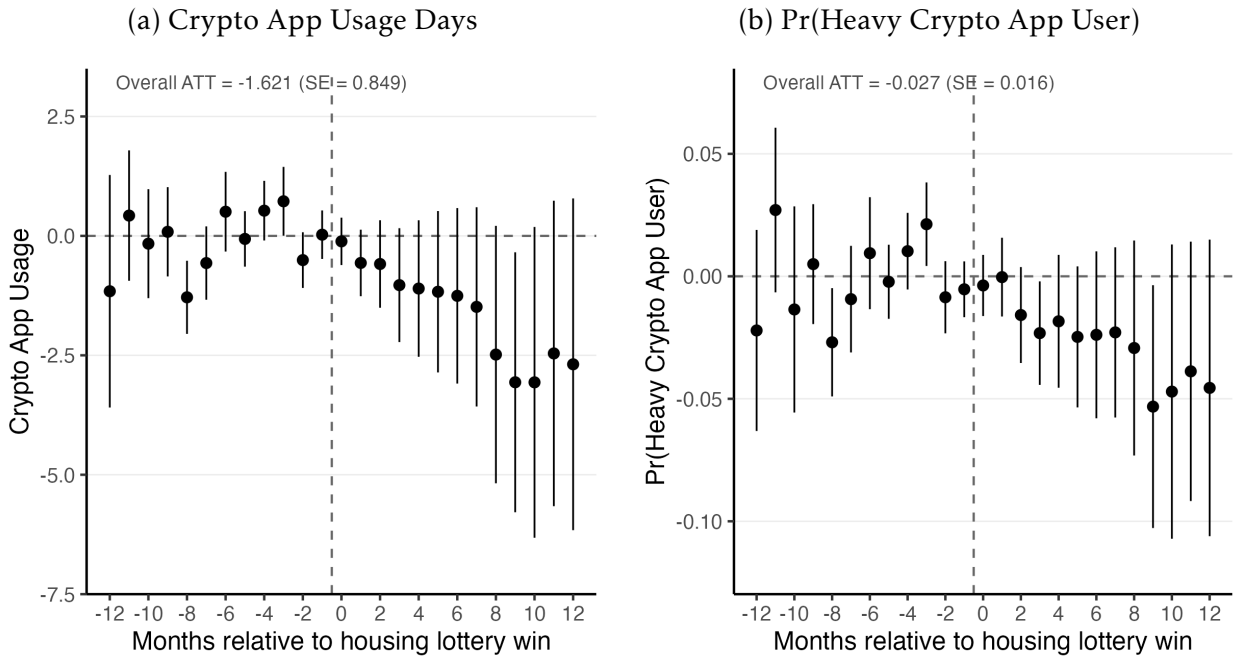
Where $Y_{i,t}$ will be an indicator for heavy crypto usage and the number times logged into a crypto app in month t. G_i is lottery winner i's announcement/contract date. α_t and δ_i are time and individual fixed effects respectively. Since our treatment is staggered, we estimate our effects using the method proposed in Callaway and Sant'Anna (2021). Prediction 5 implies that after winning individuals decrease their high-risk activity, so $\beta_k < 0$ for $k > 0$.

[29] While winners must finance the purchase (e.g., through mortgage borrowing) and are subject to strict resale and occupancy restrictions, this is still a sizeable implicit wealth transfer.

[30] The contract date is usually two weeks after the announcement date and our data has monthly granularity.

[31] Many thanks to Jaemin Woo and coauthors for sharing their data and institutional details.

Figure 8: Crypto App Usage Around a Housing Lottery Win



Notes: Figure plots difference-in-differences estimates of the effect of winning a housing lottery on cryptocurrency app usage, relative to the contract date. Panel (a) shows monthly crypto app usage days winsorized at the 95th percentile. Panel (b) shows the probability of being a heavy crypto app user. Vertical bars show 95% confidence intervals. The dashed line marks the contract date. Source: KCB and SKT.

Results Figure 8 shows that after the contract date, winners' crypto app usage decreases. Eight months later, winners are 3 percentage points less likely to be a heavy user and app usage declines by 2.5 interactions per month. Relative to usage in the month before the contract date, this represents a 25% and 31% decline in crypto heavy and app interactions respectively. While these magnitudes are large, they are also marginally significant. The standard errors are large, because of the small number of lottery winners we have in our sample (approximately 1,000). In ongoing work, we hope to identify more lottery winners by merging on more projects.

5.5 Alternative Explanations

While the evidence in Sections 4 and 5 is broadly consistent with Friedman-Savage motives, several features of the data also point to an important role for other mechanisms. Most clearly, beliefs matter (consistent with, for example Weber et al. (2023)). In the survey, cryptocurrency holders report substantially higher expected Bitcoin returns. The correlation between cryptocurrency interest and social media usage can also reflect social learning. Appendix Figure G.3 also shows that aggregate interest in cryptocurrency comoves strongly with bitcoin prices, consistent with extrapolative beliefs driving cryp-

tocurrency investments. At the same time, other results are harder to reconcile with a purely beliefs-based account. Expectations alone do not explain why participation is concentrated among households with salient financial goals, and how participation fluctuates with changes in individual financial circumstances, such as unemployment and homeownership, that are not directly related to cryptocurrency prices. In the next section, we further engage with the interaction between risk-seeking motives and overoptimism.

Intrinsic enjoyment and addiction also appear relevant for some parts of the data. These mechanisms can help explain why some individuals participate even when expected returns are poor, and why risky activity may be more common among individuals under economic stress. In particular, the increase in cryptocurrency usage following unemployment or increases in unsecured borrowing is compatible not only with gambling for goals, but also with forms of escapism or self-medication. Similarly, heavy engagement with social media and other highly immersive digital environments may be consistent with habit formation or complementary entertainment motives. However, these explanations also seem incomplete on their own. A simple entertainment motive predicts broad gambling participation, but in its most basic form it does not naturally explain why households substitute across instruments with different skewness. Likewise, an addiction-based account cannot readily explain why high-risk investment declines when a salient goal is achieved. More broadly, our results suggest that risk-taking in our data is not driven purely by hedonic motives.

Our interpretation, therefore, is not that alternative explanations are absent, but that they do not by themselves explain the full pattern of evidence. But the survey evidence on goals, the cross-sectional evidence on the choice of gamble, the rise in cryptocurrency engagement following negative shocks, and the decline after homeownership all point to an additional mechanism in which households use high-risk investment as a means of pursuing salient but difficult-to-attain goals. In this sense, Friedman–Savage motives appear to complement, rather than replace, the other forces emphasized in the literature.

6 Welfare Consequences of Gambling Motives

Our evidence in Section 5 suggests that endogenous risk-taking, in the spirit of Friedman and Savage (1948), plays a role in cryptocurrency investment. If one interprets these motives as genuine preferences, gambling optimizes expected utility ex ante. However, our survey evidence also shows that cryptocurrency investors are optimistic about returns. In this section, we examine how these two forces—risk-seeking and potential

overoptimism—interact. We show that genuine risk-taking preferences can *amplify* the negative consequences of belief distortions.

6.1 Welfare Consequences of Gambling and Optimism

Working example. To frame ideas, consider a Korean man in his mid-30s. Assume that his major financial goal is to buy a house, which necessitates a down payment of $200,000 USD. We assume homeownership results in a utility boost of $\theta = 1$, roughly a permanent 5% increase in consumption (for a log-utility agent). These parameters indicate that, in the absence of any investment opportunities, an agent with net worth greater than $W^* = \$316,395.3$ will buy a home; the others are priced out of the housing market.

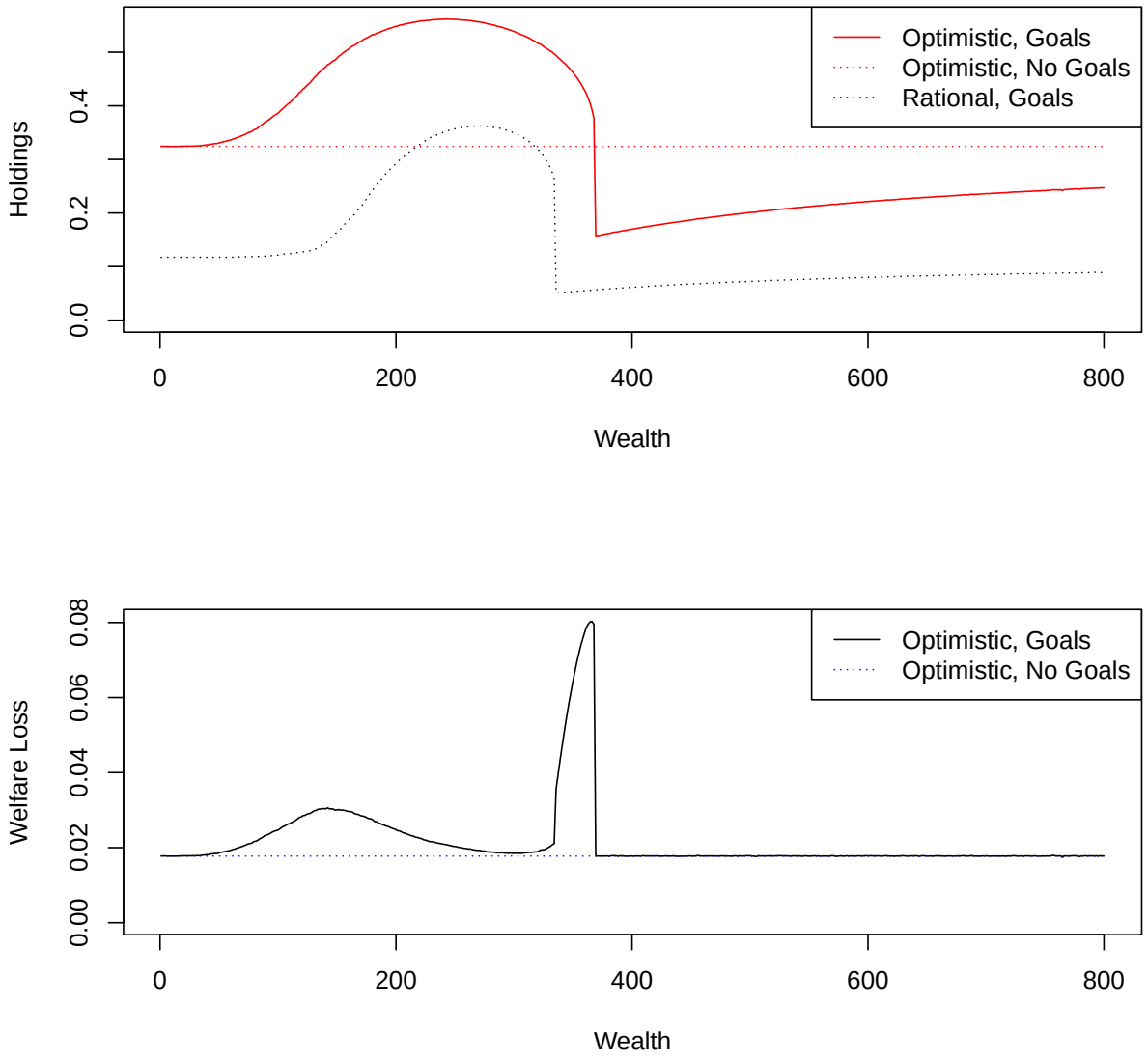
The agent has two investment opportunities: he can either invest in a riskless asset with return $r_f = 5\%$, or cryptocurrency, which the agent perceives to have expected returns $\mu = 40\%$ and volatility $\sigma = 100\%$. The agent chooses the share $\alpha \in [0,1]$ of net worth W to allocate to cryptocurrency to maximize subjective expected utility. While we have assumed previously that the agent held rational expectations about the return of cryptocurrency, now we assume that the true expected return of cryptocurrency is instead 20%—the agent was overoptimistic about the expected returns of the risky asset by 20%. We now trace out the welfare implications of such overoptimism.

Allocation to the high-risk asset. The top panel of Figure 9 plots the agent's optimal choice of crypto allocation, α^*, as a function of net worth. The dotted black line shows the optimal choice for an agent with "rational" beliefs, which, for simplicity, we take to mean that cryptocurrency has an expected excess return of zero; that is, the agent views it as a pure gamble.[32] Consistent with Proposition 1, an agent with "rational" beliefs and net worth around W^* will choose to gamble due to locally convex preferences.

The solid red line depicts the agent's choice when optimistic beliefs are added to goals, while the dotted black line plots the agent's allocation into the risky asset with rational beliefs. Optimism substantially increases overall crypto participation: the solid red line is always above the dotted black line. Importantly, optimism and gambling motives *together* create a powerful force for cryptocurrency participation. To illustrate this, the dotted red line plots the benchmark allocation for agents with the same optimistic beliefs but without gambling motives (i.e., those with log utility over wealth). Comparing the

[32] We do not take a stance on whether the true expected return of cryptocurrency is zero. Similar conclusions apply when the agent is excessively optimistic about cryptocurrency's expected returns relative to a rational benchmark.

Figure 9: Welfare losses from distorted beliefs



Notes: Figure shows the results of the simulations described in Section 6. The top panel plots the optimal allocation of wealth to the risky asset, α^*, as a function of net worth. The solid red line and the dotted red line show the allocations for optimistic agents with and without goal-driven gambling motives, respectively. The dotted black line shows the allocation for an agent with goal-driven gambling motives with rational expectations. The bottom panel plots the welfare losses relative to the corresponding "rational" agent.

filled and dotted red curves highlights that cryptocurrency participation is particularly elevated among two groups.

First, to the left of W^* are low net-worth agents who would not have gambled under rational beliefs. For them, the goal is so unattainable that taking on extreme risk would primarily expose them to the concave downside of utility rather than help them purchase a home. Optimism about cryptocurrency enables them to reach for goals, where they convince themselves that the upside of goal attainment outweighs the downside risk. Second, just to the right of W^* are agents with a higher net worth who also would not have gambled under rational beliefs. These agents would safely attain their goal at the cost of lower consumption rather than introduce additional risk. For this group, optimism about cryptocurrency may also allure them to take on risk.

It is worth noting two additional groups at the extremes. On the left, individuals very far from their goals with low net worth are less affected by the gambling incentive. Intuitively, these individuals do not believe the risky asset is enough to allow them to reach their goal. On the right, high net–worth individuals far above their goals invest *less* in cryptocurrency relative to agents without goals. Intuitively, these individuals fear that a loss in cryptocurrency could push their wealth below the goal threshold (which is not a concern for those in the dotted red line), and this potential discrete utility drop increases their effective risk aversion.

Welfare consequences. To highlight how gambling motives shape the welfare consequences of distorted beliefs, we define the following version of regret $\Delta U(W, \pi, \pi_0) = E_{\pi_0}[U(W|\pi_s = \pi_0)] - E_{\pi_0}[U(W|\pi_s = \pi)]$, where $E_{\pi_0}[U(W|\pi_s)]$ is the expected utility under the objective distribution π_0, of an agent who invests to optimize $U(W)$ with subjective beliefs $\pi_s = \pi$. By definition, $E_{\pi_0}[U(W|\pi_s)]$ is maximized when $\pi_s = \pi_0$: $\Delta U(W, \pi, \pi_0)$ captures the utility loss of holding distorted beliefs $\pi \neq \pi_0$.

The bottom panel of Figure 9 plots $\Delta U(W, \pi, \pi_0)$ across W. Optimistic beliefs for a log utility agent generates utility losses of around -0.02, or roughly 2% of net worth. Relative to this benchmark, aspirational motives substantially increase the utility loss for the aforementioned two groups of people. For the former (who should have viewed their goals as out of reach), overoptimism makes them reach for their goal, with the relative neglect of the downside risk creating a utility loss. For the latter (who should have played it safe after attaining their goal), overoptimism about cryptocurrency generates a substantial risk of them losing their goals, similarly creating a large utility loss. In either case, utility loss due to overoptimism about cryptocurrency is significantly higher, reaching up to 8% of their net worth.

Discussion: Welfare Implications of Belief Distortions Our results also speak to a broader literature on how belief distortions translate into economic behavior and welfare. A large body of work (Shiller et al., 1981; Barber and Odean, 2001; Baker and Wurgler, 2007; Greenwood and Shleifer, 2014; Bordalo et al., 2019) documents systematic belief distortions in financial markets, including extrapolation from recent returns, overconfidence, and other forms of animal spirits, which can generate substantial trading activity and price fluctuations. At the same time, some literature emphasizes that even sizable differences in beliefs often translate into relatively modest differences in actions (Giglio et al., 2021), where frictions such as adjustment costs or cognitive uncertainty may attenuate the impact of biased beliefs. Our results could help reconcile these perspectives: the impact of biased beliefs is shaped not only by the cognitive biases themselves, but also by the structure of opportunities faced by households. When individuals use risky assets to reach for salient financial goals, our model would predict they invest much more aggressively on their beliefs, with larger welfare losses due to belief distortions.

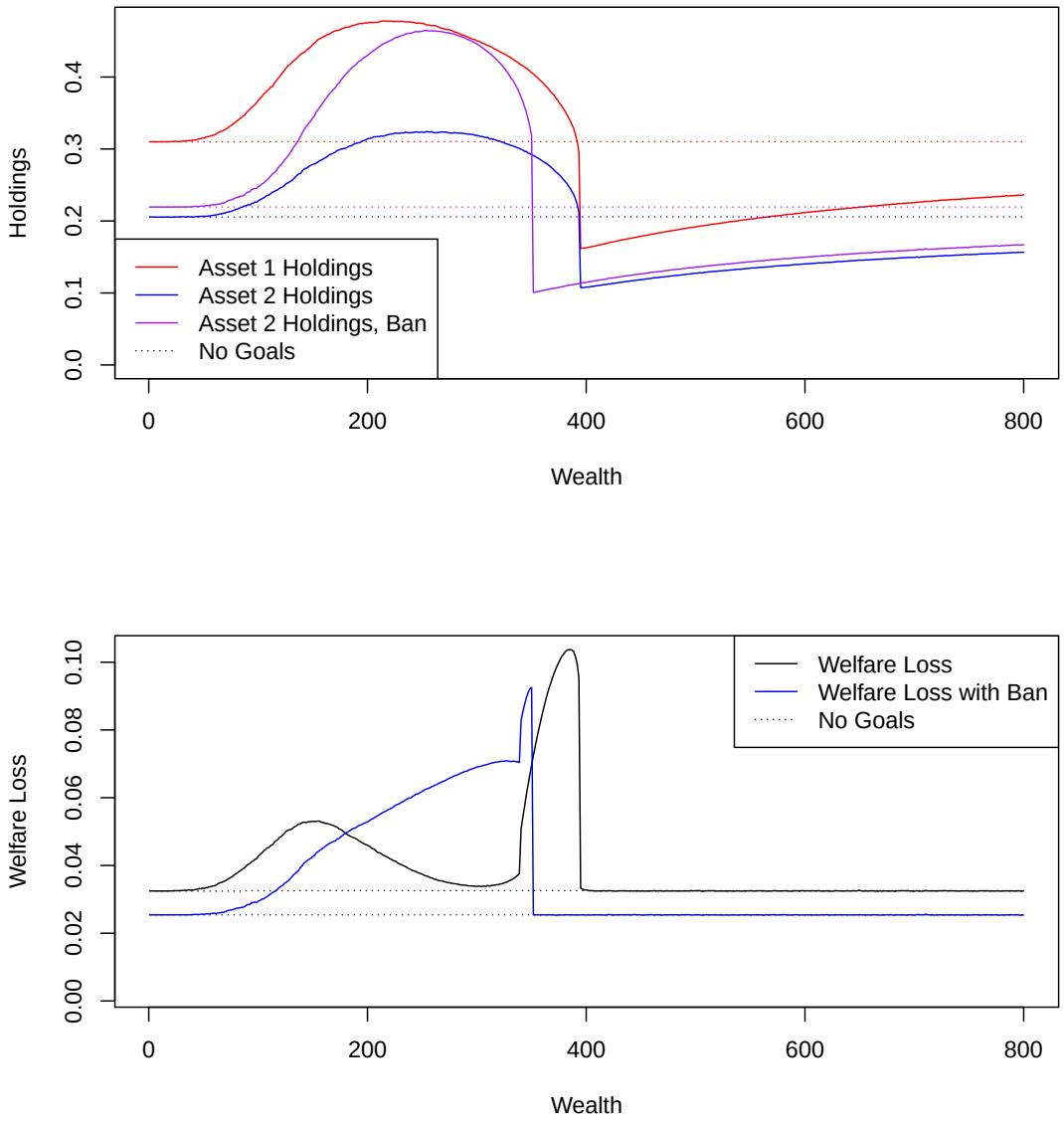
6.2 Regulation and Spillovers

The analysis above shows that gambling motives, when coupled with overoptimism, can generate substantial welfare losses. A natural response from policymakers could be to consider regulating speculative markets when they appear overheated, through disclosure requirements, advertising restrictions, investor protections, or even outright bans.[33] However, our model suggests that the welfare effects of regulation can be nuanced. If speculative demand reflects not only optimism about a specific asset, but also a broader demand for risk driven by hard-to-reach goals, restricting one market need not eliminate speculation—it may simply redirect it. When the underlying motive remains, limiting one form of risk-taking can lead to substitution into others (Kearney, 2005).

Cross-Asset Substitution To formalize this point, we extend the calibration above by introducing a second risky asset. The first asset can be thought of as cryptocurrency, while the second represents an alternative risky asset with the same volatility as the first but a lower subjective expected return of 30%. The top panel of Figure 10 plots asset holdings across the wealth distribution. In the baseline, agents with gambling motives allocate positive shares of wealth to both assets, but hold more of the first asset. We then consider a ban on holdings of the first asset. The purple line in the top panel shows that, following the ban, households partially substitute into the second asset, mostly among

[33] See Kim and Yang (2018).

Figure 10: Asset Spillover



Notes: Figure shows the results of the simulations described in Section 6. The top panel plots the optimal allocation of wealth to cryptocurrency, α^*, as a function of net worth. The solid black and blue lines show the allocations for optimistic agents with and without goal-driven gambling motives, respectively. The bottom panel plots the welfare losses relative to the corresponding "rational" agent.

intermediate-wealth households for whom gambling motives are most pronounced.

The welfare effects of the ban depend on the nature of the alternative asset. If agents are relatively well-calibrated about the alternative asset, the ban can improve welfare by redirecting risk-taking toward a less distorted asset.[34] On the other hand, if agents are similarly biased about the alternative asset—suppose that the agents are overoptimistic about the alternative asset's returns by the same amount (20%), the picture is less favorable. As shown in the second panel of Figure 10, welfare losses remain substantial and become concentrated among households that substitute most aggressively into the alternative asset. In this case, restricting one market may reduce activity locally while leaving the underlying welfare problem largely unchanged, or worse for certain populations. The second panel also highlights the necessity of risk-seeking motives: if one removes goal-driven gambling motives, the dotted horizontal lines show that the welfare losses (and the efficacy of the ban) are minimal.

This exercise is deliberately stylized, but highlights that the welfare consequences of regulating speculative markets depend critically on both belief distortions and substitution across assets. Policies that target a single market may have limited effects if they do not address the underlying demand for high-risk, lottery-like payoffs.

7 Conclusion

Why do households turn to highly risky, lottery-like financial assets? This paper argues that part of the answer lies not only in beliefs, preferences, or ease of access, but also in the growing distance between ordinary economic circumstances and salient life goals. When homeownership, family formation, retirement security, or upward mobility seem unattainable through conventional saving, high-risk investment can become attractive as a means of pursuing those goals. In that sense, speculative demand may be a symptom of a broader economic conditions: frustration with the set of feasible paths to a better life.

Our results suggest an alternative perspective on speculative behavior that complements the existing literature. Much of this literature emphasizes which assets attract retail investors and how belief distortions shape trading. We instead highlight how demand for risk depends on households' economic circumstances, in particular the interaction between financial goals and the feasibility of achieving them. This perspective also has broader implications for the welfare effects of distorted beliefs. In standard settings, optimism or extrapolation may have limited impact on behavior because households re-

[34] There are still minor welfare losses due to the fact that one has banned a potentially valuable means of pursuing goals.

main disciplined by risk and uncertainty. But when risky assets are viewed as a means of reaching salient goals, these same belief distortions can have much larger effects.

Our findings point toward several directions for future research. One is to better understand the formation of goals themselves: which goals become salient, how social comparison and local prices shape them, and why some households view them as fixed rather than adjustable. A second is to study substitution across speculative domains more broadly, including options, sports betting, prediction markets, and other high-skew activities. A third is to explore dynamics: whether repeated disappointment, addiction, or habit formation interact with goal-based gambling motives over time. If an increasing share of households come to view traditional milestones as out of reach, speculative behavior may become a recurring feature of modern household finance rather than an episodic anomaly. Understanding that possibility requires taking seriously not only how people think about returns, but also how they think about their economic objectives.

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A Theoretical Appendix

A.1 Proofs

Proof. Denote W as the net worth, and $I < W$ as the amount committed to the gamble. We start with the following first order condition for I:

$$\begin{aligned} &\max p_H \cdot u(W + (R_H - 1)I) + p_L u(W + (R_L - 1)I) + \epsilon \cdot V((R_H - 1)I, p) \\ &\quad \implies p_H(R_H - 1)u'(W_H) + p_L(R_L - 1)u'(W_L) + \epsilon(R_H - 1)V_1 = 0 \end{aligned} \tag{A.1}$$

By implicit function theorem, by taking the derivative of the above with respect to W, one obtains:

$$\begin{aligned} &p_H(R_H - 1)u''(W_H) \cdot \left(1 + (R_H - 1)\frac{\partial I}{\partial W}\right) + p_L(R_L - 1)u''(W_L) \cdot \left(1 + (R_L - 1)\frac{\partial I}{\partial W}\right) \\ &+ \epsilon(R_H - 1)^2 V_{11} \cdot \frac{\partial I}{\partial W} = 0 \\ &\implies -\left(p_H(R_H - 1)^2 u''(W_H) + p_L(R_L - 1)^2 u''(W_L) + \epsilon(R_H - 1)^2 V_{11}\right)\frac{\partial I}{\partial W} \\ &= (p_H(R_H - 1)u''(W_H) + p_L(R_L - 1)u''(W_L)) \end{aligned} \tag{A.2}$$

By concavity of u and V, we thus have that $\frac{\partial I}{\partial W}$ is proportional to:

$$p_H(R_H - 1)u''(W_H) + p_L(R_L - 1)u''(W_L) \equiv \alpha(u''(W_H) - u''(W_L)), \tag{A.3}$$

where we have by the risk neutral pricing that $p_H(R_H - 1) + p_L(R_L - 1) = p_H R_H + p_L R_L - 1 - 0$. □

Proof. Consider the following value functions:

$$V(W) = 2 \cdot u(W/2),\ V_G(W) = \max_c u(c) + p_H u(R_H(W - c)) + p_L \cdot \bar{u}. \tag{A.4}$$

First, note:

$$V_G(W) \geq \max_c u(c) + p_H u(R_H(W - c)) + p_L u(R_L(W - c)), \tag{A.5}$$

where above inequality can be easily seen due to the fact that u is concave, which automatically implies:

$$p_H u(R_H(W - c)) + p_L u(R_L(W - c)) \leq u(W - c). \tag{A.6}$$

Thus, an agent gambles if and only if $V_G(W) > V(W)$.

Next, by envelope theorem,

$$V'(W) - V'_G(W) = u'(W/2) - u'(c^*), \tag{A.7}$$

where c^* satisfies the FOC: $u'(c^*) = p_H R_H \cdot u'(R_H(W-c))$. Given that $p_H R_H < 1$, this naturally implies that $c^* > R_H(W-c^*) \implies c^* > \frac{1}{2}W$, which implies that $V(W) - V_G(W)$ is strictly increasing in W.

Putting the above two together, we have from the first fact that there exists W^* such that:

$$V_G(W) > V(W) \tag{A.8}$$

if and only if $W < W^*$, and that is the precise instance in which the agent decides to take on the gamble.

□

Proof. We compare three value functions in W that correspond to the value of the following set of options:

1. $V_{safe,0}(W)$: investing in the safe asset and not attaining the goal
2. $V_{safe,1}(W)$: investing in the safe asset and attaining the goal
3. $V_{Gamble}(W)$: investing in the risky asset and attaining the goal only when the risky asset pays off.

We focus our attention on W such that each three options are feasible. In particular, we need $W > H$ (for the second option to be viable). One can easily characterize the following expressions for each value function:

$$\begin{aligned} &V_{safe,0}(W) = 2 \cdot u(W/2),\ V_{safe,1}(W) = 2 \cdot u((W-H)/2) + \theta \\ &V_{Gamble}(W) = u(c^*) + p_L \cdot u(R_L \cdot (W-c^*)) + p_H \cdot u(R_H \cdot (W-c^*) - H) + p_H \cdot \theta, \end{aligned} \tag{A.9}$$

where c^* (the optimal first period consumption given gambling). By taking derivatives and applying the envelope theorem (and the Euler condition from the optimality of c^*), we obtain the following expressions for the derivatives:

$$\begin{aligned} &V'_{safe,0} = u'(W/2),\ V'_{safe,1} = u'((W-H)/2) \\ &V'_{Gamble} = p_L R_L \cdot u'(R_L(W-c^*)) + p_H R_H \cdot u'(R_H \cdot (W-c^*) - H) = u'(c^*) \end{aligned} \tag{A.10}$$

Thus, from the fact that u is concave (and hence u' is monotonically decreasing), suffices to show:

$$(W-H)/2 \leq c^* \leq W/2 \tag{A.11}$$

for the c^* that satisfies:

$$u'(c^*) = p_L R_L u'(R_L(W-c^*)) + p_H R_H \cdot u'(R_H(W-c^*)-H) \tag{A.12}$$

In particular, suffices to show the following set of inequalities:

$$\begin{aligned} u'(W/2) &< p_L R_L u'(R_L W/2) + p_H R_H u'(R_H W/2 - H) \\ u'((W-H)/2) &> p_L R_L u'(R_L(W+H)/2) + p_H R_H u'(R_H(W+H)/2 - H). \end{aligned} \tag{A.13}$$

From the fact that u' is a decreasing function, a sufficient condition for the above inequality is:

$$\begin{aligned} W/2 > R_H W/2 - H &\iff W < \frac{2}{R_H - 1} H \\ (W-H)/2 > R_L(W+H)/2 &\iff W < \frac{1+R_L}{1-R_L} H, \end{aligned} \tag{A.14}$$

which holds by assumption. Denote $\eta = \min\left\{\frac{2}{R_H-1}, \frac{1+R_L}{1-R_L}\right\}$.

Next, we compare the relative levels of these value functions. Note that we assume that $\lim_{c \mapsto 0} u'(c) = \infty$, we have that $V_{safe,0} > V_{safe,1}$ as $W \mapsto 0$. Furthermore, note that for θ sufficiently large, we have:

$$u(\eta H/2) - u((\eta-1)H/2) < \theta/2. \tag{A.15}$$

The above conditions imply that a) $V_{safe,0}$ and $V_{safe,1}$ satisfy a single-crossing condition, with there existing $W^* \in [0, \eta H]$ such that $V_{safe,0}(W) < V_{safe,1}(W)$ if and only if $W > W^*$. □

Next, what are the conditions for $V_{Gamble}(W^*)$ to be above $u(W^*/2) = u(W^*/2 - H/2) + \theta/2$?

Lemma 1. $V_{Gamble}(W^*) > V_{safe,0}(W^*) = V_{safe,1}(W^*)$

Proof. The general idea behind the proof is as follows. We hope to show that there exists a consumption level c such that

$$2 \cdot u(W^*/2) < u(c) + p_H\left(u(R_H(W-c)-H) + \theta\right) + p_L u(R_L(W-c)). \tag{A.16}$$

One can arrange the inequality to comparing two terms:

$$p_H \cdot \overbrace{[u(R_H(W-c)-H)+\theta-u(R_H(W-c))]}^{\text{Benefit of discrete choice}} > \overbrace{2u(W^*/2)-[u(c)+p_H \cdot u(R_H(W-c))+p_L \cdot u(R_L(W-c))]}^{\text{Gain from smoothing}}. \tag{A.17}$$

Furthermore, note that by assumption, we have $p_H \cdot R_H(W^*-c)+p_L \cdot R_L(W^*-c)+c=W^*$, so the right hand side is positive and reflects the utility gain from being able to smooth consumption across states. The idea behind the proof is that the right hand side is a higher order term / negligible as the gamble becomes more marginal ($R_H, R_L \mapsto 1$). First, note the left hand side can be bounded above 0 as long as the individual sufficiently cuts consumption: for $\eta > 0$, there exists $\gamma > 0$ such that:

$$u(R_H(W/2+\gamma H)-H)+(1-\eta)\theta >= u(R_H(W/2+\gamma H)), \tag{A.18}$$

where the proof follows from concavity of u and $R_H \cdot \gamma \leq 0.5$. This means that for $c \geq W^*/2-\gamma H$, the LHS is bounded below by $\eta \cdot \theta$. In contrast, one can show that the RHS is bounded above by:

$$u'(\min\{c, R_L(W^*-c)\}) \cdot |\max\{c, R_H(W^*-c)\}-\min\{c, R_L(W^*-c)\}|, \tag{A.19}$$

where for $c \in [W^*/2-\gamma H, W^*/2]$ is bounded above by $(R_H-R_L)\cdot 2 \cdot H$, which goes to 0 as $R_H, R_L \mapsto 1$ (while the other W^* does not change as it is solely based on H and u, as desired).

□

Finally, we want to show that for $W \mapsto \frac{2}{R_H-1}H$, we get the single crossing. Intuitively, as $W \mapsto \infty$, we obtain: $u(W/2-H) \approx u(W/2)$ (H becomes negligible relative to total wealth, and the difference is bounded by $H \cdot u'(W/2-H)$ which goes to 0). In particular, this immediately implies:

$$V_{safe,1} = 2u((W-H)/2)+\theta, \tag{A.20}$$

while $V_{Gamble} \approx 2 \cdot u(W/2)+p_H \cdot \theta < V_{safe,1}$, as desired.

A.2 Optimal Gamble

As before, consider the preferences are $U = u(c_1) + u(c_2) + \theta \cdot g$, where $u(\cdot)$ is strictly increasing, strictly concave, and continuously differentiable, and $g \in \{0,1\}$ denotes the purchase of an indivisible good delivering utility $\theta > 0$. The indivisible good costs $G > 0$ units of consumption, and the agent begins with wealth W. In period 1, the agent chooses consumption c_1 and savings $s = W - c_1$. Now, in period 2, the agent allocates savings into a fair gamble over terminal wealth (x_H, x_L) with probabilities $(p, 1-p)$ satisfying $p \cdot x_H + (1-p) \cdot x_L = s$. After the realization of the gamble, the agent chooses whether to purchase the indivisible good or not.

Define the indirect value function $V(x) = \max\{u(x), u(x-G)+\theta\}$. The agent optimizes

$$\max_{c_1, p, x_H, x_L} \quad u(c_1) + pV(x_H) + (1-p)V(x_L),$$

subject to

$$c_1 + s = W, \qquad px_H + (1-p)x_L = s.$$

We first focus on the interior region in which the indivisible good is purchased only in the high state.

Solving the model In the region where the good is purchased only in the high state, the second-period problem reduces to:

$$\max_{p, x_H, x_L} \quad p\Big(u(x_H - G) + \theta\Big) + (1-p)u(x_L),, \text{ subject to } px_H + (1-p)x_L = s.$$

Optimizing the Lagrangian $\mathcal{L} = p(u(x_H - G) + \theta) + (1-p)u(x_L) + \lambda\Big(s - px_H - (1-p)x_L\Big)$. implies: $x_H - G = x_L$: Intuitively, the agent is equalizing the marginal utility of standard consumption across the two scenarios. Optimizing the Lagrangian with respect to p then yields (if $p \in (0,1)$)

$$c^* \equiv x_H - G = x_L = (u')^{-1}\left(\frac{\theta}{G}\right) \tag{A.21}$$

Given that $p(c^* + G) + (1-p)c^* = s$, we thus obtain: $p^* = \frac{s - c^*}{G}$, and we have a nice characterization of the second period utility of savings, given by:

$$J(s) = u(c^*) + \frac{\theta}{G}(s - c^*). \tag{A.22}$$

This implies that in the interior crossing region, the continuation value is affine in savings. That simplifies the analysis quite significantly. The period-1 problem thus reduces to the

following FOC: $u'(c_1) = \frac{\theta}{G}$, which implies

$$c_1 = c^* = (u')^{-1}\left(\frac{\theta}{G}\right). \tag{A.23}$$

In other words, in the interior solution case, consumption is equalized across period 1, the low state of period 2, and the high state of period 2 after paying for the indivisible good, and this consumption level is briefly pinned down by $(u')^{-1}\left(\frac{\theta}{G}\right)$, which is *fixed* as we vary W. In the interior gambling region, additional marginal wealth is translated into higher savings, which generate a higher probability of attaining the goal: $p_H^* = \frac{W-2c^*}{G}$. For this solution to be interior, we thus need:

$$2c^* < W < 2c^* + G.$$

One can easily show the converse: if the above constraints are satisfied, due to the concavity of the objective function, the individual indeed gambles (and attains the goal if and only if the lottery pays off), with c_1, x_H, and x_L as described above.

The optimal return and probability of each outcome in the interior region is then the following. In the intermediate wealth region $2c^* \leq W \leq 2c^* + G$, the corresponding returns and probability are:

$$r_H^*(W) = \frac{c^* + G}{W - c^*},\ r_L^*(W) = \frac{c^*}{W - c^*},\ p^*(W) = \frac{W - 2c^*}{G}.$$

This implies the following comparative statics of the optimal lottery as one varies wealth: the probability of winning (and hence attaining the goal) increases monotonically in wealth (p^*). As W decreases, the lottery becomes increasingly right-skewed: the returns r_H^* increases while the probability of winning p^* decreases (while the expected value is fixed at 1).

A.3 Formalization of Alternative Explanations for Gambling

Entertainment To formalize the idea that gambling can generate intrinsic utility, we draw from Conlisk (1993). Consider an agent with wealth W, of which she can spend $I < W$ on gambling. Her utility is given by:

$$U(W, I) \equiv p_H \cdot u(W + (R_H - 1)I) + p_L \cdot u(W + (R_L - 1)I) + \epsilon V((R_H - 1)I, p). \tag{A.24}$$

In other words, an agent's utility from gambling is given by her expected utility over wealth, along with direct utility from gambling. Following Conlisk (1993), $\epsilon V(G, p)$ is how much an agent enjoys the prospect of winning G with probability p (with the alternative of losing $G \cdot \frac{p}{1-p}$ with probability $1 - p$), where V is increasing and concave in G. The following proposition characterizes the agent's choice of gambling.

Proposition 4. *The agent's optimal choice of gambling $I^*(W)$ is positive for all agents. Assuming decreasing relative risk aversion, $I^*(W)$ is increasing in W.*

Desperation To formalize desperation, we modify a standard concave utility function $u(c)$ into $v(c) = \max\{u(c), \bar{u}\}$, where $\bar{u}$ represents some reserve level of utility that agents can get from effectively 0 private consumption. The agent optimizes over c and R_2, $u(c_1) + E[v(c_2)]$, where $R_2 \cdot (W - c_1) = c_2$. For simplicity, we assume for the agent that $\bar{u}$ is sufficiently low – $2u(W/2) > u(W) + \bar{u}$: or else, the agent (even in the absence of gambling) will choose to consume fully today and rely on the reserve. In that case, the following proposition characterizes gambling motives driven by desperation.

Proposition 5. *There exists a $W_D^* \geq 0$, such that the agent prefers to gamble iff $W < W_D^*$. For $W \approx W_D^*$, agents who choose to gamble consume more now than agents who choose not to.*

A.4 Microfoundation for discrete goals

Formally, we use a simplified version of the model in (Bordalo et al., 2025; Conlon and Kwon, 2025). Suppose true utility boost from spending G_c on housing is linear and given by:

$$u = \theta \cdot G_c + \epsilon.$$

This implies that under rationality, Proposition 3 implies that individuals do not gamble. Now, suppose that the agent instead estimates the expected utility of investing G_c towards a goal by sampling the utility outcomes of similar levels of investment. Formally, let:

$$\pi_s(g'|g) \sim \pi(g') \cdot S(g', g), \tag{A.25}$$

with the agent estimating the expected returns of goal intensity g with:

$$\int \pi_s(g'|g) \cdot E[u|g']dg'. \tag{A.26}$$

To capture categorical judgment, we draw on the model of (Bordalo et al., 2025), where one introduces categorical judgments as an additional feature $F_G = I(G_c > G^*)$ (e.g. being "successful") that further influences similarity judgment. The key is that this irrelevant feature (irrelevant in the sense that this feature does not independently influence expected utility) still matters for sampling.

Formally, we let:

$$S(g, g') = \exp(-\frac{\kappa}{2}(g - g')^2) \cdot \delta^{F_g \neq F'_g},$$

where the first component captures the regular distance function, and the second component captures the categorical judgment: the agent judges two levels of goal consumption in different categories to be discretely less similar. Intuitively, whenever an agent thinks of people "buying" the house, the utility she samples are closer to people buying nicer houses: similarly, people not buying are discretely more similar to lower levels of goal achievement.

B Grandata Details

As described in Section 3, our study uses Grandata, a data collaboration among Korea Credit Bureau (KCB), SK Telecom(SKT), and Shinhan Card. That data are an anonymized individual-level panel. We construct our primary analysis sample following the steps described in Section 3. In contrast to the KCB data, the SKT and Shinhan Card datasets include no records for periods in which individuals are inactive. As a result, the number of individuals available varies across periods. We show the coverage by month in Appendix Table B.1. Over the entire 2021–2023 period, we obtain a balanced panel of 987,571 individuals jointly observed in KCB, SKT, and Shinhan Card data.

Table B.1: Monthly number of individuals by year

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2021	1,018,122	1,026,049	1,048,487	1,055,416	1,061,864	1,076,184	1,082,803	1,089,944	1,105,681	1,113,281	1,120,438	1,133,991
2022	1,125,738	1,132,377	1,147,399	1,153,893	1,160,173	1,172,868	1,179,733	1,186,481	1,198,135	1,204,673	1,210,457	1,221,495
2023	1,227,571	1,234,815	1,249,315	1,258,192	1,267,251	1,281,541	1,291,342	1,301,675	1,345,892	1,355,960	1,365,075	1,364,415

Notes: Table shows the number of observations by month in the final restricted KCB + SKT + Shinhan sample. In total, there are 1,427,629 individuals in the sample.

The remainder of this Appendix provides additional details on variables in our final sample from each of the three datasets (KCB, SKT, and Shinhan Card). For each data source, we include summary statistics and descriptions of the variables in our sample. We denote raw variables in capital letters and derived variables in lowercase letters. We also provide additional information on some variables to clarify their sources.

B.1 Additional Details on KCB Variables

- Estimated annual income (ICM)
  - Income is estimated based on loan contract details and card usage amounts.
  - If an individual has recently borrowed money from financial institutions, KCB can directly observe their accurate income, as it regularly receives updates on individuals' financial conditions from these institutions.
  - If no recent loan is observed, KCB estimates income based on available information, such as card usage amounts and historical loan contracts.
  - Specific details of the estimation method are confidential.
- Net Assets (NET_ASST)

  - Net assets valuations capture total real estate asset value less liabilities.
  - The variable is constructed using the following information: place of residence, average market price of the owned property (house/apartment, excluding buildings and multi-tenant buildings), family relationships recorded on the resident's registration (e.g., spouse), and outstanding loans.

- Employment (has_job)
  - To identify unemployment, we use the KCB occupation category variable (JB_TP). According to correspondence with the data provider, JB_TP is updated when new financial transaction records (e.g., loan applications) are generated.
  - These updates usually incorporate information such as employment status and company address provided during financial transactions. There is some variation depending on the individual's direct income reporting (as described above).

- Spending (CD_USE_AMT)
  - Includes card spending of all types (credit and check) across all card companies, rounded to ten thousand KRW units.
  - In places where we report log spending, we use log(1+spending).

Table B.2: Summary Statistics - KCB Variables

Variable	N	Mean	Std. Dev.	Pctl. 25	Pctl. 50	Pctl. 75
NET_ASST	40,983,039	314,872.129	342,105.120	111,820.000	215,710.000	385,440.000
ICM	41,400,274	38,682.509	21,705.366	26,000.000	33,700.000	44,000.000
CD_USE_AMT	42,568,726	1,676.149	2,367.126	430.000	1,080.000	2,140.000
K_SCORE	42,568,726	850.169	193.387	794.000	920.000	962.000
LN_BAL	42,568,726	30,359.439	83,013.656	0.000	0.000	15,750.000
HOUS_LN_BAL	42,568,726	14,705.518	58,004.149	0.000	0.000	0.000
CRDT_LN_BAL	42,568,726	7,002.048	23,107.629	0.000	0.000	0.000
CAR_LN_BAL	42,568,726	958.294	5,901.043	0.000	0.000	0.000
LN_BAL_CD	42,568,726	615.039	3,538.555	0.000	0.000	0.000
LN_BAL_CAP	42,568,726	1,300.242	8,249.159	0.000	0.000	0.000
LN_BAL_INS	42,568,726	1,273.954	15,876.309	0.000	0.000	0.000
LN_BAL_SAV	42,568,726	619.840	5,768.815	0.000	0.000	0.000
DLQ_CNT	42,568,726	0.004	0.113	0.000	0.000	0.000
OWN_HOUS_CNT	42,568,726	0.404	0.749	0.000	0.000	1.000
has_job	42,568,726	0.641	0.480	0.000	1.000	1.000
has_house	42,568,726	0.337	0.473	0.000	0.000	1.000
has_loan	42,568,726	0.301	0.459	0.000	0.000	1.000
has_second_loan	42,568,726	0.137	0.344	0.000	0.000	0.000
any_delinquencies	42,568,726	0.002	0.044	0.000	0.000	0.000

Notes: Table shows summaries of KCB variables across all consumer-months in our final sample. Variables in capital letters are directly from the original dataset; those in lowercase letters are derived.

Table B.3: Variable Descriptions - KCB Variables

Variable	Description
SEX	Gender Indicator, which is equal to 1 if male, 0 if female.
AGE	Age category in 5-year intervals from 20 to 70+. The 20 group may include individuals under 20.
JB_TP	Occupation category: Large company employee, Small company employee, Certified Professional employee, Owner or CEO, Small Business Owner (hereafter, SBO), Certified Professional SBO, Unemployed or other
HOME_ ZIP	Residential postal code
NET_ASST	Net real asset evaluation amount (1 K. KRW)
ICM	Estimated annual income (1 K. KRW)
CD_USE_AMT	Aggregated monthly card spending across all card companies (1 K. KRW)
K_SCORE	Credit score
LN_BAL	Total Loan balance (1 K. KRW)
HOUS_LN_BAL	Mortgage loan balance (1 K. KRW)
CRDT_LN_BAL	Credit loan balance (Loan without collateral) (1 K. KRW)
CAR_LN_BAL	Car loan balance (1 K. KRW)
LN_BAL_CD	Card loan balance (1 K. KRW)
LN_BAL_CAP	Capital loan balance (1 K. KRW)
LN_BAL_INS	Insurance loan balance (1 K. KRW)
LN_BAL_SAV	Savings Bank loan balance (1 K. KRW)
DLQ_CNT	Number of total overdue
OWN_HOUS_CNT	Number of House Ownership
has_job	Employment dummy; defined based on whether Occupation category(JB_TP) is Unemployment or other.
has_house	House Ownership dummy; defined based on whether Number of House Ownership (OWN_HOUS_CNT) is at least 1.
has_loan	Loan usage dummy; defined based on whether at least one of mortgage loan balance (HOUS_LN_BAL), car loan balance (CAR_LN_BAL), credit loan balance (CRDT_LN_BAL) is positive.
has_second_loan	Second-tier loan(Non-bank Depository Institution loan) usage dummy; defined based on whether at least one of Card loan balance (LN_BAL_CD), Capital loan balance (LN_BAL_CAP), Insurance loan balance (LN_BAL_INS), or Savings Bank loan balance (LN_BAL_SAV) is positive.
any_delinquencies	Delinquency indicator; defined based on whether Number of total overdue (DLQ_CNT) is positive.

Notes: Table describes KCB variables in our final sample. Variables in capital letters are directly from the original dataset; those in lowercase letters are derived.

B.2 Additional Details on SKT Variables

- App (including websites) usage days (*_*_DAY)
  - SKT records a usage event when an individual opens an mobile application or website at least once.
  - Some N/A values occur when the individual did not consent to SKT marketing, in which case all app-usage variables are missing. In December 2023, 74% of individuals in the SKT sample had provided marketing consent.

Table B.4: Summary Statistics - SKT Variables

Variable	N	Mean	Std. Dev.	Pctl. 25	Pctl. 50	Pctl. 75
uses_crypto_app	31,547,276	0.152	0.359	0.000	0.000	0.000
uses_crypto_app_heavy	31,547,276	0.051	0.219	0.000	0.000	0.000
uses_crypto_app_super_heavy	31,547,276	0.015	0.123	0.000	0.000	0.000
uses_crypto_app_day	4,785,292	28.887	35.669	3.000	13.000	43.000
uses_stock_app	31,547,276	0.414	0.492	0.000	0.000	1.000
uses_stock_app_day	13,047,896	20.206	24.569	3.000	11.000	27.000
uses_game_app	31,547,276	0.207	0.405	0.000	0.000	0.000
uses_game_app_day	6,525,973	13.504	19.117	1.000	4.000	18.000
uses_comm_app	31,547,276	0.647	0.478	0.000	1.000	1.000
uses_comm_app_day	20,421,159	17.590	20.765	3.000	10.000	25.000
uses_news_app	31,547,276	0.600	0.490	0.000	1.000	1.000
uses_news_app_day	18,936,450	17.841	25.921	2.000	7.000	22.000
uses_edu_app	31,547,276	0.350	0.477	0.000	0.000	1.000
uses_edu_app_day	11,041,541	6.187	10.085	1.000	2.000	6.000
skt_delinquencies	42,568,726	0.058	0.233	0.000	0.000	0.000
skt_marketing_status	42,568,726	0.741	0.438	0.000	1.000	1.000

Notes: Table shows summaries of SKT variables across all consumer-months in our final sample. Variables in capital letters are directly from the original dataset; those in lowercase letters are derived.

Table B.5: Variable Descriptions - SKT Variables

Variable	Description
uses_crypto_app	Crypto app (including website) usage dummy; calculated using the Number of Coin app usage days (FIN_COIN_DAY) and defined only for those who consented to SKT marketing.
uses_crypto_app_heavy	Dummy variable for using the Crypto app (including website) at least 30 days in a month; defined same as the uses_crypto_app.
uses_crypto_app_super_heavy	Dummy variable for using the Crypto app (including website) at least 83 days (Overall Pctl. 90) in a month; defined same as the uses_crypto_app.
uses_crypto_app_day	Number of Crypto app (including website) usage; calculated using the same variable as uses_crypto_app and defined only for users.
uses_stock_app	Stock app (including website) usage dummy; calculated using the Number of Stock app usage days (FIN_STOCK_DAY) and defined only for those who consented to SKT marketing.
uses_stock_app_day	Number of Stock app (including website) usage; calculated using the same variable as uses_stock_app and defined only for users.
uses_game_app	Game app (including website) usage dummy; calculated using the Number of various Game app usage days (GAME_ROLE_DAY, GAME_RYTHME_DAY, GAME_BOARD_DAY, GAME_SIMUL_DAY, GAME_ARCADE_DAY) and defined only for those who consented to SKT marketing and defined only for those who consented to SKT marketing.
uses_game_app_day	Number of Game app (including website) usage; calculated using the same variable as uses_game_app and defined only for users.
uses_comm_app	Online forum app (including website) usage dummy; defined only for those who consented to SKT marketing.
uses_comm_app_day	Number of online forum app (including website) usage; calculated using the same variable as uses_comm_app and defined only for users.
uses_news_app	News app (including website) usage dummy; calculated using the Number of online forum app usage days (INFO_NEWS_DAY) and defined only for those who consented to SKT marketing.
uses_news_app_day	Number of News app (including website) usage; calculated using the same variable as uses_news_app and defined only for users.
uses_edu_app	Education app (including website) usage dummy; calculated using the Number of Miscellaneous Educational app usage days (EDU_ETC_DAY) and defined only for those who consented to SKT marketing.
uses_edu_app_day	Number of Education app (including website) usage; calculated using the same variable as uses_edu_app and defined only for users.
skt_delinquencies	SKT payment delinquency indicator; defined based on whether the Number of SKT payment overdue (BF_OVERDUE_CNT) is positive.
skt_marketing_status	SKT marketing consent indicator; defined based on whether the individual had no usage among 26 app categories.

Notes: Table describes SKT variables in our final sample. Variables in capital letters are directly from the original dataset; those in lowercase letters are derived.

B.3 Additional Details on Shinhan Card Variables

- Shinhan Card consumption categories
  - There are 19 major categories based on industry classification. There is no overlap in spending across these categories.
  - There are 8 additional special-purpose categories based on Shinhan's internal classification: oversea travel, premium hotel, Jeju travel, convenience store, delivery app, EV charging, Tesla charging, Starbucks. There is no overlap in spending across these categories. We currently do not use these categories.

Table B.6: Summary Statistics - Shinhan Card Variables

Variable	N	Mean	Std. Dev.	Pctl. 25	Pctl. 50	Pctl. 75
SHC_BUY_LUX_TF	42,568,726	0.014	0.117	0.000	0.000	0.000
shinhan_total_day	42,568,726	39.568	63.476	9.290	24.714	50.600
luxury_consumption_day	42,568,726	3.712	15.618	0.000	0.161	2.323
necessary_consumption_day	42,568,726	11.163	17.792	1.367	6.032	14.097
shc_med_amt_day	42,568,726	3.312	12.764	0.000	0.129	1.867
shc_food_amt_day	42,568,726	5.354	7.699	0.161	2.567	7.400

Notes: Table shows summaries of Shinhan Card variables across all consumer-months in our final sample. Variables in capital letters are directly from the original dataset; those in lowercase letters are derived.

Table B.7: Variable Descriptions - Shinhan Card Variables

Variable	**Description**
SHC_BUY_LUX_TF	Luxury Purchase dummy (Model-based estimate)
shinhan_total_day	Daily Shinhan card consumption (KRW); calculated based on All 19 major category consumption variables.
luxury_consumption_day	Daily Shinhan card luxury consumption (KRW) ; calculated based on 6 Luxury consumption category consumption variables - Nightlife (SHC_ENT_AMT), Luxury hotel (SHC_HOTEL_AMT), Beauty (SHC_BEAUTY_AMT), Sports&Culture&Leisure (SHC_CUL_AMT), Travel (SHC_TRAVEL_AMT).
necessary_consumption_day	Daily Shinhan card necessary consumption (KRW) ; calculated based on 5 Necessary consumption category consumption variables - Large discount store (SHC_MART_AMT), Small retail shop (SHC_SSM_AMT), Medical (SHC_MED_AMT), Transportation (SHC_TRANS_AMT), Clothing (SHC_CLOTHES_AMT).
shc_med_amt_day	Daily Shinhan card medical consumption (KRW); calculated based on Medical category consumption variable (SHC_MED_AMT).
shc_food_amt_day	Daily Shinhan card restaurant consumption (KRW); calculated based on Restaurant category consumption variable (SHC_FOOD_AMT).

Notes: Table describes Shinhan Card variables in our final sample. Variables in capital letters are directly from the original dataset; those in lowercase letters are derived.

C Additional Survey Details and Results

This Appendix provides more detailed information about the linked survey we conducted with SKT in March 2026.

C.1 Additional Variable Definitions

- "Expected Bitcoin (Stock) Returns" is what respondents think a 1 million KRW investment in Bitcoin (the Korean stock market—KOSPI index fund) will be worth in 1 year. We also elicited 5 year expectations. The units are in returns: for example, 1 implies a doubling of the initial investment.

- "Risk Seeking" is an indicator for whether a respondent prefers any option other than a 100% change of a 5% increase in wealth, holding the downside fixed at zero and expected value the same. First, participants were told to provide us with a best guess of their total assets (multiple choice). Then, we took the midpoint of each asset group, and asked participants choose between five options:

  1. 100% chance of being 5% richer
  2. 50% chance of being 10% richer, 50% no change
  3. 10% chance of being 50% richer, 90% no change
  4. 5% chance of being 100% richer, 95% no change
  5. 1% chance of being 500% richer, 99% no change

  In the survey, the gains were presented in monetary terms. For example, if they selected that their assets were between 1-2 billion KRW, the options presented were "100% chance of being 75 million KRW richer" etc.

- "Needs High Risk" is an indicator for whether a respondent needs high-risk investments to achieve their goals, in response to the following question "Think about your most important financial goals. For each of the actions below, choose and rank the top three most realistic ones in terms of whether you would be able to reach your goals if you relied only on that one action." The options were:

  1. Saving regularly in a bank account
  2. Advancing in my job or career (e.g., promotions, raises)
  3. Starting a side business or freelance work

4. Making low-risk investments (e.g., index funds) or contributing to a retirement account
5. Investing in high-risk assets (e.g., options, speculative stocks)
6. Buying lottery tickets or betting on events (e.g., sports or racing)

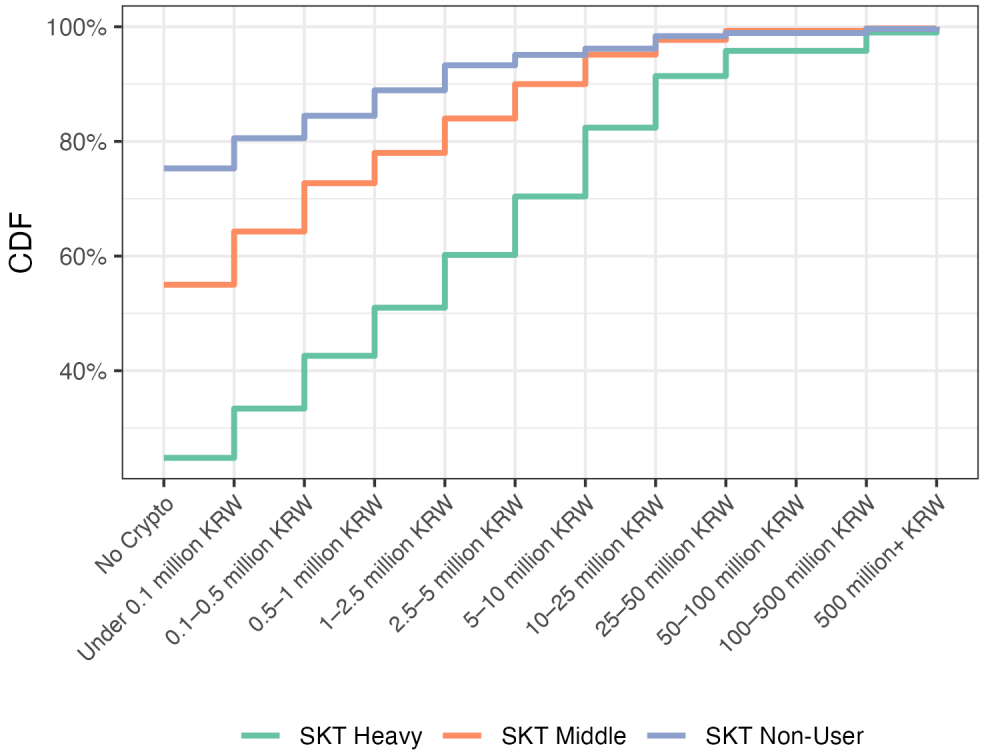
C.2 Additional Tables and Figures

Table C.1: Summary Statistics of Survey Sample

Statistic	SKT Heavy	SKT Middle	SKT Non-User	All
Male	0.82	0.57	0.39	0.54
Average Age	43.14	43.68	42.46	42.98
Married	0.59	0.54	0.44	0.50
Employed	0.87	0.77	0.65	0.74
Owns Home	0.58	0.56	0.51	0.54
Lives in Seoul	0.27	0.28	0.21	0.24
Currently Has Crypto	0.75	0.45	0.25	0.42
Currently Has Crypto And Significant	0.26	0.17	0.10	0.16
Ever Owned Crypto	0.83	0.56	0.36	0.53
Average Income Approx (million KRW)	69.50	58.73	53.92	58.77
Average Assets Approx (million KRW)	479.70	389.11	354.72	392.34
Average Crypto Approx (million KRW)	22.20	5.50	5.10	8.94
Average Stock Approx (million KRW)	103.18	63.37	59.75	70.29
Median Income Approx (million KRW)	62.50	62.50	37.50	62.50
Median Assets Approx (million KRW)	300.00	300.00	300.00	300.00
Median Crypto Approx (million KRW)	0.75	0.00	0.00	0.00
Median Stock Approx (million KRW)	17.50	7.50	7.50	7.50

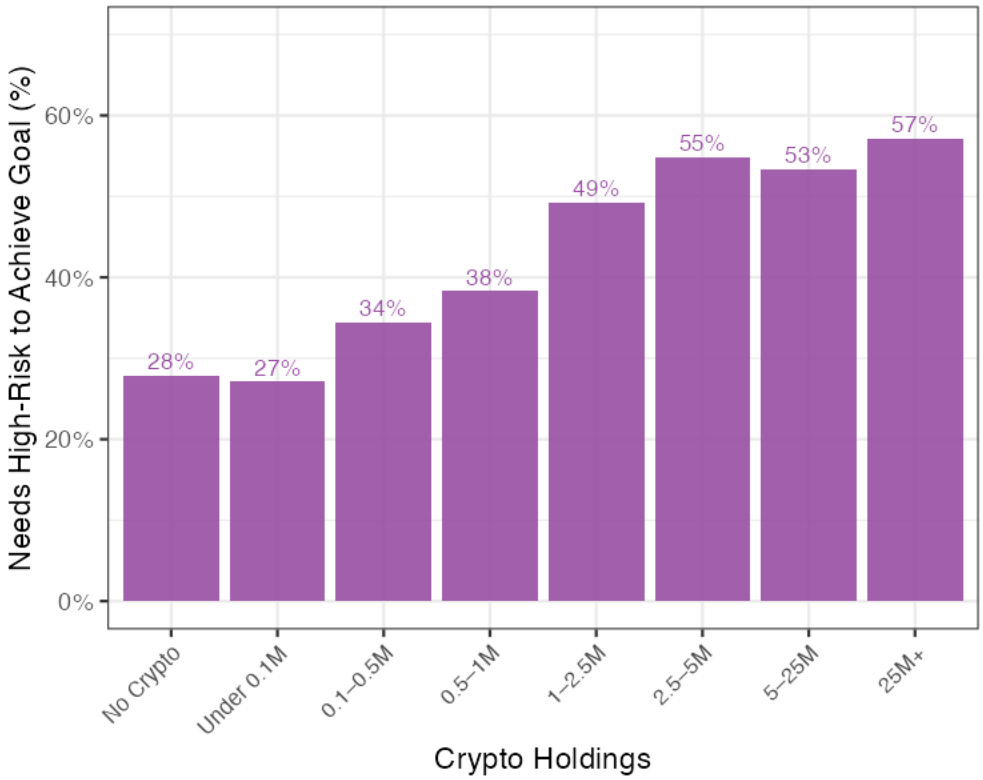
Notes: Table summarizes the survey sample described in Section 3.2. Unless otherwise stated, all statistics are shares. "'Currently Has Crypto And Significant" is an indicator for whether the respondent answered "Yes" when asked whether losing all their crypto holdings would have a significant impact on their financial well-being. Income, assets, crypto and stock holdings are in millions of KRW (1 million KRW $\approx$ \$700 USD). These values are approximations because responses were elicited in brackets. To compute means and medians, we assign each observation the midpoint of its bracket, except for the top-coded category ("More than"), for which we use the lower bound. Source: SKT survey.

Figure C.1: Distribution of Self-Reported Crypto Holdings by SKT Usage Group



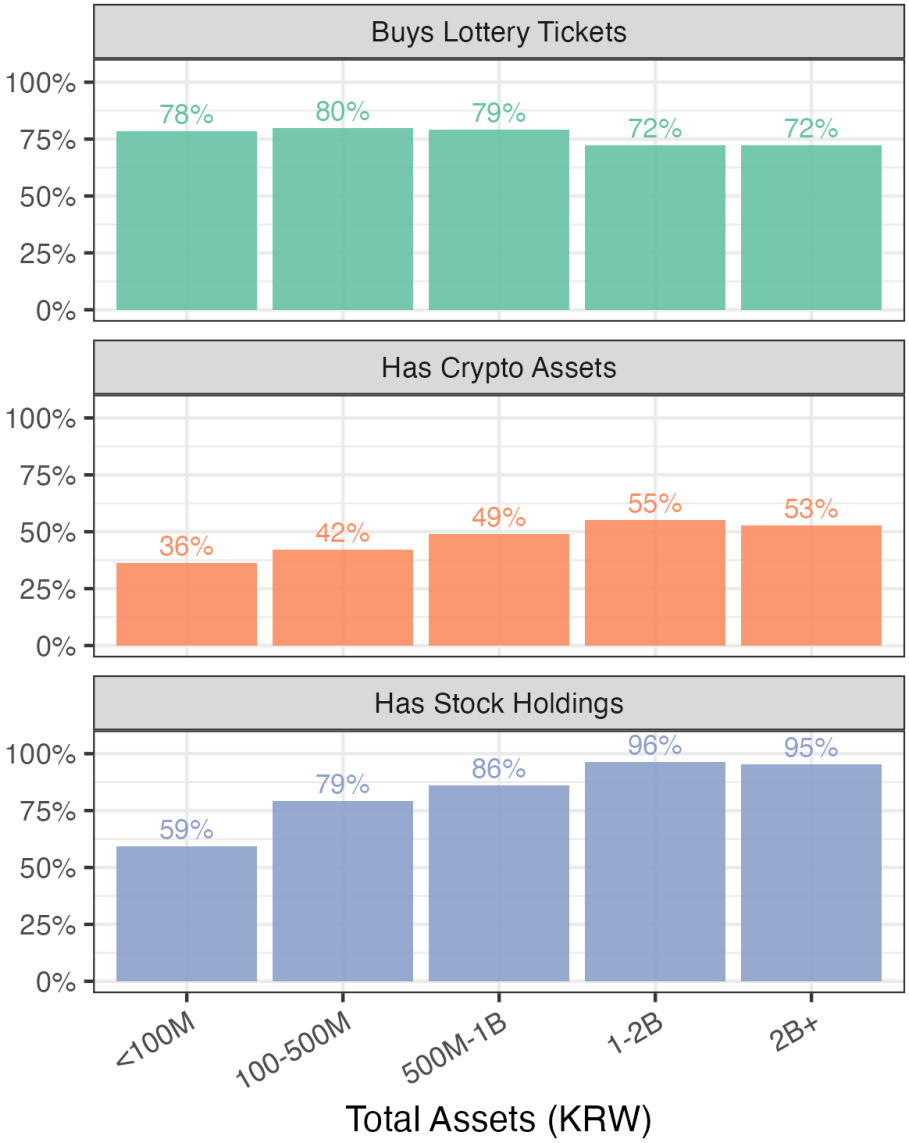
Notes: Figure plots the cumulative distribution of self-reported cryptocurrency holdings separately for SKT heavy users, middle users, and non-users. Source: SKT survey.

Figure C.2: Share Needs High-Risk Investments to Achieve Goal, by Crypto Holdings



Notes: Figure plots the share of respondents who report that high-risk investments are necessary to achieve their most important financial goal, separately by self-reported crypto holdings. Percentages are shown above each bar. Source: SKT survey.

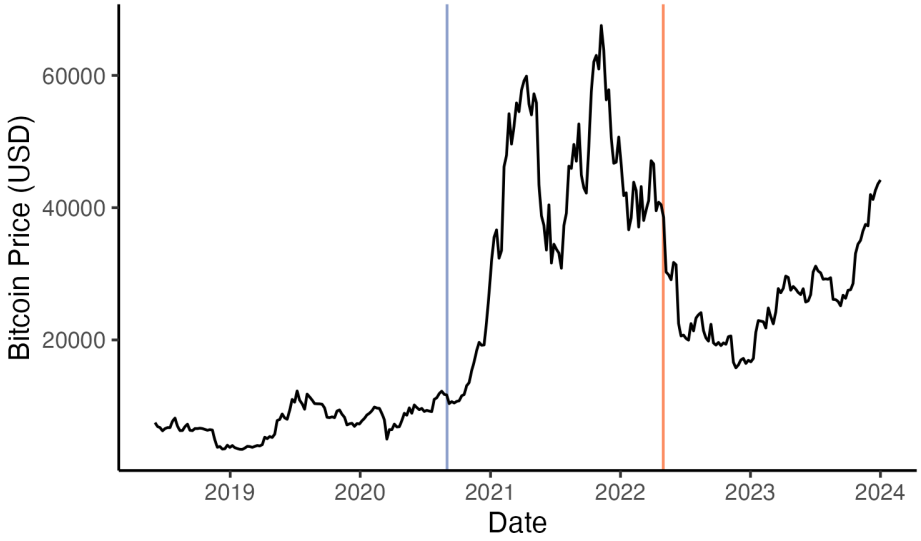
Figure C.3: Lottery, Crypto, and Stock Participation by Assets



Notes: Figure shows the share of survey respondents who buy lottery tickets, hold crypto assets, and have stock holdings of at least 1 million KRW, by household assets. Source: SKT survey.

D Event Study Details

Figure D.1: Bitcoin Prices: Boom & Bust Events



Notes: Figure shows Bitcoin prices over time. The orange line depicts our "bust" event in May 2022. The blue line depicts our "boom" event in September 2020. Source: Bitcoin price data.

We compare the outcomes of heavy crypto users and others around two large changes in Bitcoin prices: a boom in prices at the end of 2020, and a bust in early 2022. Appendix Figure D.1 illustrates these events. We define the start of the boom as September 2020. Over the following eight months, the price of Bitcoin increased by nearly 500%. We define the start of the bust as May 2022, when Bitcoin prices returned to their mid-2021 level after a second run-up. Over the next eight months, prices fell by around half, reaching their lowest level since the start of the boom.

Formally, our empirical strategy is a difference-in-differences design:

$$Y_{i,t} = \sum_{\substack{m \in \mathcal{M} \\ m \neq m_0}} \beta_m \left(\text{HeavyUser}_i \times \mathbf{1}\{t = m\}\right) + \alpha_i + \gamma_t + \varepsilon_{i,t}. \tag{D.1}$$

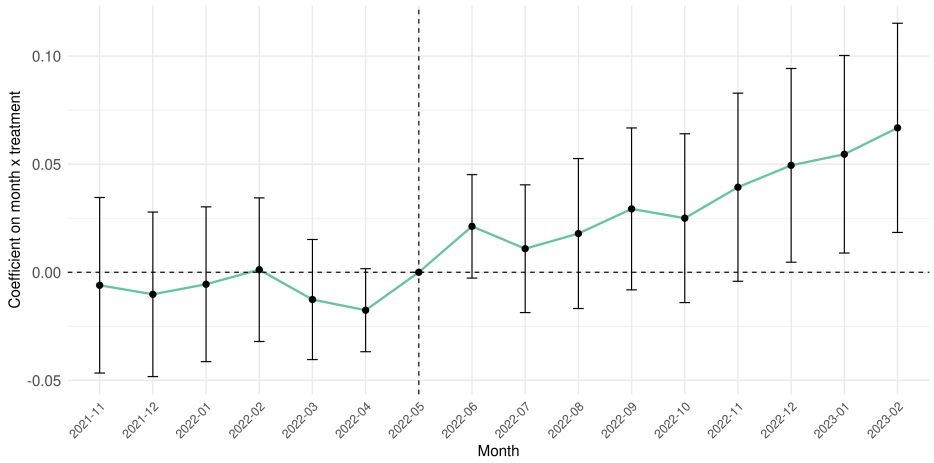
Here, $Y_{i,t}$ is the outcome of interest (e.g., delinquency, home ownership) for individual i in month t. We scale the outcome by 100 so that our results are interpretable as percentage point changes. The indicator HeavyUser_i equals one if a user is a heavy crypto app user and zero otherwise. We measure HeavyUser_i prior to the event start (January 2021 for the boom, July 2021 for the bust), to capture individuals who likely had investments exposed to the price changes. We include individual fixed effects, α_i, and time fixed effects, γ_t. Our coefficients of interest are β_m, which capture the time-varying difference in outcomes

between heavy crypto users and others.

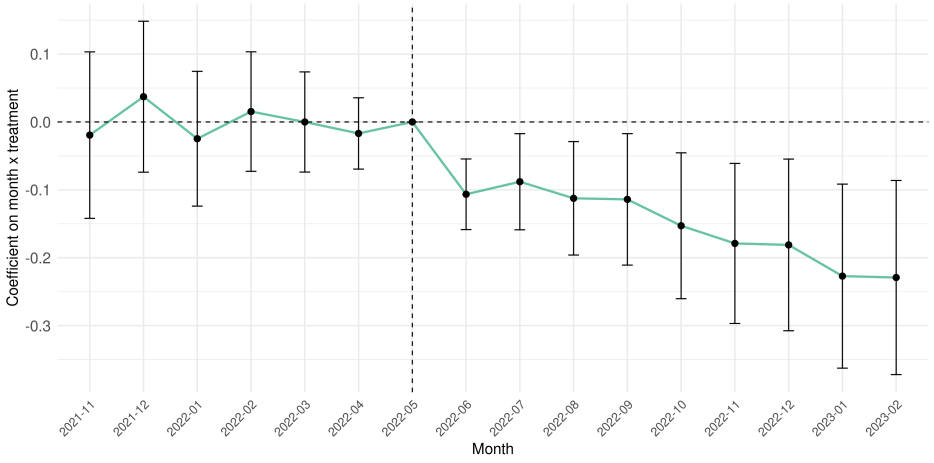
Bust Event. Figure D.2 shows the effects of a crypto price crash on heavy crypto users. Panel (a) shows that they are approximately 0.05 percentage points more likely to become delinquent after the crash. This effect is economically large, reflecting a 20% increase in the delinquency rate compared to the average for heavy-users in Table 4 (as of July 2021). Panel (b) shows that the share of heavy users making a luxury purchase also decreases by 0.2 percentage points after the crash, a 13% decrease (from a baseline of 1.5 percent).

Figure D.2: Heavy Crypto App Users Around a Crypto Price Crash

(a) Delinquency



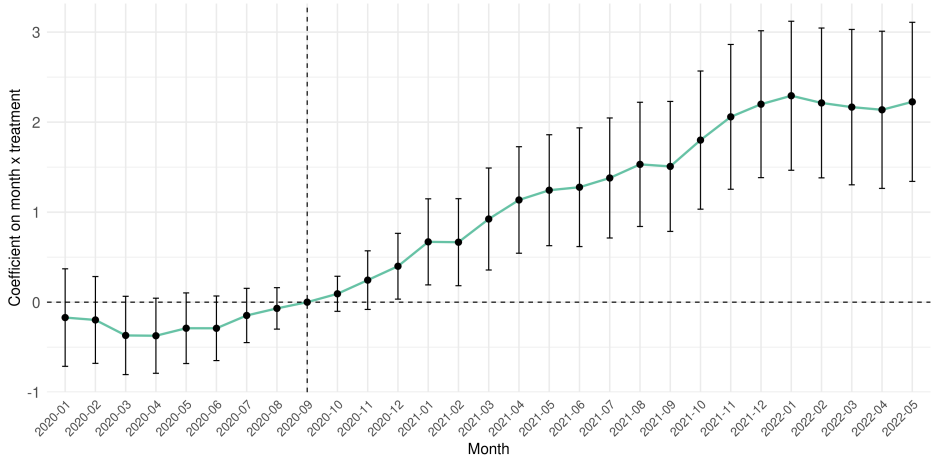
(b) Luxury Purchases



Notes: Figure shows estimates from the regression in Equation D.1 around the Bitcoin price "bust" in May 2022. The outcome in panel (a) is whether the individual had any delinquent loans in the month. The outcome in panel (b) is whether the individual had any luxury purchases in the month. Both outcomes are rescaled by 100 so that they are interpretable as percentage point changes. Standard errors are clustered at the individual level. Bars display 95% confidence intervals. Source: KCB, SKT, and Shinhan Card.

Boom Event. Figure D.3 shows that cryptocurrency price booms coincided with a relative increase in homeownership among heavy crypto users. Following the 2020 price boom, heavy users became about 2 percentage points more likely to own a home than comparable non-heavy users, a 6% increase relative to the heavy-user mean in Table 4. While these results show no clear pre-trend, the pre-period overlaps with the onset of COVID-19, which could have reduced differential trends across groups. We therefore interpret these results as suggestive.

Figure D.3: Heavy Crypto App Users and Home Ownership Around a Crypto Price Boom



Notes: Figure shows estimates from the regression in Equation D.1 around the Bitcoin price "boom" in September 2020. The outcome is whether an individual owned a home in the month. The outcome is rescaled by 100 so that it is interpretable as a percentage point change. Standard errors are clustered at the individual level. Bars display 95% confidence intervals. Source: KCB and SKT

E Debt shocks

Changes in Debt. We next study changes in cryptocurrency interest around new borrowing. Taking on unsecured debt may reflect financial distress or a desire to increase consumption. Propositions 5 and 1 highlight how these circumstances may also coincide with individuals gambling from aspiration- or desperation-motives. We restrict our sample to 547,882 individuals who have no outstanding credit loans in the pre-period.

Table E.1: Credit Loan and Changes in Cryptocurrency Interest

	Δ Crypto Usage		**Δ Crypto Heavy Usage**		**Δ Avg Crypto Usage**	
	(1)	(2)	(3)	(4)	(5)	(6)
Use CreditLoan	0.0209***	0.0128***	0.0286***	0.0200***	3.4552***	2.4496***
	(0.0028)	(0.0029)	(0.0018)	(0.0018)	(0.1076)	(0.1092)
All Controls		✓		✓		✓
R^2	0.0001	0.0035	0.0008	0.0062	0.0046	0.0310
Observations	547,882	502,567	547,882	502,567	547,882	502,567

Notes: Table shows results from Equation 4. The sample includes all individuals who never had a credit loan in the pre-period (January-June 2021). The outcome in columns 1-2 is the difference in indicators (-1, 0, or 1) for whether individual i used a crypto app in any month in the pre- vs. post-period (July 2021-June 2022). The outcome in columns 3–4 is analogous but for "heavy usage", defined as using cryptocurrency apps more than 30 distinct times within the month. The outcome in columns 5-6 is the average monthly crypto usage. "All controls" are those in Figure F.1 (see Appendix F). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses.

Table E.1 shows the results using the same design, but where $\text{Shock}_{post,i}$ represents an indicator for taking a credit loan in the post period. Columns (2) and (4) suggest that when individuals obtain a new credit loan they become 1.3 and 2.0 percentage points more likely to be a crypto user and heavy user, respectively.

F Multivariate Predictors of Heavy Crypto Use

The regression model in Figure F.1 is:

$$Y_i = \beta_0 + \beta_1 \text{Male}_i + \beta_2 \text{Live Alone}_i + \beta_3 \text{Own House}_i \tag{F.1}$$

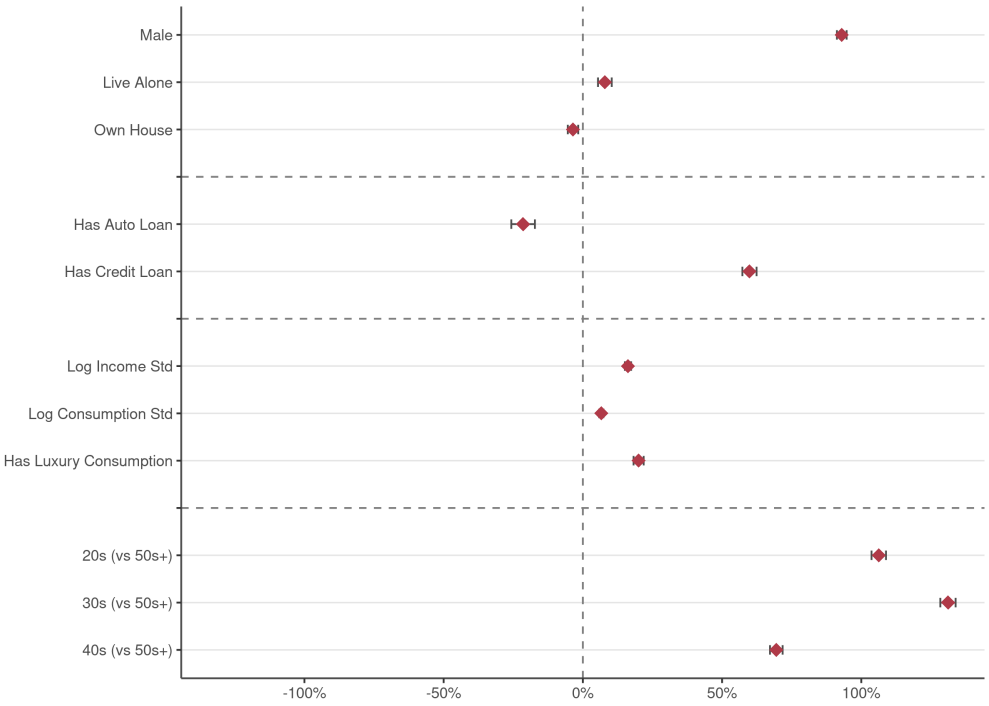
$$+ \beta_4 \text{Has Auto Loan}_i + \beta_5 \text{Has Credit Loan}_i \tag{F.2}$$

$$+ \beta_6 \text{Log Income Std}_i + \beta_7 \text{Log Consumption Std}_i \tag{F.3}$$

$$+ \beta_8 \text{Has Luxury Consumption}_i + \text{AgeGroup}_i + \varepsilon_i. \tag{F.4}$$

All coefficients except the intercept are shown in Figure F.1. Y_i is a dummy for heavy crypto app usage. Own house is an indicator for whether you or your family own a home. Log income and log consumption have been standardized. AgeGroup_i is a categorical variable indicating whether the individual is in their 20s, 30s, 40s, and 50s and above.

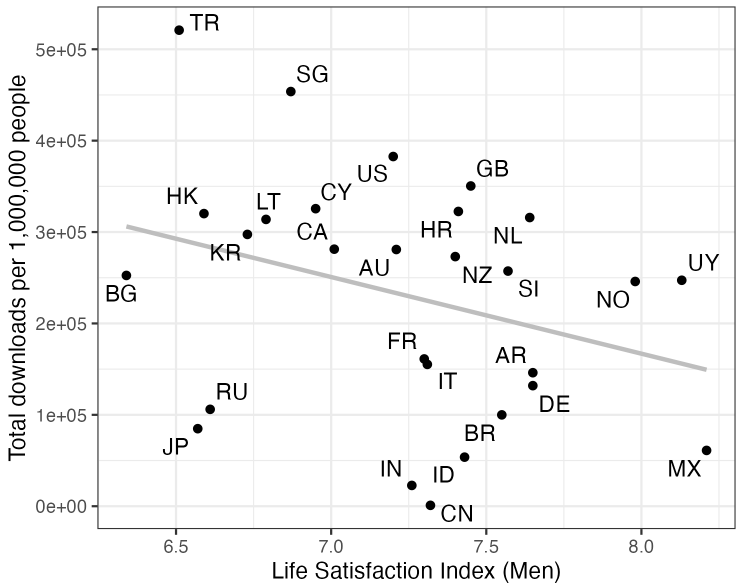
Figure F.1: Predictors of Heavy Crypto App Usage: Demographics, Debt, and Spending



Notes: Figure shows the predictors of heavy crypto usage from the multivariate regression in Equation F.1, on a cross-sectional sample in July 2021. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times in the month. The magnitudes on the horizontal axis are the size of the coefficient divided by the mean of the outcome variable. Source: KCB and SKT.

G Additional Figures

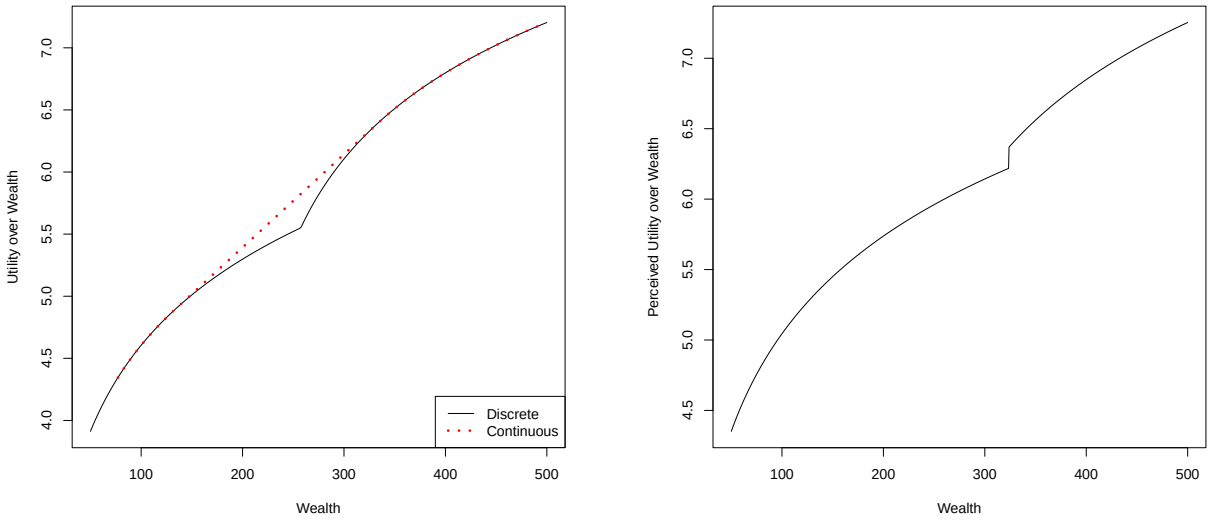
Figure G.1: Cryptocurrency Interest vs. Male Life Satisfaction (Levels)



Notes: Figure shows cryptocurrency exchange application downloads (per one million individuals) against male life satisfaction across countries. Source: World Values Survey Wave 7 and Auer et al. (2025).

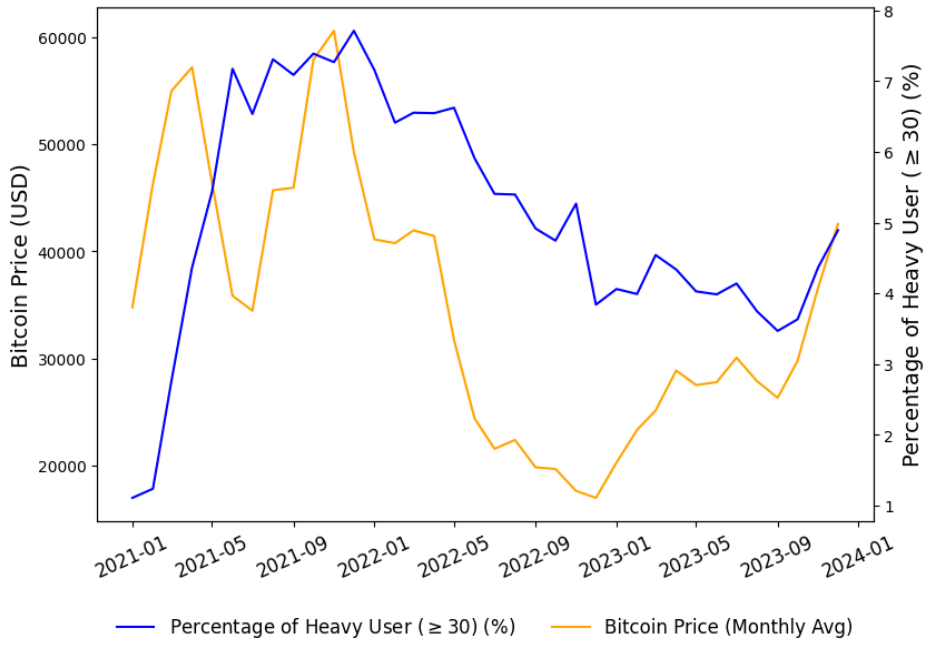
Figure G.2: Discrete goals and convex preferences

(a) Continuous Goals Re-Concavifies Utility (b) Perceived Utility and Convexification



Notes: Figure shows utility over wealth with continuous goals and categorical reasoning.

Figure G.3: Cryptocurrency Engagement, Time Series

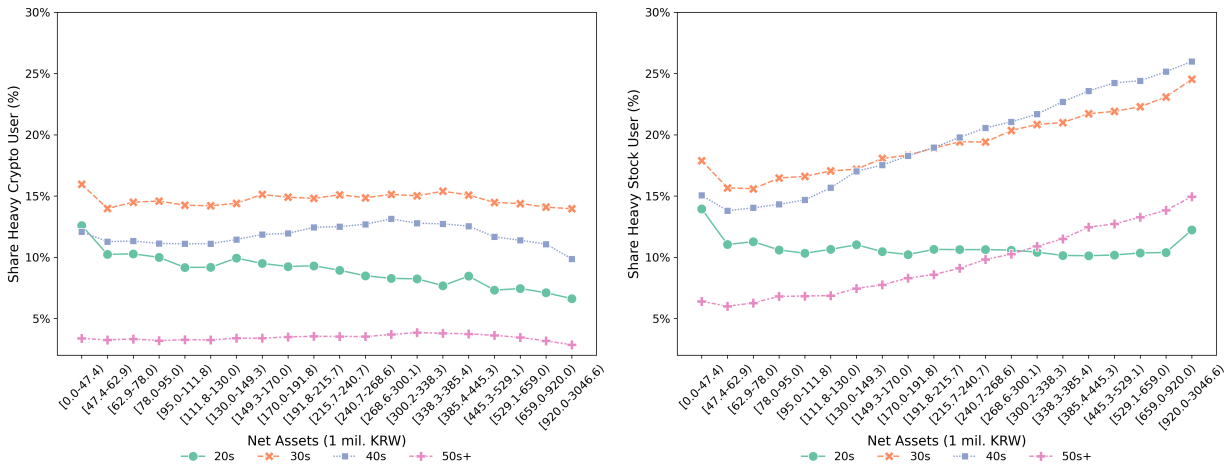


Notes: Figure shows engagement with crypto apps versus Bitcoin prices. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. "Percentage of Heavy User" is the share of all individuals who are heavy users. Source: SKT and Bitcoin price data.

Figure G.4: Crypto and Stock Usage across Age and Wealth

(a) Crypto Apps

(b) Stock Apps

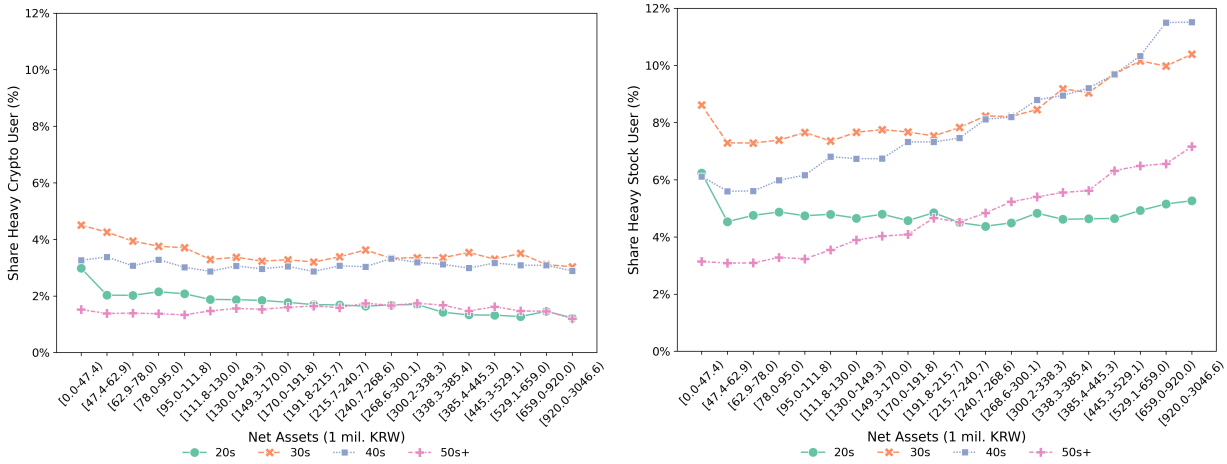


Notes: Figure shows the percentage of men who are heavy crypto users and heavy stock users. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. We use an analogous definition for stock apps. Net assets are in ventiles. Source: KCB and SKT.

Figure G.5: Percentage of Women App Heavy Users by Assets x Age

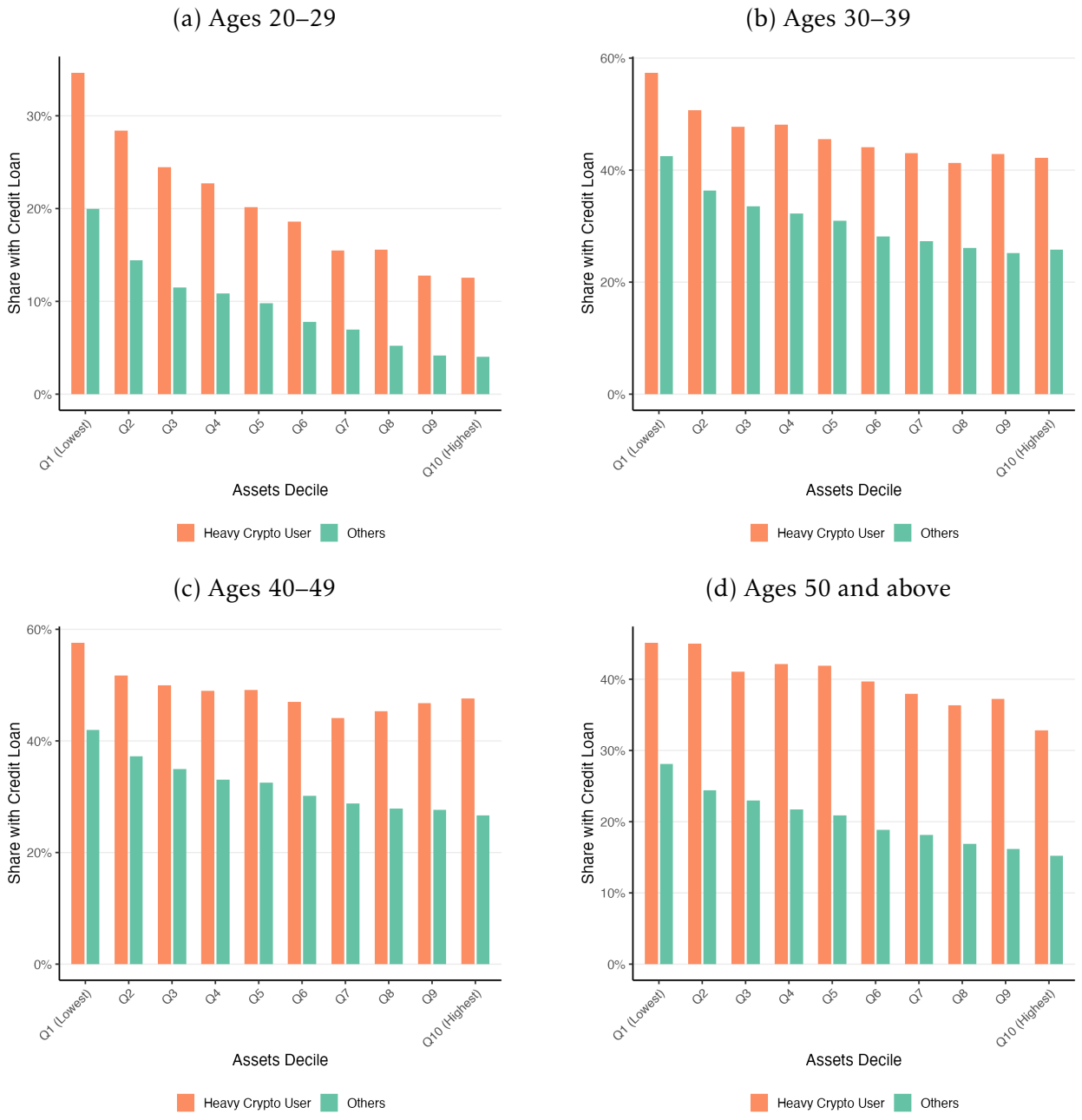
(a) Crypto Apps

(b) Stock Apps



Notes: Figure shows the percentage of women who are heavy crypto users and heavy stock users. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. We use an analogous definition for stock apps. Net assets are in ventiles. Source: KCB and SKT.

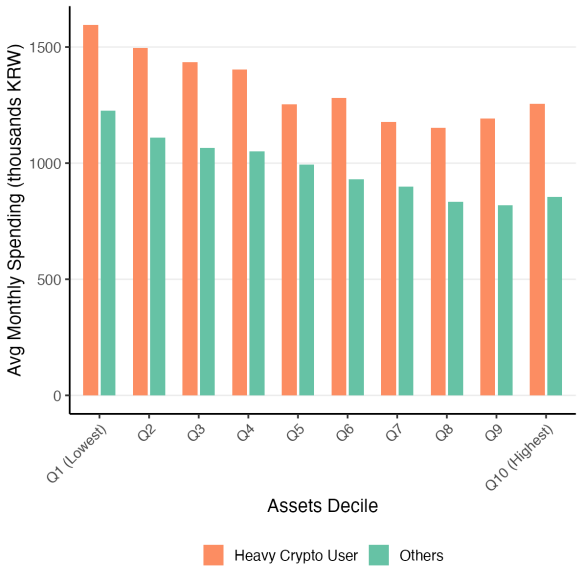
Figure G.6: Heavy Crypto Users vs. Others: Unsecured Loans by Assets, by Age Group



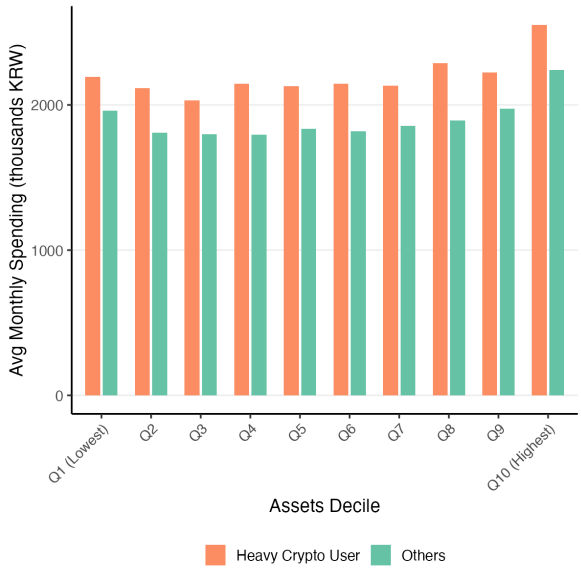
Notes: Figure shows the share of individuals with unsecured loans by asset decile, separately for heavy crypto users and others, for each age group and for the full sample. Net assets are in deciles. All variables are measured as of July 2021. Source: KCB and SKT.

Figure G.7: Heavy Crypto Users vs. Others: Spending by Assets, by Age Group

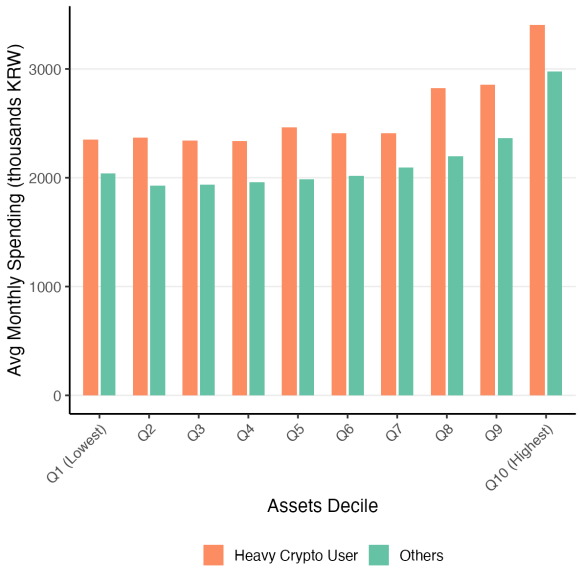
(a) Ages 20–29



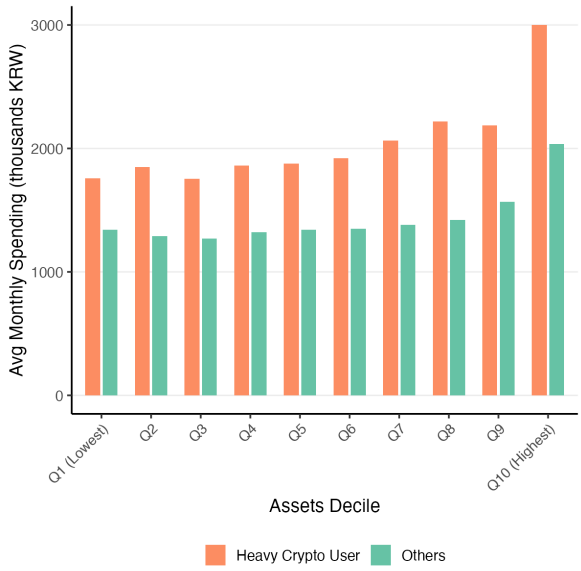
(b) Ages 30–39



(c) Ages 40–49



(d) Ages 50 and above



Notes: Figure shows average monthly spending by asset decile, separately for heavy crypto users and others, for each age group and for the full sample. Net assets are in deciles. Spending is measured in thousands of KRW. All variables are measured as of July 2021. Source: KCB and SKT.

H Additional Tables

Table H.1: Representativeness of Data

	July 2021 Sample	KOSIS (2021)
Age Group		
0 - 14		6,087,471 (11.8%)
15 - 29	212,993 (19.7%)	9,200,080 (17.9%)
30 - 39	198,635 (18.3%)	6,954,619 (12.8%)
40 - 49	228,895 (21.1%)	8,115,933 (15.8%)
50 or above	442,280 (40.8%)	21,379,968 (41.6%)
Location		
Seoul	299,142 (27.6%)	9,472,127 (18.3%)
Non-Seoul	783,661 (72.4%)	42,265,944 (81.7%)
Gender		
Share Male	50.8%	50.0%

	July 2021 Sample	KOSIS (2021M7)
Employment Rate	64.3%	61.3%

	July 2021 Sample	KOSIS (2021)
Annual Income Median (1,000 KRW)	33,000	32,060
Annual Income Mean (1,000 KRW)	38,370	38,560

Notes: Table shows summary statistics comparing our analysis sample (described in Section 3) with the Korean population, based on data from the Korean Statistical Information Service (KOSIS). Annual income refers to equivalised household income.

Table H.2: Sample Summary Statistics by Crypto App Usage (January 2021)

	Non-Crypto Users	All Crypto Users	Heavy Crypto Users
KCB: Share with Loan by Type			
Credit loan	0.23	0.37	0.47
House loan	0.12	0.15	0.18
Auto loan	0.07	0.08	0.10
KCB: Median Loan Balance Among Non-Zero			
Credit loan (1,000 KRW)	16,290	27,040	30,905
House loan (1,000 KRW)	89,250	112,850	116,930
Auto loan (1,000 KRW)	11,415	12,290	12,530
KCB: Other			
Average Annual Income (1,000 KRW)	37,001.33	43,619.76	47,232.13
	(20,248.30)	(24,748.65)	(26,892.38)
Median Annual Income (1,000 KRW)	32,000.00	37,000.00	40,860.00
Average Net Assets (1,000 KRW)	265,690.49	255,102.18	254,124.85
	(295,628.81)	(274,786.37)	(279,982.43)
Average Monthly Card Spending (1,000 KRW)	1,397.47	1,799.85	2,036.77
	(2,119.30)	(2,388.25)	(2,518.00)
Share Unemployed	0.36	0.25	0.18
Share owns Home	0.34	0.32	0.34
Share owns Foreign Car	0.01	0.02	0.03
Share with Delinquency	0.0022	0.0029	0.0031
Share Male	0.50	0.76	0.83
Share under 40	0.36	0.57	0.55
SKT: Usage			
Share Using Stock App	0.34	0.78	0.86
Share Using Game App	0.15	0.27	0.28
Share Using Online Forum App	0.24	0.56	0.54
Share Using Education App	0.32	0.53	0.56
Shinhan Card: Spending by Category			
Luxury Spending (1,000 KRW)	68.88	93.34	103.04
	(376.61)	(439.19)	(413.39)
Total Spending (1,000 KRW)	974.36	1,207.69	1,327.60
	(1,726.54)	(1,987.33)	(1,860.49)
Food Spending (1,000 KRW)	98.34	148.36	172.36
	(160.12)	(199.52)	(222.19)
Department Store Spending (1,000 KRW)	32.48	45.35	48.14
	(339.78)	(403.54)	(358.76)
Medical Spending (1,000 KRW)	84.77	88.90	98.42
	(363.77)	(379.17)	(405.15)
Observations	717,202	42,850	8,424

Notes: Table provides summary statistics for the analysis sample in January 2021. Unless otherwise noted, means are reported with standard deviations in parentheses. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times in the month. Source: KCB, SKT, and Shinhan Card.