Gambling for Goals*

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Abstract

As young adults in advanced economies have grown more pessimistic about their economic prospects in recent years, gambling-like financial activities have proliferated. We link these trends through a Friedman-Savage (1948) motive: when life goals such as homeownership or marriage seem out of reach, 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 the theory, individuals who place greater importance on hard-to-reach financial goals are more likely to exhibit risk-seeking preferences and to engage in high-risk investment. Conversely, 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 interest in cryptocurrency. A calibrated version of the model generates high-risk investment among an "unhappy middle" who aspire to homeownership but cannot reach it without risk, as observed in the data, and shows how goal-driven risk-taking can increase the welfare costs of overoptimism.

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"[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 increasing concern about 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 apparent 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); Helliwell et al. (2024) .

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 using an original survey linked to millions of credit bureau, credit card spending, and mobile app usage records from Korea. Consistent with the theory, those who view high-risk investment as necessary to achieve their financial goals are substantially more likely to exhibit risk-seeking preferences and to hold cryptocurrency, even conditional on expectations. Interest in cryptocurrency also rises during adverse unemployment events, and declines after individuals win the right to purchase price-regulated housing through a lottery. Our findings suggest that an individual's risk preferences are context-dependent and shaped by their economic goals.

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 rationalize gambling by allowing utility to be locally convex over intermediate wealth, so that some individuals prefer a fair gamble with a small chance of a large, status-altering gain. We generate this in our model by having 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 four empirical predictions. First, high-risk investment appeals to individuals who strongly aspire to goals that are unattainable through safe saving. Second, distance to goal shapes demand for risk: those who are close to their goal do not gamble, and those very far from the goal do not gamble or prefer highly right-skewed, low-probability, high-payoff gambles. Third, achieving a salient goal reduces demand for risk, while negative shocks that move individuals further from their goals can increase it. Fourth, conditional on goals and a similar level of wealth, those who gamble partially "give up" and reallocate resources toward current consumption.

Testing these predictions is challenging because it requires jointly observing eco-

[2]In one survey of American adults, three-fourths of respondents who participate in high-risk financial activities—including cryptocurrency trading, prediction markets, and sports betting—reported doing so because they felt financially behind (Northwestern Mutual, 2026). In another survey, two-thirds of Gen Z and millennial respondents stated 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).

nomic circumstances, 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 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 (see, e.g., Stevenson and Lee, 2019; OECD, 2024; Lewis-Kraus, 2025; Jung-a, 2026).

We first document patterns of cryptocurrency app usage, a measure of an individual's interest in high-risk financial assets in the administrative data.[3] Usage is widespread, particularly among men in their 30s and 40s: almost a quarter use a cryptocurrency app in a given month, and nearly 10% are "heavy users," logging on at least 30 times. Consistent with demand for right-skewed assets being strongest among those who cannot attain their goals risklessly, cryptocurrency app usage is modestly decreasing in assets, unlike stock-app usage, which rises sharply with assets. Inconsistent with crypto interest purely reflecting small "entertainment" bets, usage is tied to 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.

We then present evidence from our survey that directly measures financial goals, beliefs, and high-risk financial behaviors. Respondents report the importance of a range of goals—including homeownership, retirement, and broader status-oriented objectives like increasing their attractiveness as a romantic partner. Consistent with our model, cryptocurrency holders place greater importance on these goals and are more likely to view high-risk investment as necessary to achieve them, even conditional on expected returns. We provide evidence this is driven by goals shaping risk-preferences: in a lottery choice task, those who place greater importance on goals are more likely to choose risk-seeking options. Demand for high-risk assets also varies systematically with distance to goals. Among aspiring homeowners, cryptocurrency ownership is hump-shaped in assets, while stock ownership is increasing. Together, the survey evidence strongly supports the model's first two predictions.

[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 3.3 shows that cryptocurrency app usage is a strong predictor of actual holdings in linked survey data.

Next, we use within-individual variation in the administrative data to test how risk-taking responds to changes in economic circumstances, the model's third prediction. We first ask 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. We show that cryptocurrency app usage falls significantly around a home purchase, more so than for any other app category except real estate. While suggestive, homeownership decisions are endogenous and related to past financial outcomes and expectations about the future. For example, family formation can increase both the likelihood of homeownership and risk aversion.

To address these endogeneity concerns, we exploit Korea's housing lottery, which quasi-randomly allocates rights to purchase price-regulated housing. We identify 1,892 individuals who are likely to be winners, and compare winners to not-yet-treated future winners in a difference-in-differences design.[4] Following the announcement of lottery results, cryptocurrency app interactions decline by 21% for winners relative to pre-win. The decline is larger in the Seoul capital area, where house prices have risen most sharply in recent years, and we find no comparable decline for stock apps. These results provide evidence that attaining a difficult-to-reach goal reduces demand for high-risk assets.

We also test whether demand for high-risk investment increases when goals become harder to attain through saving. We focus primarily on unemployment. 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 close our empirical analysis by examining the model's final prediction and considering alternative explanations for our evidence. In the model, individuals who view conventional saving as insufficient to reach their goals reallocate resources toward current consumption. Consistent with this, cryptocurrency users spend more conditional on wealth, and are more likely to hold unsecured debt. We then consider alternative explanations for high-risk investment, including enjoyment, addiction, and optimism. While each may contribute to the aggregate level of holdings, they have difficulty explaining key empirical patterns we document: the relationship between risk-taking and financial goals, the link between goal distance and the choice of right-skewed gambles, and the changes in cryptocurrency usage following housing-lottery wins and unemployment events.

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

In the final section of the paper, we calibrate a quantitative version of our model, targeting cryptocurrency and stock participation rates across asset levels among aspiring homeowners. Friedman-Savage motives are necessary for the model to reproduce the hump in cryptocurrency ownership observed in the data: without goals, participation costs and belief dispersion cause participation in both assets to generally rise with wealth. The estimated goal cost is close to the down payment on an entry-level apartment in the Seoul metropolitan area, an untargeted moment. Removing goals reduces cryptocurrency ownership by 34 percentage points among households with 50-100 million KRW.

We also use the model to examine the welfare consequences of distorted beliefs in the presence of goals. We find that when individuals are overoptimistic, Friedman-Savage preferences can amplify the welfare costs of belief distortions. Taking median survey beliefs as rational, optimistic households at the 75th percentile of the cryptocurrency belief distribution invest roughly 60% of their wealth in cryptocurrency when near their goals. The resulting welfare loss is about four times larger than without goals.

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), and provides evidence that inequality and social conditions shape perceptions of opportunity, life satisfaction, fragility, and redistributive policies (Helliwell et al., 2024; Knoll et al., 2017; Berman, 2022; Rajan, 2011; Landier and Plantin, 2017). We focus on the financial consequences of economic frustration: when discontent stems from difficulty attaining salient goals, 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 retirement), and test the theory by leveraging survey evidence and within-person variation in distance to goals.[5]

Our paper also contributes to a literature explaining demand for high-risk assets, lotteries, and gambling. Theoretically, Friedman and Savage (1948) and Markowitz (1952) posit reduced-form preferences over wealth that generate both local risk aversion and a taste for lotteries. Subsequent work microfounds convexities through indivisible con-

[5]Our use of variation from a home-purchase subsidy lottery also relates to studies that explore the effects of rent control or housing assistance (e.g., Diamond et al., 2019; Öst and Johansson, 2023; Collinson et al., 2024). Unlike these programs, the lottery we study affects homeownership rather than rental costs.

sumption or investment (Kwang, 1965; Jones, 2008; Crossley et al., 2016; Vasquez, 2017; Kaboski et al., 2022), consumption commitments (Chetty and Szeidl, 2007), and aspirations or social comparison (Becker et al., 2005; DeMarzo et al., 2008; Genicot and Ray, 2017; Corgnet et al., 2026). We build on these insights, showing that salient and discrete goals can generate local convexity in perceived utility. We emphasize that discreteness can arise in a wide variety of settings, especially because behavioral distortions such as categorical thinking (Mullainathan et al., 2008; Bordalo et al., 2025; Conlon and Kwon, 2025) can make nominally continuous goals perceived as if they were discrete. This perspective broadens the scope of when Friedman–Savage-type motives may arise.[6]

We also add to a large body of empirical work that seeks to understand gambling motives across a variety of settings, such as state or national lotteries (e.g., Kearney, 2005; Grote and Matheson, 2013; Lockwood et al., 2025), "prize-linked savings" where lottery-like prizes are offered as incentives to save (e.g., Kearney et al., 2010; Gertler et al., 2023), or horse and sports betting (e.g., Thaler and Ziemba, 1988; Golec and Tamarkin, 1998; Snowberg and Wolfers, 2010; Herskowitz, 2021). Our empirical analyses contribute in two important ways. First, most of this literature studies demand for a fixed gamble whereas our framework predicts that the *type* of gamble an individual prefers varies based on their economic circumstances. Second, we focus on Friedman-Savage motives in investment rather than lotteries: despite similarities, financial assets typically involve a larger share of household wealth and have more direct consequences for portfolio choice.

Our paper finally 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 investor heterogeneity in the cross-section. In this sense, our work is closer in spirit to Kumar (2009), Liu et al. (2022a), and Jiang et al. (2024). Relative to these findings, which largely emphasize fixed individual characteristics, we provide a framework in which such motives arise endogenously from households' economic circumstances.

[6]Other work has attributed risk-seeking behavior to direct enjoyment (Conlisk, 1993), or behavioral distortions such as probability weighting (Barberis, 2013; Barberis and Huang, 2008), salience (Bordalo et al., 2022), and anticipation or sensation-seeking (Loewenstein, 1987; Grinblatt and Keloharju, 2009). We discuss these and other alternative motives for gambling, in Section 6.

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. We highlight two potential drivers: the difficulty of reaching some traditional goals and the increasing salience of difficult-to-attain goals.

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).

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 between 1997-2012) 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"

[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).

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

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. An agent is endowed with initial wealth W_1 and has utility over consumption $u(c)$, which is strictly increasing, strictly concave, and continuously differentiable, with $u'(0^+) = \infty$, $u'(\infty) = 0$, and $u(0^+) = -\infty$. In period two, the agent can attain a financial goal $g \in \{0,1\}$ at cost $G > 0$. If attained, the goal delivers a discrete utility boost $\theta > 0$. 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 allocates period-one wealth across current consumption c_1, a safe asset paying $R_S = 1$, and a risky asset paying $\tilde{R}_R \in \{R_L, R_H\}$ where $R_L < 1 < R_H$. The high and low returns occur with probabilities p_H and $p_L = 1 - p_H$, respectively, and the risky asset is actuarially fair: $p_H R_H + p_L R_L = 1$. Letting I_S and I_R denote investment in the safe and risky assets and setting the discount rate to one, the agent solves:

$$\max_{c_1,\, I_S,\, I_R,\, \tilde{g}\in\{0,1\}} \quad u(c_1) + \mathbb{E}\Big[u(\tilde{c}_2) + \theta \cdot \tilde{g}\Big] \qquad \text{s.t.} \qquad \begin{aligned} W_1 &= c_1 + I_S + I_R, \\ \widetilde{W}_2 &= I_S + \tilde{R}_R \cdot I_R = \tilde{c}_2 + G \cdot \tilde{g}, \end{aligned} \tag{1}$$

with $I_R \geq 0$. For simplicity, we allow the agent to borrow at the riskless rate. In other words, the agent is choosing a portfolio in period 1, and then deciding whether to attain the goal $\tilde{g}$ in period 2 in a state-contingent way, *after* the return is realized.

Solving the model. We solve the model using backward induction. Entering period two with wealth $\widetilde{W}_2$, the agent optimizes $U_2(\widetilde{W}_2) \equiv \max_{\tilde{g}\in\{0,1\}}\{u(\widetilde{W}_2 - G\tilde{g}) + \theta\tilde{g}\}$, where $\tilde{g} = 1$ is feasible only if $\widetilde{W}_2 > G$. She attains the goal if and only if

$$\theta \;\geq\; \mathcal{W}(\widetilde{W}_2) \;\equiv\; u(\widetilde{W}_2) - u(\widetilde{W}_2 - G). \tag{2}$$

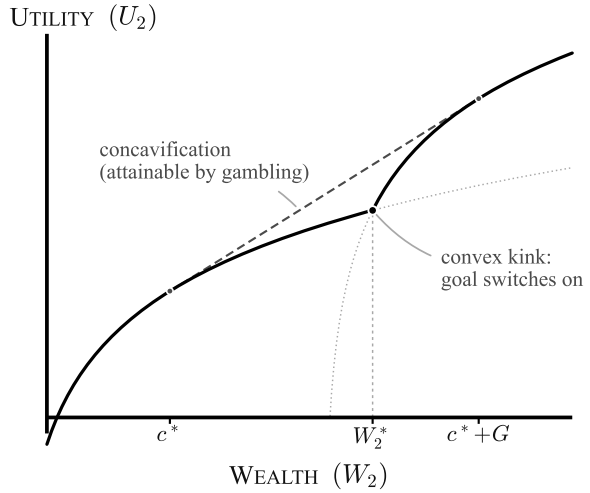
Because u is concave, $\mathcal{W}$ is strictly decreasing. Equation (2) therefore defines a single wealth threshold.

Lemma 1. *There is a unique W_2^* solving $\theta = \mathcal{W}(W_2^*)$. The agent attains the goal if and only if $\widetilde{W}_2 \geq W_2^*$, where $\partial W_2^*/\partial\theta < 0$ and $\partial W_2^*/\partial G > 0$. The indirect utility U_2 is continuous and strictly increasing, is concave on either side of W_2^*, and has a* convex kink *at W_2^*. Moreover, $c^* < W_2^* < c^* + G$, where $c^* \equiv (u')^{-1}(\theta/G)$.*

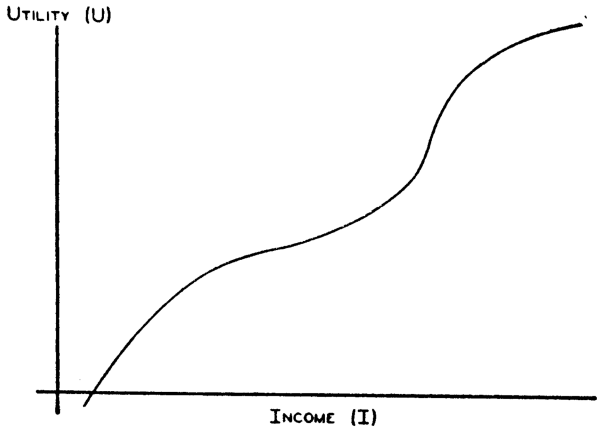
Panel (a) of Figure 1 plots U_2: the discrete goal locally convexifies utility over wealth, endogenously generating a curve of the form hypothesized by Friedman and Savage (1948), shown in panel (b). The convexity is centered at the point at which the agent is indifferent between spending G to attain the goal or to increase consumption.

Figure 1: Goals generating convexity

(a) Utility over Wealth Given Discrete Goals



(b) Friedman-Savage Utility (JPE)



Notes: Panel (a) shows period-two indirect utility U_2 implied by (1) for $u(c) = \log c$, $G = 200$, and $\theta = 2$. The two branches $u(x)$ and $u(x - G) + \theta$ are dotted; U_2 is their upper envelope, with a convex kink at W_2^*. The dashed line is the concavification of U_2, tangent at c^* and $c^* + G$. Panel (b) displays the third figure in Friedman and Savage (1948).

The period-one problem is then

$$\max_{I_{\mathcal{S}},\, I_{\mathcal{R}} \geq 0} \quad u\Big(W_1 - I_{\mathcal{S}} - I_{\mathcal{R}}\Big) + \mathbb{E}\Big[U_2\Big(I_{\mathcal{S}} + \tilde{R}_{\mathcal{R}} \cdot I_{\mathcal{R}}\Big)\Big]. \tag{3}$$

Given that the asset is actuarially fair, the problem is equivalent to the agent choosing state-contingent wealth:

$$\max_{c_1, x_L, x_H} \; u(c_1) + p_L U_2(x_L) + p_H U_2(x_H) \qquad \text{s.t.} \qquad c_1 + p_L x_L + p_H x_H = W_1, \quad x_H \geq x_L.$$

The above equation implies that the agent chooses the risky asset only when it matters for goal attainment.[9] The agent thus only contemplates three candidate plans: give up on the goal, attain it risklessly, or attain it only in the high state. For each choice the agent otherwise perfectly smooths consumption across periods and states.

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

Proposition 1. *There exist unique thresholds* $0 < W_L^* < W_H^* < \infty$ *with the following properties.*

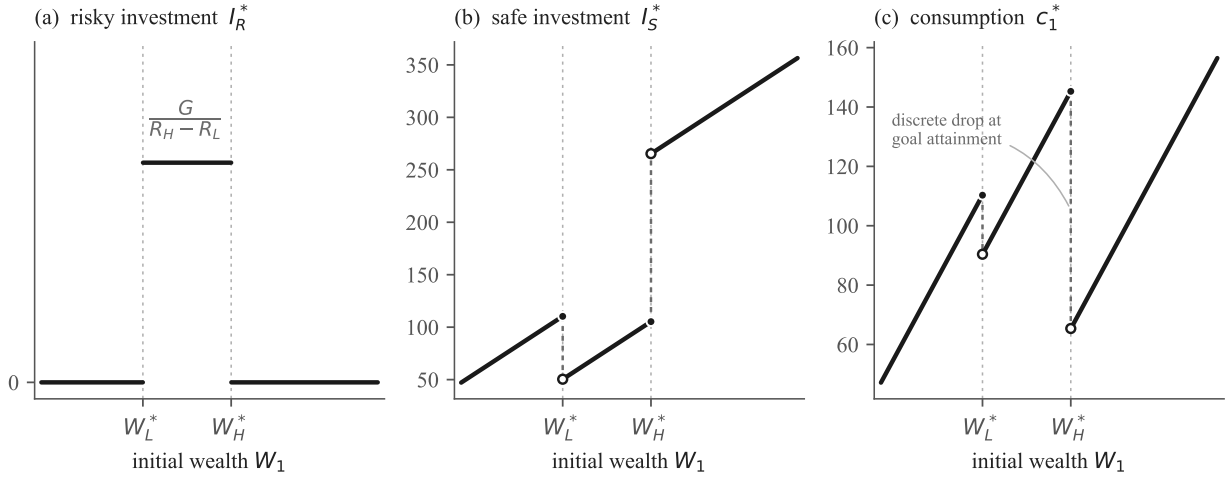
(a) ***Gambling.*** $I_{\mathcal{R}}^*(W_1) > 0$ *if and only if* $W_1 \in (W_L^*, W_H^*)$*; otherwise* $I_{\mathcal{R}}^* = 0$.

(b) ***Goal attainment.*** *If* $W_1 < W_L^*$*, the agent gives up on her goal. If* $W_1 \in (W_L^*, W_H^*)$*, she attains it only when the gamble pays off. If* $W_1 > W_H^*$*, she attains it risklessly.*

(c) ***Portfolio.*** *For* $W \in (W_L^*, W_H^*)$*,* $I_{\mathcal{R}}^* = \frac{G}{R_H - R_L}$*, and* $I_{\mathcal{S}}^* = \frac{W_1 - p_H G}{2} - \frac{R_L G}{R_H - R_L}$*. Outside the interval,* $I_{\mathcal{R}}^* = 0$*, with* $I_{\mathcal{S}}^* = W_1/2$ *below* W_L^* *and* $I_{\mathcal{S}}^* = (W_1 + G)/2$ *above* W_H^*.

(d) ***Consumption.*** *Consumption is* $W_1/2$ *below* W_L^**,* $(W_1 - p_H G)/2$ *on* (W_L^*, W_H^*)*, and* $(W_1 - G)/2$ *above* W_H^**. It rises within each region and falls discontinuously at* W_L^* *and* W_H^*.

Figure 2: Investment, savings, and consumption as functions of wealth



Notes: Policy functions from Proposition 1 ($u = \log$, $G = 200$, $\theta = 2$, $p_H = 0.2$, $R_H = 3$). Filled circles denote the value attained at a threshold; open circles denote the limit from the other side.

Figure 2 plots the key policy functions. As described in Proposition 1(a)–(c), goal-driven gambling is strongest among an "unhappy middle" whose goals are attainable

[9] If the goal is attained in both states or in neither, then U_2 is concave: replacing the gamble with its expected value strictly raises utility.

if the gamble pays off, but are otherwise unreachable with riskless savings. 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. As described in Proposition 1(d), goals also affect consumption. For goal attainment, saving and risk-taking are substitutes: individuals confident about reaching their goals through saving must defer consumption, whereas those who gamble reallocate resources toward current consumption.

Which Gamble? So far, we have assumed that the agent is choosing between riskless savings and an exogenous 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. Formally, suppose the agent can choose p_H, p_L, r_H, r_L subject to actuarial fairness: $p_H \cdot r_H + p_L \cdot r_L = 1$. 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 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 optimally choose highly skewed bets—low-probability, high-payoff "lottery-like" outcomes. As individuals move closer to their goals, the required payoff shrinks, and they shift toward less extreme gambles. In this sense, distance to the goal shapes not only the demand for risk, but also the form of risk-taking.[10]

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, and cannot scale downward.[11] Proposition 3 shows that such discreteness (or, more generally, convexity in returns to spending on the good) is essential.

Proposition 3. *Suppose an agent can instead choose a continuous expenditure $G_c \in \mathbb{R}_0^+$ to obtain utility $\theta(G_c)$. 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.*

[10] 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(d). 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(d) is restored: relative to an agent choosing a safer gamble, a slightly poorer agent selecting a riskier gamble consumes more.

[11] Appendix Figure G.1a shows that when a goal behaves like any standard consumption good—that is, the agent can scale down its consumption with decreasing marginal utility—the local convexity that drives gambling disappears.

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. First, convexity may arise naturally from indivisibilities or fixed adjustment costs. As emphasized by Chetty and Szeidl (2007), durable consumption, housing upgrades, and other lumpy investments generate regions of inaction.[12] 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.[13]

But indivisibility need not be purely financial, and may also be psychological. 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 et al., 2008; Bordalo et al., 2025), is that people reason in discrete categories or classes—e.g., rich vs poor, successful vs ordinary.[14] In Appendix A.3, we formalize this insight by drawing on the model of Bordalo et al. (2025) and Conlon and Kwon (2025). Appendix Figure G.1b shows results: even with the option of continuous scaling $\theta(G_c)$, if individuals perceive utility gains categorically, 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.

Empirical Predictions. Our framework implies that people may demand risk because a gamble offers a perceived path to goals that feel otherwise out of reach. Risk appetite should therefore depend on one's perceived economic circumstances. Corollary 1 describes how our propositions translate into a set of predictions that we bring to the data.

Corollary 1. *Our model predicts the following:*

1. ***Difficult-to-reach goals generate demand for gambles:*** *Gambling appeals most to individuals who have goals that are difficult to attain risklessly.*

[12] In Chetty and Szeidl (2007), they refer to this region of inaction as a $(S\text{-}s)$ 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.

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

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

2. ***Risk appetite shaped by distance to goal:*** *The demand for gambling is hump-shaped in distance to goals. Individuals close to the goal do not gamble, and those far from the goal do not gamble or prefer highly right-skewed gambles.*

3. ***Shocks to economic circumstances:*** *Gambling decreases once the agent attains her goals. Conversely, a negative shock to net worth can induce gambling, especially for those previously able to achieve their goals risklessly.*

4. ***Gambling as "partially giving up":*** *Conditional on the goal and a similar level of wealth, those who gamble consume more today.*

We next test these predictions using survey and administrative data that jointly measure goals, economic circumstances, and engagement with high-risk financial activities. Section 6 discusses additional explanations for financial risk-taking, including beliefs and entertainment motives, and how they may interact with Friedman-Savage motives.

3 Data: GranData and Linked Survey

To test the theory's empirical predictions, we use an original survey combined with credit bureau, credit card, and mobile app usage records in Korea. This section describes the administrative data, which allow us to measure debt, spending, assets, and cryptocurrency app engagement at scale, and the survey, which directly measures goals, beliefs, risk preferences, and financial behaviors. Korea provides a particularly informative setting given its declining housing affordability and evolving demographic structure.

3.1 GranData Overview

We use GranData, a linked individual-level panel combining information from Korea's dominant credit bureau, largest telecommunications company, and largest credit card company. Together, these data provide broad, representative coverage of many aspects of the working-age population in Korea. Table 1 summarizes coverage. We describe key variables and our analysis sample. Appendix B provides more details.

Credit Bureau Records. Credit bureau records come from the Korean Credit Bureau (KCB), covering 47 million individuals or 90% of the 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

Table 1: Basic Structure of Data

Data Type	Provider	Sample Period	# of Variables
Credit bureau	KCB	2015Q4 - 2019Q2 (Quarterly)	140
		2019M7 - 2024M5 (Monthly)	140
Mobile	SKT	2021M1 - 2023M12 (Monthly)	215
Credit card	Shinhan Card	2019M6 - 2024M5 (Monthly)	119
Survey	SKT	March 2026 (Cross Section)	58

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

debt and spending are provided to KCB from financial institutions. Income and assets are estimated using information from loan applications, contracts, 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 unique app-by-day usage instances recorded by the provider.[15]

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 H.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.

[15]This measure is therefore not necessarily capped at the number of days in a month. For example, if an individual used three social media apps on 20 days each, our measure would equal 60.

Sample Representativeness. To better understand our final sample, we compare it with administrative data from the Korea Statistical Information Service (KOSIS). Appendix Table H.8 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 18.3%) and includes a relatively larger share of individuals under age 50.

3.2 High-Risk Financial Activity in GranData.

In the GranData, our primary measure of high-risk financial activity is cryptocurrency mobile app usage. Relative to general stock trading apps, these apps serve as a comparatively clean proxy for high-risk investment.[16] We describe this measure, its correlates, and evidence that it captures meaningful exposure to cryptocurrency. We provide additional validation of our measure from a linked survey in Section 3.3.

Measure Summary & Correlates. We construct two main individual-by-month measures of cryptocurrency usage. 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.

Table 2 summarizes the primary sample in July 2021 by cryptocurrency app usage.[17] Engagement with cryptocurrency 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 were "heavy users" and used a crypto app more than 30 times in the month.[18] Cryptocurrency app users are younger, are more likely to have debt, and on average spend more each month. They also have somewhat lower assets, in contrast with stock app usage, which rises sharply in wealth (see Appendix Figures G.3 and G.4).

To characterize the relationship of cryptocurrency engagement with the usage of other apps, Appendix Figure G.5 reports a multivariate regression of heavy crypto use on standardized usage of nine other app categories, with controls including age, gender, income, assets, and total phone time. Heavy crypto app use is most strongly associated with so-

[16] In particular, our measure includes major Korean cryptocurrency trading platforms, such as Upbit and Bithumb, but excludes general stock trading platforms, which do not typically list cryptocurrencies in Korea and can be used for a wide variety of investments.

[17] Appendix Figure G.2 shows the time series patterns. There is a strong relationship between interest in cryptocurrency and Bitcoin returns, consistent with other contexts (Weber et al., 2023; Auer et al., 2025).

[18] 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).

Table 2: 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
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)
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. Table H.9 contains the same summary statistics for January 2021. Source: KCB, SKT, and Shinhan Card.

cial media, real estate, and video entertainment.[19] For real estate apps, a one-standard-deviation increase in usage corresponds to a 22% higher probability of heavy crypto use, consistent with a link between cryptocurrency investment and housing-related goals.

Economic Exposure. To show that our measure captures meaningful exposure to cryptocurrency, in Appendix C we measure how the spending of crypto users respond to changes in Bitcoin prices (Mankiw and Zeldes (1991) conduct a similar analysis for stocks). Our estimates imply that the spending of crypto app users responds differentially to cryptocurrency price changes: a doubling of Bitcoin prices relative to the sample mean corresponds to a 2.0 percent increase in daily spending among all crypto app users, 4.1 percent among heavy users, and 6.0 percent among "super heavy users" (above the 90th percentile among users). We also examine responses to Bitcoin price boom and bust episodes. A 2020 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).

3.3 Targeted 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.

Sample Details. The survey was administered to mobile phones 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 those we use in the GranData, though the exact criteria differ slightly due to data provider constraints.[20] Appendix D contains several checks for sample quality, addressing standard concerns about attention and experimenter demand.

[19] Real estate platforms include Naver, Hogangnono, and Zigbang, services similar to Zillow or Redfin in the United States. Video entertainment apps include YouTube and TikTok.

[20] 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 aligns with those in the administrative data.

Crypto App Usage and Holdings. Appendix Table H.10 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 ($15,857 USD) compared to 5.5 million KRW ($3,929 USD) for middle users. Figure G.6 shows the full 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 uses survey evidence to assess the first two predictions of Corollary 1. Cryptocurrency holders place greater importance on financial goals and are more likely to view high-risk investment as necessary to achieve them, even conditional on subjective expected returns. Consistent with Prediction 1, respondents who attach greater importance to these goals are also more likely to choose risk-seeking options in a lottery task. Consistent with Prediction 2, distance to homeownership shapes risk-taking: cryptocurrency engagement is hump-shaped in assets, while stock-app engagement is increasing.

4.1 Goals and Risk-Taking

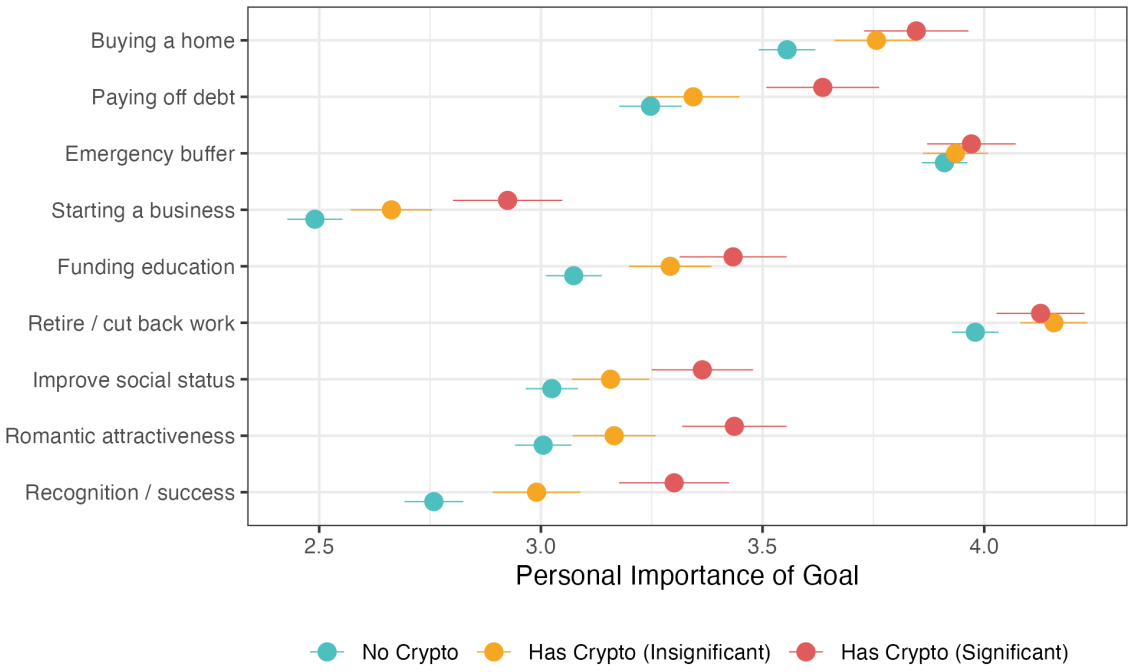
Goals Predict High-Risk Investment. We begin by examining self-reported financial goals. Respondents rated the importance of nine goals, including buying a home, paying off debt, building an emergency buffer, starting a business, funding education, retirement, improving social status, romantic attractiveness, and recognition. They were also asked whether they view high-risk investments as necessary to achieve their most important goal. We classify respondents as having no crypto, insignificant crypto, or significant crypto based on whether losing all holdings would materially affect their well-being.[21]

Figure 3 reports mean importance of goals by crypto holdings. Consistent with Prediction 1 of Corollary 1, across almost all goals, respondents with greater crypto exposure report higher goal importance. These 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.[22] For example, a one standard deviation increase in the importance of "having the financial resources that improve my attractiveness as a romantic partner" corresponds to a 4.6pp (31%) increase

[21] 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?"

[22] This is broadly consistent with the original example in Friedman and Savage (1948) which discusses a jump into the "'middle' or 'upper' class."

Figure 3: 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.

in the probability of having significant cryptocurrency. Consistent with the notion that it is difficult-to-reach goals that are particularly important for explaining high-risk investment, Appendix Figure G.7 shows that the share of individuals who directly report needing high-risk investment to achieve their goals increases steeply in crypto holdings.

One concern is that these holdings may be too small for such goals to be plausible, even under optimistic beliefs about cryptocurrency returns. In the data, however, a meaningful share of crypto owners hold substantial amounts. Combining current holdings with respondents' beliefs about crypto returns over the next five years in a good scenario, 25% of crypto owners expect gains equivalent to more than 7% of their current assets, and 10% expect gains exceeding 33%. For heavy users, these gains correspond to 53M KRW ($38,000 USD) at the 75th percentile and 340M KRW ($243,000 USD) at the 90th percentile, which represent a substantial fraction of the resources needed to attain major financial goals; for example, the downpayment required to purchase an entry-level apartment in the Seoul metropolitan area is around 100M KRW ($71,000 USD).[23]

[23] In July 2026, average apartment prices in the first and second quintiles of the Seoul metropolitan area were approximately 230M and 414M KRW, respectively (KB Kookmin Bank, 2026). Under a 30 percent equity requirement, these correspond to downpayments of approximately 69M and 124M KRW. The equity share reflects Korean mortgage rules, under which first-time homebuyers can borrow up to 70 percent of

Table 3: Risk Seeking Preferences and Crypto on Goals

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk Seeking	Currently Owns Crypto				
Average Goal Importance	0.059***	0.11***				0.10***
	(0.018)	(0.017)				(0.017)
Needs High Risk for Goal	0.21***		0.10***			0.090***
	(0.027)		(0.027)			(0.028)
Expected 1Yr Bitcoin Returns				0.033***		0.027**
				(0.013)		(0.012)
Risk Seeking					0.056**	0.024
					(0.024)	(0.024)
Demographic Controls	✓	✓	✓	✓	✓	✓
Observations	2139	2139	2139	2139	2139	2139
R^2	0.084	0.076	0.059	0.053	0.052	0.089

Notes: Table shows regressions of risk-seeking preferences and cryptocurrency ownership on goals. Full variable definitions are in Appendix D.1. "Risk-Seeking" indicates preferring a risky lottery over a sure gain when both have the same expected value. "Currently Owns Crypto" indicates whether the respondent reports owning cryptocurrency. "Average Goal Importance" is an individual's average response across goals in Figure 3. "Needs High Risk" is whether the respondent reported that high-risk investment was one of the most realistic ways to achieve their most important financial goals. "Expected 1Yr Bitcoin Returns" are expected Bitcoin returns over 1 year, winsorized at 400%. Demographic controls include sex, income, education, age, marital status, home ownership, employment, and assets. The regressions are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in our GranData sample. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses. Source: SKT survey.

Goals Predict Gambling in a Lottery Choice Task. To tighten the connection between difficult-to-reach goals and risk-seeking preferences, we elicit risk preferences in a lottery choice task. Respondents choose between a guaranteed 5% increase in their wealth and lotteries with higher payoffs but lower probabilities, holding expected values constant. We label respondents as risk-seeking if they prefer a fair gamble to the certain payoff.[24]

While risk preferences are often treated as primitives, column (1) of Table 3 suggests that they may be shaped, at least in part, by underlying goals. Risk-seeking is strongly predicted by both goal importance and the perceived need for high-risk investment to achieve the goal. Even controlling for sex, income, education, age, marital status, home ownership, employment, assets, and goal importance, respondents who separately report needing high-risk investment to achieve their goals are 21 percentage points more likely to choose a lottery response that implies risk-seeking preferences.

Goals Matter Beyond Beliefs and Preferences. Finally, we examine how cryptocurrency ownership relates to expectations, risk preferences, and goals. Columns (2)–(5) of Table 3 show that goals, expected returns, and risk-seeking preferences each strongly predict crypto ownership, even with the demographic controls described above.[25] Column (6) is the key specification, which includes goals, expectations, risk preferences, and demographics simultaneously. The relationship between goals and cryptocurrency holdings remains strong: a one-standard-deviation increase in average goal importance raises the probability of owning crypto by 22.9%. The corresponding increases are 12.5% for perceived need for high-risk investment and 8.0% for expectations. The coefficients on goals change little between column (2) and (6), while the coefficient on risk preferences is much lower in column (6) than (5), suggesting that goals capture distinct sources of variation that may otherwise be attributed to inherent risk appetite.

These results suggest that difficult-to-reach goals generate demand for risky assets. Our model also makes predictions about how *distance* to goal shapes risk preferences (Corollary 1, Prediction 2). We provide evidence in support of these predictions next.

4.2 Distance to Goals

Our theory makes several additional predictions about how distance to one's economic goals shapes risk preferences. Measuring this distance is challenging: even within a given

the purchase price (Financial Services Commission, 2025).

[24] Appendix D.1 reports the full question and response options.

[25] The positive coefficient in column (4) is also consistent with Weber et al. (2023), who find a 12 percentage-point gap between holders and non-holders among U.S. households.

goal, such as "romantic attractiveness," individuals may differ substantially in their perceptions and aspirations. To explore Prediction 2, we therefore focus on one goal, homeownership, and use individuals' current assets to proxy for distance to the goal.

Figure 4: Distance to Housing Goal Shapes Holdings of Crypto vs. Stocks



Notes: Figure shows the share of individuals who hold crypto or stocks by assets, among non-homeowners who rate buying a home as an extremely important goal (5 out of 5). Responses are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. Appendix Figure G.10 shows that cryptocurrency ownership in the 50–100M KRW asset group is statistically higher than in each of the lower- and higher-asset groups (joint one-sided $p = 0.039$). Source: SKT survey.

Prediction 2 has two implications. First, individuals closer to their goals prefer assets with less right skew than those farther away. Survey participants perceive stock returns to be less skewed than crypto returns (Appendix Figures G.8 and G.9); therefore, among non-homeowners with similar housing goals, holdings should shift from cryptocurrency toward stocks as assets rise. Second, for a fixed high-risk asset, gambling should be hump-shaped in goal distance. Those very far from their goals do not take risk because even high-risk investments may not offer a realistic path to attainment, while those close to their goal avoid high-risk assets because the goal is already within reach. Risk should therefore be most prevalent among individuals at intermediate distances.

Figure 4 provides suggestive evidence consistent with both implications. Among non-homeowners who rate homeownership as extremely important, stock ownership is highest among those with more than 100 million KRW ($71,000 USD) in assets, while cryptocurrency ownership is hump-shaped and peaks among those with 50–100 million KRW. This pattern is consistent with the theory: higher-asset respondents closer to the housing

goal have less need for high-risk investment, while lower-asset respondents may be too far away for cryptocurrency to provide a realistic path to attainment. Consistent with this interpretation, Appendix Figure G.11 shows that the lowest-asset respondents are most likely to view a state-run lottery as the most realistic way to achieve their goals. Overall, the results suggest that risk-taking depends not only on financial frustration, but also on distance to one's life goals and on whether available assets can help attain them.

5 Evidence from Changes in Goal Distance

This section tests Prediction 3 of Corollary 1: an individual's demand for risk should change as they achieve or move further away from their goals. Using within-individual variation in the administrative data, we show that interest in cryptocurrency declines after individuals win the right to purchase price-regulated housing through a lottery, and increases during unemployment episodes.

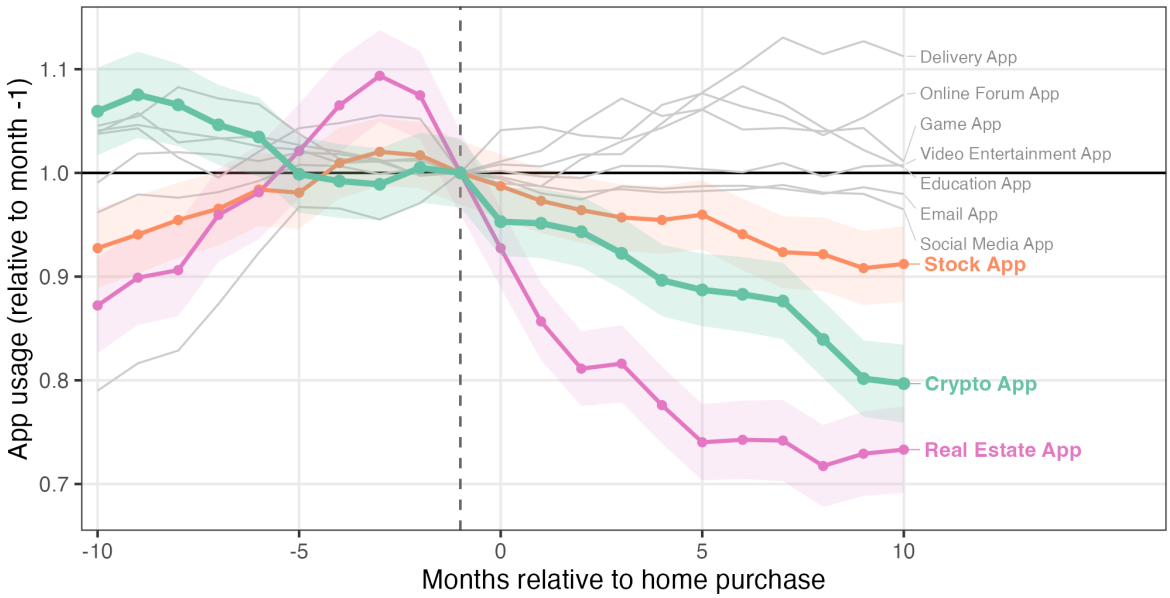
5.1 Goal Attainment: Evidence from the Korean Housing Lottery

The survey evidence in Section 4 suggests that homeownership is an important financial goal, especially among cryptocurrency investors. Motivated by this finding, we first explore app usage around the time individuals purchase a home. We then examine the causal effects of winning the right to purchase price-regulated housing.

Motivating Evidence. Figure 5 plots mean app usage by category in the months surrounding any home purchase between July 2021 and December 2023, relative to usage in month −1. We restrict the sample to individuals who did not own a home in July 2021. The figure shows that crypto app usage falls by around 20% in the year after the home purchase, a larger decline than for any other app category except real estate. The drop is specific to high-risk investment rather than a general reduction in phone usage: other categories show little systematic change. However, these patterns are only suggestive, as households that purchase homes may differ along a number of unobservable dimensions.[26] For example, family formation or higher expected income growth could drive both homeownership and lower crypto app use.

[26]Indeed, as the figure illustrates, crypto app usage declines prior to the purchase, consistent with individuals reducing risky investment once it becomes clear that they have accumulated enough assets to purchase a home.

Figure 5: App Usage Around a Home Purchase



Notes: Figure plots mean app usage by category in the months before and after a home purchase, relative 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.

Homeownership Lottery Institutional Details. To address endogeneity concerns, we exploit quasi-random variation from South Korea's housing subscription system (*cheongyak*), which allocates rights to purchase newly constructed apartments. Applicants must generally be non-homeowners and contribute to a designated savings account. Within each project, applicants are ranked by a priority score based on family composition, savings history, and years without homeownership. When a project is oversubscribed, as is typical in the capital region, a random lottery is implemented among the most qualified applicants, which generates quasi-random assignment in winners. We restrict our analysis to oversubscribed projects where this lottery mechanism operates.

Winning the lottery grants the right to purchase an apartment at a regulated presale 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 160M KRW ($114,000 USD), though Lee (2024) notes that some units are discounted by as much as 1 Billion KRW ($714,000 USD). As a result, lottery assignment induces a discrete change in distance to homeownership. For each likely winner, we define the event date as the start of the period in which winners could sign the purchase contract, which typically occurs within two weeks of the lottery announcement.[27] Because these projects are new constructions, move-in typically occurs two to three years later.

[27] Our data are monthly, and the results are unchanged if we instead use the announcement date.

Sample Construction. Applicant rosters for the housing lottery are not publicly available. We therefore identify likely winners by matching lottery projects to geographic locations in the credit bureau data and identifying households that first appear at these locations around the project's move-in date that match the eligibility rules, similar to Arkolakis et al. (2026).[28] We identify 1,892 individuals in the administrative data who appear to be lottery winners during a 36 month period between January 2021 and December 2023.[29] Appendix E provides more details on the construction and validation.

Empirical Specification. In our baseline design, we compare likely winners to future winners who have not yet reached their own contract date. This design allows to avoid making comparison to never-treated households who may differ on unobservables related to lottery priority. The key identifying assumption is that, absent a lottery win, outcomes for earlier winners would have evolved similarly to those of later winners. This assumption is plausible because lottery wins are random among high-priority applicants, and the pool of such applicants is large enough that the timing of a win cannot reasonably be anticipated. We also find no evidence of differential pre-trends in the event-study estimates we present below.

We address concerns with two-way fixed effects estimation under staggered treatment timing using the method of Callaway and Sant'Anna (2021).[30] Our differences-in-differences specification for lottery winner i and calendar time t is:

$$Y_{i,t} = \sum_{k} \beta_k \mathbb{I}(k = t - G_i) + \alpha_t + \delta_i + \epsilon_{i,t} \tag{4}$$

$Y_{i,t}$ is an indicator for heavy crypto usage or the number of times logged into a crypto app in month t. G_i is potential lottery winner i's contract date. α_t and δ_i are time and individual fixed effects. As a first-stage check, Panel (a) of Appendix Figure G.13 shows that housing debt rises by nearly 30M KRW ($21,400 USD) in the months after the contract

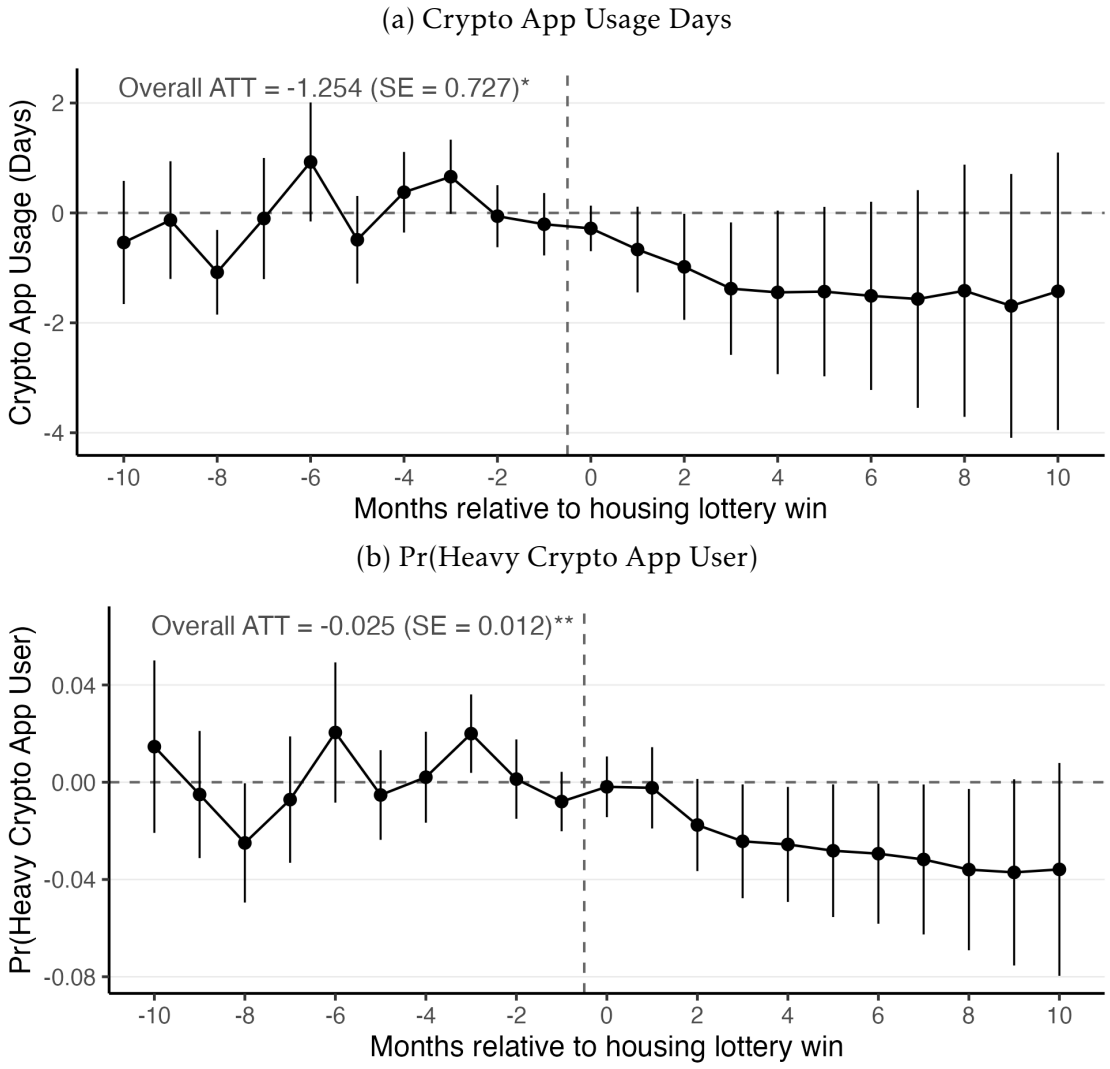
[28] We impose filters that mirror the eligibility requirements. First, we require that no member of the household owned residential property prior to the application date, consistent with the lottery's non-homeownership requirement. Second, we require that at least one household member transitions into homeownership after the lottery announcement, ensuring the household is a purchaser rather than a renter or secondary occupant. Finally, we restrict our sample to oversubscribed projects where allocations are lottery-driven and winners were likely to not be able to buy a comparable house otherwise.

[29] Within each household, we keep the youngest adult male. Our results are not sensitive to this choice.

[30] Callaway and Sant'Anna (2021) estimates group-time average treatment effects, avoiding negative weighting under heterogeneous treatment effects (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). Appendix Figure G.14 reports the efficient estimator of Roth and Sant'Anna (2023), which imposes a stronger assumption of quasi-random treatment timing. We conservatively use the less restrictive estimator: the efficient estimator yields slightly larger effects on both outcomes, each significant at 5%.

date. Prediction 3 implies that after winning individuals decrease their high-risk activity, so that $\beta_k < 0$ for $k > 0$ would be consistent with our model of Friedman-Savage motives.

Figure 6: Change in Cryptocurrency Use 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. The top left of each panel reports the overall average treatment effect on the treated. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Source: KCB and SKT.

Results. Figure 6 shows that cryptocurrency use declines after the housing-lottery contract date, consistent with Prediction 3. Panel (a) shows that, ten months after the contract date, crypto app usage falls by nearly two days per month on average, a 21% decline relative to the month before the contract date. Panel (b) shows a four-percentage-point

decline in the probability of being a heavy crypto user, a 32% decrease. The top left of each panel reports the average treatment effect on the treated comparing the pre- and post-periods. The effects are statistically significant at the 10 and 5 percent levels for crypto usage days and heavy crypto use, respectively. Overall, the results suggest that goal attainment reduces demand for high-risk financial activity.

Robustness. We conduct additional analyses to clarify the interpretation of the results. First, we show that the effects are largest where homeownership was initially most difficult to attain. We split lottery wins into those in the Seoul metropolitan area (Sudogwon), where housing is least affordable, and those outside it. Consistent with the model's prediction, Appendix Figure G.12 shows that the decline in cryptocurrency engagement is strongest among Sudogwon lottery winners.

We further show that the decline in cryptocurrency use does not appear to reflect a broad liquidation of financial assets to meet housing-related expenses, such as moving costs. Appendix Figure G.13 shows a slight rise in household consumption but no corresponding decline in stock-app usage, suggesting that the response is specific to cryptocurrency rather than a general reduction in financial-market activity.

A remaining possibility is that homeownership affects cryptocurrency engagement through a standard portfolio-choice channel. Winners acquire a large, illiquid asset, often financed with leverage, which may crowd out other risky financial investments (Cocco, 2005). This mechanism is difficult to fully separate from our theory, since attaining homeownership necessarily changes both goals and balance sheets. However, the fact that winners outside Sudogwon do not reduce cryptocurrency engagement, despite also acquiring housing, suggests that balance-sheet crowd-out is unlikely to be the whole story. To provide further evidence, we next turn to adverse economic shocks, which move goals further out of reach without creating a new illiquid asset.

5.2 Goals Moving Further Out-of-Reach: Unemployment Events

Prediction 3 also suggests that adverse shocks can increase demand for high-risk investment by pushing salient goals further out of reach. We test our theory by measuring how cryptocurrency engagement shifts around unemployment events.

Sample Construction and Specification. 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:

$$\Delta Y_i = \beta_0 + \beta_{unemp} \cdot \text{HasUnemploy}_{post,i} + \gamma \cdot W_{pre,i} + \epsilon_i. \tag{5}$$

$\Delta Y_i \equiv \overline{Y}_{post,i} - \overline{Y}_{pre,i}$ 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 the change in cryptocurrency engagement between individuals who experienced unemployment and those who did not.

Table 4: 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

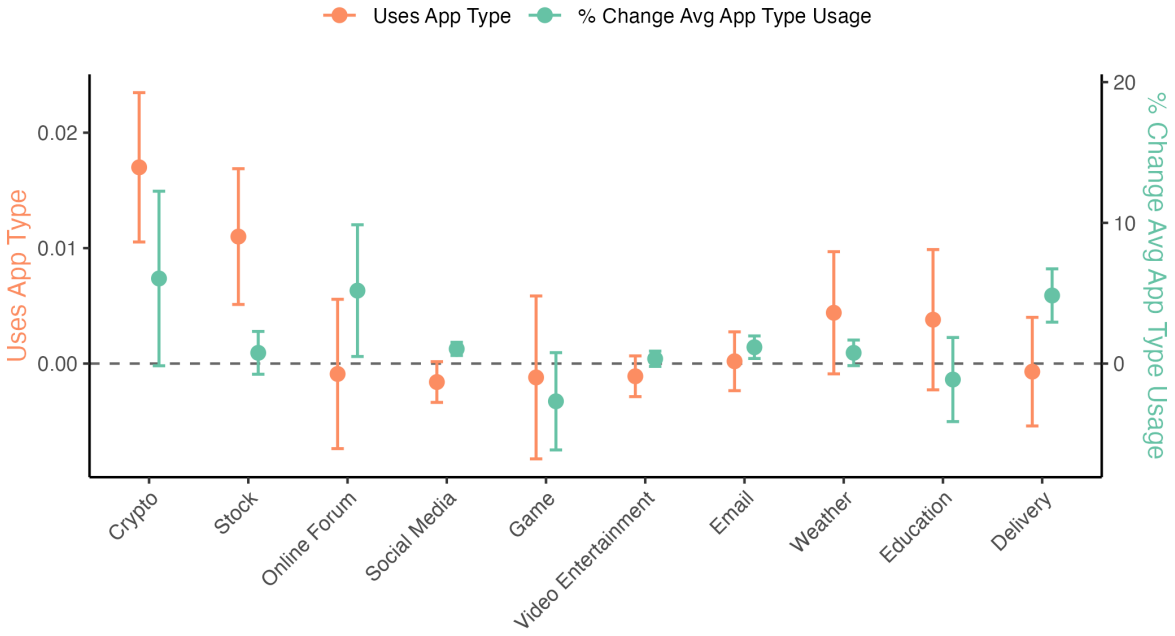
Notes: Table shows results from the regression in Equation 5. The sample includes all individuals who were continuously employed in the pre-period (January-June 2021). The outcome in columns 1-2 is the difference in indicators (-1, 0, or 1) for whether individual i used a crypto app in any month in the 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" include gender; indicators for homeownership, living alone, having a credit loan, and having an auto loan; log income; log consumption; and age-decade fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses.

Results. Table 4 shows that individuals who become unemployed increase their cryptocurrency usage relative to other similar individuals who remain employed. Columns (2) and (4), which include controls, show that becoming unemployed is associated with 1.7 and 0.86 percentage point increases in the probability of being a crypto user and a heavy crypto user, respectively, in the post-period relative to the pre-period. These estimates correspond to approximately 6% and 8% increases relative to pre-period means. Column (6) shows that cryptocurrency app usage increases by 0.2 interactions per month

on average, a 6% increase relative to the pre-period mean.

Placebo: Other Apps. Figure 7 shows that the results are not driven by a general increase in phone usage during unemployment. We re-estimate the specifications in columns (2) and (6) of Table 4 with app usage in other categories, such as online forums and real estate apps, as outcomes. Following unemployment, cryptocurrency app usage rises markedly, stock-trading apps increase more modestly, while the remaining categories show small or insignificant responses. These patterns suggest unemployment episodes are uniquely tied to the use of high-risk assets, relative to other applications.

Figure 7: Effects of Unemployment Experience by App Types



Notes: Figure shows coefficients from the regression in Equation 5. Orange points correspond to regressions analogous to column (2) of Table 4, using different app categories as outcomes. Green points correspond to regressions analogous to column (6) of Table 4, with coefficients scaled by pre-period mean usage in each category. Bars show 95% confidence intervals.

Results Strongest Among Prior Non-Users. The model predicts that adverse shocks should induce risk-taking primarily among individuals who were not taking risk before unemployment; for prior gamblers, a negative shock may push the goal too far out of reach. We therefore repeat the analysis among individuals with no pre-period cryptocurrency use. Consistent with the theory, Appendix Table H.13 shows stronger effects in this group. Prior non-users are 3 percentage points more likely to become crypto users after

unemployment and 1 percentage point more likely to become heavy users. By contrast, Appendix Table H.14 shows small and insignificant changes among prior crypto users.

Crypto Usage and New Unsecured Debt. We find similar patterns around increases in unsecured borrowing. Using the same timing and design as the unemployment analysis, Appendix Table H.15 shows that individuals who take on new unsecured debt also increase cryptocurrency usage. These episodes may reflect expense shocks or tighter financial constraints that move goals further out of reach, increasing the appeal of high-risk investment. However, because unsecured borrowing is endogenous and may also reflect changes in financial behavior or risk tolerance, we view these results as suggestive.

6 Consumption and Additional Explanations

This section presents additional evidence on the mechanisms behind high-risk investment. We show that cryptocurrency app users borrow and spend more conditional on wealth, consistent with Prediction 4 of Corollary 1. We then discuss alternative explanations for risk-taking, including intrinsic enjoyment, addiction, and optimistic beliefs.

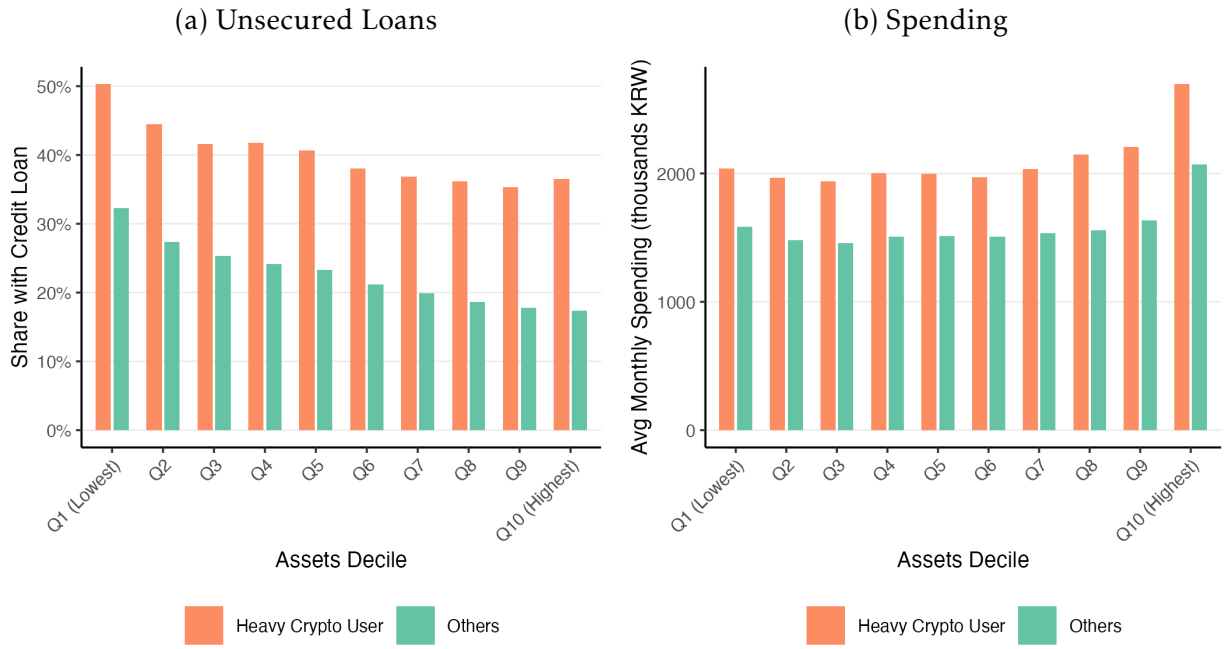
6.1 Gambling and Consumption

The final prediction in Corollary 1 is that individuals who gamble toward aspirational goals "partially give up" on traditional saving and, conditional on wealth and goals, reallocate resources toward current consumption. Table 2 provides suggestive evidence consistent with this. While heavy crypto users have incomes that are roughly 20% higher, they spend around 50% more on food, luxury goods, and department stores.

Figure 8 provides additional evidence. Across the asset distribution, both unsecured debt and average spending are substantially higher for heavy crypto users. For example, panel (a) shows that in the fifth asset decile, 41% of heavy crypto users hold unsecured loans, compared to 23% of others. Panel (b) shows that in the fifth asset decile, heavy users spend an average of 1.99M KRW per month versus 1.51M KRW for others. Appendix Figures G.15, G.16, G.17 show these patterns hold across age groups and in multivariate regressions controlling for gender, age, income, and other individual characteristics. The combination of higher consumption and unsecured debt helps alleviate a potential concern that the higher consumption is financed by unobserved wealth.

Our results are consistent with Prediction 4. In the model, individuals who view their goals as attainable only through high-risk investment reduce saving and shift toward cur-

Figure 8: Crypto Heavy Users vs Others: Unsecured Debt and Spending by Assets



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

rent consumption. The higher spending and greater use of unsecured debt among heavy crypto users, conditional on assets, align with this mechanism and with existing evidence in Lee and Yoo (2025). However, these patterns could also reflect heterogeneity in underlying preferences: individuals with self-control problems may both consume more and take more risk. We discuss this and other alternative explanations next.

6.2 Alternative explanations

While the evidence in Sections 4 and 5 support the importance of Friedman-Savage motives, other factors may also play important roles. We now consider alternative explanations for risk-seeking behavior, including intrinsic enjoyment, addition, self-control, prospect theory, and beliefs. We discuss why these explanations do not appear to explain our full set of results.

Intrinsic Enjoyment. Gambling may confer direct utility beyond its expected effect on wealth. Individuals may derive utility from sensation-seeking (Grinblatt and Keloharju, 2009), the thrill of large gains (Loewenstein, 1987), or as a form of "escapism" when facing economic hardship (Conlisk, 1993; Asness, 2024). While these motives can help

explain why gambling-like activities are widespread, they leave several patterns unexplained. First, if individuals derive intrinsic-enjoyment from gambling they would still do so after housing or unemployment shocks. Second, intrinsic-enjoyment motives are most natural for small-stakes gambles, where they dominate the potential costs of losses; however, Section 3.2 shows individuals often hold enough cryptocurrency to substantially affect their spending, delinquency, and homeownership. Third, neither intrinsic-enjoyment nor escapism naturally predicts individuals will substitute *across* instruments with different skewness in a way that is correlated with goals (as in Section 4.2).

Addiction. Gambling can also be habit-forming or difficult to quit (Becker and Murphy, 1988; Gruber and Köszegi, 2001). Trading and other forms of financial risk-taking have also become cheaper, faster, and more gamified (Asness, 2024), potentially increasing the risk of addiction. While these forces are important, 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. Once these goals, such as homeownership, are attained, demand should fall, as we document in Section 5. By contrast, addiction implies demand for risk even in the absence of goals, and even when gambling may jeopardize already attained goals. Our results therefore suggest that risk-taking is not driven purely by hedonic motives.

Self-Control. Other notions of self-control (e.g., present bias) could help explain why gambling is correlated with higher spending and unsecured borrowing in the cross-section: high-risk investment may resemble other activities that disproportionately appeal to people with self-control problems. But self-control does not predict risk appetite falling after a housing-lottery win nor increasing after unemployment. Impatience or present-bias also have ambiguous implications for large-stakes financial risk-taking, since large-stakes gambling crowds out other forms of current consumption.

Prospect Theory. If financial goals serve as reference points, prospect theory could be a natural way to interpret our findings: households who perceive salient goals as out of reach may feel they are in the loss domain, where they become risk-seeking (Kahneman and Tversky, 1979). While this interpretation is closely related to our theory, there are some differences. First, it is not obvious that difficult-to-attain goals should strongly enter the reference point. In expectation-based models, unlikely goals receive limited weight in personal equilibrium (Kőszegi and Rabin, 2006). Second, prospect theory predicts that households in the loss domain become more willing to take *any* form of risk. Our theory

predicts that individuals should instead prefer certain *types* of gambles over others, with more desperate households choosing more right-skewed bets, as we document in Section 4. Finally, since prospect theory is descriptive rather than embedded in a standard consumption framework, it is difficult to study welfare, as we will do in Section 7.

Subjective Beliefs. Subjective beliefs also play an important role in speculative investment. If households view high-risk assets as offering high expected returns, this can generate participation (e.g., Weber et al., 2023). However, Table 3 shows that goals predict cryptocurrency ownership even after controlling for expected returns and, as we will show in Section 7, belief heterogeneity does not appear to explain the hump shape of crypto holdings in Figure 4.[31] It is also difficult to explain why beliefs for crypto in particular should change after homeownership or unemployment.

Summary. Our interpretation is not that alternative explanations are absent. Entertainment, addiction, reference dependence, and optimistic beliefs are all likely important contributors to household investment in high-risk assets, especially in aggregate. Rather, the full pattern of evidence is consistent with an additional mechanism: preferences for risk are context-dependent and shaped by salient life goals.

Importantly, Friedman-Savage motives can also interact with alternative mechanisms. A household may begin gambling because a risky asset appears to offer the only route to a goal, and continue to gamble because of addiction or habit-formation. Overoptimistic beliefs can also make Friedman–Savage motives especially powerful: when the upside of a gamble is tied to a salient goal, biased beliefs can translate into larger investments and larger welfare losses. We discuss this interaction in Section 7.

7 Model Calibration and Counterfactual Analyses

Motivated by our empirical evidence, we calibrate a quantitative version of our model. This exercise serves three purposes. First, it shows that a model in which households aspire to a housing goal can reproduce the hump-shaped pattern we observe, with gambling concentrated among an "unhappy middle." Second, it allows us to estimate how

[31] Belief-based explanations often have ambiguous predictions about the cross-section of holdings. If optimism 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).

cryptocurrency holdings would change for this group without gambling motives. Third, it shows how gambling motives can amplify the welfare losses from overoptimism.

7.1 Model and Estimation

We estimate a quantitative version of our model that incorporates multiple assets, participation costs, and belief heterogeneity. Our estimation targets the cross-sectional patterns in cryptocurrency and stock ownership among aspiring homeowners in Figure 4.

Model. We extend the two-period model in Section 2.2 to include two risky assets, cryptocurrency and stocks, whose gross returns are uncorrelated and lognormal with subjective mean net returns μ_s, μ_c and log volatilities σ_s, σ_c. We normalize the risk-free gross return to one. Participation in each risky asset requires a fixed cost F_s, F_c, which may capture time or psychological costs of participation.[32] In period two, the household can spend G to attain housing and receive utility gain θ, as in the baseline model. We assume agents have log utility and set the length of a period to five years.

Beliefs. We allow households to disagree about mean returns, consistent with the evidence in Table 3 that expected returns are heterogeneous and strongly predict cryptocurrency holdings. For risky asset j, a household's beliefs are given by

$$\mu_j(z) = \bar{\mu}_j + \eta_j z, \qquad j \in \{s, c\}, \qquad z \sim \mathcal{N}(0,1) \tag{6}$$

where $\bar{\mu}_j$ is the population median belief and η_j governs cross-sectional disagreement.[33] One concern is that a model in which beliefs vary with wealth could reproduce essentially any cross-sectional pattern in holdings, including the hump we observe. However, Appendix Figure G.18 shows that mean and median expected five-year returns for stocks and cryptocurrency do not vary strongly across asset bins. If anything, respondents in the 50-100 million KRW asset bin, where the hump in cryptocurrency holdings is most pronounced, are more optimistic about stocks and no more optimistic about cryptocurrency

[32] A large literature on household portfolio choice introduces fixed participation costs to explain the strong positive relationship between wealth and stock-market participation. These costs may capture monetary expenses, cognitive or information-acquisition costs, real or perceived time costs, or other psychological costs; see, e.g., Campbell (2006), Gomes and Michaelides (2005), and Vestman (2019).

[33] A single factor imposes that optimism about stocks and crypto is perfectly correlated across households, which reduces the number of belief types the solver must handle. Appendix F shows that our conclusions are unchanged with uncorrelated optimism. In the survey data, optimism about stocks and crypto has a correlation of 0.58.

than respondents in the 100-500 million KRW bin. We therefore hold the distribution of beliefs fixed across wealth and allow disagreement to enter only through η_j.

Goals. In principle, both the level and importance of goals could also vary across households. To separate this potential heterogeneity from belief heterogeneity, we focus on a sample of individuals who plausibly have similar goals: non-homeowners who rate buying a home as an extremely important goal, as in Figure 4.

Estimation. We estimate the model in two steps. In the first step, we calibrate $\bar{\mu}_j$ using the survey median five-year return beliefs, $\bar{\mu}_s = 0.345$ for stocks and $\bar{\mu}_c = 0.446$ for cryptocurrency. In the second step, we estimate the remaining eight parameters—θ, G, F_s, F_c, σ_s, σ_c, η_s, and η_c—by minimizing the sum of squared distances between model-implied and empirical ownership shares. We target the eight ownership shares in Figure 4: cryptocurrency and stock ownership in each of four asset bins among aspiring homeowners. For each candidate parameter vector, we solve the agent's period-one portfolio problem under her subjective beliefs. We solve the problem over a grid of initial wealth and integrate over return realizations and belief heterogeneity using Gaussian quadrature.[34] Appendix F provides more details on estimation.

Identification. While the eight parameters are estimated jointly, we provide intuition for the empirical patterns that identify each. The goal parameters G and θ are primarily identified by the location and height of the hump in cryptocurrency holdings: G determines the wealth region in which households must gamble to attain the goal, while θ governs how many individuals are drawn into the gamble. Fixed costs F_s and F_c are identified by the upward slope in participation across wealth, as discussed by Campbell (2006). The dispersion in mean beliefs, η_s and η_c, governs the share of households whose beliefs are extreme enough to change their participation decision, and is therefore primarily identified by overall participation rates. Finally, return volatilities, σ_s and σ_c, determine the degree to which each asset functions as a gamble and therefore help shape relative participation near the gambling region across the two assets.

[34] Because our primary measure, asset participation, is discrete, our model predictions can be locally unstable near indifference regions. For numerical stability, we smooth by replacing the participation indicator with a logistic approximation in the utility difference between participation and non-participation, with scale $\tau = 0.0005$. The smoothing affects only households close to indifference.

7.2 Results and Model Fit

The calibrated model closely reproduces the cross-sectional patterns in asset ownership, including the hump in cryptocurrency holdings near the housing goal.

Parameter Estimates. Table 5 shows the parameter estimates. The estimated utility gain from housing, $\theta = 3.21$, is large, but captures the full lifetime utility boost the agent gains from acquiring housing. Under log utility, an agent buys the house if period-two wealth exceeds $G/(1 - e^{-\theta})$. At our estimate, this threshold is $1.04 \times G$. Thus, households choose to buy almost as soon as they can afford to do so and leave relatively little left for consumption in that period. The estimated goal cost, G, is 103 million KRW ($74,000 USD), similar to the downpayment required for a relatively inexpensive apartment in the Seoul metropolitan area (69-124 million KRW; see footnote 23), a key unmatched moment. Fixed participation costs are about 2.5 million KRW ($1,800 USD) for stocks and 0.2 million KRW ($140 USD) for cryptocurrency. The stock-market cost is similar to values in Vestman (2019), while the lower cryptocurrency cost may capture lower monetary or psychological costs of purchasing these assets.[35]

Table 5: Calibration Parameter Estimates

θ	G	F_s	F_c	σ_s	σ_c	η_s	η_c
3.214	1.027	0.025	0.002	0.135	1.298	0.821	2.615
(1.990)	(1.905)	(0.139)	(0.333)	(0.442)	(0.325)	(1.335)	(3.692)

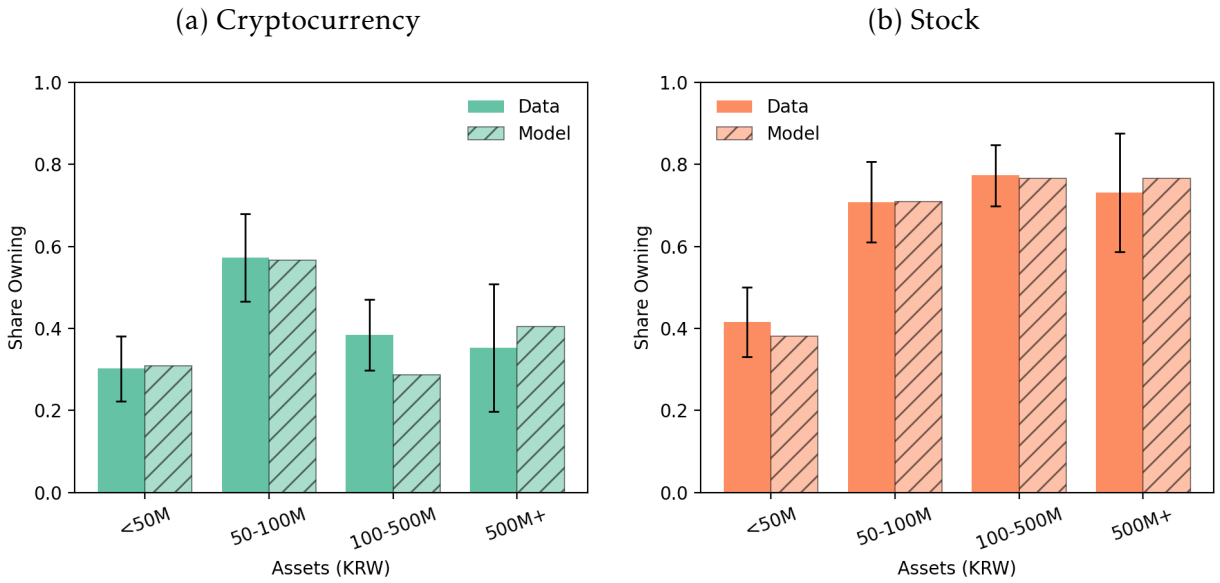
Notes: Table shows jointly-estimated parameters with standard errors in parentheses. θ is the utility gain from attaining the housing goal; G is the cost of the goal; F_s and F_c are the fixed costs of participating in stocks and cryptocurrency, respectively; σ_s and σ_c are the log volatilities of five-year returns; and η_s and η_c are the standard deviation, across households, of mean believed returns. The parameters G, F_s, and F_c are expressed in hundreds of millions of KRW.

The estimated log volatility is $\sigma_s = 0.13$ for stocks, or about 6% per year, somewhat below the roughly 20% per year realized on the KOSPI, and $\sigma_c = 1.30$ for cryptocurrency, or about 58% per year, similar to the roughly 50% per year realized for Bitcoin. Finally, households disagree far more about cryptocurrency than about stocks. We estimate $\eta_c = 2.62$ for cryptocurrency, more than three times the $\eta_s = 0.82$ we estimate for stocks. These estimates imply that about 30% of households expect cryptocurrency to lose nearly all of its value over five years, while the top quarter expect it to more than triple.

Model Fit. The model fits the eight ownership moments closely and reproduces the hump in cryptocurrency holdings. Figure 9 plots empirical and model-implied ownership

[35] In particular, Vestman (2019) estimates costs of $667 USD and $2,000 USD for two types of consumers.

Figure 9: Ownership of Cryptocurrency and Stocks by Assets, Data vs. Model



Notes: Figure compares empirical and model-implied asset ownership by wealth, among non-homeowners who aspire to purchase a home. Solid bars are the same as in Figure 4. Hatched bars show the corresponding model-implied shares at the parameter estimates in Table 5. Black bars display 95% confidence intervals.

side by side. Cryptocurrency ownership peaks in the 50-100 million KRW bin in both the data (57.3%) and the model (56.7%), and closely matches the lowest bin (30.2% versus 31.0%). Stock ownership rises sharply from the first to the second bin and then flattens, again closely matching the data.

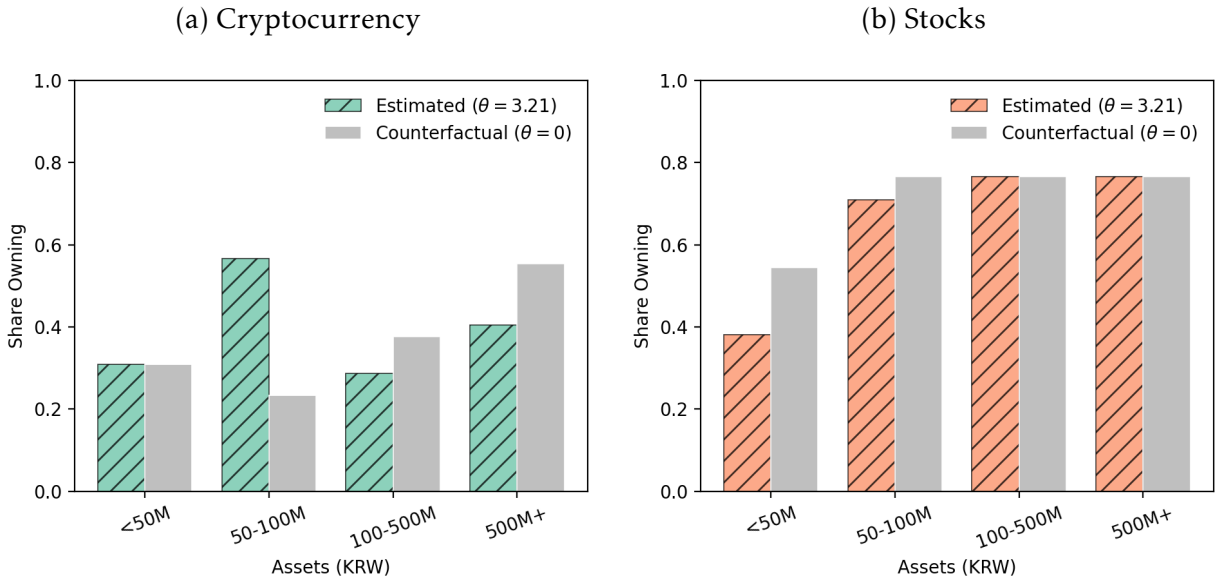
The goal motive is important for the model's fit to the data. Appendix Figure G.19 shows that a re-estimated model without goals does not generate the hump-shaped pattern in cryptocurrency ownership. Intuitively, households in higher asset bins hold the same beliefs and face the same fixed costs as households in lower bins, but have more wealth over which to spread those costs. Without goals, this generally pushes participation upward with wealth rather than producing a hump. Consistent with this force, the model's largest misses are in the upper wealth bins for both assets, where the model predicts slight increases in ownership while the data show slight declines.

7.3 Counterfactual Holdings without Goals

Shutting off the gambling motive substantially reduces cryptocurrency ownership among households near the housing goal. Figure 10 compares ownership under the calibrated model to a counterfactual with $\theta = 0$, holding all other parameters fixed. In the 50-100 million KRW bin, cryptocurrency ownership falls by 34 percentage points, from 57% to 23%. By contrast, stock participation for this group rises slightly. Without the goal, these

individuals reduce their gambling and substitute toward safer assets.

Figure 10: Counterfactual Ownership without Gambling Motives



Notes: Figure shows model-implied ownership by assets at the estimated parameters and under a counterfactual that shuts off the gambling motive. Hatched bars are the same as in Figure 9. Grey bars are model-implied outcomes when $\theta = 0$, holding all other parameters fixed.

Outside this region, removing the goal has smaller effects. Cryptocurrency ownership is essentially unchanged in the lowest wealth bin and rises among wealthier households, from 29% to 38% in the 100-500 million KRW bin and from 41% to 55% above 500 million KRW. The latter effect is driven by richer households who no longer need to be cautious to protect their homeownership.

7.4 Welfare Consequences of Overoptimism with Gambling Motives

Our evidence thus far suggests that goal-driven risk taking helps explain high-risk investment. If these motives reflect genuine preferences and correct beliefs, gambling may maximize expected utility ex ante. However, some households may also hold overoptimistic beliefs about cryptocurrency returns, as suggested by prior work: 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 or salient outcomes (Kahneman and Tversky, 1979; Bordalo et al., 2022; Barber and Odean, 2008).

We study how these forces interact using the calibrated model. Given that we wish to avoid taking a stance on what "correct" beliefs about cryptocurrency returns should be, we take the following conservative approach. We assume that the median survey respondent is rational about cryptocurrency, and compare them to "optimists" who are at the

75th percentile of the belief distribution (holding beliefs about stocks at the median). We then measure for which individuals such optimism is most consequential, for both their asset allocation and welfare losses.

Effects on Asset Allocation. Panels (a) and (b) of Figure 11 plot optimal cryptocurrency and stock holdings across initial wealth. The dotted black lines show choices under median beliefs, while the solid colored lines show choices for households optimistic about cryptocurrency. Optimism sharply increases cryptocurrency holdings for households below the housing threshold. Around 50-100 million KRW in assets, optimistic households with goals invest roughly 60% of their wealth in cryptocurrency. Without the goal ($\theta = 0$), cryptocurrency holdings of optimistic households are much flatter across wealth and substantially lower near the goal. This response also extends to stocks: optimistic households with goals reduce their stock holdings to zero when wealth is below 100 million KRW.

Welfare Consequences. Panel (c) shows that goal-driven motives also amplify the welfare losses from cryptocurrency optimism. Let π_0 denote the median-belief return distribution and π the optimistic belief distribution. We define the welfare loss as

$$\Delta U(W, \pi, \pi_0) = \mathbb{E}_{\pi_0}[U(W; a^*(\pi_0))] - \mathbb{E}_{\pi_0}[U(W; a^*(\pi))] \tag{7}$$

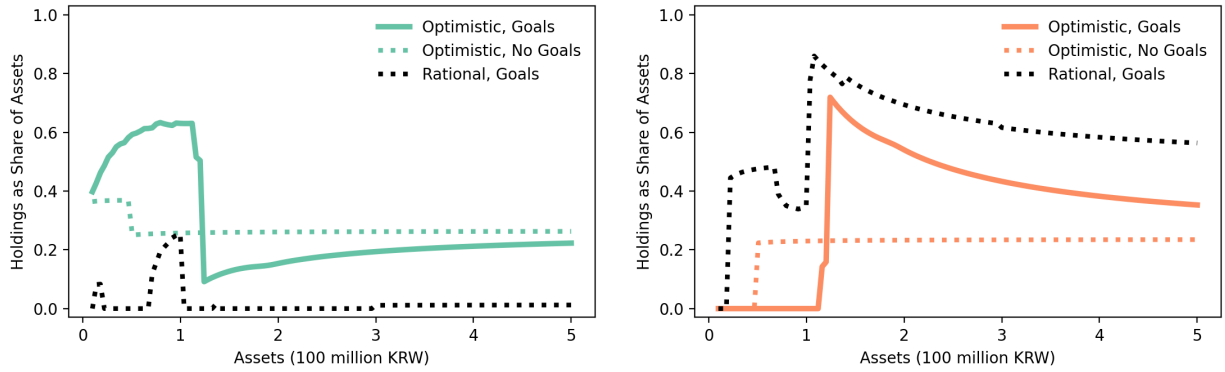
where $a^*(\pi)$ denotes the portfolio chosen under beliefs π. We evaluate both portfolios under the same median-belief return distribution and measure the utility loss from choosing the portfolio implied by optimistic beliefs. As Panel (c) illustrates, the welfare loss is largest for those near the housing goal. Overoptimism on one hand induces households below the goal to reach excessively for an unlikely goal, while on the other hand induces households who previously could safely attain the goal to gamble and risk losing it. In both cases, the welfare cost of overoptimism is much larger than without goal-driven motives, reaching roughly four times the no-goal loss near the housing threshold. In wealth-equivalent terms, an overoptimistic individual without goals is as well off in expectation as a rational individual who had approximately 7% less wealth. With goals, this difference increases up to almost 20% in the gambling region (Appendix Figure G.20).

Discussion. Our results speak to a broader literature on how belief distortions translate into economic behavior and welfare. A large body of work (e.g., 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. At the same time, recent works, including Giglio et al. (2021), show that differences in beliefs often translate

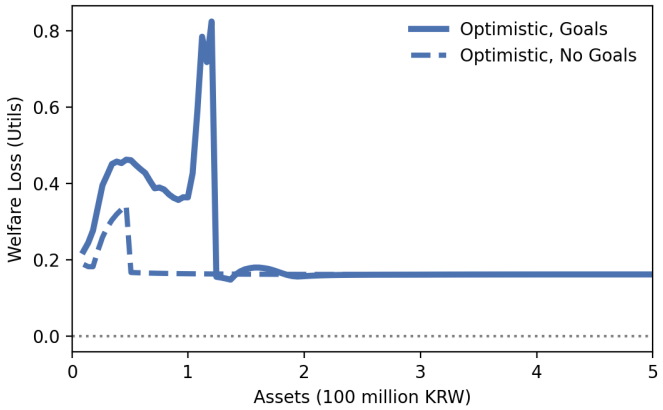
Figure 11: Holdings and Welfare Losses from Cryptocurrency Overoptimism

(a) Cryptocurrency Holdings

(b) Stock Holdings



(c) Welfare Loss from Overoptimism



Notes: Figure shows the results of simulations described in Section 7.4. Panels (a) and (b) plot the share of wealth held in each risky asset across initial wealth. "Optimistic" households hold beliefs at the 75th percentile of the cryptocurrency belief distribution; "Rational" households hold median beliefs. Panel (c) plots the resulting welfare loss, defined as the utility attained by an optimistic household under the median return distribution relative to a household with median beliefs. "No Goals" sets $\theta = 0$, holding all other parameters at their estimated values. Wealth is measured in hundreds of millions of KRW.

into relatively modest differences in actions, which may attenuate the impact of biased beliefs. Our results could reconcile these perspectives: the impact of biased beliefs depends not only on the bias itself, but also on the economic context households face. When risky assets offer a perceived path to salient goals, households act more aggressively on optimistic beliefs, amplifying their welfare consequences.

A related implication concerns the regulation of speculative assets. Our calibration shows substitution between stocks and cryptocurrency that depends on the extent to which households view cryptocurrency as more volatile and useful for gambling. To the extent that other assets offer similarly volatile, high-upside payoffs, restricting one speculative asset, such as cryptocurrency, may redirect demand toward other gambles, such as high-risk options, rather than eliminate it. The effectiveness of such policies therefore depends on the available substitutes and households' beliefs about them. More broadly, policies aimed at a single asset may have limited effects if they do not address the broader economic conditions (e.g., housing affordability, upward mobility) that make high-risk, lottery-like payoffs appealing as a way to pursue otherwise difficult-to-reach goals.

8 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 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 remain disciplined by risk and uncertainty. But when risky assets are viewed as a means to reach 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 of Lemma 1. $\mathcal{W}(x) = u(x) - u(x-G)$ is continuously differentiable with $\mathcal{W}'(x) = u'(x) - u'(x-G) < 0$ by strict concavity, so $\mathcal{W}$ is strictly decreasing. As $x \downarrow G$, $u(x-G) \to -\infty$ and so $\mathcal{W} \to \infty$; as $x \to \infty$, $\mathcal{W}(x) \le G\,u'(x-G) \to 0$. Hence there is a unique W_2^* with $\mathcal{W}(W_2^*) = \theta$, and $u(x-G)+\theta \ge u(x) \iff \theta \ge \mathcal{W}(x) \iff x \ge W_2^*$. Implicit differentiation of $\mathcal{W}(W_2^*) = \theta$ gives $\partial W_2^*/\partial\theta = 1/\mathcal{W}' < 0$ and $\partial W_2^*/\partial G = -u'(W_2^* - G)/\mathcal{W}' > 0$. U_2 is the upper envelope of two continuous increasing functions, hence continuous and increasing, and equals u below W_2^* and $u(\cdot - G) + \theta$ above, each concave. Its one-sided derivatives at W_2^* are $u'(W_2^*)$ and $u'(W_2^* - G)$, and $u'(W_2^*) < u'(W_2^* - G)$ since u' is strictly decreasing. Finally, by the mean value theorem $\theta = \int_{W_2^*-G}^{W_2^*} u'(w)\,dw = G\,u'(\xi)$ for some $\xi \in (W_2^* - G, W_2^*)$; since $u'(c^*) = \theta/G$ and u' is strictly monotone, $\xi = c^*$. □

Proof of Proposition 1. Note that the objective in (3) is concave and differentiable except where a state's wealth crosses W_2^*, but it is *not* globally concave. We therefore characterize the optimum by comparing value functions across candidate regimes rather than by first-order conditions alone. For $q \in [0,1]$, define the function $\varphi(q; W_1) \equiv 2\,u\Big(\frac{W_1 - qG}{2}\Big) + q\,\theta$, which intuitively captures the value of attaining the goal with probability q while smoothing consumption perfectly across periods and states. Note that the function φ is strictly concave in q, with unconstrained peak at $q^*(W_1) = (W_1 - 2c^*)/G$, which is increasing in wealth.

By Jensen's inequality, any optimum has $I_{\mathcal{R}}^* = 0$ (so $x_L = x_H$) or only attains the goal in good states of the world. Consider the corresponding three value functions.

- *Never attain.* $\max u(c_1) + u(x)$ s.t. $c_1 + x = W_1$ gives $c_1 = x = W_1/2$ and value $2u(W_1/2) = \varphi(0; W_1)$.
- *Always attain.* $\max u(c_1) + u(x-G) + \theta$ s.t. $c_1 + x = W_1$ gives $c_1 = x - G = (W_1 - G)/2$ and value $2u((W_1 - G)/2) + \theta = \varphi(1; W_1)$.
- *Attain in the high state only.* We maximize $u(c_1) + p_L u(x_L) + p_H[u(x_H - G) + \theta]$ subject to $c_1 + p_L x_L + p_H x_H = W_1$. The first-order conditions give $u'(c_1) = u'(x_L) = u'(x_H - G)$, hence $c_1 = x_L = x_H - G \equiv c$; the constraint then gives $c + p_L c + p_H(c + G) = W_1$, so $c = (W_1 - p_H G)/2$ and the value is $2u((W_1 - p_H G)/2) + p_H\theta = \varphi(p_H; W_1)$.

The agent's problem is thus

$$V(W_1) = \max\Big\{\varphi(0; W_1),\ \varphi(p_H; W_1),\ \varphi(1; W_1)\Big\}. \tag{A.1}$$

To prove that there exists a $[W_L^*, W_H^*]$ such that gambling is optimal if and only if $W \in [W_L^*, W_H^*]$, We establish a single crossing result between the three value functions. Note that $\partial\varphi/\partial q = \theta - G\,u'((W_1 - qG)/2)$ and $\partial^2\varphi/\partial q^2 = \frac{G^2}{2}u''((W_1 - qG)/2) < 0$, so φ is strictly concave in q with unconstrained peak at $q^*(W_1) = (W_1 - 2c^*)/G$, which is strictly increasing in W_1. Denote $\Delta_0 \equiv \varphi(p_H) - \varphi(0)$ and $\Delta_1 \equiv \varphi(p_H) - \varphi(1)$. Then, gambling is optimal exactly when $\Delta_0 > 0$ and $\Delta_1 > 0$.

Observe:

$$\Delta_0'(W_1) = u'\Big(\tfrac{W_1 - p_H G}{2}\Big) - u'\Big(\tfrac{W_1}{2}\Big) > 0, \qquad \Delta_1'(W_1) = u'\Big(\tfrac{W_1 - p_H G}{2}\Big) - u'\Big(\tfrac{W_1 - G}{2}\Big) < 0,$$

because u' is strictly decreasing and $\frac{W_1 - G}{2} < \frac{W_1 - p_H G}{2} < \frac{W_1}{2}$ for $p_H \in (0,1)$. As $W_1 \downarrow p_H G$ we have $\Delta_0 \to -\infty$, and as $W_1 \to \infty$, $\Delta_0 \to p_H\theta > 0$ (since $u'(\infty) = 0$); hence Δ_0 has a unique root $W_L^* > p_H G > 0$. Similarly, as $W_1 \downarrow G$, $\Delta_1 \to +\infty$, and as $W_1 \to \infty$, $\Delta_1 \to -(1 - p_H)\theta < 0$; hence Δ_1 has a unique root W_H^*. Thus, these three value functions only cross once.

Thus, suffices to prove that there exists a W such that gambling is optimal. Note that for $\widehat{W} \equiv 2c^* + p_H G$ ($c^* \equiv (u')^{-1}(\theta/G)$), we have $q^*(\widehat{W}) = p_H$, so $\varphi(\cdot; \widehat{W})$ attains its maximum over $[0,1]$ at p_H. Strict concavity and $p_H \in (0,1)$ give $\varphi(p_H) > \varphi(0)$ and $\varphi(p_H) > \varphi(1)$, so $\Delta_0(\widehat{W}) > 0$ and $\Delta_1(\widehat{W}) > 0$. Thus, we obtain $W_L^* < \widehat{W} < W_H^*$.

The remaining expressions for consumption and portfolio follow immediately from the expressions for c in each of the three cases and inverting x_H and x_L into $I_{\mathcal{R}}$ and $I_{\mathcal{S}}$: $I_{\mathcal{R}}^* = (x_H - x_L)/(R_H - R_L) = G/(R_H - R_L)$ and $I_{\mathcal{S}}^* = c - R_L G/(R_H - R_L)$. □

Proof of Proposition 2. The agent chooses (c_1, x_L, x_H) and now also p_H, subject to $c_1 + p_L x_L + p_H x_H = W_1$. Conditional on attaining the goal only in the high state, the argument in Step 1 above gives $c_1 = x_L = x_H - G$ for any fixed p_H, so the value is $\varphi(q; W_1)$ with $q = p_H$. The agent therefore maximizes $\varphi(q; W_1)$ over $q \in [0,1]$, and by Step 2 the solution is $q^* = (W_1 - 2c^*)/G$ clipped to $[0,1]$. Substituting q^* into $c = (W_1 - qG)/2$ gives $c = c^*$, independent of W_1. The implied gross returns follow from $x_H = c^* + G$, $x_L = c^*$, and savings $W_1 - c^*$. Finally $\partial q^*/\partial W_1 = 1/G > 0$ and $\partial r_H^*/\partial W_1 = -(c^* + G)/(W_1 - c^*)^2 < 0$. □

Proof of Proposition 3. This result follows trivially from the weak concavity assumption of θ and Jensen's inequality. □

A.2 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:

$$U(W, I) \equiv p_H \cdot u(W + (R_H - 1)I) + p_L \cdot u(W + (R_L - 1)I) + \epsilon V((R_H - 1)I, p). \tag{A.2}$$

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.3 Microfoundation for Discrete Goals

We start by relaxing the assumption that an agent's goals are necessarily discrete, $g \in \{0, 1\}$, but rather can be scaled in a concave manner. We first reiterate the conclusion of Proposition 3: the ability to scale down one's goal in a weakly concave manner obviates the need for gambling. We then draw on a simplified version of the model in (Bordalo et al., 2025; Conlon and Kwon, 2025) to microfound how categorical reasoning over goal attainment can re-convexify utility over wealth.

Perfectly scalable goal Suppose the goal is continuously scalable, so that spending $G_c \geq 0$ on it delivers

$$u \;=\; \theta(G_c) + \epsilon, \qquad \theta(G_c) \;=\; \theta \cdot \min\left\{\frac{G_c}{G}, 1\right\}, \tag{A.3}$$

where ϵ is mean-zero noise. The continuous goal $\theta(G_c)$ interpolates the discrete goal of Section 2, where the agent may choose to attain any fraction of the original goal.

Appendix Figure G.1a plots what the option of scaling down goals does to utility over wealth. Writing $c^* = G/\theta$ for the consumption level at which the marginal utility of consumption equals the marginal return to goal spending, one can easily show that the agent's indirect utility is

$$V^c(W) = \max_{0 \le G_c \le G} u(W - G_c) + \theta(G_c) = \begin{cases} u(W), & W \le c^*, \\ u(c^*) + \dfrac{\theta}{G}(W - c^*), & c^* < W \le c^* + G, \\ u(W - G) + \theta, & W > c^* + G, \end{cases} \tag{A.4}$$

which is the concavification of U_2 of Figure 1. This implies that under rationality, individuals do not gamble, consistent with Proposition 3.

Simulation of utility Next, suppose that an agent is not quite certain what her preferences and utility over investing G_c towards a goal are. Rather, she relies on cognitively simulating the utility outcome of such an investment outcome. Following Bordalo et al. (2025) and Conlon and Kwon (2025), we model this as sampling the utility outcomes of *similar* levels of goal spending (e.g. how happy was a particular person spending a particular amount on housing?).

Formally, let π denote the unconditional distribution of goal spending. The agent draws comparison levels G_c' from

$$\pi_s(G_c' \mid G_c) \propto \pi(G_c') \cdot S(G_c', G_c), \tag{A.5}$$

and values G_c at the resulting sample mean of the true payoff,

$$\hat{\theta}(G_c) = \int \pi_s(G_c' \mid G_c)\, \mathbb{E}[u \mid G_c']\, dG_c'. \tag{A.6}$$

Categorical reasoning The similarity function $S(G_c', G_c)$ captures the psychology of how an agent judges two consider two levels of goal investment to be similar to each other (e.g. is living in this home worth G_c' similar to living in that home worth G_c?). Importantly, we assume that the agent is subject to *categorical reasoning* when judging the similarity between different levels of goal investment. For example, she may judge spending more than a million dollars on housing puts one in a "separate category" to one that spends less (and hence discretely less similar). Following Bordalo et al. (2025), we introduce an additional feature

$$F(G_c) = I(G_c > G^*), \qquad 0 < G^* < G,$$

and assume the following specification for the similarity function:

$$S(G_c, G_c') \;=\; \exp\!\left(-\frac{\kappa}{2}(G_c - G_c')^2\right) \cdot \delta^{I[F(G_c)\neq F(G_c')]}, \qquad \delta \in (0,1]. \tag{A.7}$$

The first term is the usual distance-based similarity, and the second captures categorical reasoning: two levels of goal spending on opposite sides of G^* are judged discretely less similar. The parameter δ indexes the strength of categorical reasoning, with *lower* δ meaning *stronger* categorization, and $\delta = 1$ implying no categorical thinking. Intuitively, whenever the agent thinks about people who "bought" the house, the utility she samples is drawn disproportionately from people who bought nicer houses; people who did not buy are discretely more similar to lower levels of goal attainment.

Finally, perceived utility over wealth is

$$\widehat{V}(W) \;=\; \max_{0\leq G_c\leq W} \; u(W - G_c) + \hat{\theta}(G_c). \tag{A.8}$$

Numerical implementation Appendix Figure G.1b plots the simulated perceived utility over wealth, where we continue to set $u(c) = \log c$, $G = 200$ and $\theta = 2$. We assume the category boundary of G^*, with similarity width $\kappa^{-1/2} = 45$ and $\delta = 0.05$. Finally, when estimating $\hat{\theta}(G_c)$, we assume that the sampling distribution π is symmetric around G_c, extending the domain of hypothetical goal expenditure if necessary (e.g. to levels below 0 or above G if necessary). While this assumption is largely not essential, it makes $\widehat{V}$ well-behaved near the grid boundaries $G_c \mapsto 0$ and $G_c \mapsto G$.

Perceived convexity at the category boundary As shown in Figure G.1b, perceived utility inherits the concavity of u away from the category boundary. Closer to the category boundary G^*, however, an agent's simulation of utility changes discontinuously due to categorical reasoning, despite the fact that the true return to G_c in (A.3) is linear and contains no such discontinuity. The takeaway is that a categorical thinker behaves as though her goal were indivisible. Because the categorical feature F is by construction irrelevant to true payoffs, this perceived convexity is entirely driven by how an agent reasons through different consumption categories. Conversely, if one turns down categorical reasoning ($\delta \to 1$), perceived utility becomes concave over wealth again, with no gambling motive.

What this exercise suggests is that the key force that generates Friedman-Savage motives need not be physical indivisibility, but also potentially psychological forces that cause an individual to perceive economic outcomes through a categorical lens — "homeowner" versus "renter," "comfortable" versus "behind." This possibility is also consistent

with a broader set of goals we document in our survey evidence in Section 4, such as retirement security and social standing, which are in principle continuously scalable.

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 H.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.

For some analyses, we further restrict the sample to those who have provided consent to share data with SKT. Although consent is not directly observed, we follow the data provider's recommendation and proxy for consent by assuming that individuals with no app usage during the entire sample period did not provide consent.

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.

KCB Variables. Summary statistics and short variable descriptions are in Appendix Tables H.2 and H.3.

Estimated annual income (ICM) is based on loan contract details and card usage amounts. If an individual recently borrowed money from a financial institution, KCB will observe their updated income. 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) valuations capture total real estate asset value less liabilities. The variable is constructed using 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.

To identify unemployment (has_job), 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 in when JB_TP will be updated by

KCB, which depends 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).

SKT Variables. Summary statistics and short variable descriptions are in Appendix Tables H.4 and H.5.

App usage days (*_*_DAY) are constructed by SKT. SKT records a usage event when an individual opens a mobile application or website at least once. In particular, opening the same app more than once a day counts once towards this variable (because for example, the individual could accidentally re-open the app or browser), but opening two different apps on the same day counts twice. Some N/A values occur when the individual did not consent to SKT marketing, in which case all app-usage variables are missing. Using no app usage over the entire sample as a proxy for consent, in December 2023, 74% of individuals in the SKT sample had provided marketing consent.

Shinhan Card Variables. Summary statistics and short variable descriptions are in Appendix Tables H.6 and H.7.

There are 19 major Shinhan Card consumption 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: overseas travel, premium hotels, Jeju travel, convenience stores, delivery apps, EV charging, Tesla charging, and Starbucks. There is no overlap in spending across these categories.

C Cryptocurrency Price Changes & Economic Outcomes

In this appendix, we measure how economic outcomes respond to changes in cryptocurrency prices for crypto app users.

Measurement We use Bitcoin prices as a proxy for cryptocurrency asset prices, similar to the approach of Aiello et al. (2023a), who assume that investors purchase a market-weighted portfolio of Bitcoin and Ethereum. Survey data show that 76% of Korean crypto investors held Bitcoin (Korean Financial Consumer Protection Foundation, 2024), and the returns of the 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). Measurement of holdings would likely only attenuate our estimated effects of price changes on outcomes toward zero.

C.1 Spending Responses

We first measure how the spending of crypto app users responds to changes in Bitcoin prices. We estimate regressions of the form:

$$\Delta Y_{it} = \beta_1 \Delta P_t \times I^c_{it} + \beta_2 I^c_{it} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{C.1}$$

where ΔY_{it} is the change in individual i's daily spending from month $t-1$ to t, and ΔP_t is the contemporaneous change in Bitcoin prices.[36] 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. We also present results from a specification in which 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. 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 time fixed effects, γ_t, absorb aggregate changes in consumption (e.g., due to seasonality).

Table H.12 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 2.0 percent increase in daily spending among all crypto app users, 4.1 percent among heavy users, and 6.0 percent among super heavy users.[37]

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

[37] The fact that the response is stronger for those who use cryptocurrency apps more frequently is consis-

C.2 Boom & Bust Events

To better understand responses to extreme events, we compare the outcomes of heavy crypto users and others around two large changes in Bitcoin prices: a boom at the end of 2020, and a bust in early 2022. Appendix Figure G.22 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:

$$Y_{i,t} = \sum_{\substack{m \in \mathcal{M} \\ m \neq m_0}} \beta_m \left(\text{HeavyUser}_i \times \mathbf{1}\{t = m\}\right) + \alpha_i + \gamma_t + \varepsilon_{i,t}. \tag{C.2}$$

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 G.23 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 2 (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).

Boom Event Figure G.24 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

tent 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 1.4M KRW ($1000 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 H.10), which is consistent with attenuation (and skew in the distribution of holdings).

comparable non-heavy users, a 6% increase relative to the heavy-user mean in Table 2. 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.

D Survey Appendix

This Appendix supplements Section 3.3 and provides more detailed information about the linked survey we conducted with SKT in March 2026.

D.1 Details

SKT administered the survey through targeted texts via their mobile phone network. The survey was active over a 24 hour period staring on March 19, and yielded 2,301 responses. We sampled 500 heavy crypto-app users, 700 middle users, and 1,101 non-users. Heavy users were defined as individuals who used a crypto app on at least 50 of the past 60 days, middle users are those with 10 to 40 days of crypto app usage over the past 60 days, and non-users did not use any crypto app over this period. Only Korea residents aged 25-55 were allowed to participate. Participants were compensated with SKT loyalty credits.

Survey Implementation and Sample Quality. Appendix Table H.10 displays the demographics of our sample. Because the survey intentionally oversamples cryptocurrency users, it is not designed to be representative of the population. As a benchmark, we compare non-users with the population-level statistics in Appendix Table H.8. Non-users are similar in terms of the share living in Seoul, employment, and median income, although women are somewhat overrepresented. As in the administrative data in Table 2, cryptocurrency use is substantially more concentrated among men.

To limit experimenter demand and priming, the survey was advertised and described as a general study of investment choices rather than as a study specifically about cryptocurrency. Respondents were recruited directly from SKT's customer base rather than from a standing online survey panel. This recruitment method limits concerns about bots and professional survey-taking. Survey completion times provide additional evidence against low-effort responding: although the survey was designed to be short, fewer than 3% of respondents completed it in two minutes or less. We also included a standard attention check (Appendix D.2.3). SKT advised that failures on this check likely partly reflected confusion related to the question implementation rather than inattention. We therefore retain the full sample in our baseline analysis. Appendix Table H.11 shows that our main conclusions are qualitatively unchanged when restricting the sample to respondents who passed the attention check.

Constructed Variable Definitions. The survey instrument is below in Appendix D.2. There are some measures we refer to frequently in the main text, which we constructed

the following way:

- "Expected 1Yr Bitcoin (Stock) Returns" is the middle scenario of question 3 in block D.2.3. 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% chance of a 5% increase in wealth to question 3 in block D.2.2.
- "Needs High Risk" is an indicator for whether a respondent needs high-risk assets to achieve their goals, in response to question 2 in block D.2.2.

D.2 Survey Instrument

This appendix contains our survey instrument. Response options are listed inline in brackets, separated by semicolons.

D.2.1 Demographics and Screeners

1. Introduction and consent.
2. Please enter your age. (Only Korea residents aged 25 to 55 may participate in this survey).
3. As of today, what is your best guess for the current value of your total assets (including cash, investments, home, and car)? [*Under 50 million KRW; 50 million to under 100 million KRW; 100 million to under 500 million KRW; 500 million to under 1 billion KRW; 1 billion to under 2 billion KRW; 2 billion KRW or more*]
4. As of today, what is your best guess for the current value of your stock holdings (including retirement accounts, mutual funds, and ETFs)? [*Less than 1 million KRW; 1 million to under 5 million KRW; 5 million to under 10 million KRW; 10 million to under 25 million KRW; 25 million to under 50 million KRW; 50 million to under 100 million KRW; 100 million to under 500 million KRW; 500 million KRW to under 1 billion KRW; 1 billion KRW or more*]

D.2.2 Financial Goals, Risk Preferences, and General Perceptions

1. Many people have important financial or life goals they would like to reach in the next 5-10 years. Please indicate how important each of the following goals is to you. [*Scale from 1-5, where 1 = not important at all, 5 = very important*]

- Buying a home or apartment
- Paying off debt (e.g., credit card, mortgage, student loan)
- Building a financial buffer for emergencies
- Starting or expanding a business
- Funding education (for yourself or family)
- Being able to retire, stop working, or significantly cut back on working
- Improving my social status (standing relative to others)
- Having the financial resources that improve my attractiveness as a romantic partner
- Wanting to be recognized by others as successful by earning a lot of money

2. Think about your most important financial goal. For each of the actions below, rank how realistically you would be able to reach your goals if you relied only on that one action. Please select the three most realistic methods ranking them from 1st to 3rd.

    - Saving regularly in a bank account
    - Making low-risk assets (e.g., index funds) or contributing to a retirement account
    - Advancing in my job or career (e.g., promotions, salary increases)
    - Starting a side business or freelance work
    - Investing in high-risk assets (e.g., cryptocurrencies, options)
    - Buying lottery tickets or betting on events (e.g., Sports Toto / horse racing)

3. You will now be shown several hypothetical scenarios in which your wealth increases. Choose the option that you prefer most. [*Which option participants saw depended on their response to the value of their assets in the "Demographics + Screeners" block. We made all lotteries have an expected value of a 5% increase in wealth. For example, for individuals whose assets were 500 million to 1 billion KRW:*]

    - 100% chance of gaining [*37.5 million*] KRW
    - 50% chance of gaining [*75 million*] KRW, 50% chance of no change
    - 10% change of gaining [*375 million*] KRW, 90% chance no change
    - 1% chance of gaining [*3.75 billion*] KRW, 99% chance of no change

4. Please indicate how much you agree or disagree with the following statements. [*Scale from 1-5, where 1 = strongly disagree, 5 = strongly agree*]

    - I admire people who own expensive homes, cars, and clothes
    - I like a lot of luxury in my life
    - I'd be happier if I could afford to buy more things

D.2.3 Expectations

The next questions are about your expectations for the future values of different assets. There are no right or wrong answers. For each question please provide three numbers.

- Lowest value: you think the asset only has a small chance (about 5%) of falling below this value
- Middle value: your best guess of what the asset will be worth
- Highest value: you think the asset has only a small chance (about 5%) of rising above this value

1. After 1 year, approximately what will a 1 million KRW KOSPI asset be worth? (If there is no change, the value is 1 million KRW).

    - Lowest value: *[text entry]*
    - Middle value: *[text entry]*
    - Highest value: *[text entry]*

2. After 5 years, approximately what will a 1 million KRW KOSPI asset be worth? (If there is no change, the value is 1 million KRW).

    - Lowest value: *[text entry]*
    - Middle value: *[text entry]*
    - Highest value: *[text entry]*

3. Bitcoin is a cryptocurrency that people can hold and trade. After 1 year, approximately what will a 1 million KRW worth of Bitcoin be worth? (If there is no change, the value is 1 million KRW).

    - Lowest value: *[text entry]*

- Middle value: *[text entry]*
- Highest value: *[text entry]*

4. After 5 years, approximately what will a 1 million KRW worth of Bitcoin be worth? (If there is no change, the value is 1 million KRW).
   - Lowest value: *[text entry]*
   - Middle value: *[text entry]*
   - Highest value: *[text entry]*
5. The next question is an attention check. To verify that you read our questions carefully, please select Tuesday or Thursday and not any other option from the list below.

   What is your favorite day of the week? *[Monday; Tuesday; Wednesday; Thursday; Friday; Saturday; Sunday]*

D.2.4 Interest in Cryptocurrencies

1. Do you think investing in cryptocurrency is a risky investment? *[Scale from 1–5, where 1 = strongly disagree, 5 = strongly agree]*
2. How many days per week do you use apps related to cryptocurrency? *[At least once a day; 5–6 days; 3–4 days; 1–2 days; Once or twice a month; Do not use/never use]*
3. Do you currently own any cryptocurrencies directly or through ETFs? *[Yes; No; Unsure]*

[If has crypto:]

4. As of today, what is the best guess for the current value of your cryptocurrency holdings? *[Under 100,000 KRW; 100,000 to under 500,000 KRW; 500,000 to under 1 million KRW; 1 million to under 2.5 million KRW; 2.5 million to under 5 million KRW; 5 million to under 10 million KRW; 10 million to under 25 million KRW; 25 million to under 50 million KRW; 50 million to under 100 million KRW; 100 million to under 500 million KRW; more than 500 million KRW]*
5. If all of your cryptocurrency holdings went to KRW 0 tomorrow, would this have a significant negative impact on your financial well-being? *[Yes, there would be a significant negative impact on my financial well-being; No, there would be little or no impact on my financial well-being; Other]*

6. Please indicate how much you agree or disagree with the following statements. *[Scale from 1–5, where 1 = strongly disagree, 5 = strongly agree]*

    - Without investing in crypto, reaching my financial goals would be substantially more difficult
    - Even if I didn't make money in crypto, I would still think it is fun
    - Crypto is an investment rather than a gamble
    - I have friends who have made lots of money in crypto
    - I enjoy talking to my friends about crypto

[If does not have crypto:]

7. Have you ever owned any cryptocurrency, directly or via ETFs? *[Yes; No; Unsure]*

8. ***[If used to own:]*** Why do you no longer hold crypto today? Select up to three of the most important reasons.

    - Too much volatility
    - Investment losses
    - Was a burden or stress in daily life
    - Thought it was a good time to sell because it went up enough
    - No longer had the time or lost interest
    - Achieved my original goals
    - Needed the cash
    - Other

9. ***[If never owned:]*** Why have you never owned crypto? Select up to three of the most important reasons.

    - Seems very unstable and volatile
    - Preference for safer methods such as savings or deposits
    - Crypto is not a tangible / real asset
    - Seems over-valued and over-hyped
    - Others have lost a lot of money in crypto
    - Too difficult to set up
    - Have never thought about it
    - Other

D.2.5 Concluding Demographics

1. Which category best describes your highest level of education? *[Middle school graduate or below; High School Graduate; Bachelor's degree; Associate degree (2-year college); Master's degree or higher]*
2. What was your total household income, before taxes, in 2024? *[Less than 25 million KRW; 25 million to under 50 million KRW; 50 million to under 75 million KRW; 75 million to under 100 million KRW; 100 million to under 150 million KRW; 150 million KRW or more]*
3. Do you own a home? *[Yes; No]*
4. What is your sex? *[Male; Female]*
5. What is your marital status? *[Married; Unmarried; Other]*
6. Are you employed? *[Yes; No; Other]*
7. Please select any activities you have engaged in before from the following list. *[Purchased lottery tickets (e.g., Lotto 6/45, instant lottery); Sports betting (e.g., Sports Toto); Horse racing betting; Other licensed racing betting (e.g., bicycle or motorboat racing); Visited a casino (e.g., Kangwon Land); None]*
8. On average, how much money do you spend on lottery tickets per month? *[0 KRW; Less than 5,000 KRW; 5,000–10,000 KRW; 10,000–25,000 KRW; 25,000–50,000 KRW; 50,000 KRW or more]*
9. What is your financial goal for the next 10 years? *[Open text]*
10. Is there any feedback you would like to share? *[Open text]*

E Housing Lottery Details

E.1 Institutional Setting and Lottery Assignment

South Korea's housing subscription system (*cheongyak*) allocates rights to purchase newly constructed apartments before construction is complete. Applicants generally must belong to a non-homeowning household and contribute to a designated housing savings account. Within each project, applicants are ranked by a priority score based on savings history, family composition, and years without homeownership. When a project is oversubscribed, as is typical in the capital region, a random lottery is implemented among the most qualified applicants. We restrict our analysis to projects where this operates.

Lottery participation should not be interpreted as participation in a simple, passive lottery. Applicants generally must satisfy subscription-period and contribution requirements for a designated housing savings account in order to receive high priority in the lottery process, although the exact requirements vary across projects. For example, in standard public-housing lottery projects in the Seoul metropolitan area, applicants are considered first-priority if they have maintained the relevant savings account for at least 12 months and made at least 12 monthly contributions.[38] Thus, lottery winners are likely to have invested time in the application process and actively searched for eligible housing projects. At the same time, as emphasize below, the identifying variation in our primary design does not come from comparing such households to passive non-applicants.

E.2 Identifying Likely Winners

We identify likely winners from project locations, residential moves, eligibility rules, and subsequent homeownership, similar to the procedure developed in Arkolakis et al. (2026). We begin with a list of 2,178 lottery projects from the Cheongyak Home portal that includes the number of units offered, the total number of applications, and the ratio of applicants per unit. We then match lottery projects to KCB geographic cells ("bizcells") corresponding to the completed apartment complexes. Because there is no administrative link between the lottery records and the credit bureau, we match projects to bizcells using postal codes, administrative addresses, and normalized apartment names.

Within each matched project-bizcell, we classify a household as a likely winner if three conditions hold. First, the household appears at the project bizcell around the project's move-in date. Second, no member of the household owned residential property before the application date, consistent with the lottery's non-homeownership requirement. Third, at

[38] https://www.applyhome.co.kr/ar/ara/selectSubscrptIntroQualfView.do#cate2

least one member transitions into homeownership after the lottery announcement. The final condition helps distinguish purchasers from renters and other occupants of the same apartment complex.

We then impose several project and data-quality restrictions, as in Arkolakis et al. (2026). We keep projects for which the ratio of inferred winners to official unit supply lies between 0.1 and 1. Ratios below this range suggest that the project-to-bizcell match captures little of the apartment complex, while ratios above one suggest contamination from nearby housing. We restrict the sample to oversubscribed projects and exclude conversion sales (*bunyang jeonhwan*; 분양전환) and vacancy sales (*gongga sedae*; 공가세대). We also require adequate panel coverage and valid baseline covariates, retain at most one lottery win per household, and drop cases in which changes in the address-based household identifier appear to generate duplicate households.

For the final sample, we retain individuals who appear to win between January 2021 and December 2023, have app-usage records in the SKT data, and are the youngest adult male in their household. This procedure identifies 1,892 likely winners. As a validation of the procedure, Panel (a) of Appendix Figure G.13 shows that housing debt rises by nearly 30M KRW in the months after the contract date. This increase is consistent with the identified households financing the purchase of their lottery apartments.

E.3 Additional Details

Transfers and Secondary Purchasers In principle, a household observed purchasing and moving into a lottery complex could have acquired the unit from the original winner. In practice, resale restrictions rule out this channel in our sample. The shortest restriction in the capital-region projects studied by Arkolakis et al. (2026) was three years, longer than the typical 20-34 month period between announcement and move-in, so the restriction remained binding at move-in for every project. Winners therefore could not legally transfer their purchase rights before moving in. Many price-regulated projects also impose residence requirements, further ensuring that the households in our sample are the original lottery winners rather than secondary purchasers.

F Calibration Appendix

This appendix contains additional details on our calibration in Section 7.

Objective Function. As discussed in Section 7, we estimate eight of the model parameters targeting the eight ownership shares in Figure 4. In particular, the objective function minimizes the sum of squared distances between the model-implied and empirical moments. To compute the objective function, we discretize the state and choice variables, and compute expectations by integrating over a Gauss-Hermite quadrature with 12 nodes for stocks and 64 nodes for crypto, since the latter has a long right tail. We also use five Gauss-Hermite nodes to determine belief types, z, bounded below by -0.95.

Wealth is discretized into 121 evenly-spaced points from 0.1 to 7.5 (units are in 100,000 KRW). Savings is dicretized onto a 300 log-spaced grid with end points derived endogenously from the wealth grid. The consumption grid (as a share of wealth) has 80 equally-spaced points between 0.02 and 0.98. The share of a portfolio in a single asset is discretized into 21 points between 0 and 1, which implies that the two-asset simplex has 231 points (since the share in stocks and crypto must sum to no more than 1).

Since our matched moments in Figure 4 are on the extensive margin (share owning each asset), the objective function can have discontinuities, making it more challenging for an optimizer to find a solution. To avoid optimization problems, we smooth the value function using a standard logistic CDF. In particular, the decision to own asset j is:

$$\frac{1}{1+\exp(-\{\max_{\mathcal{A}_j} V_1 - \max_{\mathcal{A}_{-j}} V_1\}/\tau)} \tag{F.1}$$

where V_1 is the first-period value function and $\mathcal{A}_j$, $\mathcal{A}_{-j}$ is the set of assets with and without j respectively. τ is the smoothing parameter, as $\tau \to 0$ there is no smoothing. Under a structural interpretation, τ determines the scale of an idiosyncratic taste shock for participating in an asset class. To ensure no discontinuities, but to be as close as possible to the original decision rule, we set $\tau = 0.0005$.

For our welfare calculations, we use a finer grid, which increases computation time. In particular, we use a trapezoidal rule with 12 stock nodes and 1,000 crypto nodes, and solve for consumption and portfolio weights continuously using SLSQP. This additional computation time is manageable because welfare is calculated only once (rather than iteratively for every potential choice of parameter values).

Estimation. To find the solution that minimizes the objective function, we first evaluate the function at 128 starting points determined by Sobol search. We then polish the three best solutions using Nelder-Mead. We choose reasonable bounds for all parameters and ensure our solution is not near the bounds: we search for $\theta \in [0,5], G \in [0.01,8], F_s \in [0.001,0.9], F_c \in [0.001,0.9], \sigma_s \in [0.02,1], \sigma_c \in [0.05,2], \eta_s \in [0,2], \eta_c \in [0,10]$.

Standard Errors. To compute the standard errors in Table 5, we estimate the moment Jacobian, G, as well as the variance-covariance matrix of the empirical moments, Ω. The variances are then given by: $G^{-1}\Omega(G^{-1})'$. For Ω, we use the standard errors in Figure 4 in a diagonal matrix. When computing G, we set the finite-difference step for each parameter to half the distance between its upper and lower bounds. We use this relatively large step size to ensure that the moment Jacobian is invertible, given that our belief distribution is discretized and the moments vary on the extensive margin.

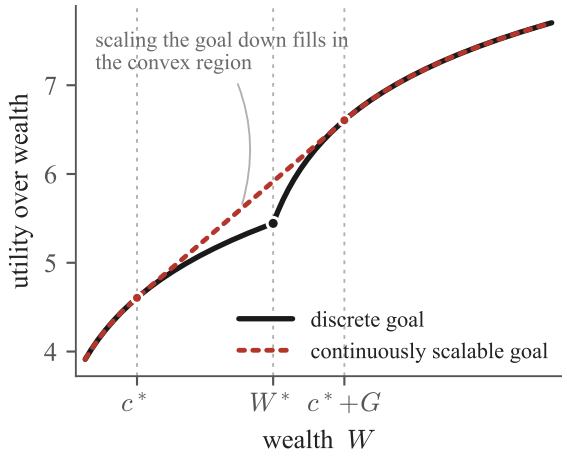
Robustness. We conduct two robustness exercises. First, we re-estimate the full model without a goal motive (setting $\theta = 0$ and removing G, which no longer affects choices). Appendix Figure G.19 shows that the re-optimized model fails to match the hump-shaped pattern in the data. This exercise differs from the counterfactual in Figure 10, which sets $\theta = 0$ without re-optimizing the model.

Second, we re-estimate the full model assuming independent, rather than correlated, beliefs about stocks and cryptocurrency. Appendix Figure G.21 plots the model-implied share with crypto and stocks, as well as counterfactual shares without the goal. The green and orange bars show that our model with independent beliefs is still able to recover the hump in crypto and upwards slope in stocks as in Figure 4, although the fit to the data is somewhat worse. We also estimate a slightly higher $\theta = 4.41$. Intuitively, with independent beliefs, some individuals who would otherwise use crypto to gamble are too pessimistic about crypto relative to stocks, weakening the hump-shaped pattern and requiring a stronger goal motive to match the data.

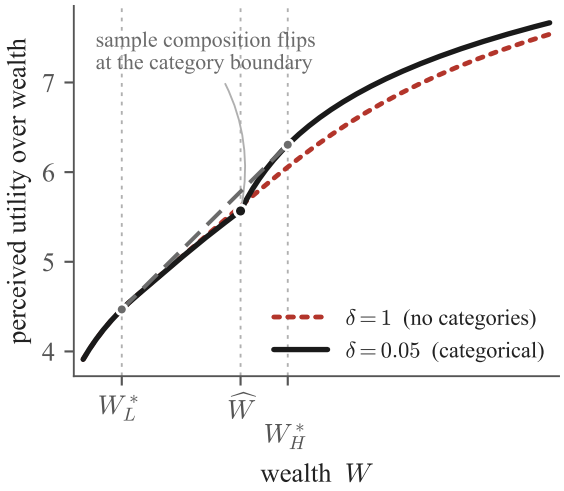
G Additional Figures

Figure G.1: Discrete goals and convex preferences

(a) Continuous goals re-concavify utility

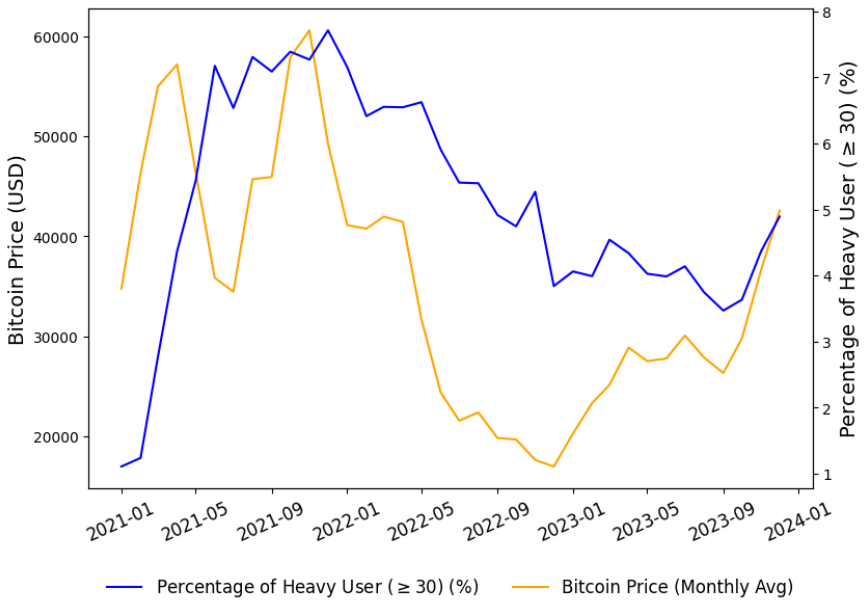


(b) Categorical reasoning restores convexity



Notes: Panel (a) plots utility over wealth for the discrete goal of Section 2, $U_2(W) = \max\{u(W), u(W-G)+\theta\}$ (solid), and for the same goal made continuously scalable, V^c in (A.4) (dotted). Panel (b) plots perceived utility over wealth $\widehat{V}$ in (A.8) for the same scalable goal, with categorical reasoning on (solid, $\delta = 0.05$) and off (dotted, $\delta = 1$). Without categorical reasoning ($\delta = 1$), wealth over utility is concave. $\widehat{W}$ marks the wealth at which her optimal goal spending jumps across the category boundary. Parameters: $u(c) = \log c$, $G = 200$, $\theta = 2$, $G^* = 160$, $\kappa^{-1/2} = 45$.

Figure G.2: Cryptocurrency Engagement, Time Series

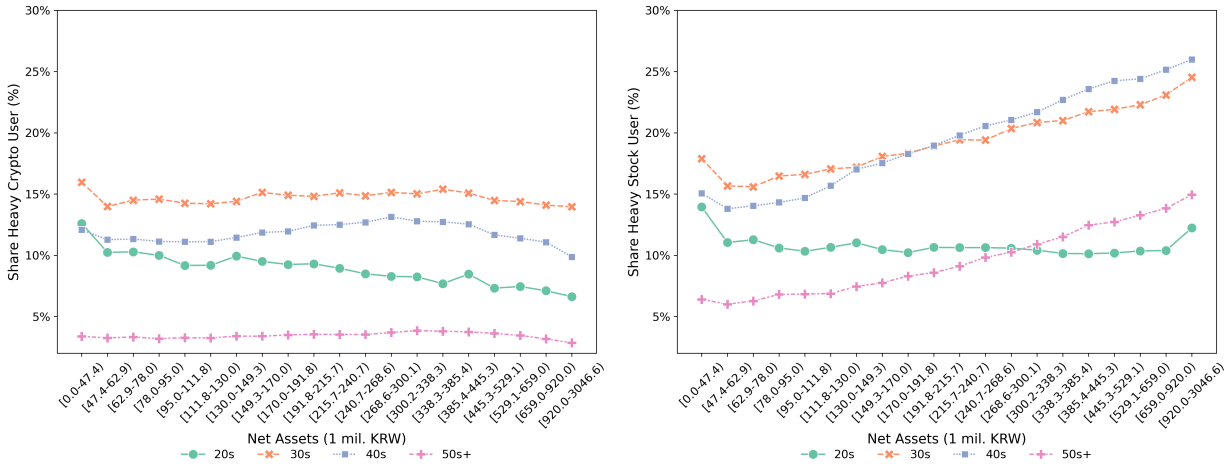


Notes: Figure shows engagement with crypto apps versus Bitcoin prices. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. "Percentage of Heavy User" is the share of all individuals who are heavy users. Source: SKT and Bitcoin price data.

Figure G.3: Crypto and Stock Usage across Age and Wealth

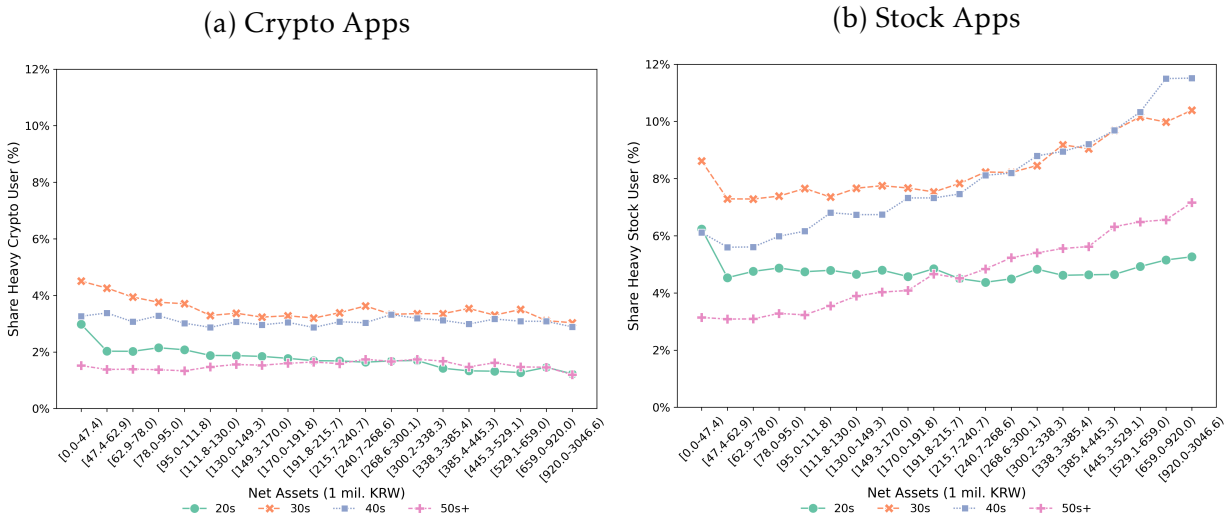
(a) Crypto Apps

(b) Stock Apps



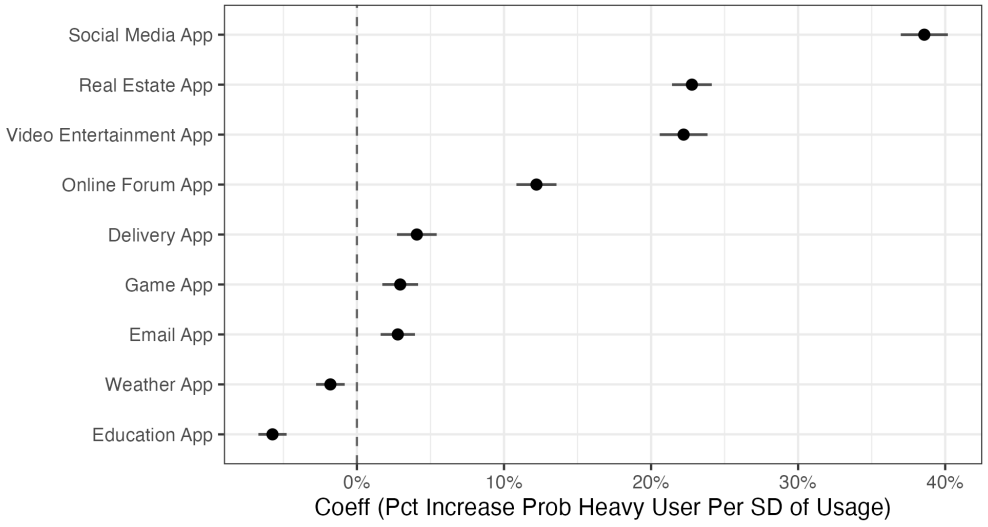
Notes: Figure shows the percentage of men who are heavy crypto users and heavy stock users. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. We use an analogous definition for stock apps. Net assets are in ventiles. Source: KCB and SKT.

Figure G.4: Percentage of Women App Heavy Users by Assets x Age



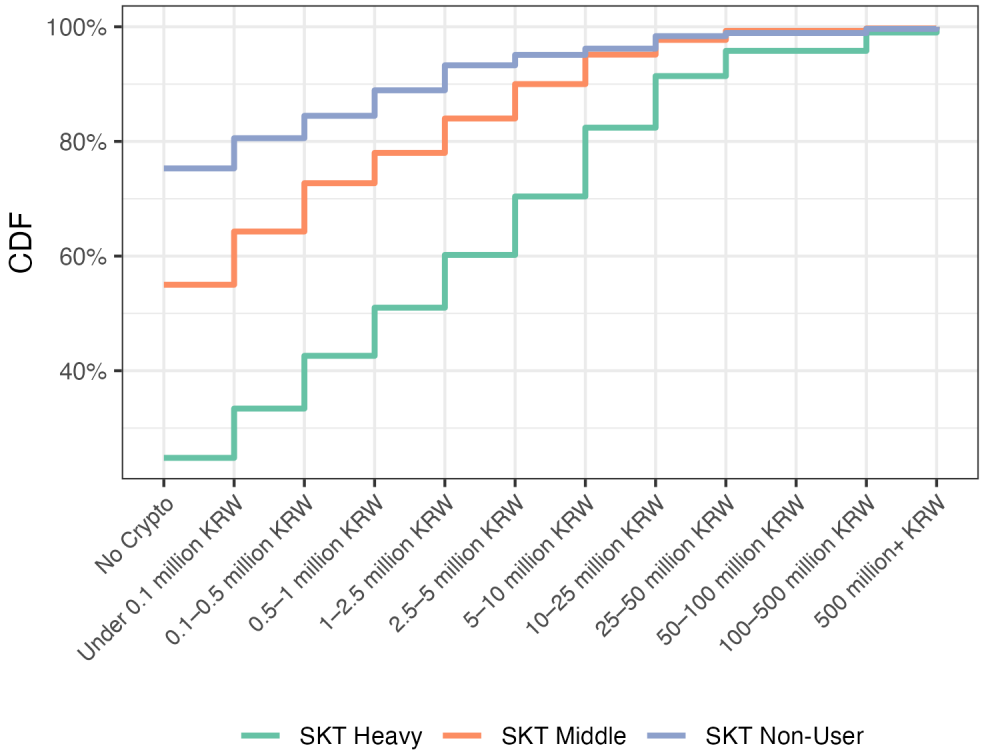
Notes: Figure shows the percentage of women who are heavy crypto users and heavy stock users. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. We use an analogous definition for stock apps. Net assets are in ventiles. Source: KCB and SKT.

Figure G.5: Other Apps as Predictors of Heavy Crypto Usage



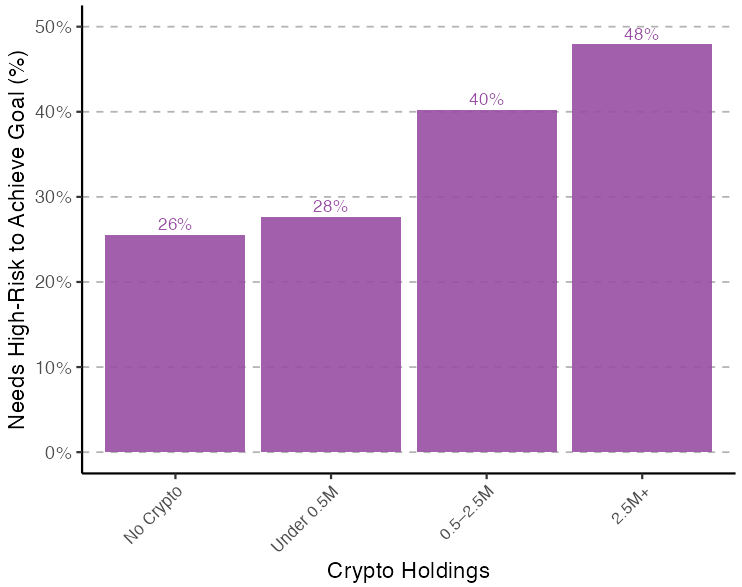
Notes: Figure shows coefficients from a multivariate regression of an indicator for heavy cryptocurrency app usage on usage of other app categories. Usage of other apps is standardized by subtracting the mean and dividing by the standard deviation. The regression also includes controls for total data 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. Horizontal bars show 95% confidence intervals. Source: KCB and SKT.

Figure G.6: Distribution of Self-Reported Crypto Holdings by SKT Usage Group



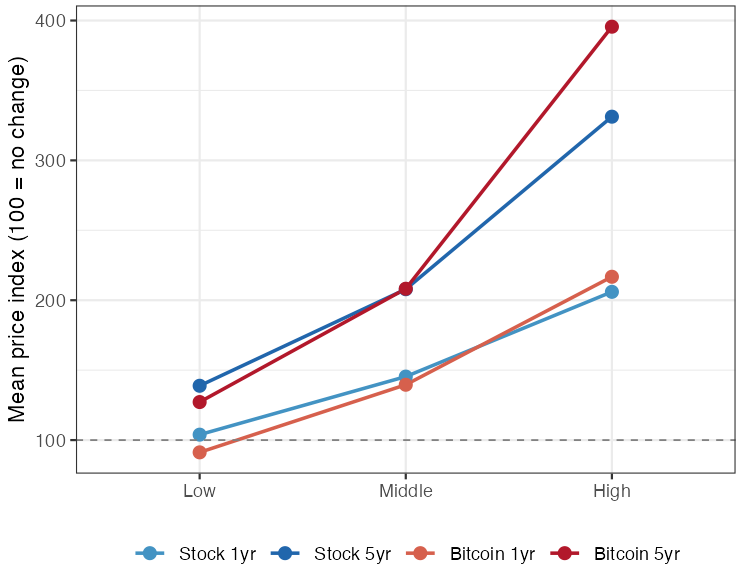
Notes: Figure plots the cumulative distribution of self-reported cryptocurrency holdings separately for SKT heavy users, middle users, and non-users. Source: SKT survey.

Figure G.7: Share Needs High-Risk Investments to Achieve Goal, by Crypto Holdings



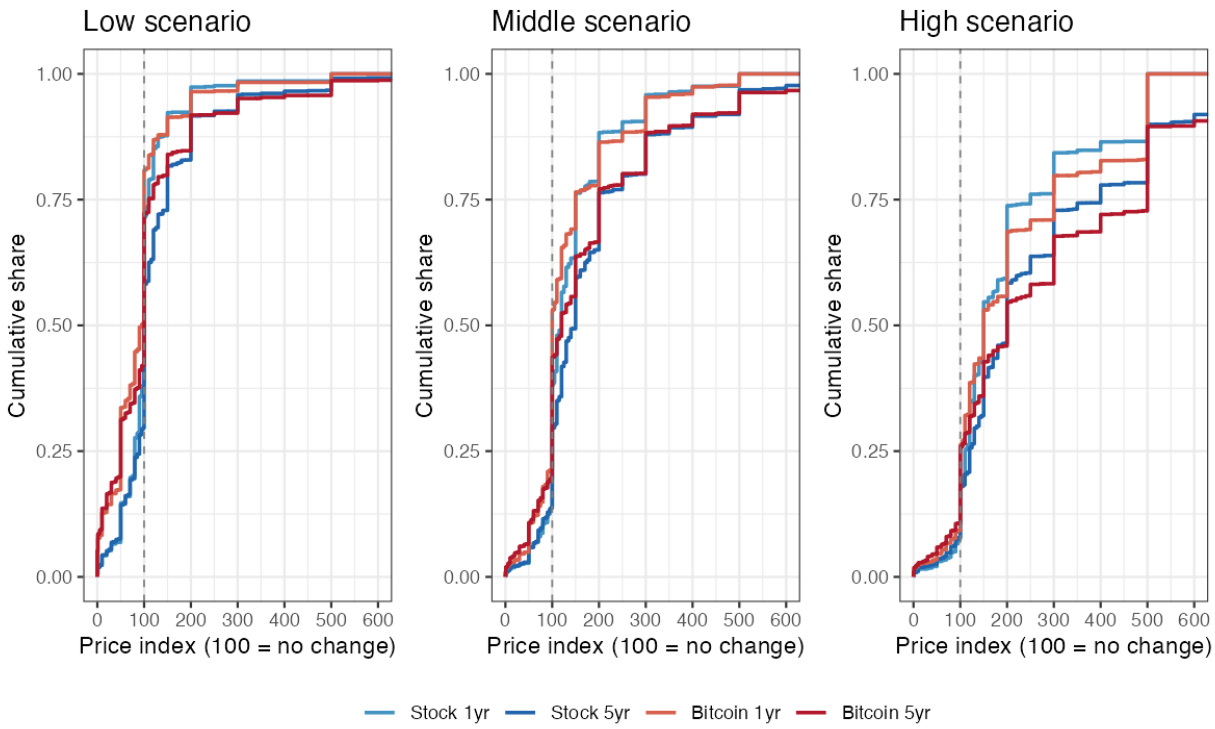
Notes: Figure plots the share of respondents who report that high-risk investments are necessary to achieve their most important financial goal, separately by self-reported crypto holdings. Percentages are shown above each bar. Responses are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. Source: SKT survey.

Figure G.8: Average of Low, Middle, and High Return Beliefs



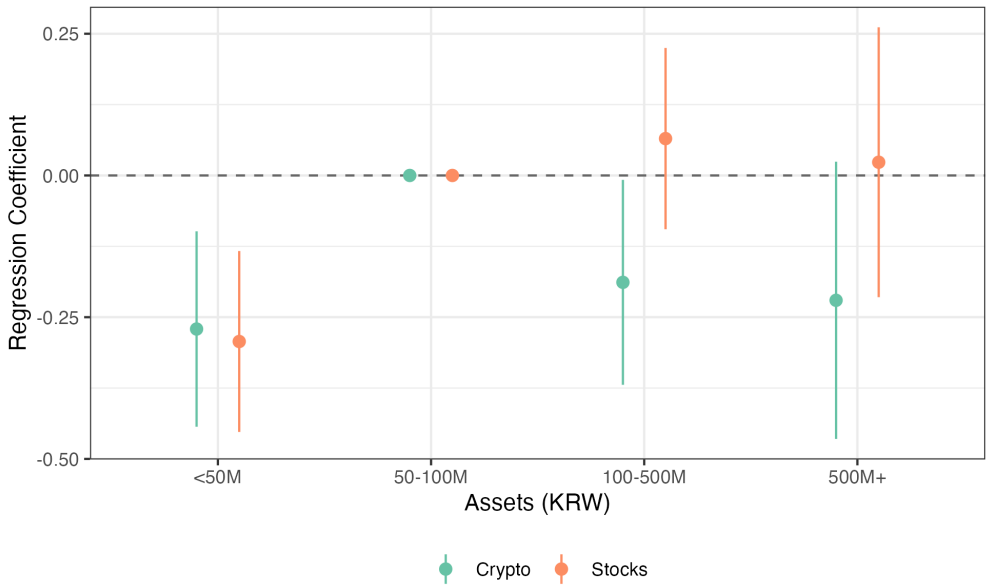
Notes: Figure plots the mean of respondents' low, middle, and high scenario return beliefs for Bitcoin and the Korean stock market (KOSPI index fund), separately for 1-year and 5-year horizons. The price index is normalized so that 100 denotes no change in value; for example, 200 implies a doubling of the initial investment. The dashed line marks the no-change threshold. Responses are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. Source: SKT survey.

Figure G.9: CDF of Low, Middle, and High Return Beliefs



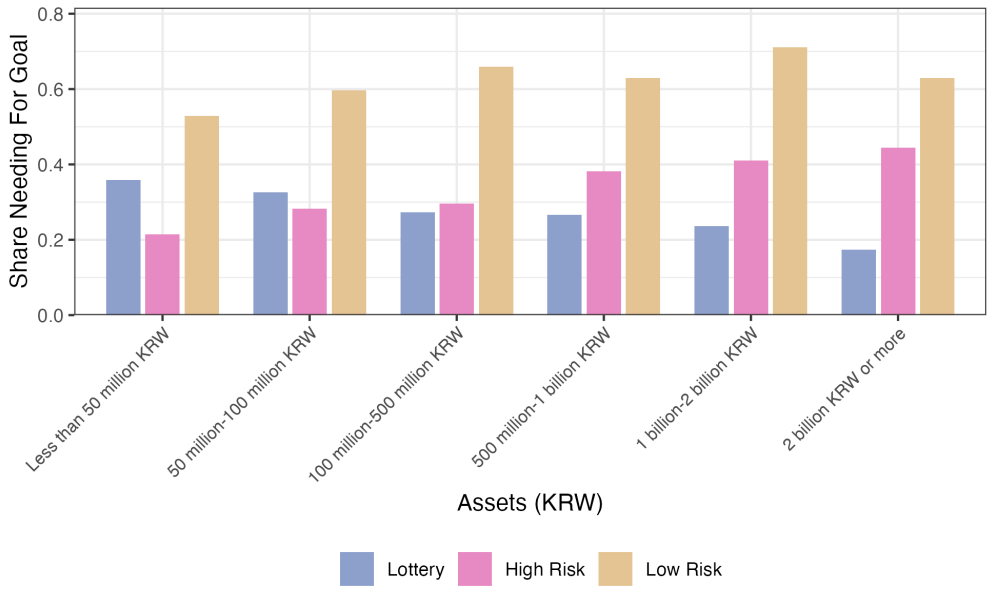
Notes: Figure plots the cumulative distribution of respondents' return beliefs separately by scenario (low, middle, high) for Bitcoin and the Korean stock market (KOSPI index fund), for 1-year and 5-year horizons. The price index is normalized so that 100 denotes no change in value. The dashed vertical line marks the no-change threshold. Responses are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. Source: SKT survey.

Figure G.10: Distance to Housing Goal Shapes Holdings of Crypto vs. Stocks



Notes: Figure plots coefficients from regressions of indicators for cryptocurrency and stock ownership on asset categories, omitting the 50–100M KRW category. The sample consists of non-homeowners who rate buying a home as extremely important. Vertical bars show 95% confidence intervals. For cryptocurrency, we also conduct one-sided tests of the hypothesis that ownership in the 50–100M KRW group exceeds ownership in each other asset category. The corresponding (p)-values are 0.001, 0.020, and 0.039 for the <50M, 100–500M, and 500M+ groups, respectively. An intersection-union test that the 50–100M KRW group exceeds all three other groups therefore yields p=0.039. Regressions are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. Source: SKT survey.

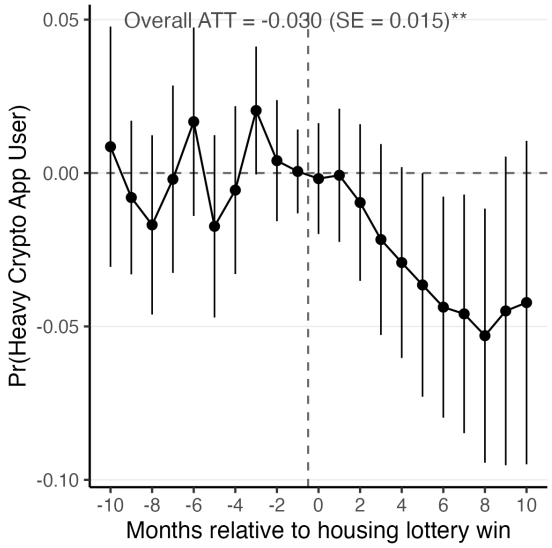
Figure G.11: Importance of Different Ways to Achieve Goals by Assets



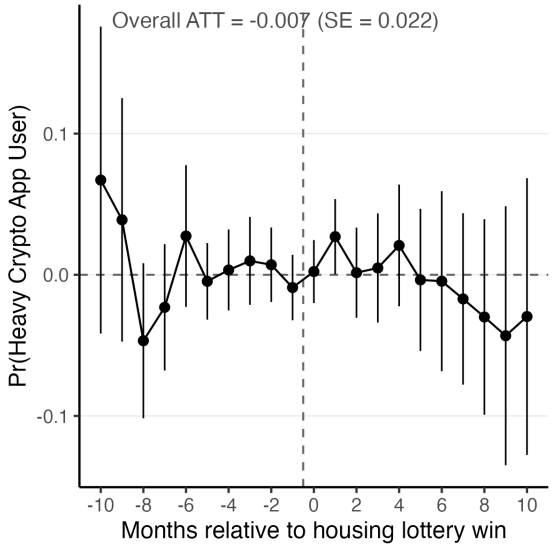
Notes: Figure shows responses to what types of actions are most realistic for achieving goals. "Lottery" means buying lottery tickets or betting on events (e.g., sports or racing), "high risk" means investing in high-risk assets (e.g., options, speculative stocks), and "low risk" means making low-risk investments (e.g., index funds) or contributing to a retirement account. The outcome is whether any of these options were ranked among the top three. Responses are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. Source: SKT survey.

Figure G.12: Change in Cryptocurrency Use Around a Housing Lottery Win: Sudogwon

(a) Pr(Heavy Crypto App User) in Sudogwon



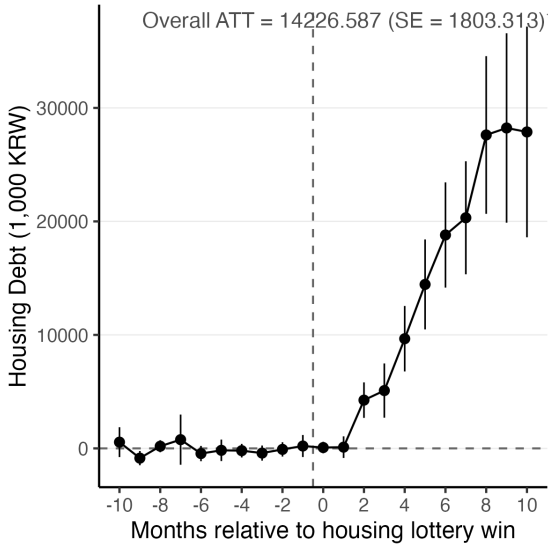
(b) Pr(Heavy Crypto App User) in Non-Sudogwon



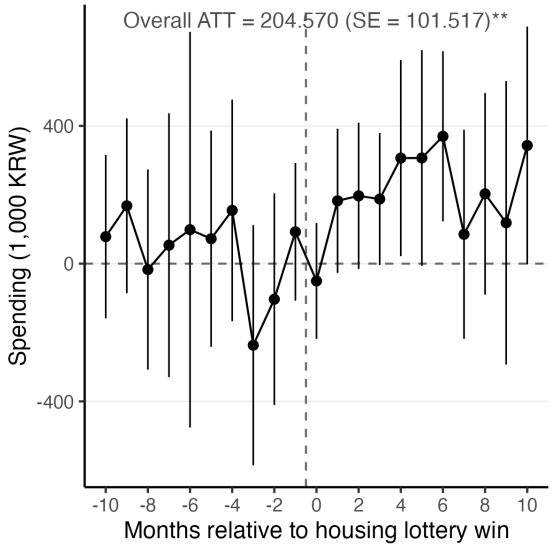
Notes: Figure plots difference-in-differences estimates of the effect of winning a housing lottery on various outcomes, relative to the contract date. Panel (a) shows the probability of being a heavy crypto app user among winners in the Sudogwon region. Panel (b) shows the probability of being a heavy crypto app user among winners in the Non-Sudogwon region. Vertical bars show 95% confidence intervals. The dashed line marks the contract date. Source: KCB and SKT.

Figure G.13: Change in Additional Outcomes Around a Housing Lottery Win

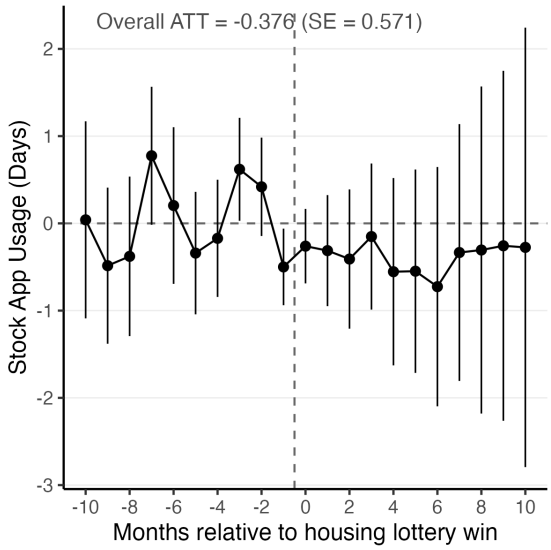
(a) Housing Debt



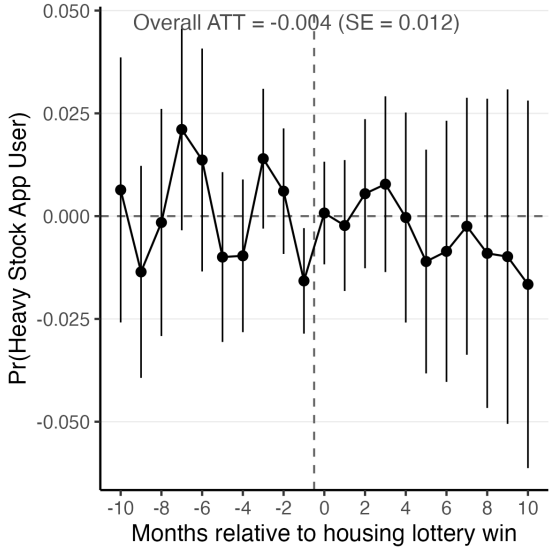
(b) Spending



(c) Stock App Usage



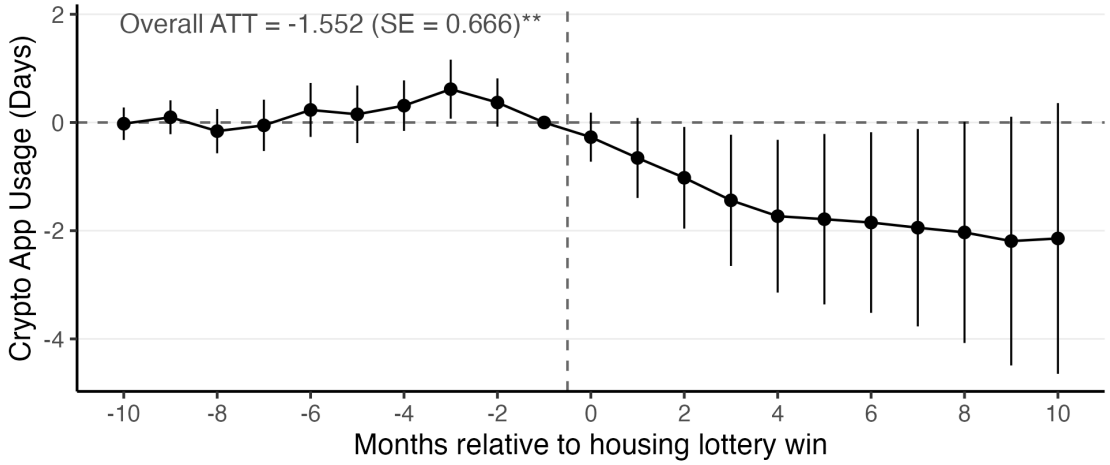
(d) Pr(Heavy Stock App User)



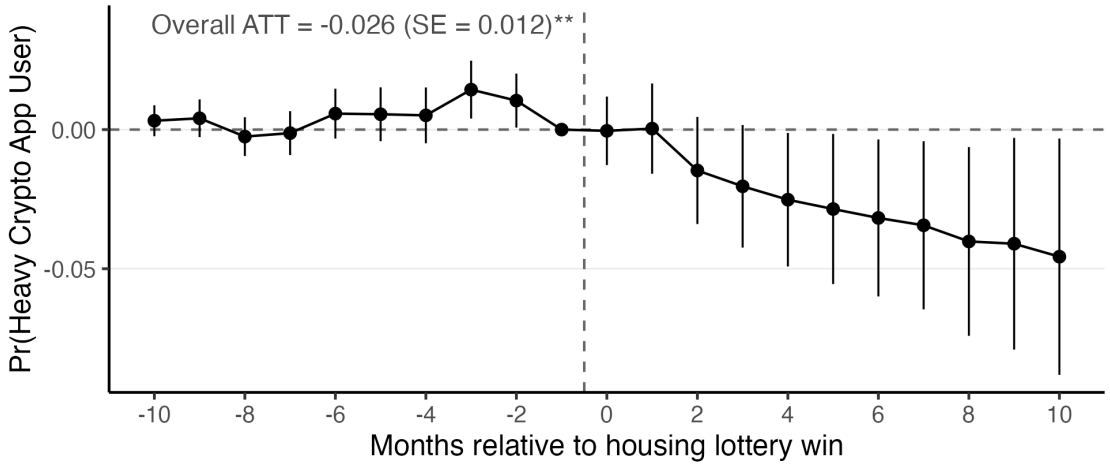
Notes: Figure plots difference-in-differences estimates of the effect of winning a housing lottery on various outcomes, relative to the contract date. Panel (a) shows housing debt. Panel (b) shows spending. Panel (c) shows monthly stock app usage days winsorized at the 95th percentile. Panel (d) shows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

Figure G.14: Cryptocurrency Around a Housing Lottery Win: Roth and Sant'Anna

(a) Crypto App Usage Days

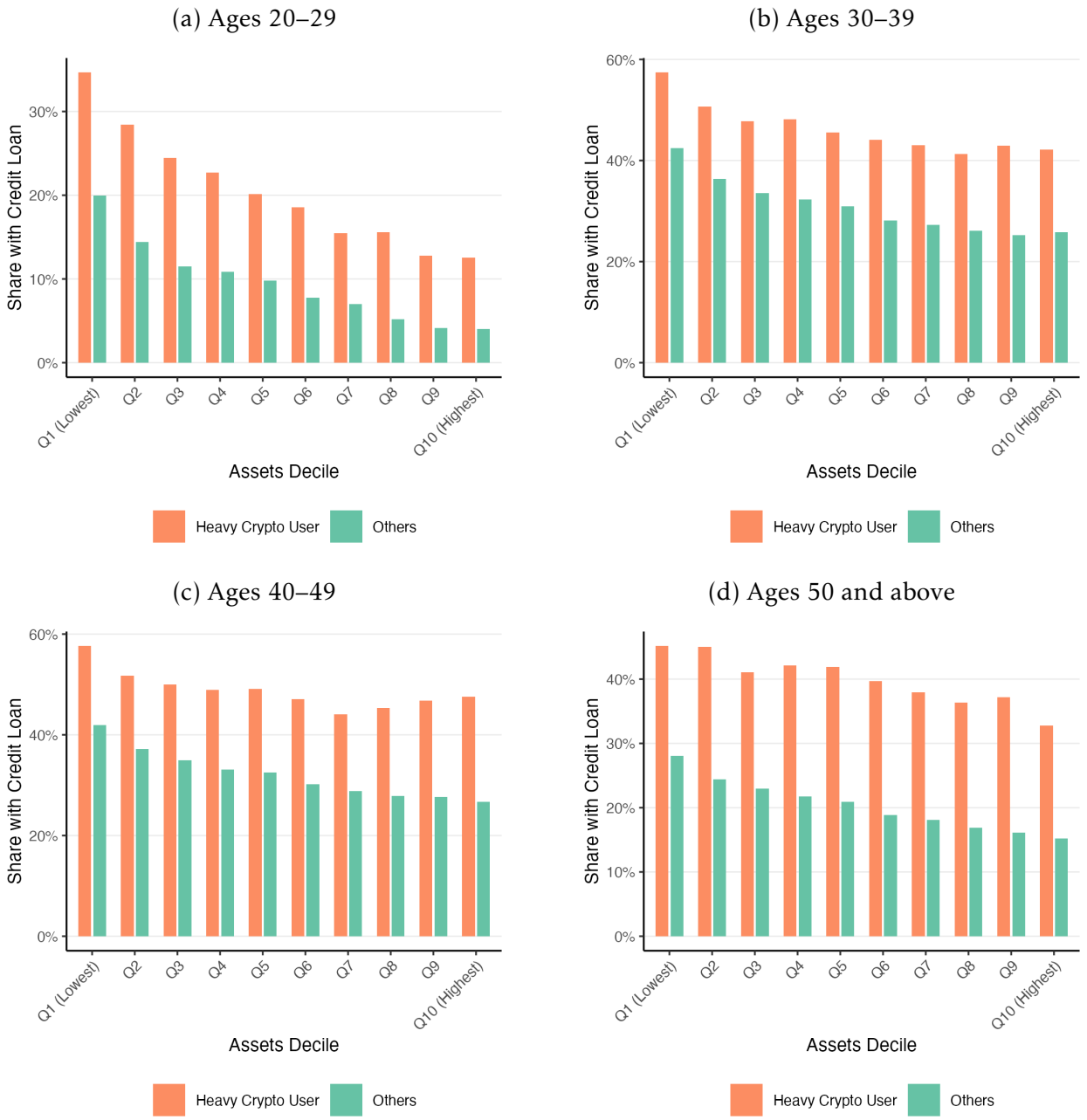


(b) Pr(Heavy Crypto App User)



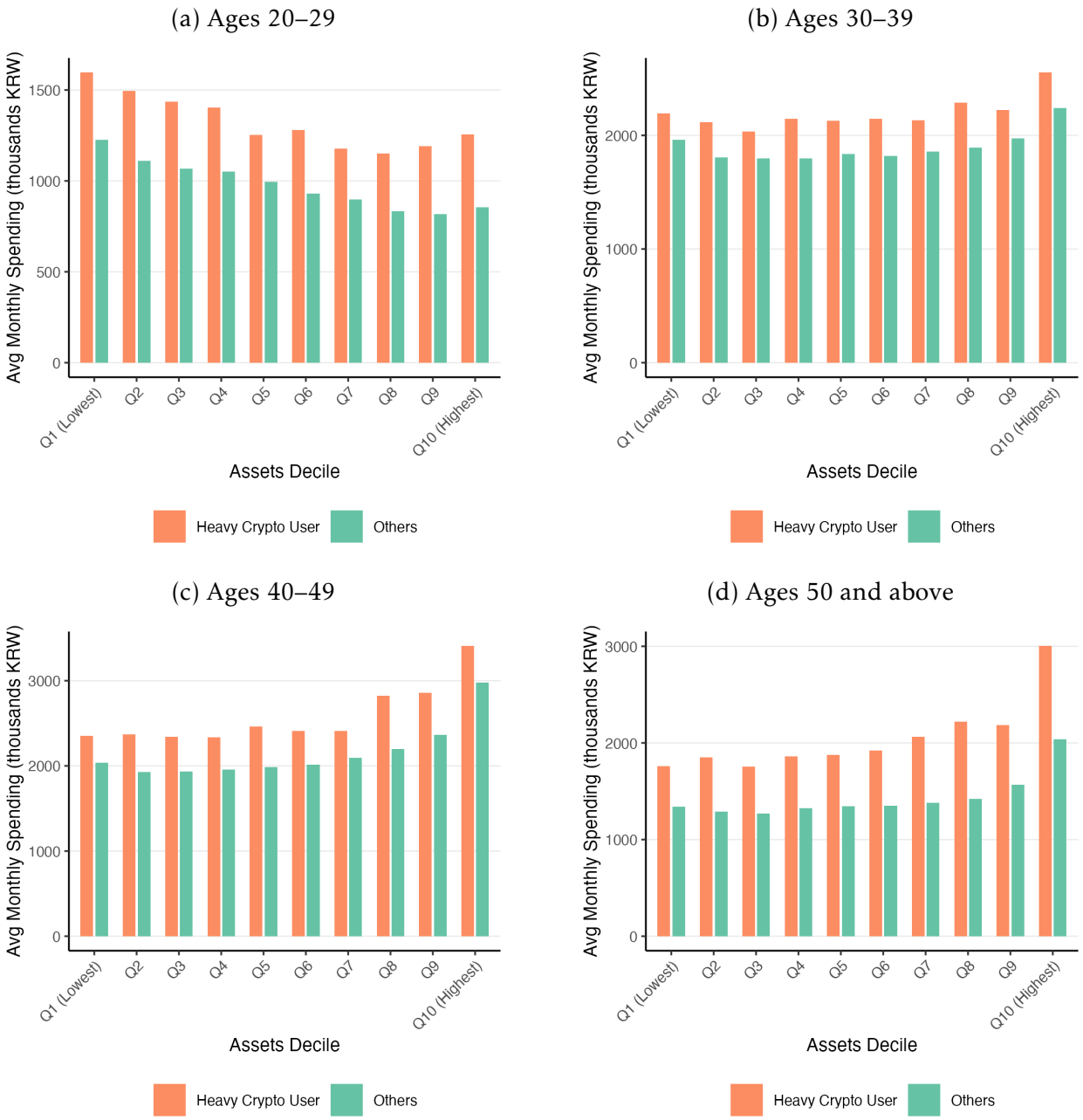
Notes: Figure replicates Figure 6 using the efficient estimator of Roth and Sant'Anna (2023), which imposes quasi-random treatment timing. Vertical bars show 95% confidence intervals. The top left of each panel reports the overall average treatment effect on the treated. Source: KCB and SKT.

Figure G.15: Heavy Crypto Users vs. Others: Unsecured Loans by Assets, by Age Group



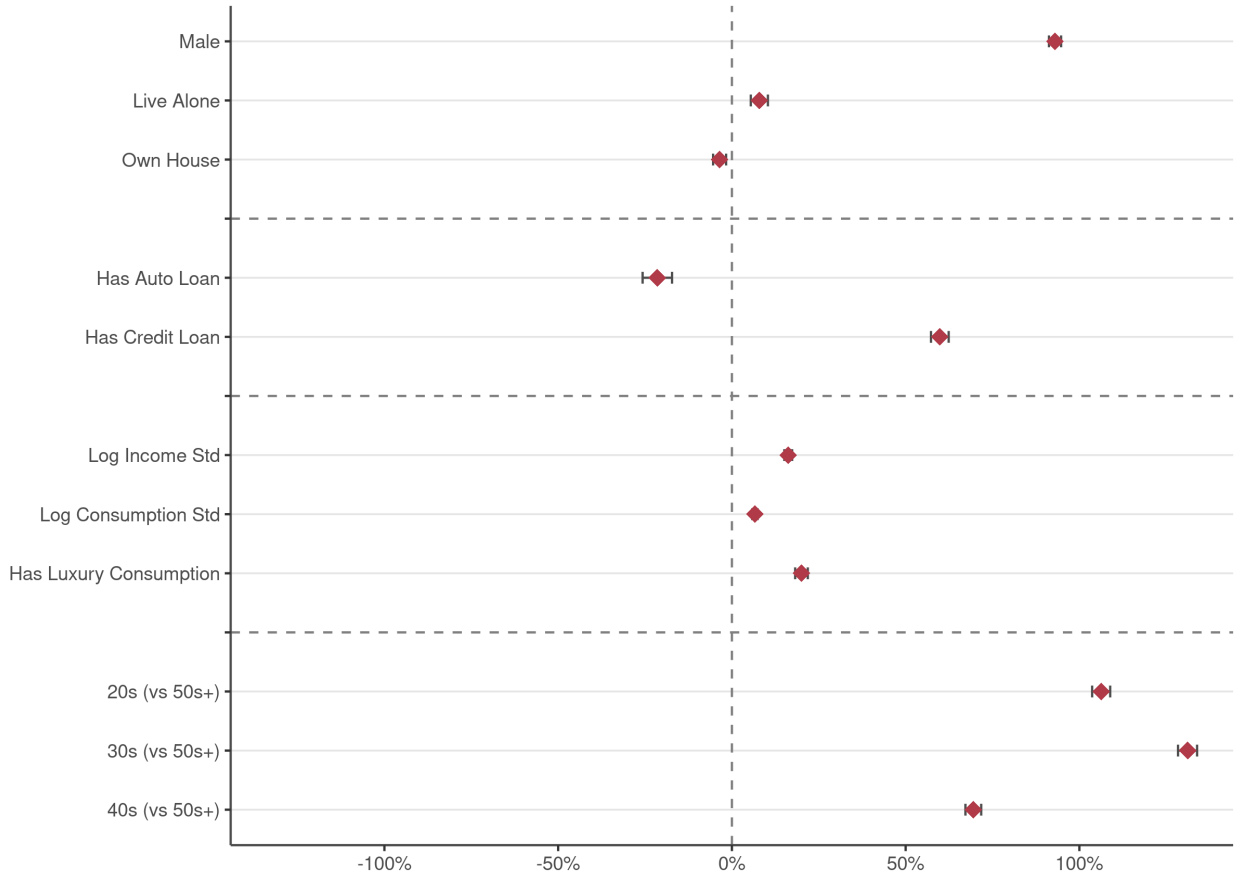
Notes: Figure shows the share of individuals with unsecured loans by asset decile, separately for heavy crypto users and others, for each age group and for the full sample. Net assets are in deciles. All variables are measured as of July 2021. Source: KCB and SKT.

Figure G.16: Heavy Crypto Users vs. Others: Spending by Assets, by Age Group



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.

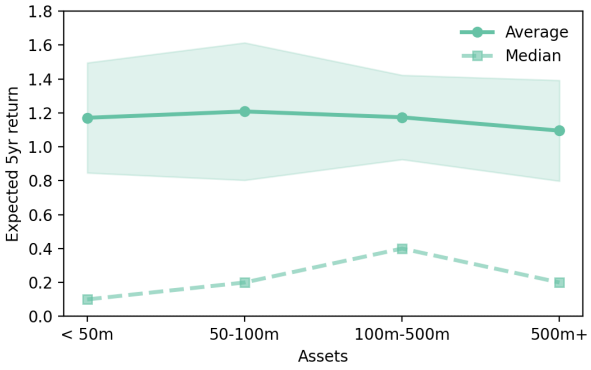
Figure G.17: Predictors of Heavy Crypto App Usage: Demographics, Debt, and Spending



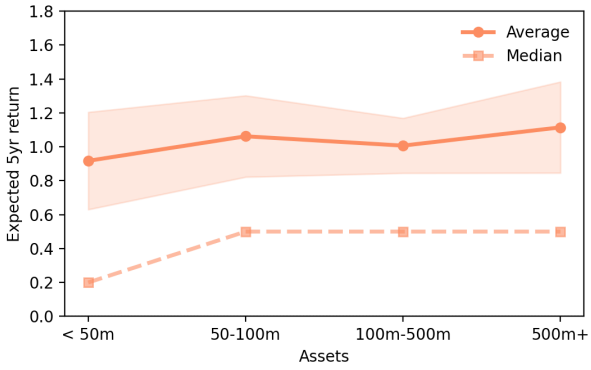
Notes: Figure shows the predictors of heavy crypto usage from a single multivariate regression on a cross-sectional sample in July 2021. All coefficients (except for the constant) are shown. Own house is an indicator for whether you or your family own a home. Log income and log consumption have been standardized. AgeGroup_i is a categorical variable indicating whether the individual is in their 20s, 30s, 40s, and 50s and above. 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.

Figure G.18: Beliefs About Crypto and Stocks Across the Wealth Distribution

(a) Cryptocurrency Returns



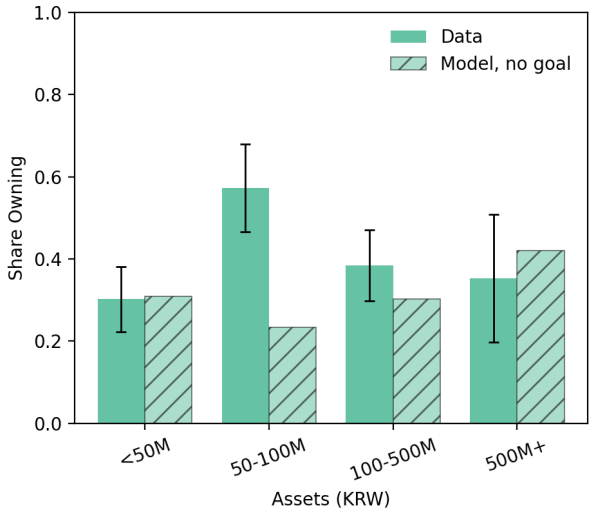
(b) Stock Returns



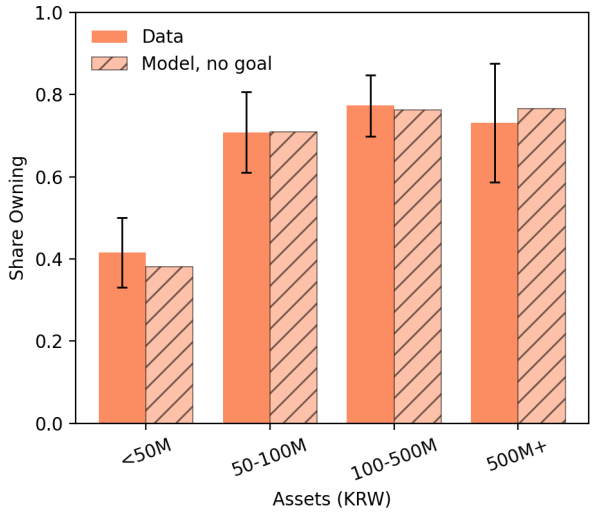
*Notes:*Figure plots mean and median expected five-year returns on cryptocurrency (Bitcoin) and the Korean stock market (KOSPI index fund) by respondent assets. Returns are taken from each respondent's middle, or most likely, scenario and expressed as net returns, so that 0 denotes no change in value and 1 denotes a doubling of the initial investment. Shaded regions denote 95% confidence intervals for the mean. The horizontal axis collapses the survey's six asset brackets into four bins, with the top bin combining all respondents reporting more than 500 million KRW. Responses are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. *Source:* SKT survey.

Figure G.19: Data vs. Model with No Goal

(a) Cryptocurrency

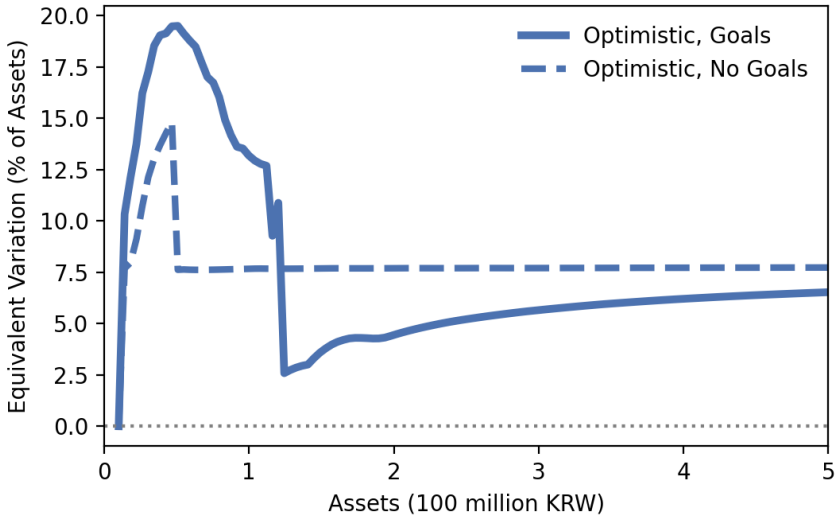


(b) Stock



Notes: Figure compares empirical and model-implied asset ownership by wealth, among non-homeowners who aspire to purchase a home, as in Figure 9. Here, however, the model is re-estimated with the gambling motive shut off by removing θ and G. Hatched bars show model-implied shares at these re-estimated parameters.

Figure G.20: Wealth-Equivalent for Overoptimism

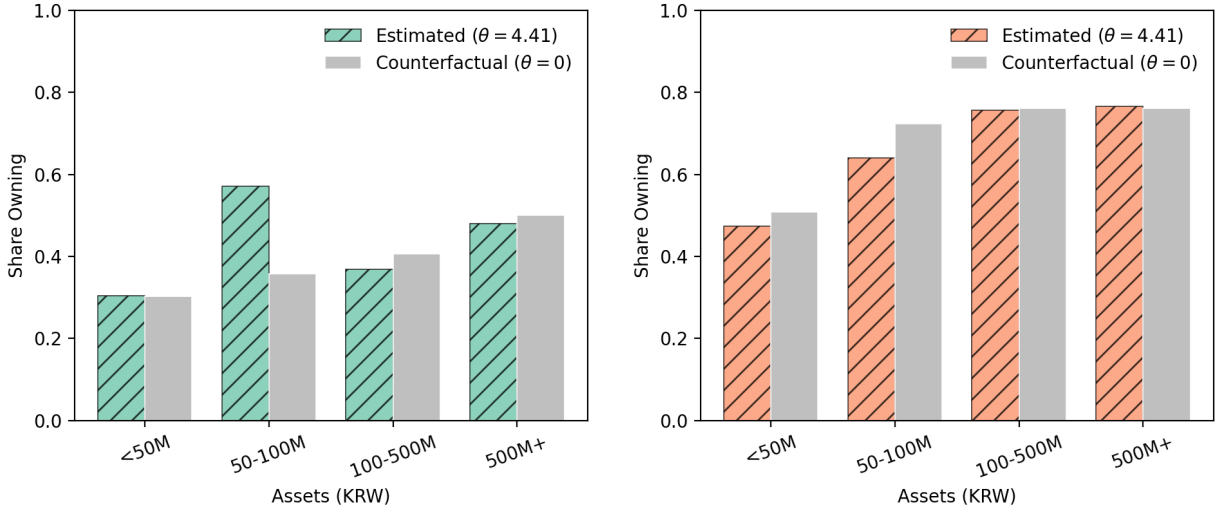


Notes: Figure shows the welfare loss from overoptimism in wealth-equivalent terms (see Figure 11(c) for welfare loss in utils). In particular, the outcome is how much less wealth a rational agent needs to achieve the same level of expected utility as an overoptimistic agent. "No Goals" sets $\theta = 0$, holding all other parameters at their estimated values. Wealth is measured in hundreds of millions of KRW.

Figure G.21: Data vs. Model Uncorrelated Beliefs

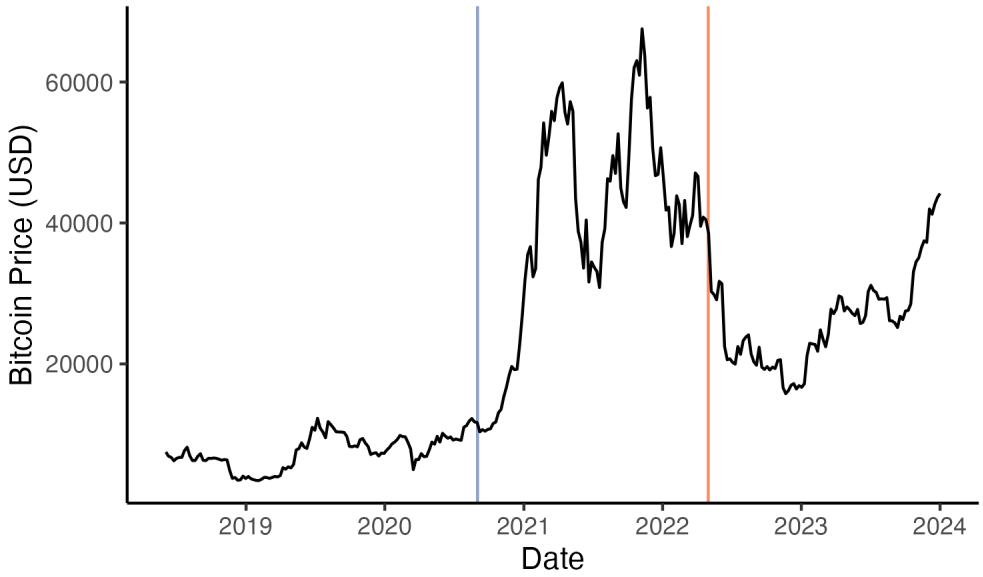
(a) Cryptocurrency

(b) Stock



Notes: Figure shows model-implied ownership by assets at the estimated parameters and under a counterfactual that shuts off the gambling motive. In this specification of the model, individuals have uncorrelated beliefs about stocks and crypto. Hatched bars are the same as in Figure 9. Grey bars are model-implied outcomes when $\theta = 0$, holding all other parameters fixed.

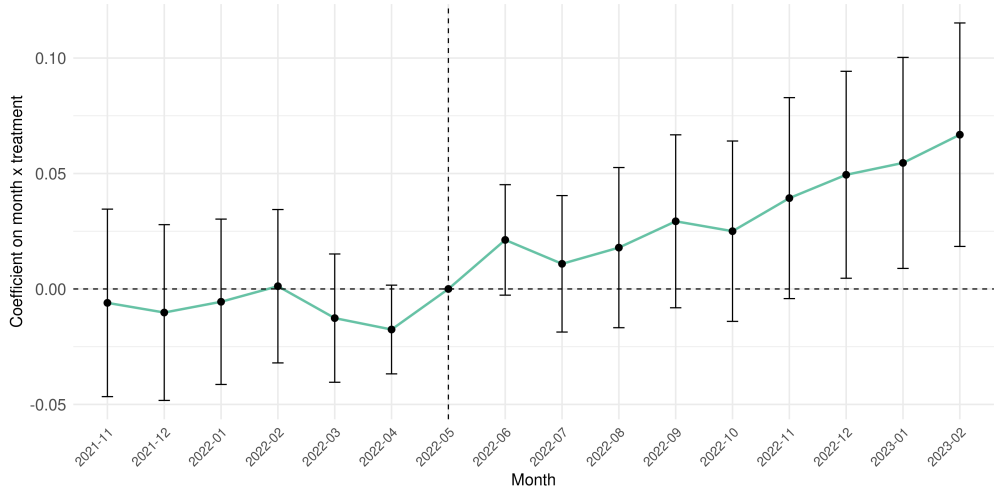
Figure G.22: Bitcoin Prices: Boom & Bust Events



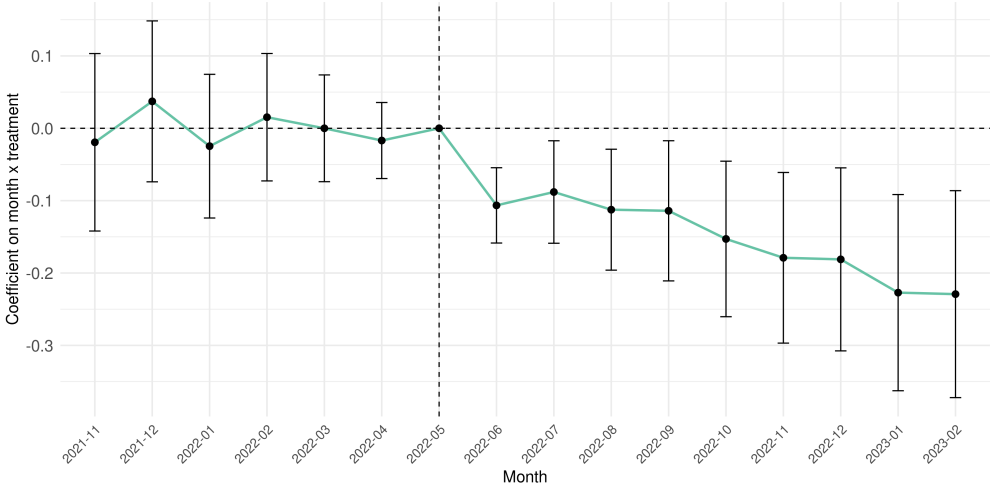
Notes: Figure shows Bitcoin prices over time. The orange line depicts our "bust" event in May 2022. The blue line depicts our "boom" event in September 2020. Source: Bitcoin price data.

Figure G.23: Heavy Crypto App Users Around a Crypto Price Crash

(a) Delinquency

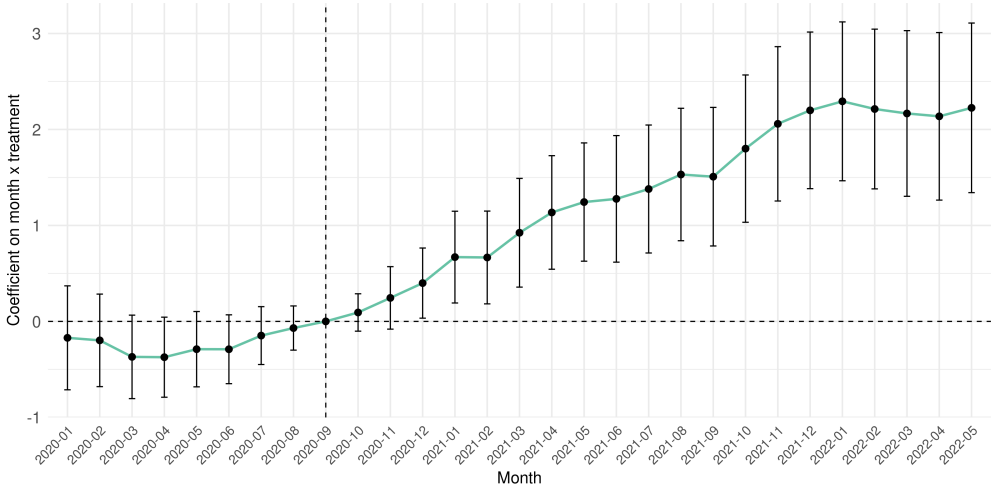


(b) Luxury Purchases



Notes: Figure shows estimates from the regression in Equation C.2 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.

Figure G.24: Heavy Crypto App Users and Home Ownership Around a Crypto Price Boom



Notes: Figure shows estimates from the regression in Equation C.2 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

H Additional Tables

Table H.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.

Table H.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 H.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.

Table H.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 H.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.
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.

Table H.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 H.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.

Table H.8: 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.9: 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
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)
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.

Table H.10: 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 3.3. 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. 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.

Table H.11: Risk Seeking Preferences and Crypto on Goals (Fully Attentive Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk Seeking	Currently Owns Crypto				
Average Goal Importance	0.088***	0.074***				0.065**
	(0.030)	(0.027)				(0.028)
Needs High Risk for Goal	0.22***		0.092**			0.071
	(0.046)		(0.043)			(0.044)
Expected 1Yr Bitcoin Returns				0.022		0.020
				(0.023)		(0.023)
Risk Seeking					0.094**	0.070*
					(0.037)	(0.038)
Demographic Controls	✓	✓	✓	✓	✓	✓
Observations	733	733	733	733	733	733
R^2	0.093	0.12	0.12	0.11	0.12	0.14

Notes: Table shows regressions of risk-seeking preferences and cryptocurrency ownership on goals. The table runs the same specification as Table 3 but filters to participants who responded Tuesday or Thursday to the attention check (Appendix D). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses. Source: SKT survey.

Table H.12: 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	
$\Delta P_t \times I^c_{it}$	0.0250*	0.0258*	0.0507**	0.0520**	0.0772**	0.0765**	0.0234***	0.0227***
	(0.0137)	(0.0138)	(0.0209)	(0.0219)	(0.0284)	(0.0296)	(0.0062)	(0.0068)
I^c_{it}		0.3614***		0.5525***		0.2913		0.3067***
		(0.0925)		(0.1582)		(0.2322)		(0.0754)
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.0046	0.0046	0.0046	0.0046	0.0046	0.0046	0.0454	0.0454
Observations	30,489,505	30,489,505	30,489,505	30,489,505	30,489,505	30,489,505	4,581,662	4,581,662

Notes: Table shows results from the regression in Equation C.1. 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 H.13: Unemployment Shock and Cryptocurrency Interest (Previous Non-Users)

	Δ Crypto Usage		Δ Crypto Heavy Usage		Δ Avg Crypto Usage	
	(1)	(2)	(3)	(4)	(5)	(6)
HasUnemploy	0.0469***	0.0297***	0.0136***	0.0100***	0.3283***	0.2353***
	(0.0036)	(0.0036)	(0.0017)	(0.0018)	(0.0554)	(0.0573)
All Controls		✓		✓		✓
R^2	0.0006	0.0376	0.0003	0.0134	0.0001	0.0124
Observations	340,191	322,900	340,191	322,900	340,191	322,900

Notes: Table shows the same specification as Table 4, but additionally restricting the sample to individuals who were non-crypto users in the pre-period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses.

Table H.14: Unemployment Shock and Cryptocurrency Interest (Previous Users)

	Δ Crypto Usage		Δ Crypto Heavy Usage		Δ Avg Crypto Usage	
	(1)	(2)	(3)	(4)	(5)	(6)
HasUnemploy	0.0249***	0.0146***	0.0041	0.0040	-0.2715	-0.0995
	(0.0048)	(0.0048)	(0.0048)	(0.0049)	(0.2939)	(0.2949)
All Controls		✓		✓		✓
R^2	0.0002	0.0465	0.0000	0.0006	0.0000	0.0308
Observations	134,036	128,090	134,036	128,090	134,036	128,090

Notes: Table shows the same specification as Table 4, but additionally restricting the sample to individuals who were crypto users in the pre-period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses.

Table H.15: 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 the same specification as Table 4, but for credit loans. The sample includes all individuals who never had a credit loan in the pre-period (January-June 2021). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses.