Gambling for Goals[*]

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

May 2026

Abstract

As young adults in advanced economies have become increasingly 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. We conclude with a stylized calibration that shows how goal-driven risk preferences can amplify the welfare costs of overoptimism.

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

[†]costas.arkolakis@gmail.com. Yale University.

[‡]spencer_kwon@brown.edu. Brown University.

[§]drussel@g.harvard.edu. Harvard University.

[¶]cshi@g.harvard.edu. Harvard University.

[‖]hyang@sogang.ac.kr. Sogang University.

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

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

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

— **Reddit user (2022)**

1 Introduction

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

At the same time, there has been 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 return beliefs. 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, one's distance from their goal shapes their 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.

We begin by documenting 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 somewhat 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.

Next, we use within-individual variation in the administrative data to test how risk-

[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.

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 inherently related to past financial outcomes and expectations about the future.

To address these endogeneity concerns, we exploit Korea's housing lottery, which quasi-randomly allocates rights to purchase price-regulated housing. We identify 1,347 individuals who are likely to be winners and compare them to not-yet-treated future potential winners in a difference-in-differences design, similar to Arkolakis et al. (2026).[4] Following the announcement of lottery results, cryptocurrency app interactions decline by 21% for winners relative to the pre-win month. 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 intrinsic enjoyment, addiction, and optimistic beliefs. While each may contribute, they have difficulty explaining some of the broad 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.

In the final section of the paper, we examine the welfare implications of our theory. If

[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.

investors hold rational expectations and aspire to difficult-to-reach goals, gambling could, in principle, enhance welfare by enabling the pursuit of high-risk, high-reward opportunities. However, when individuals are overoptimistic, Friedman-Savage preferences can amplify belief distortions, generating substantial welfare losses relative to a rational expectations benchmark. In a stylized calibration, some overly optimistic households make risky investments in pursuit of unlikely gains, effectively engaging in costly gambles that leave them worse off on average. At the same time, restricting access to one form of high-risk investment can lead individuals to substitute toward alternative gambles in pursuit of the same goals, making the welfare effects of these interventions ambiguous. Put simply, if difficult-to-reach goals drive gambling, a policy maker may have to address the underlying causes of this difficulty, rather than simply banning particular assets.

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 how inequality and social conditions shape perceptions of opportunity and life satisfaction (Helliwell et al., 2024; Knoll et al., 2017; Berman, 2022). We focus on the financial consequences of rising dissatisfaction: 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 preferences for high-risk assets and gambling. Friedman and Savage (1948) posit a reduced-form utility over wealth that generates both local risk aversion and a taste for lotteries, which Markowitz (1952) modifies to preferences over relative levels of wealth. A body of work microfounds these preferences over wealth from indivisible consumption (Kwang, 1965; Jones, 2008; Vasquez, 2017). Others model gambling as directly entering utility (Conlisk, 1993; Asness, 2024), or emphasize behavioral distortions such as probability weighting (Barberis, 2013; Barberis and Huang, 2008), salience (Bordalo et al., 2022), and non-pecuniary motives like

[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.

anticipation or sensation-seeking (Loewenstein, 1987; Grinblatt and Keloharju, 2009). Closely related to our framework are consumption commitments, where discrete fixed costs generate convexity in utility (e.g., Chetty and Szeidl, 2007). We build on this insight and emphasize that the key ingredient is the presence of salient, discrete goals that generate local convexity in perceived utility. We discuss alternative microfoundations such as categorical thinking (Mullainathan et al., 2008; Conlon and Kwon, 2025; Bordalo et al., 2025), which can make nominally continuous goals behave as if they were discrete. This perspective broadens the scope of when Friedman–Savage-type motives may arise.[6]

Finally, our paper contributes to the large literature on retail investor behavior. This literature has shown that retail attention is often drawn to "flashy" or salient assets (Barber and Odean, 2008), lottery-like stocks (e.g., Bali et al., 2019; Kumar, 2009; Barberis and Huang, 2008), and cryptocurrency (e.g., Kogan et al., 2024; Aiello et al., 2023b; Weber et al., 2023; Auer and Tercero-Lucas, 2022; Pursiainen and Toczynski, 2022). Instead of focusing on which asset classes disproportionately attract retail investors, we study investor heterogeneity in the cross-section. In this sense, our work is closer in spirit to Liu et al. (2022a) and Jiang et al. (2024). Relative to these findings, which emphasize fixed individual characteristics, we provide a framework in which such motives arise endogenously from households' economic circumstances. Our framework also yields predictions not only for overall risk-taking, but for the types of gambles individuals choose.

2 Gambling for Goals: A Theory

This section motivates and introduces a model in which difficult-to-attain financial goals lead to risk-taking (Friedman and Savage, 1948). 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.[7] 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,

[6] Relative to Lockwood et al. (2025), who study state-run lotteries, our focus is primarily on more moderate-upside gambles.

[7] See footnote 1.

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).[8] 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 after 1997) respondents reported perceiving themselves as financially behind due to unfavorable social comparisons rather than objective indicators (Intuit Credit Karma, 2024).[9] These responses align with recent psychology studies suggesting that social media use can lead to increased upward social-comparisons and lower self-esteem (Vogel et al., 2014; Verduyn et al., 2020; McComb et al., 2023). In another survey, Generation Z respondents reported believing, on average, that financial "success" requires a \$588,000 annual salary and \$9.5 million in net worth (Kelly, 2024). For many, these outcomes are difficult to attain through conventional wealth accumulation.

2.2 Model

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

Setup Consider a two-period model in which an agent is endowed with initial wealth W_0, has concave utility over consumption $u(c)$, and can attain a financial goal $g \in \{0,1\}$ in period two at cost G. If attained, the goal delivers a discrete utility boost θ. The goal can reflect a purchase of a large durable good or investment (e.g., buying a home, starting a new business), or other broader material objectives (e.g., attaining a different social class). The goal is discrete: the agent cannot continuously "scale down" the goal and substitute

[8] 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).

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

it for a cheaper alternative. We discuss this discreteness in more detail below. The agent can save at the riskless rate $R_0 = 1$ or invest in a “risky gamble” which returns R_H or R_L with probabilities p_H or p_L, respectively, and where $p_H R_H + p_L R_L = 1$. For simplicity the agent’s discount rate is 1. The agent therefore solves:

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

Figure 1: Goals generating convexity

(a) Utility over Wealth Given Goals

(b) Friedman-Savage Utility (JPE)

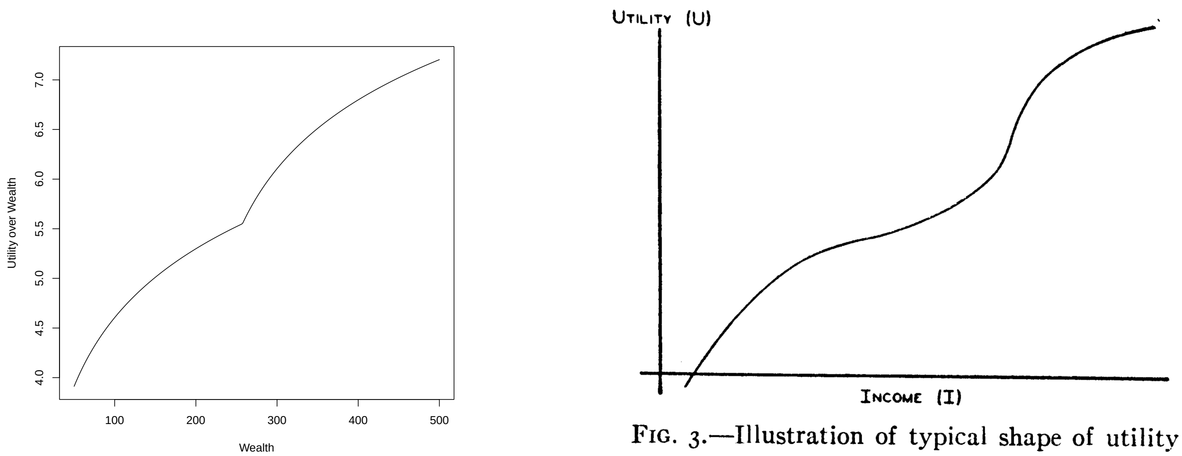


FIG. 3.—Illustration of typical shape of utility curve.

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

Implications Figure 1 illustrates how the goal locally convexifies the agent’s utility over wealth, endogenously generating a utility curve of the form hypothesized by Friedman and Savage (1948). Intuitively, the convexity is centered at the point at which the agent is indifferent between spending G to attain the goal or to increase consumption. Proposition 1 characterizes the agent’s investment, goal attainment outcomes, and consumption in different regions around this local convexity.

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

(a) ***Gambling and Goals:*** *If $W < W_L^*$, the agent gives up on her goals and invests in the safe asset. If $W \in [W_L^*, W_H^*]$, the individual prefers to gamble (i.e. chooses the risky asset), and only attains her goals when the gamble pays off ($R = R_H$). If $W > W_H^*$, the agent invests in the safe asset and risklessly attains her goals.*

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

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

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

Proposition 1(a) describes the set of individuals who will prefer to gamble and when they will attain their goals. In particular, goal-driven gambling will be strongest among individuals who aspire to goals that would not be within reach with riskless savings, but are attainable if the risky gamble pays off. In contrast, gambling does not appeal to those who can achieve their goals without risk, nor to those who cannot achieve them even with risk. Proposition 1(b) shows that goals also affect intertemporal consumption. Relative to their wealthier peers, gamblers consume more in the present. Intuitively, saving and risk-taking are substitutes: individuals confident about reaching their goals through saving must defer consumption, whereas those who gamble "partially give up" and reallocate resources toward current consumption. Empirically, conditional on the goal, those who choose the risky asset should have lower savings and higher consumption.

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

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

Proposition 2 highlights that the Friedman–Savage motive not only predicts whether individuals gamble, but also which types of gambles they prefer. Individuals who are far from their goals (but not so far as to give up entirely) optimally choose highly skewed bets—low-probability, high-payoff "lottery-like" outcomes. Intuitively, agents benefit from risk-taking only if success allows them to reach their goals. For agents far from their goals, this requires a large payoff, which under the fair-odds constraint requires a lower probability of success to limit downside risk. As agents move closer to their goals, the required payoff shrinks, and they optimally shift toward less extreme gambles that deliver success with higher probability. In this sense, distance to the goal shapes not only the demand for risk, but also the form of risk-taking.[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, they cannot scale it downward.[11] Proposition 3 formalizes this result.

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.*

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 physical or 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, 2002; Mullainathan et al., 2008; Bordalo et al., 2025), is that

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

[11]Appendix Figure F.2a 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.

[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.

people reason in discrete categories or classes—e.g., rich vs poor, successful vs ordinary.[14] In Appendix A.4, we formalize this insight by drawing on the model of Bordalo et al. (2025) and Conlon and Kwon (2025). The results are shown in Appendix Figure F.2b: even with the option of continuous scaling $\theta(G_c)$, if individuals perceive utility gains in a categorical manner, we recover Friedman-Savage utility.

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

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.*

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.

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

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.

Table 1: Basic Structure of Data

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

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

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

Mobile App Usage Activity Mobile phone activity comes from SK Telecom (SKT), which held 40% market share in December 2023. For each individual and month, the SKT data report application and website usage by category. These categories include many different online services, including cryptocurrency exchanges, real estate platforms, social media, video platforms, and education services. For each category, we observe the number of 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 B.1 for coverage by month). For most analyses we further restrict to those who have consented to sharing detailed data with SKT, around 70% of the sample.

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

[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.

atively 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 F.4 and F.5).

To characterize the relationship of cryptocurrency engagement with the usage of other apps, Figure 2 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 social 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 aspirations.

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

[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 F.3 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).

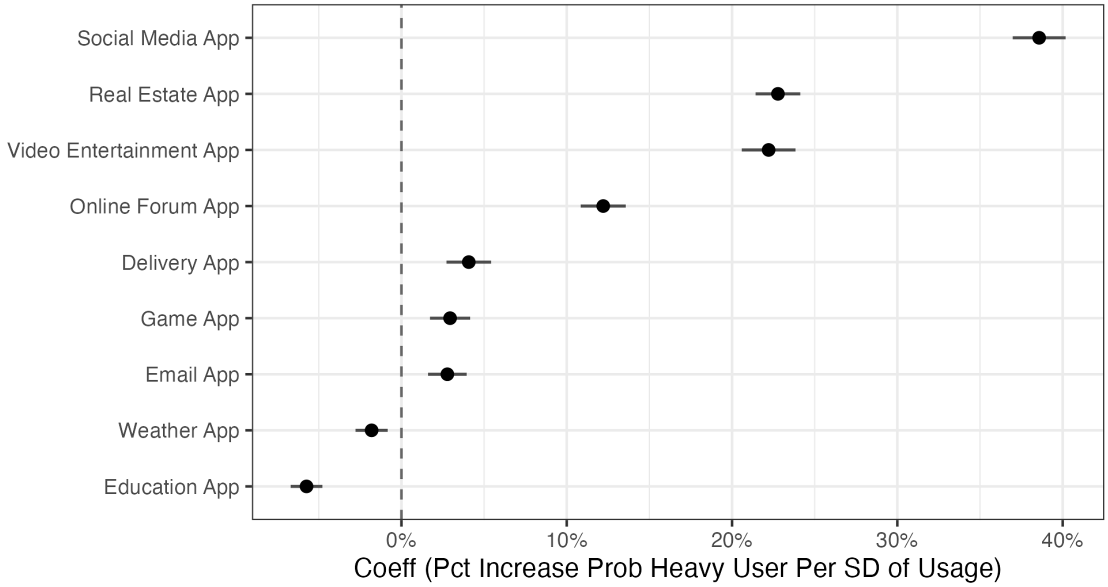
[19] Real estate platforms include Naver, Hogangnono, and Zigbang, services similar to Zillow or Redfin in the United States. Video entertainment apps include YouTube and TikTok.

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. Source: KCB, SKT, and Shinhan Card.

Figure 2: 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.

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. Appendix D contains more details.

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 Table D.1 provides sample summary statistics.

Crypto App Usage and Holdings Appendix Table D.1 shows that app usage tracks actual holdings: 25%, 45%, and 75% of non-users, middle users, and heavy users, respectively, currently hold cryptocurrency. Heavy users also hold substantially more cryptocurrency on average: 22.2 million KRW ($15,857 USD) compared to 5.5 million KRW ($3,929 USD) for middle users. Figure D.1 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.

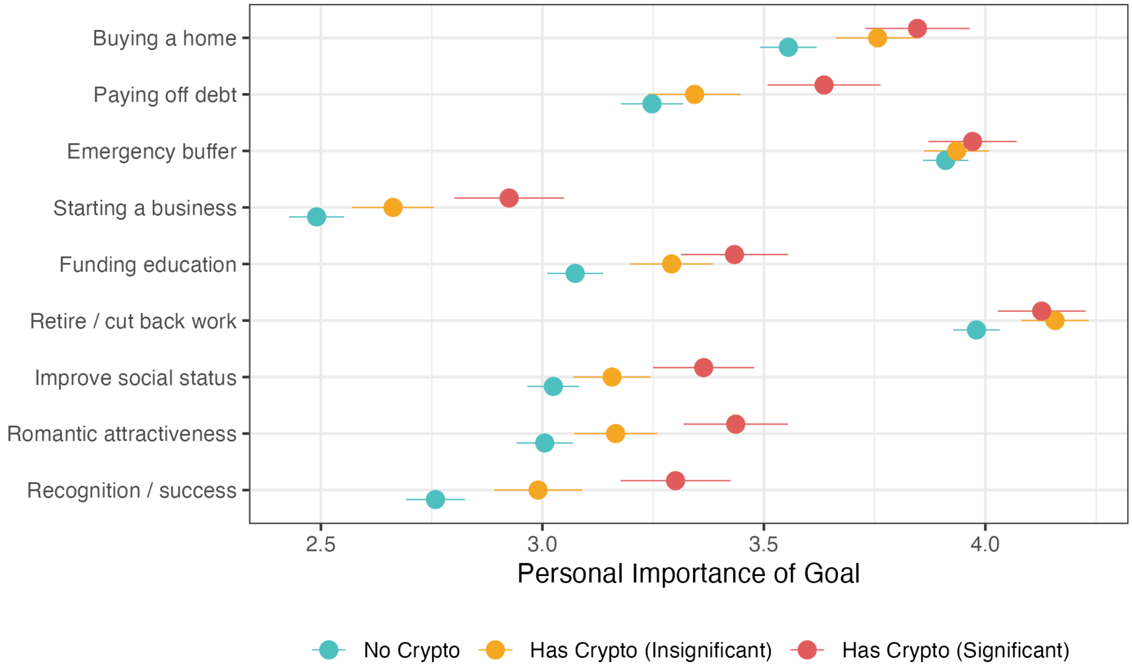
4.1 Goals and Risk-Taking

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]

[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.

[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?''

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.

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 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 D.2 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,

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

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 median downpayment requirement for buying a home in the Seoul metropolitan area is around 180M KRW ($129,000 USD).[23]

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

[23]We estimate the required downpayment by multiplying the May 2025 median apartment sale price in the capital region, 534M KRW, by an equity share of 30–40 percent. The price is reported by Seoul Shinmun (2025) using Korea Real Estate Board data. The equity-share range reflects Korean mortgage rules, under which LTV ceilings are up to 70 percent for first-time homebuyers in the capital region (Financial Services Commission, 2025). This calculation implies a cash requirement of 160–214M KRW.

[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.

lower in column (6) than (5), suggesting that goals capture distinct sources of variation that may otherwise be attributed to inherent risk appetite.

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. "Risk-Seeking" indicates preferring a risky lottery over a sure gain when both have the same expected value (Appendix D.1 reports the full question). "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.

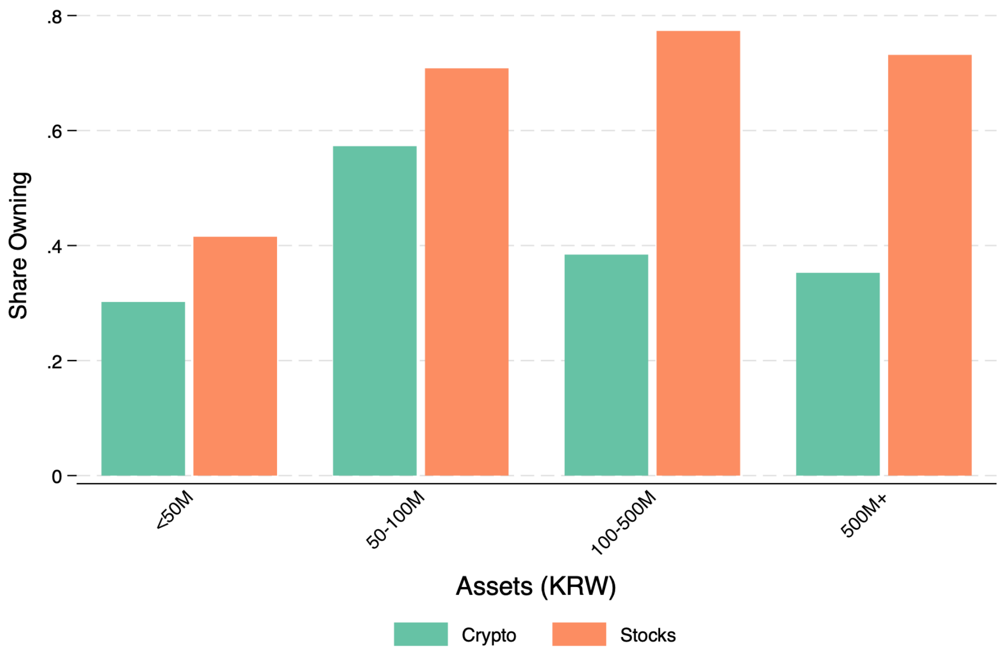
These results suggest that difficult-to-reach goals generate demand for risky assets. Our model also makes predictions about how *distance* to goal shapes risk preferences (Corollary 1, Prediction 2). We provide suggestive evidence for these predictions next.

4.2 Distance to Goals

Our theory makes several additional predictions about how distance to one's economic goals shape risk preferences. Measuring this distance is challenging: even within a given goal, such as "romantic attractiveness," individuals may differ substantially in their perceptions and aspirations. To explore Prediction 2, we therefore focus on one goal, home-ownership, and use individuals' current assets to proxy for distance to the goal.

Prediction 2 has two implications. First, individuals closer to their goals prefer assets with less skew than those farther away. Survey participants perceive stock returns to

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 D.5 shows a complementary analysis in regression. Source: SKT survey.

be less skewed than crypto returns (Appendix Figures D.3 and D.4); 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 D.6 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

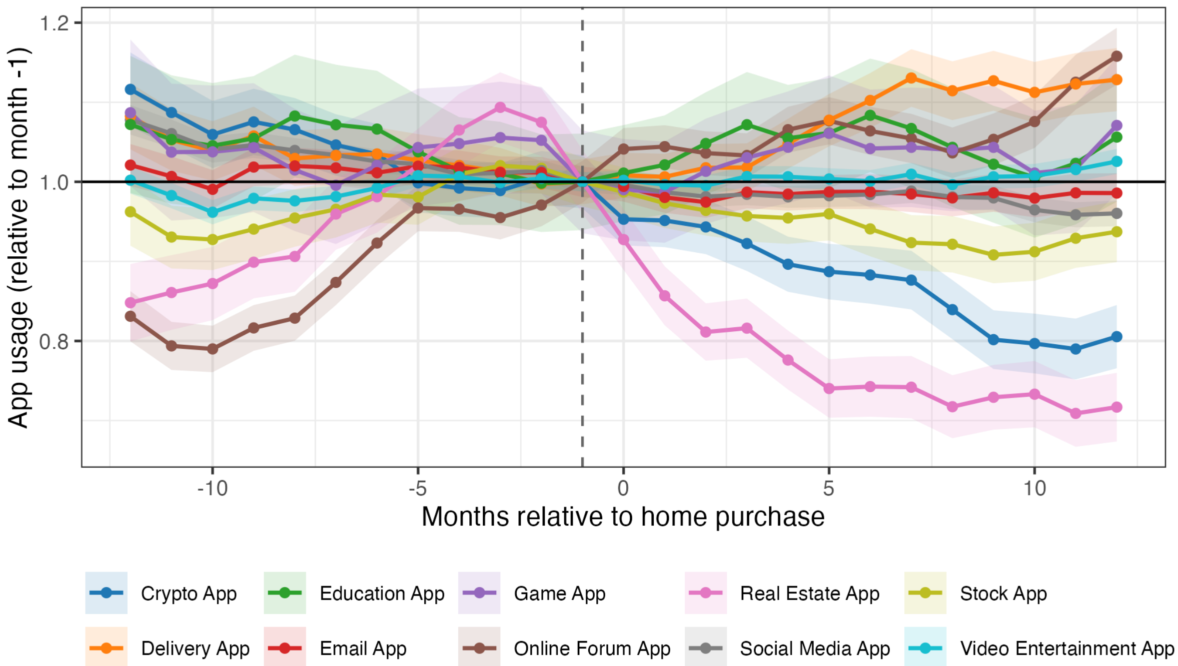
The survey evidence in Section 4 suggests that homeownership is an important financial goal, especially among cryptocurrency investors. Motivated by this finding, we first explore app usage around the time individuals purchase a home. We then examine the causal effects of winning the right to purchase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

Homeownership Lottery Institutional Details To address endogeneity concerns, we exploit variation introduced by a popular housing lottery in South Korea (*cheongyak*). Many newly built apartments are offered in the lottery, and eligible households can apply for the right to purchase units prior to construction. Applicants must generally be non-homeowners, satisfy income and asset thresholds, and contribute to a designated savings account. Within each apartment project, applicants are ranked by a priority score based on family composition, savings history, and age. When a project is oversubscribed, as is

[26] Indeed, 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.

typical in the capital region, random lottery is implemented among the most qualified, which generates quasi-random assignment in winners.

Winning the lottery grants the winner the right to purchase an apartment at a regulated pre-sale price that is often substantially below market value. Arkolakis et al. (2026) estimate that the median discount offered is approximately 20%, which translates to a discount of 160M KRW ($114,000 USD).[27] 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.[28] Because these projects are new constructions, move-in typically occurs two to three years later.

Sample Construction and Specification Applicant rosters for the housing lottery are not publicly available. We therefore follow a sample construction procedure similar to Arkolakis et al. (2026) to identify likely lottery winners. We identify 1,347 individuals in the administrative data who appear to be lottery winners during a 36 month period

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

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

between January 2021 and December 2023.[29] The key idea is to match lottery projects to geographic locations in the credit bureau data, and identify households that first appear at these locations around the project's move-in date that match the eligibility rules.[30]

We then compare likely winners to future winners who have not yet reached their own contract date. Our differences-in-differences specification for lottery winner i and calendar time t is:

$$Y_{i,t} = \sum_k \beta_k \mathbb{I}(k = t - G_i) + \alpha_t + \delta_i + \epsilon_{i,t} \tag{3}$$

$Y_{i,t}$ 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. Since our treatment is staggered, we estimate our effects using the method proposed in Callaway and Sant'Anna (2021). As a first-stage check, Panel (a) of Appendix Figure F.10 shows that housing debt rises by nearly 30M KRW ($21,400 USD) in the months after the contract date. Prediction 3 implies that after winning individuals decrease their high-risk activity, so $\beta_k < 0$ for $k > 0$.

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 pre-

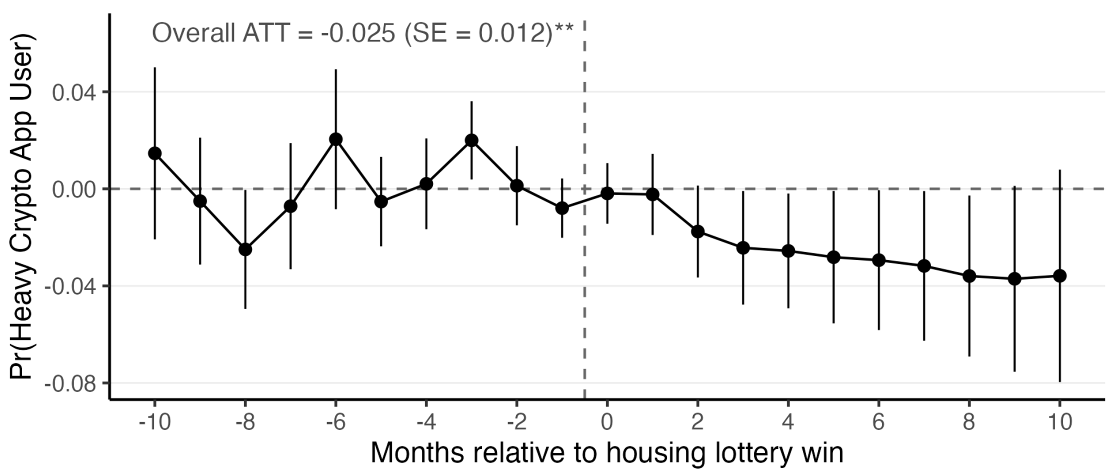
[29]When multiple household members transition into homeownership and have recorded app usage in the SKT data, we select the youngest adult male. Our results are not sensitive to this choice.

[30]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. Appendix E provides more details.

Figure 6: Change in Cryptocurrency Use Around a Housing Lottery Win

(a) Crypto App Usage Days

(b) Pr(Heavy Crypto App User)



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. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Source: KCB and SKT.

diction, Appendix Figure F.9 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 F.10 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:

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

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

Table 4: Unemployment and Changes in Cryptocurrency Interest

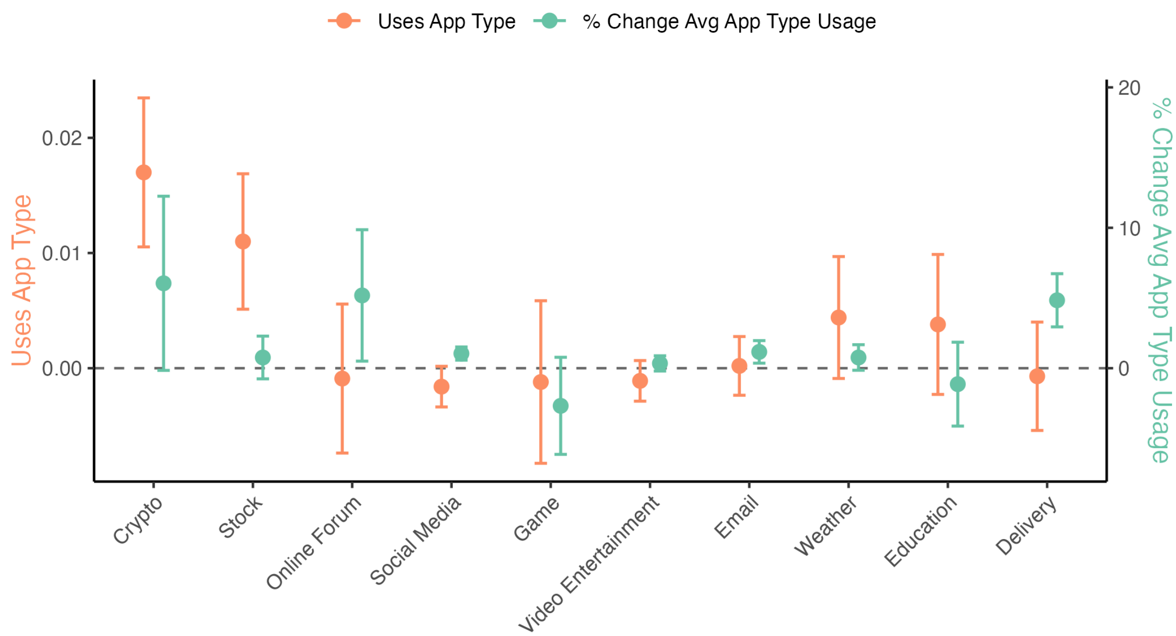
	Δ Crypto Usage		**Δ Crypto Heavy Usage**		**Δ Avg Crypto Usage**	
	(1)	(2)	(3)	(4)	(5)	(6)
HasUnemploy	0.0202***	0.0170***	0.0117***	0.0086***	0.5979***	0.2052*
	(0.0032)	(0.0033)	(0.0019)	(0.0020)	(0.1070)	(0.1074)
All Controls		✓		✓		✓
R^2	0.0001	0.0024	0.0001	0.0054	0.0001	0.0388
Observations	474,227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

Notes: Table shows results from the regression in Equation 4. The sample includes all individuals who were continuously employed in the pre-period (January-June 2021). The outcome in columns 1-2 is the difference in indicators (-1, 0, or 1) for whether individual i used a crypto app in any month in the pre- vs. post-period (July 2021-June 2022). The outcome in columns 3–4 is analogous but for "heavy usage", defined as using cryptocurrency apps more than 30 distinct times within the month. The outcome in columns 5-6 is the average monthly crypto usage. "All controls" 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 4. 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 G.3 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 G.4 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 G.5 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.

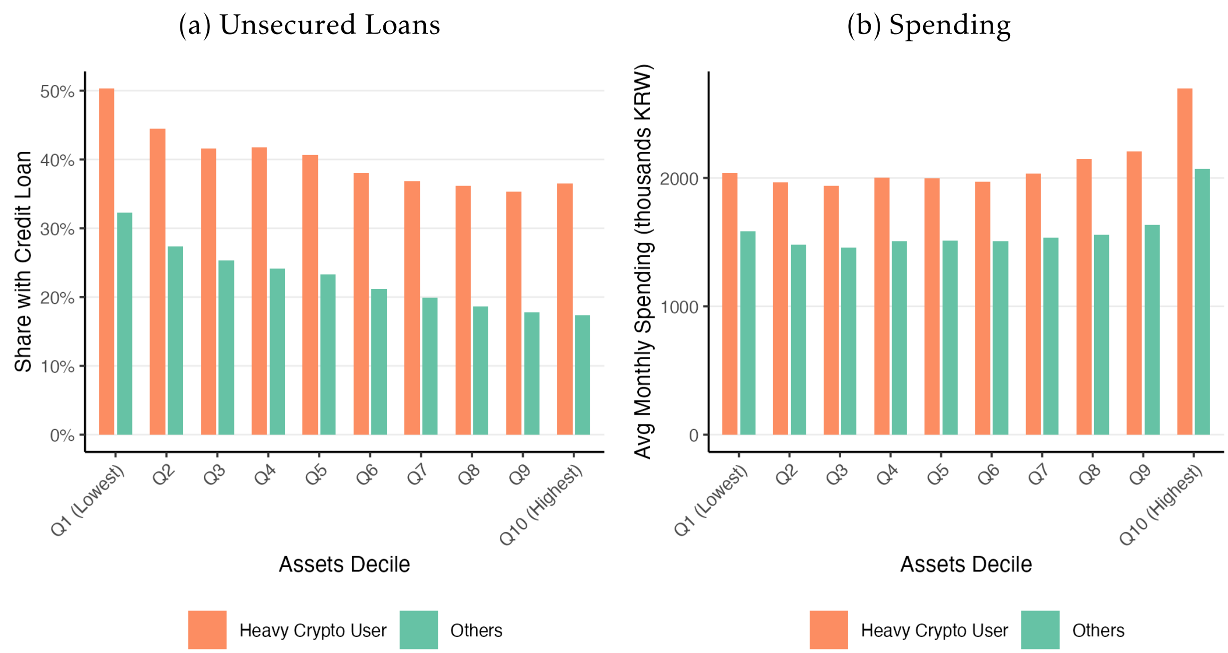
6 Consumption and Additional Explanations

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: 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.

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 F.6, F.7, F.8. 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 current 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 supports the importance of Friedman-Savage motives, other factors also likely play important roles. We now consider alternative explanations for risk-seeking behavior, and discuss the extent to which they fit our evidence.

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. These motives can help explain why gambling-like activities are widespread, but leave several patterns unexplained. First, while intrinsic-enjoyment motives are most natural for small-stakes gambles, where utility from entertainment dominates the utility cost of financial losses, evidence discussed in Section 3.2 shows that individuals often hold enough cryptocurrency to substantially affect their spending, delinquency, and homeownership, especially among heavy users. Second, intrinsic-enjoyment does not naturally predict the variation documented in Section 4.2 individuals substitute across instruments with different skewness in a way that is correlated with their goals. Finally, our survey evidence also suggests that many crypto investors have not fully abandoned their goals; indeed, they are more likely to view certain goals as important, making it unlikely that they view their behavior purely as escapism.

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 likely 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 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 this theory does not predict risk-taking changing with economic circumstances, for example, after a housing-lottery win. 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, our framework places more structure on when goals matter, what forms of risk-taking they generate, and the welfare consequences of gambling motives. 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 makes a sharper prediction: individuals should prefer certain types of gambles over others, with more desperate households choosing more right-skewed bets, as we document in Section 4. Finally, embedding goals in a standard consumption framework allows us to study welfare, especially when households hold miscalibrated beliefs, as 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 even without a Friedman–Savage motive. Consistent with this channel, Section 4 shows that expected Bitcoin returns predict cryptocurrency holdings, in line with prior evidence (e.g., Weber et al. (2023)). In the time series, aggregate crypto engagement also co-moves strongly with Bitcoin prices (Appendix Figure F.3), suggesting that extrapolative beliefs may contribute to cryptocurrency demand. However, Table 3 shows that goals and the perceived need for high-risk investment predict cryptocurrency ownership even after controlling for expected Bitcoin returns. Belief-based explanations also do not by themselves explain why optimism, or the willingness to act on it, is systematically concentrated among households for whom high-risk investment alone offers a plausible path to salient goals.[31]

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. 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 in consequential ways. 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 turn to this interaction next.

7 Welfare Consequences of 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, households may also hold overoptimistic beliefs about cryptocurrency returns, as suggested by our survey and prior work: they 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).

In this section, we study how these forces interact. We show that goal-driven risk-taking can amplify the costs of distorted beliefs. A household that views cryptocurrency as a high-return asset may invest modestly if success does not change any important life

[31] 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).

outcome. In contrast, a household that perceives the same asset as the only route to homeownership, retirement security, or financial independence may invest much more aggressively. When such households are overoptimistic, biased beliefs translate into larger investment responses and larger welfare losses than under standard concave utility.

Working Example Consider an individual who desires homeownership. Suppose a down payment requires \$200,000, and homeownership provides a utility gain of $\theta = 1$, roughly equivalent to a permanent 5% increase in consumption for a log-utility agent. Without investment opportunities, if the individual has net worth above $W^* = \$316{,}395$ they will purchase a home; otherwise they are priced out. The individual, however, can invest in either a riskless asset with return $r_f = 5\%$ or crypto, which they perceive to have expected return $\mu = 40\%$ and volatility $\sigma = 100\%$. The individual chooses share $\alpha \in [0,1]$ of net worth to allocate to crypto in order to maximize subjective expected utility. We assume the true expected return on crypto is 20%: the individual overestimates expected returns by 20 percentage points. We use this example to illustrate the welfare consequences of overoptimism.

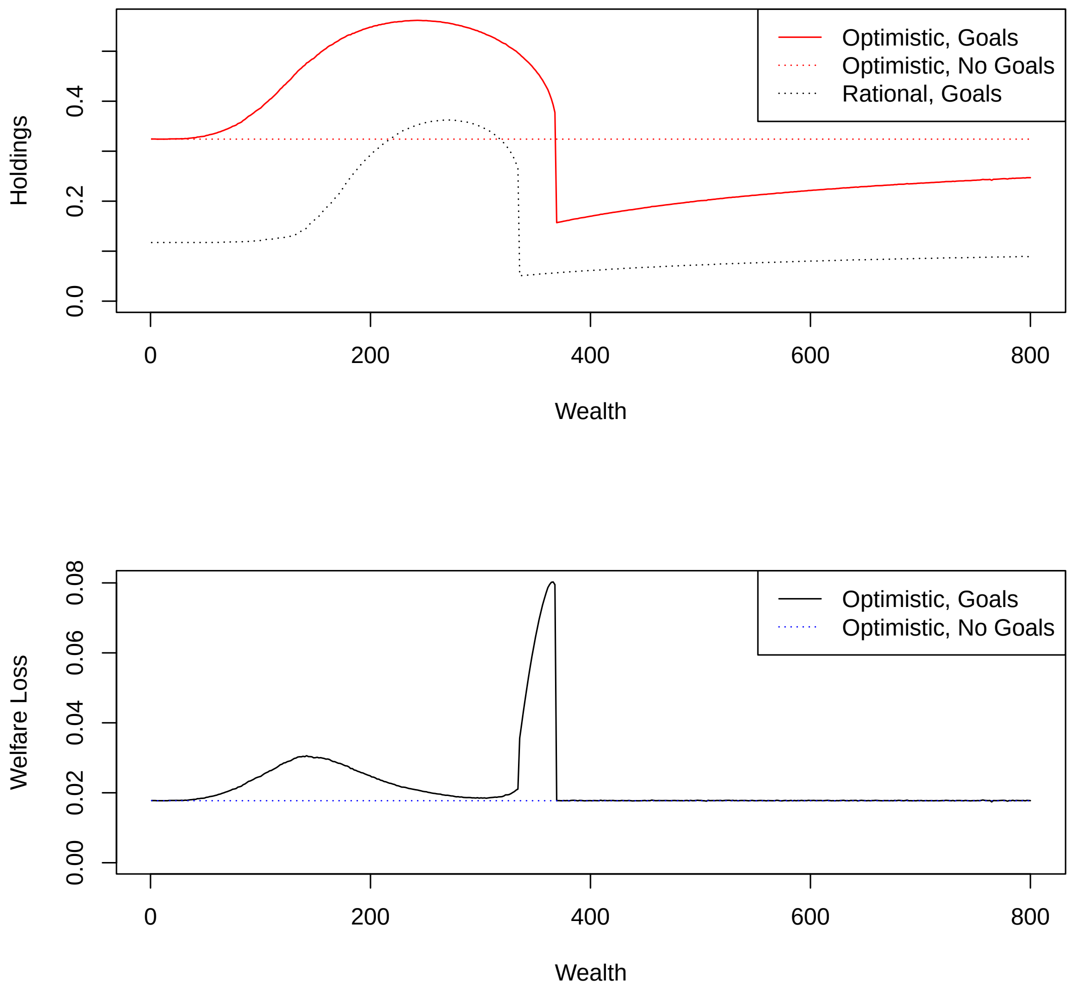
Allocation to the High-Risk Asset The top panel of Figure 9 plots the optimal cryptocurrency allocation, α^*, as a function of net worth. The dotted black line shows the choice of an agent with rational beliefs. Consistent with Proposition 1, rational agents gamble near W^*, where the goal creates local convexity. The solid red line shows allocations when optimistic beliefs interact with goal-driven preferences. The dotted red line shows the allocation of an optimistic agent without goal-driven motives ($\theta = 0$).

Comparing the two red lines in Figure 9 shows that optimism has especially large effects on allocation near the goal threshold. Below W^*, some agents whose goals would otherwise be out of reach now take risk because they overestimate the chance that crypto can close the gap. Above W^*, some agents who could attain homeownership safely by cutting consumption instead gamble, and risk falling below the goal threshold. Far from the threshold, the interaction is weaker: very low- and high-wealth agents allocate similarly to their goalless counterparts.[32]

Welfare Consequences Goal-driven motives also substantially amplify welfare losses near the homeownership threshold. To measure the welfare cost of distorted beliefs, we define regret as $\Delta U(W,\pi,\pi_0) \equiv E_{\pi_0}[U(W \mid \pi_s = \pi_0)] - E_{\pi_0}[U(W \mid \pi_s = \pi)]$, where

[32]One caveat is that high-wealth agents with goals invest slightly less than comparable log-utility agents, because losses could push them below the goal threshold.

Figure 9: Welfare losses from distorted beliefs



Notes: Figure shows the results of the simulations described in Section 7. The top panel plots the optimal allocation of wealth to the risky asset, α^*, as a function of net worth. The solid red line and the dotted red line show the allocations for optimistic agents with and without goal-driven gambling motives, respectively. The dotted black line shows the allocation for an agent with goal-driven gambling motives with rational expectations. The bottom panel plots the welfare losses relative to the corresponding "rational" agent.

$E_{\pi_0}[U(W \mid \pi_s)]$ is expected utility under the objective distribution π_0 for an agent who chooses investments using subjective beliefs π_s. Thus, $\Delta U(W, \pi, \pi_0)$ is the utility loss from holding distorted beliefs $\pi \neq \pi_0$. The bottom panel of Figure 9 plots this loss across net worth. For a log-utility agent, overoptimism generates losses of roughly 2% of net worth. Below W^*, overoptimism induces households to reach for a goal that is objectively unlikely to be attained. Above W^*, it induces households who could safely attain the goal to risk losing it. In both cases, the welfare cost of overoptimism is much larger than under standard concave utility, reaching up to 8% of net worth.

Belief Distortions and Welfare Our results also 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, including extrapolation from recent returns, overconfidence, and other forms of animal spirits, which can generate trading activity and price fluctuations. At the same time, recent works, including Giglio et al. (2021), show that differences in beliefs often translate into relatively modest differences in actions, which may attenuate the impact of biased beliefs. Our results could help reconcile these perspectives: the impact of biased beliefs is shaped not only by the cognitive biases themselves, but also by the context households face. When individuals view risky assets as a way to reach for salient financial goals, our model would predict they act much more aggressively on their beliefs, resulting in larger welfare losses due to belief distortions.

Regulation and Spillovers The analysis above shows that gambling motives, when combined with overoptimism, can generate substantial welfare losses. A natural policy response might then be to regulate speculative markets through advertising restrictions or bans.[33] Our framework suggests that the welfare effects of such policies may be ambiguous. If speculative demand reflects overoptimism about a particular asset, restricting that asset can improve welfare. However, if speculative demand for a particular asset also reflects a broader desire to use them as instruments to attain hard-to-reach goals, then restricting one market may redirect risk-taking elsewhere.

To illustrate this point, we extend the calibration by introducing a second risky asset, with the same volatility as the first but a lower subjective expected return of 30%. Appendix Figure F.11 shows that with a ban on trading the first risky asset, households partially substitute into the alternative asset, especially among intermediate-wealth house-

[33] See Kim and Yang (2018).

holds for whom gambling motives are strongest. The welfare effects depend on beliefs about the substitute asset. If households are relatively well calibrated about the alternative asset, the ban can improve welfare by redirecting risk-taking away from the more distorted market.[34] But if households are similarly overoptimistic about the substitute, welfare losses remain substantial among households that substitute aggressively.

While the exercise is deliberately stylized, it highlights a broader point. The welfare effects of regulating speculative markets depend not only on the targeted asset, but also on the motives for speculation and the availability of substitute gambles. 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 ac-

[34] The ban can still impose some welfare costs by removing a potentially valuable way to pursue goals.

tivities. 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.

References

Aiello, D., Baker, S. R., Balyuk, T., Di Maggio, M., Johnson, M. J., and Kotter, J. D. (2023a). The effects of cryptocurrency wealth on household consumption and investment. Technical report, National Bureau of Economic Research.

Aiello, D., Baker, S. R., Balyuk, T., Di Maggio, M., Johnson, M. J., and Kotter, J. D. (2023b). Who invests in crypto? wealth, financial constraints, and risk attitudes. Technical report, National Bureau of Economic Research.

Arkolakis, C., Kwak, J. H., Woo, J., and Yang, H. (2026). Housing lotteries, leverage, and family formation: Evidence from south korea.

Asness, C. (2024). The less-efficient-market hypothesis. *Journal of Portfolio Management*, 51(1).

Auer, R., Cornelli, G., Doerr, S., Frost, J., and Gambacorta, L. (2025). Crypto trading and bitcoin prices: evidence from a new database of retail adoption. *IMF Economic Review*, pages 1–36.

Auer, R. and Tercero-Lucas, D. (2022). Distrust or speculation? the socioeconomic drivers of us cryptocurrency investments. *Journal of Financial Stability*, 62:101066.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2):129–151.

Bali, T. G., Hirshleifer, D., Peng, L., Tang, Y., and Wang, Q. (2019). Social interactions and lottery stock mania.

Barber, B. M., Huang, X., Odean, T., and Schwarz, C. (2022). Attention-induced trading and returns: Evidence from robinhood users. *The Journal of Finance*, 77(6):3141–3190.

Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1):261–292.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2):785–818.

Barberis, N. (2013). The psychology of tail events: progress and challenges. *American Economic Review*, 103(3):611–616.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics*, 129(2):203–227.

Barberis, N. and Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, 98(5):2066–2100.

Becker, G. S. and Murphy, K. M. (1988). A theory of rational addiction. *Journal of political Economy*, 96(4):675–700.

Berman, Y. (2022). The long-run evolution of absolute intergenerational mobility. *American Economic Journal: Applied Economics*, 14(3):61–83.

Blanchflower, D. G., Bryson, A., and Xu, X. (2025). The declining mental health of the young and the global disappearance of the unhappiness hump shape in age. *PloS one*, 20(8):e0327858.

Bordalo, P., Gennaioli, N., Lanzani, G., and Shleifer, A. (2025). A cognitive theory of reasoning and choice. Technical report, National Bureau of Economic Research.

Bordalo, P., Gennaioli, N., Porta, R. L., and Shleifer, A. (2019). Diagnostic expectations and stock returns. *The Journal of Finance*, 74(6):2839–2874.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2018). Diagnostic expectations and credit cycles. *The Journal of Finance*, 73(1):199–227.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2022). Salience. *Annual Review of Economics*, 14:521–544.

Bryzgalova, S., Pavlova, A., and Sikorskaya, T. (2023). Retail trading in options and the rise of the big three wholesalers. *The Journal of Finance*, 78(6):3465–3514.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2):200–230.

Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R., and Narang, J. (2017). The fading american dream: Trends in absolute income mobility since 1940. *Science*, 356(6336):398–406.

Chetty, R. and Szeidl, A. (2007). Consumption commitments and risk preferences. *The Quarterly Journal of Economics*, 122(2):831–877.

Cocco, J. F. (2005). Portfolio choice in the presence of housing. *The Review of Financial Studies*, 18(2):535–567.

Collinson, R., DeFusco, A. A., Humphries, J. E., Keys, B. J., Phillips, D. C., Reina, V., Turner, P. S., and Van Dijk, W. (2024). The effects of emergency rental assistance during the pandemic: Evidence from four cities. Technical report, National Bureau of Economic Research.

Conlisk, J. (1993). The utility of gambling. *Journal of risk and uncertainty*, 6(3):255–275.

Conlon, J. J. and Kwon, S. Y. (2025). Beliefs from cues. Technical report, Working paper.

de Silva, T., Smith, K., and So, E. C. (2023). Losing is optional: Retail option trading and expected announcement volatility. *Available at SSRN*, 4050165.

Diamond, R., McQuade, T., and Qian, F. (2019). The effects of rent control expansion on tenants, landlords, and inequality: Evidence from san francisco. *American Economic Review*, 109(9):3365–3394.

Ellis, L. and Zitner, A. (2025). Americans lose faith that hard work leads to economic gains, wsj-norc poll finds. *The Wall Street Journal*.

Embrain (2021). Survey on public perceptions of cryptocurrency. https://www.trendmonitor.co.kr/tmweb/trend/allTrend/detail.do?bIdx=2185&code=0601&trendType=CKOREA.

Financial Services Commission (2025). Press release: Emergency household-debt review meeting and strengthened household-debt management measures. https://www.fsc.go.kr/no010101/84824.

Friedman, M. and Savage, L. (1948). The utility analysis of choices involving risk. *The Journal of Political Economy*, 56(4):279–304.

Giglio, S., Maggiori, M., Stroebel, J., and Utkus, S. (2021). Five facts about beliefs and portfolios. *American Economic Review*, 111(5):1481–1522.

Greenwood, R. and Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, 27(3):714–746.

Grinblatt, M. and Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity. *The Journal of finance*, 64(2):549–578.

Gruber, J. and Köszegi, B. (2001). Is addiction "rational"? theory and evidence. *The Quarterly Journal of Economics*, 116(4):1261–1303.

Harring, A. (2025). Young adults embrace 'financial nihilism' with risky crypto, stock bets as american dream feels unattainable. CNBC.

Helliwell, J. F., Layard, R., Sachs, J. D., Neve, J.-E. D., Aknin, L. B., and Wang, S. (2024). Happiness and age: Summary. World Happiness Report 2024.

Holton, E., Niv, Y., and O'Reilly, J. X. (2025). The adaptive value of stubborn goals. *Trends in Cognitive Sciences*.

Igan, D. (2024). The housing affordability crunch. *Finance & Development Magazine*, 61(4):21–24.

Intuit Credit Karma (2024). Gen z and millennials are obsessed with the idea of being rich, and it could be leading to money dysmorphia.

JCHS (2025). New report highlights unease in the housing market amid a worsening affordability crisis. https://www.jchs.harvard.edu/press-releases/new-report-highlights-unease-housing-market-amid-worsening-affordability-crisis.

Jiang, Z., Peng, C., and Yan, H. (2024). Personality differences and investment decision-making. *Journal of Financial Economics*, 153:103776.

Jones, L. E. (2008). A note on the joint occurrence of insurance and gambling. *Macroeconomic Dynamics*, 12(1):97–111.

Kahneman, D. and Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2):263–291.

Kelly, J. (2024). Gen z's benchmark for financial success is a $600k salary. https://www.forbes.com/sites/jackkelly/2024/12/04/gen-zs-benchmark-for-financial-success-is-a-600k-salary/.

Kim, C. and Yang, H. (2018). Uproar over crackdown on cryptocurrencies divides south korea. Reuters.

Knoll, K., Schularick, M., and Steger, T. (2017). No price like home: Global house prices, 1870–2012. *American Economic Review*, 107(2):331–353.

Kogan, S., Makarov, I., Niessner, M., and Schoar, A. (2024). Are cryptos different? evidence from retail trading. *Journal of Financial Economics*, 159:103897.

Korean Financial Consumer Protection Foundation (2024). Survey on virtual asset usage in korea. http://www.kfcpf.or.kr/front/evalution/research4.do.

Kőszegi, B. and Rabin, M. (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics*, 121(4):1133–1165.

Kuhnen, C. M. and Miu, A. C. (2017). Socioeconomic status and learning from financial information. *Journal of Financial Economics*, 124(2):349–372.

Kumar, A. (2009). Who gambles in the stock market? *The journal of finance*, 64(4):1889–1933.

Kwang, N. Y. (1965). Why do people buy lottery tickets? choices involving risk and the indivisibility of expenditure. *Journal of Political Economy*, 73(5):530–535.

Lanz, J. A. (2026). Gen z is betting big on prediction markets—literally. *Yahoo Finance*.

Lee, S. H. and Yoo, Y. (2025). "giving up": The impact of decreasing housing affordability on consumption, work effort, and investment.

Lin, L. and Menasce Horowitz, J. (2025). How americans are feeling about their finances as they age. https://www.pewresearch.org/social-trends/2025/11/06/how-americans-are-feeling-about-their-finances-as-they-age/.

Liu, H., Peng, C., Xiong, W. A., and Xiong, W. (2022a). Taming the bias zoo. *Journal of Financial Economics*, 143(2):716–741.

Liu, Y., Tsyvinski, A., and Wu, X. (2022b). Common risk factors in cryptocurrency. *The Journal of Finance*, 77(2):1133–1177.

Lockwood, B. B., Allcott, H., Taubinsky, D., and Sial, A. (2025). What drives demand for state-run lotteries? evidence and welfare implications. *Review of Economic Studies*, 92(4):2578–2623.

Loewenstein, G. (1987). Anticipation and the valuation of delayed consumption. *The Economic Journal*, 97(387):666–684.

Malmendier, U. and Nagel, S. (2011). Depression babies: do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, 126(1):373–416.

Manduca, R., Hell, M., Adermon, A., Blanden, J., Bratberg, E., Gielen, A. C., Van Kippersluis, H., Lee, K., Machin, S., Munk, M. D., et al. (2024). Measuring absolute income mobility: lessons from north america and europe. *American Economic Journal: Applied Economics*, 16(2):1–30.

Mankiw, N. G. and Zeldes, S. P. (1991). The consumption of stockholders and nonstockholders. *Journal of financial Economics*, 29(1):97–112.

Markowitz, H. (1952). The utility of wealth. *Journal of political Economy*, 60(2):151–158.

McComb, C. A., Vanman, E. J., and Tobin, S. J. (2023). A meta-analysis of the effects of social media exposure to upward comparison targets on self-evaluations and emotions. *Media Psychology*, 26(5):612–635.

Mullainathan, S. (2002). Thinking through categories. Technical report, Working Paper, Harvard University.

Mullainathan, S., Schwartzstein, J., and Shleifer, A. (2008). Coarse thinking and persuasion. *The Quarterly journal of economics*, 123(2):577–619.

NAHB (2026). Households priced-out by higher house prices and interest rates. https://www.nahb.org/news-and-economics/housing-economics/housings-economic-impact/households-priced-out-by-higher-house-prices-and-interest-rates.

National Association of Realtors (2025). First-time home buyer share falls to historic low of 21%, median age rises to 40. https://www.nar.realtor/newsroom/first-time-home-buyer-share-falls-to-historic-low-of-21-median-age-rises-to-40.

Northwestern Mutual (2026). Planning & progress study 2026.

Öst, C. E. and Johansson, P. (2023). The consequences of the swedish rent control system on labor income: Evidence from a randomized apartment lottery. *Journal of Public Economics*, 221:104864.

Pursiainen, V. and Toczynski, J. (2022). Retail investors' cryptocurrency investments. *Swiss Finance Institute Research Paper*, (23-51):23–51.

Saramin (2021). Survey of office workers on cryptocurrency investment. https://www.saramin.co.kr/zf_user/help/live/view?idx=108254&list_idx=381&listType=news&keyword=&menu=1&page=20.

Scanlon, K. (2025). Why my generation is turning to 'financial nihilism'. *The Wall Street Journal*.

SEBI (2025). Comparative study of growth in equity derivatives segment vis-a-vis cash market after recent measures. Technical report, Securities and Exchange Board of India.

Seoul Shinmun (2025). 5대 은행 "서울 아파트 중위 매매 가격 내년까지 오른다". https://www.seoul.co.kr/news/economy/finance/2025/07/27/20250727500078.

Shiller, R. J. et al. (1981). Do stock prices move too much to be justified by subsequent changes in dividends?

Siena College Research Institute (2024). Asfs24 crosstabs — release 2: Online sports betting. Technical report, Siena College Research Institute.

The Harris Poll (2025). Why the vibes are off, gen z tries to legitimize sports betting, and employees will rto if the office comes alive.

Twenge, J. and Blanchflower, D. G. (2025). Declining life satisfaction and happiness among young adults in six english-speaking countries. Technical report, National Bureau of Economic Research.

VanderWeele, T. J., Johnson, B. R., Bialowolski, P. T., Bonhag, R., Bradshaw, M., Breedlove, T., Case, B., Chen, Y., Chen, Z. J., Counted, V., Cowden, R. G., de la Rosa, P. A., Felton, C., Fogleman, A., Gibson, C., Grigoropoulou, N., Gundersen, C., Jang, S. J., Johnson, K. A., Kent, B. V., Kim, E. S., Kim, Y.-I., Koga, H. K., Lee, M. T., Le Pertel, N., Lomas, T., Long, K. N. G., Macchia, L., Makridis, C. A., Markham, L., Nakamura, J. S., Norman-Krause, N., Okafor, C. N., Okuzono, S. S., Ouyang, S. T., Padgett, R. N., Paltzer, J., Ritchie-Dunham, J. L., Ritter, Z., Shiba, K., Srinivasan, R., Ssozi, J., Weziak-Bialowolska, D., Wilkinson, R., Woodberry, R. D., Wortham, J., and Yancey, G. (2025). The global flourishing study: Study profile and initial results on flourishing. *Nature Mental Health*, 3(6):636–653.

Vasquez, M. (2017). Utility of wealth with many indivisibilities. *Journal of Mathematical Economics*, 71:20–27.

Verduyn, P., Gugushvili, N., Massar, K., Täht, K., and Kross, E. (2020). Social comparison on social networking sites. *Current opinion in psychology*, 36:32–37.

Vogel, E. A., Rose, J. P., Roberts, L. R., and Eckles, K. (2014). Social comparison, social media, and self-esteem. *Psychology of popular media culture*, 3(4):206.

Weber, M., Candia, B., Coibion, O., and Gorodnichenko, Y. (2023). Do you even crypto, bro? cryptocurrencies in household finance. Technical report, National Bureau of Economic Research.

Wheat, C. and Eckerd, G. (2022). The dynamics and demographics of u.s. household crypto-asset use.

Yoon, M.-s. (2025). Young koreans remain locked out of homeownership. *The Korea Herald*.

A Theoretical Appendix

A.1 Proofs

Proof of Proposition 1

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

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

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

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

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

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

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

Proof. Consider the following value functions:

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

First, note:

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

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

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

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

Next, by envelope theorem,

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

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

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

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

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

□

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

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

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

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

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

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

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

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

for the c^* that satisfies:

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

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

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

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

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

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

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

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

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

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

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

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

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

One can arrange the inequality to comparing two terms:

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

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

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

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

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

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

□

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

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

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

A.2 Optimal Gamble and Proof of Proposition 2

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

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

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

subject to

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

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

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

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

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

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

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

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

This implies that in the interior crossing region, the continuation value is affine in savings. That simplifies the analysis quite significantly. The period-1 problem thus reduces to the following FOC: $u'(c_1) = \frac{\theta}{G}$, which implies

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

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

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

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

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

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

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

A.3 Formalization of Alternative Explanations for Gambling

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

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

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

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

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

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

A.4 Microfoundation for Discrete Goals

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

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

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

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

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

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

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

Formally, we let:

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

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

B Grandata Details

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

Table B.1: Monthly number of individuals by year

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

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

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.

B.1 Additional Details on KCB Variables

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

  - Specific details of the estimation method are confidential.

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

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

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

Table B.2: Summary Statistics - KCB Variables

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

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

Table B.3: Variable Descriptions - KCB Variables

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

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

B.2 Additional Details on SKT Variables

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

Table B.4: Summary Statistics - SKT Variables

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

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

Table B.5: Variable Descriptions - SKT Variables

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

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

B.3 Additional Details on Shinhan Card Variables

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

Table B.6: Summary Statistics - Shinhan Card Variables

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

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

Table B.7: Variable Descriptions - Shinhan Card Variables

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

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

C 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.[35] 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 C.1 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.[36]

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

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

Table C.1: 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.

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 C.1 illustrates these events. We define the start of the boom as September 2020. Over the following eight months, the price of Bitcoin increased by nearly 500%. We define the start of the bust as May 2022, when Bitcoin prices returned to their mid-2021 level after a second run-up. Over the next eight months, prices fell by around half, reaching their lowest level since the start of the boom.

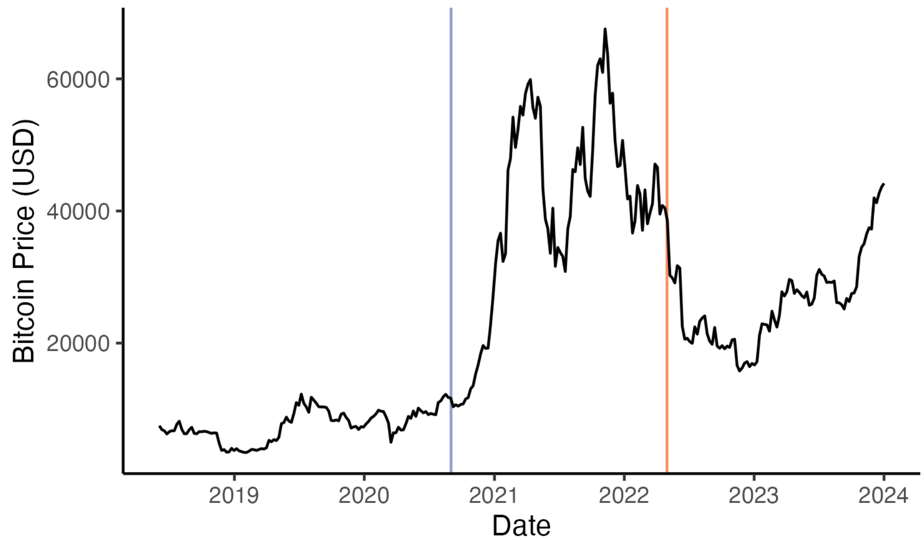
Formally, our empirical strategy is a difference-in-differences design:

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

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

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 D.1), which is consistent with attenuation (and skew in the distribution of holdings).

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



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

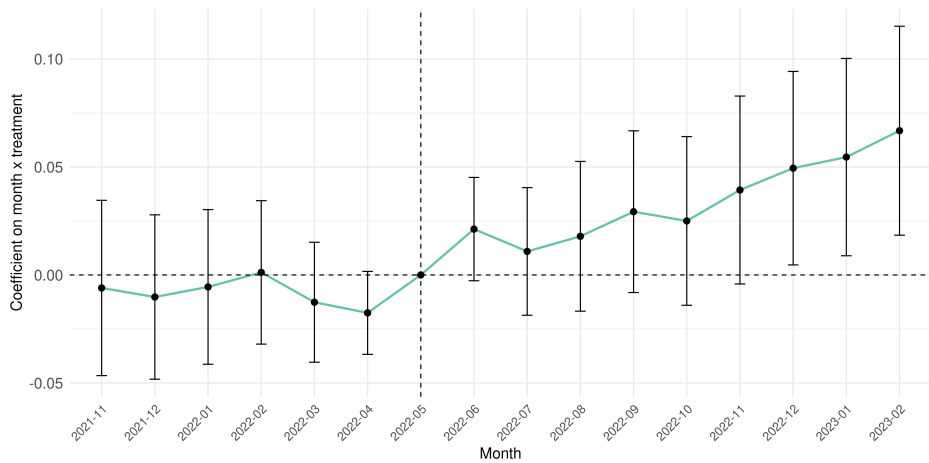
boom, July 2021 for the bust), to capture individuals who likely had investments exposed to the price changes. We include individual fixed effects, α_i, and time fixed effects, γ_t. Our coefficients of interest are β_m, which capture the time-varying difference in outcomes between heavy crypto users and others.

Bust Event Figure C.2 shows the effects of a crypto price crash on heavy crypto users. Panel (a) shows that they are approximately 0.05 percentage points more likely to become delinquent after the crash. This effect is economically large, reflecting a 20% increase in the delinquency rate compared to the average for heavy-users in Table 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).

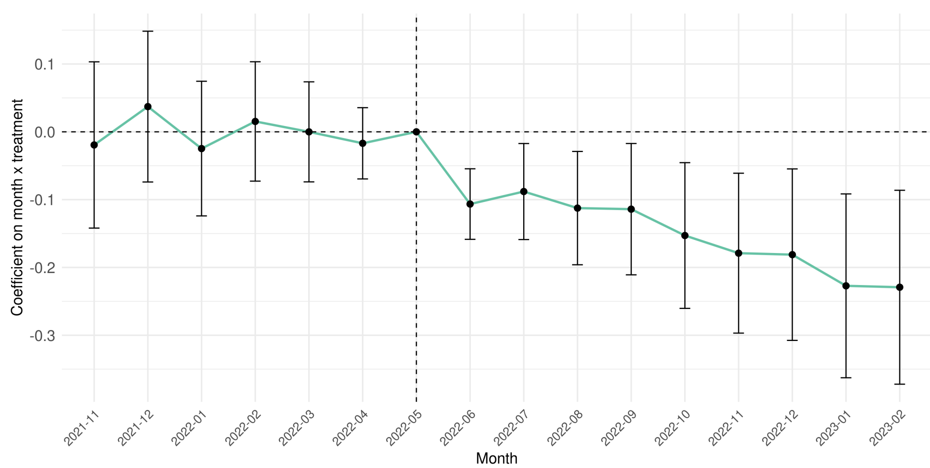
Boom Event Figure C.3 shows that cryptocurrency price booms coincided with a relative increase in homeownership among heavy crypto users. Following the 2020 price boom, heavy users became about 2 percentage points more likely to own a home than comparable non-heavy users, a 6% increase relative to the heavy-user mean in Table 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.

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

(a) Delinquency

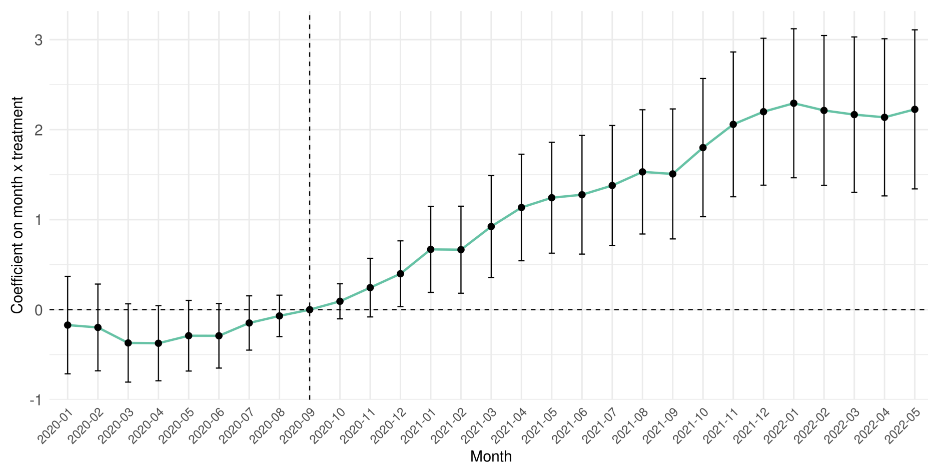


(b) Luxury Purchases



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 C.3: 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

D Additional Survey Details and Results

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

D.1 Additional Variable Definitions

- "Expected 1Yr Bitcoin (Stock) Returns" is what respondents think a 1 million KRW investment in Bitcoin (the Korean stock market—KOSPI index fund) will be worth in 1 year. We also elicited 5 year expectations, and for each horizon, low, middle, and high scenarios. Unless otherwise stated, we use the middle scenario. 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, holding the downside fixed at zero and expected value the same. First, participants were told to provide us with a best guess of their total assets (multiple choice). Then, we took the midpoint of each asset group, and asked participants to choose between four options:

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

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

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

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

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

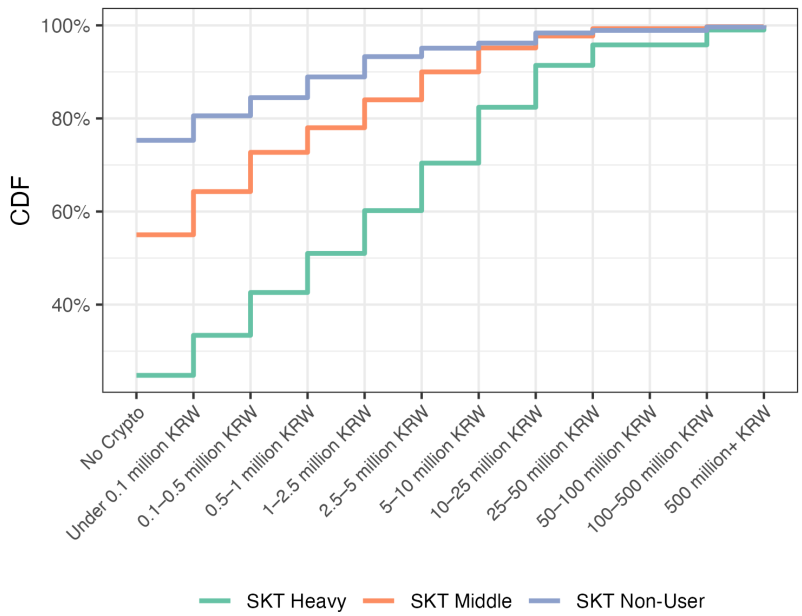
D.2 Additional Tables and Figures

Table D.1: Summary Statistics of Survey Sample

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

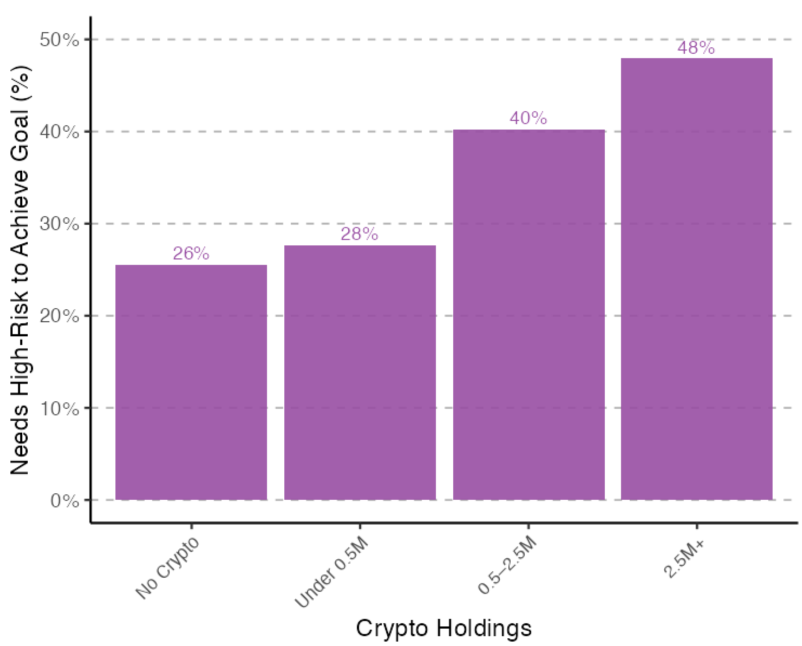
Notes: Table summarizes the survey sample described in Section 3.3. Unless otherwise stated, all statistics are shares. "'Currently Has Crypto And Significant" is an indicator for whether the respondent answered "Yes" when asked whether losing all their crypto holdings would have a significant impact 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.

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



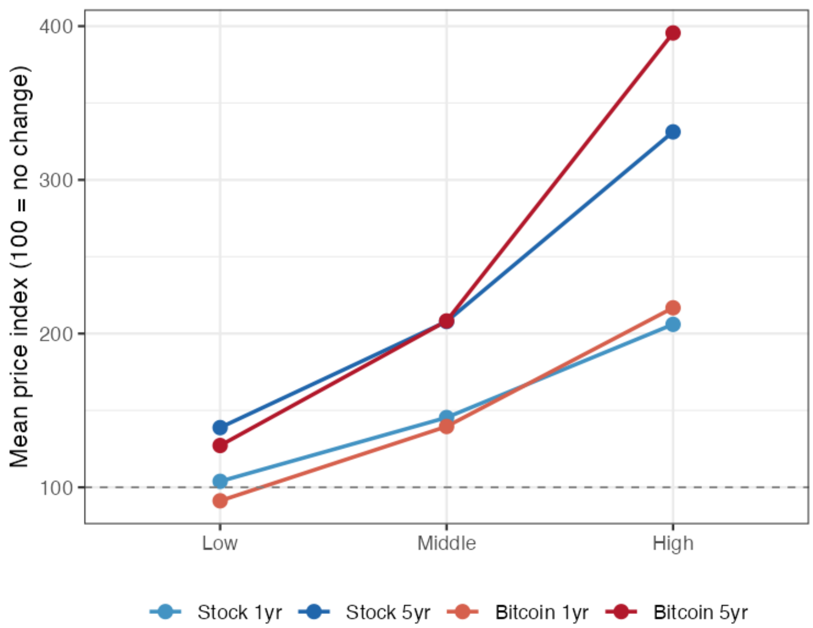
Notes: Figure plots the cumulative distribution of self-reported cryptocurrency holdings separately for SKT heavy users, middle users, and non-users. Source: SKT survey.

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



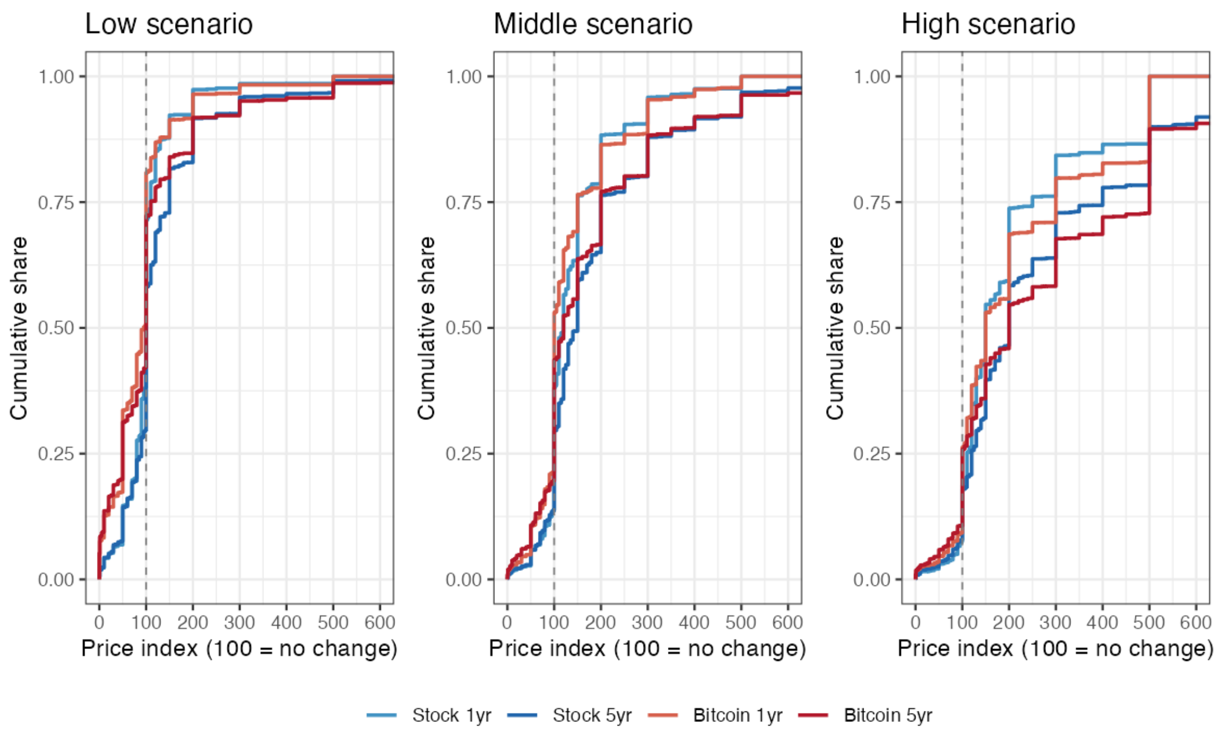
Notes: Figure plots the share of respondents who report that high-risk investments are necessary to achieve their most important financial goal, separately by self-reported crypto holdings. Percentages are shown above each bar. Responses are weighted to match the population shares of heavy, middle, and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

Figure D.3: 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 D.4: CDF of Low, Middle, and High Return Beliefs

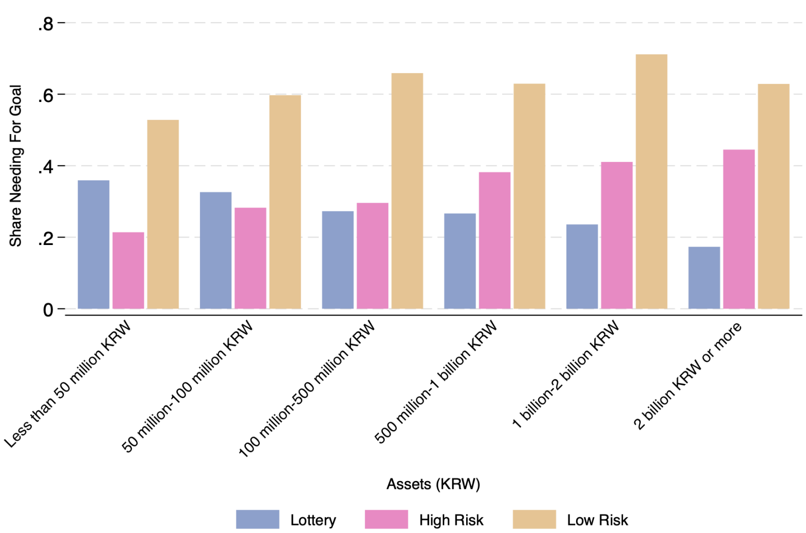


Notes: Figure plots the cumulative distribution of respondents' return beliefs separately by scenario (low, middle, high) for Bitcoin and the Korean stock market (KOSPI index fund), for 1-year and 5-year horizons. The price index is normalized so that 100 denotes no change in value. The dashed vertical 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 D.5: Distance to Housing Goal Shapes Holdings of Crypto vs. Stocks

Notes: Figure shows regression coefficients of binary indicators for stock and crypto ownership on assets among non-homeowners who currently believe buying a home is extremely important. Responses are weighted to match the population shares of heavy, middle, and non-users of cryptocurrency in the GranData sample. Source: SKT survey.

Figure D.6: 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.

E Housing Lottery Details

We identify lottery winners in a multi-stage process. For the initial matching steps, we use the crosswalk and code from Arkolakis et al. (2026) linking Cheongyak Home lottery projects to KCB geographic cells ('bizcells') corresponding to the completed apartment complexes. Because no administrative project-to-credit-bureau link is available, projects are matched to bizcells using postal codes, administrative addresses, and normalized apartment names, allowing fuzzy name matches where exact matches are unavailable.

Within each valid project-bizcell, we classify a household as a candidate winner if three conditions hold. The household is observed at the project bizcell around the move-in period; no member of the baseline household owned residential property before application; and at least one member transitions into homeownership after the project announcement. The non-homeownership condition is evaluated at the household level, using the household identifier measured before application, while individuals are tracked over time using the stable person identifier.

We then impose the analysis-sample restrictions jointly. We keep only projects for which the ratio of inferred winners to official unit supply lies between 0.1 and 1, apply the oversubscription filter, and exclude conversion sales (*bunyang jeonhwan*; 분양전환) and vacancy sales (*gongga sedae*; 공가세대). Conversion sales refer to cases in which rental housing units are sold to existing tenants after the mandatory rental period, while vacancy sales involve vacant units and therefore do not represent newly supplied housing. We also require adequate panel coverage and valid baseline covariates, retain at most one lottery win per household, and drop cases in which household-identifier changes around the move appear to generate multiple selected household identifiers.

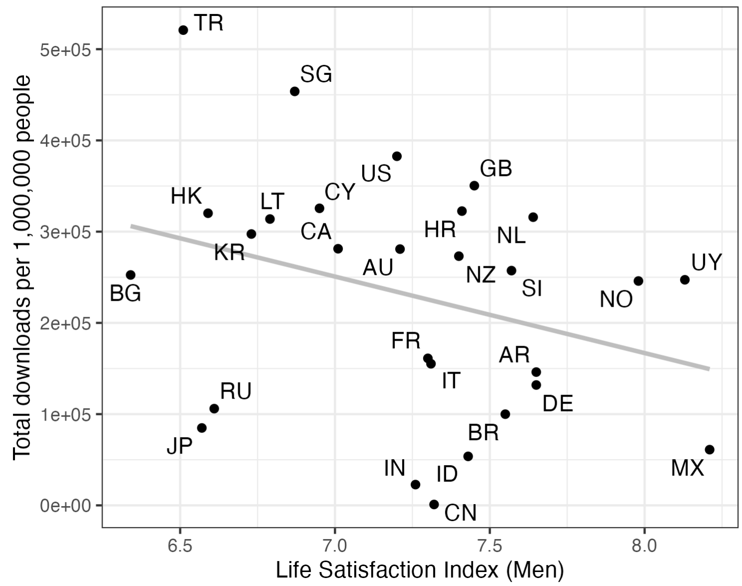
For the final sample, we retain individuals who appear to be lottery winners during the 36-month window from January 2021 through December 2023 and who have app usage activity during that period in the SKT data. We select the youngest male in each household as the analysis individual. Since winners are inferred from observed ownership transitions rather than applicant rosters, the treated sample consists of households that won the lottery and completed the purchase.

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 public and private projects and across individual cases. 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.[37] Thus, lottery winners are likely to have invested substantial time in the application process and actively searched for eligible housing projects. At the same time, the identifying variation does not come from comparing such households to passive non-applicants. As emphasized by Arkolakis et al. (2026), applicants are first ranked by priority, and when the number of applicants tied at the relevant priority threshold exceeds the number of available units, winners are selected by computerized random lottery. The resulting variation is therefore among households with similar eligibility, priority, and demonstrated interest in the project.

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

F Additional Figures

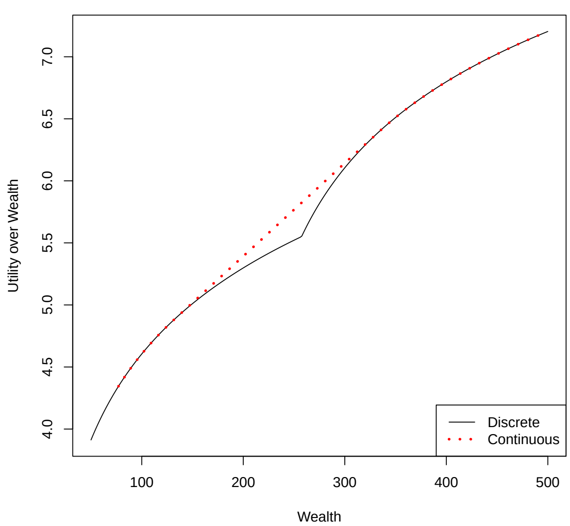
Figure F.1: Cryptocurrency Interest vs. Male Life Satisfaction (Levels)



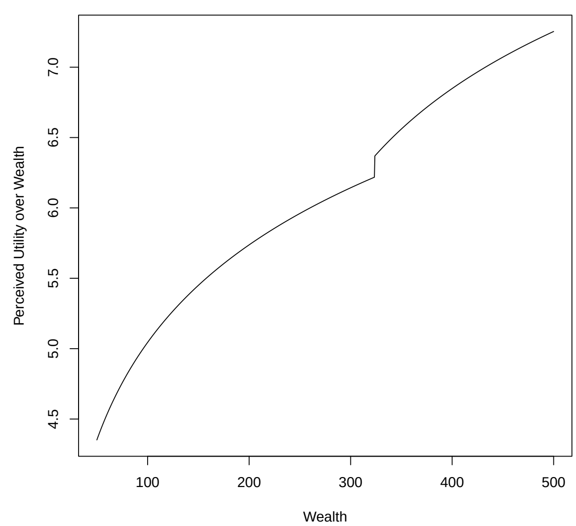
Notes: Figure shows cryptocurrency exchange application downloads (per one million individuals) against male life satisfaction across countries. Source: World Values Survey Wave 7 and Auer et al. (2025).

Figure F.2: Discrete goals and convex preferences

(a) Continuous Goals Re-Concavify Utility

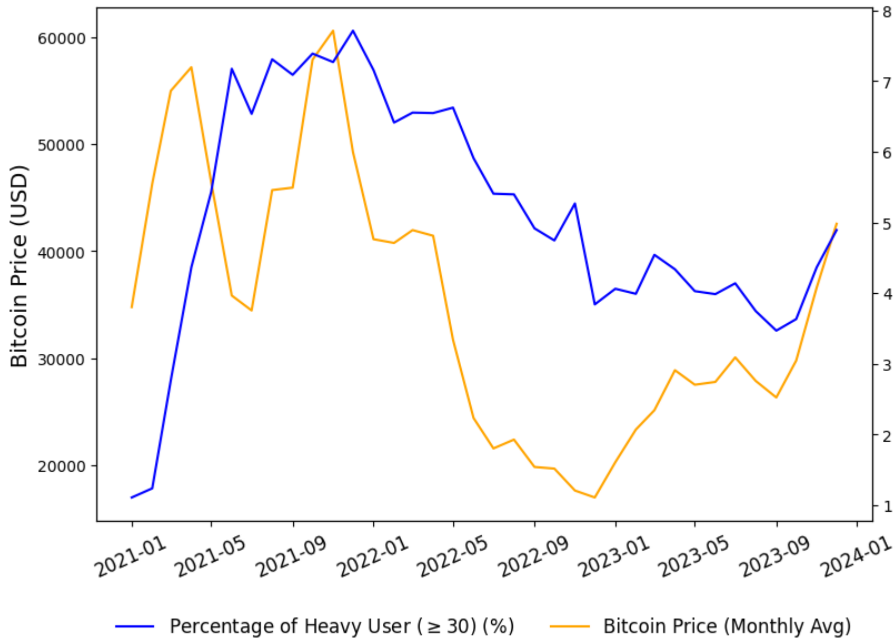


(b) Perceived Utility and Convexification



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

Figure F.3: Cryptocurrency Engagement, Time Series

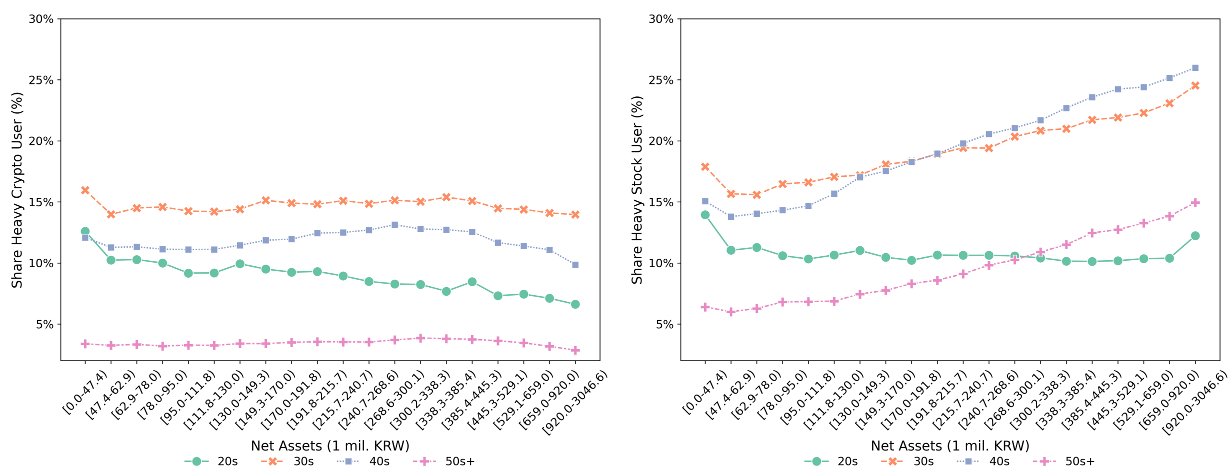


Notes: Figure shows engagement with crypto apps versus Bitcoin prices. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. "Percentage of Heavy User" is the share of all individuals who are heavy users. Source: SKT and Bitcoin price data.

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

(a) Crypto Apps

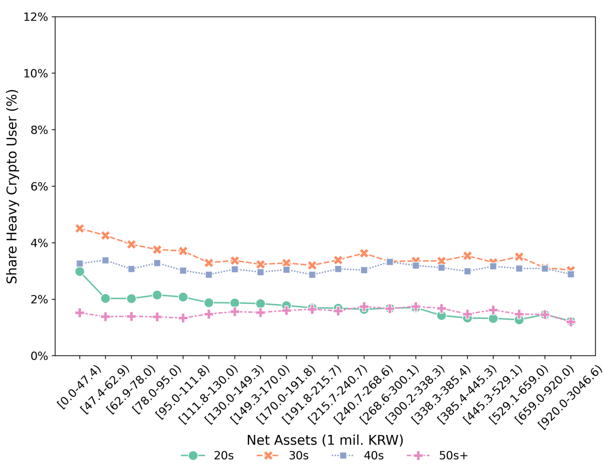
(b) Stock Apps



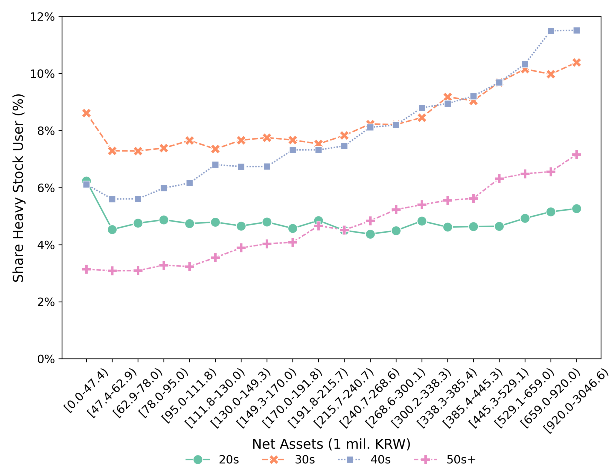
Notes: Figure shows the percentage of men who are heavy crypto users and heavy stock users. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. We use an analogous definition for stock apps. Net assets are in ventiles. Source: KCB and SKT.

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

(a) Crypto Apps

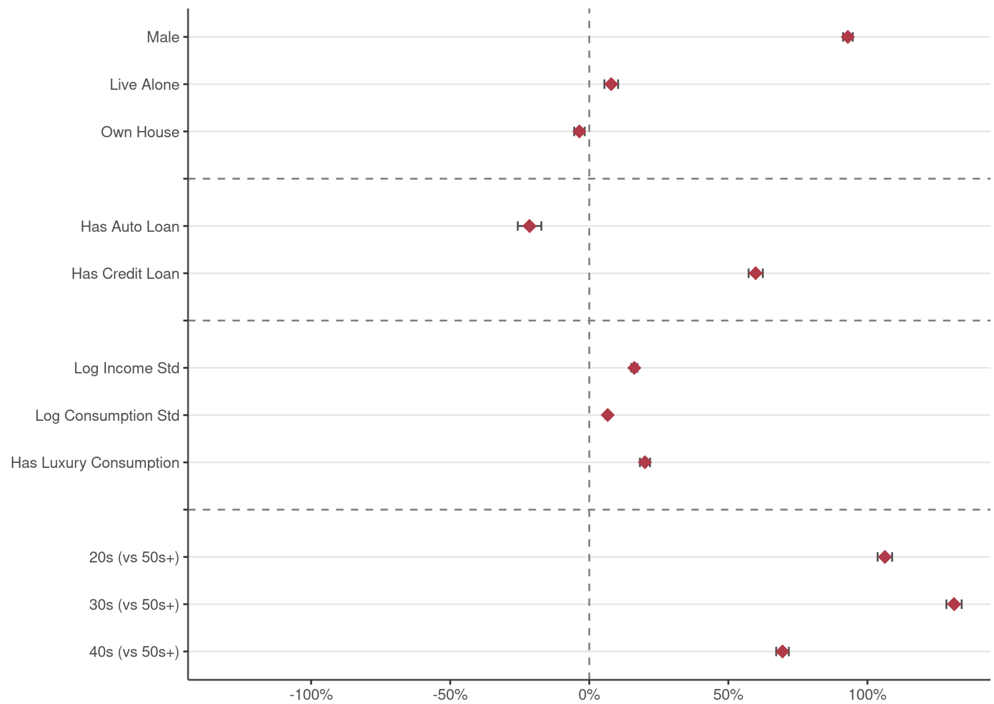


(b) Stock Apps



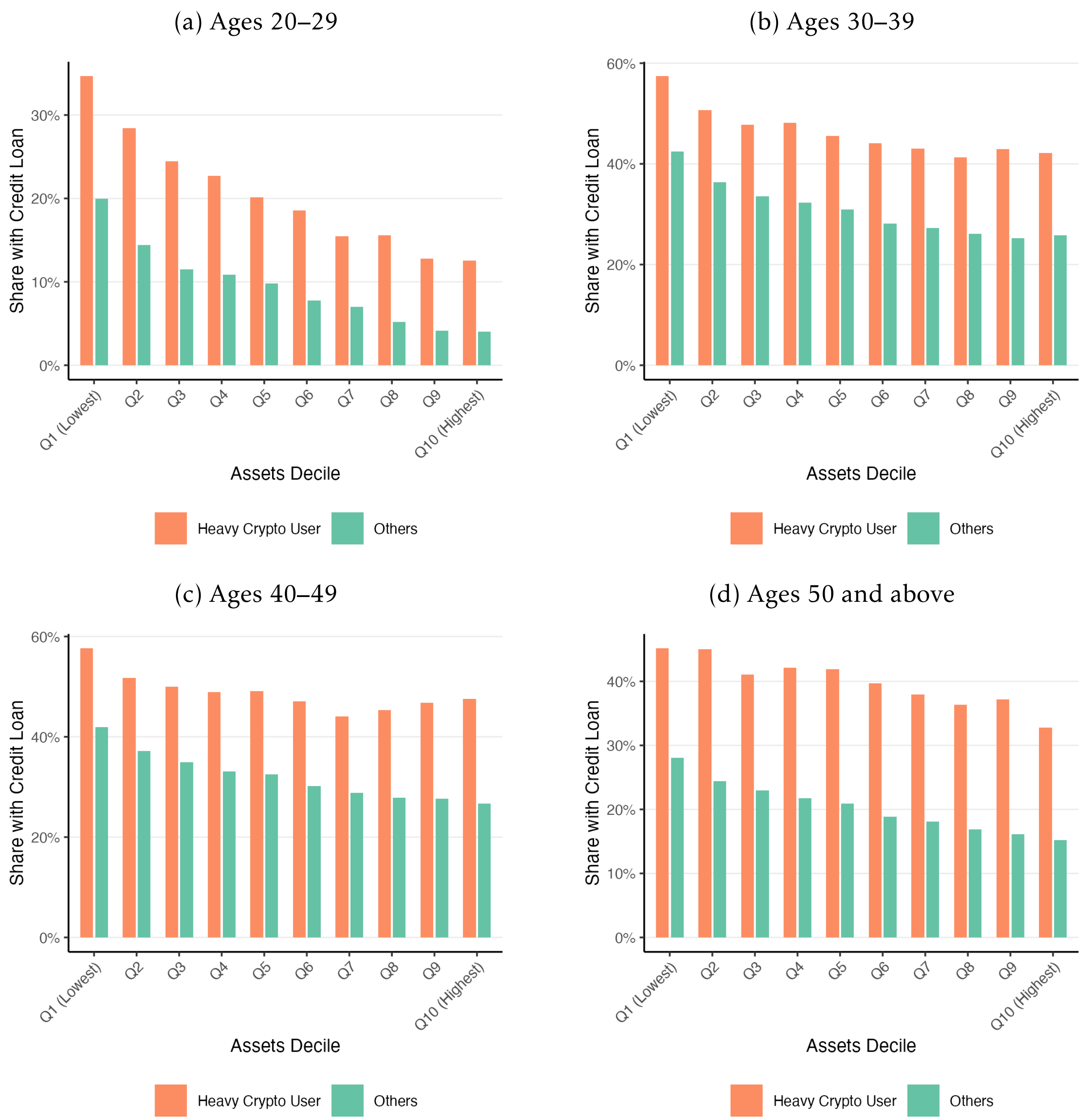
Notes: Figure shows the percentage of women who are heavy crypto users and heavy stock users. A "Heavy Crypto User" is an individual who uses cryptocurrency apps more than 30 distinct times within the month. We use an analogous definition for stock apps. Net assets are in ventiles. Source: KCB and SKT.

Figure F.6: 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 F.7: Heavy Crypto Users vs. Others: Unsecured Loans by Assets, by Age Group



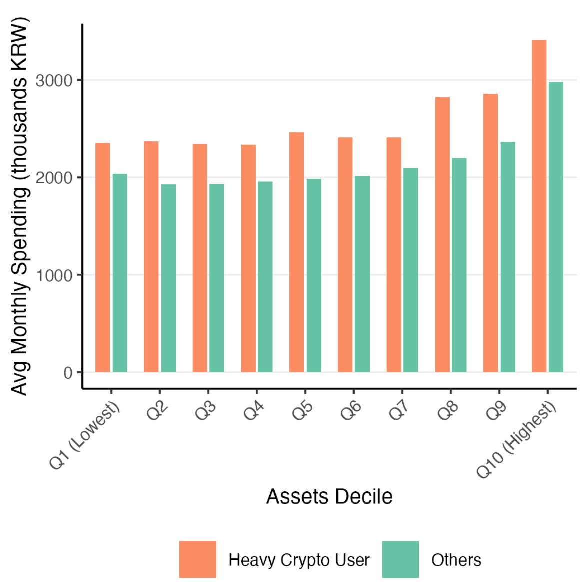
Notes: Figure shows the share of individuals with unsecured loans by asset decile, separately for heavy crypto users and others, for each age group and for the full sample. Net assets are in deciles. All variables are measured as of July 2021. Source: KCB and SKT.

Figure F.8: Heavy Crypto Users vs. Others: Spending by Assets, by Age Group

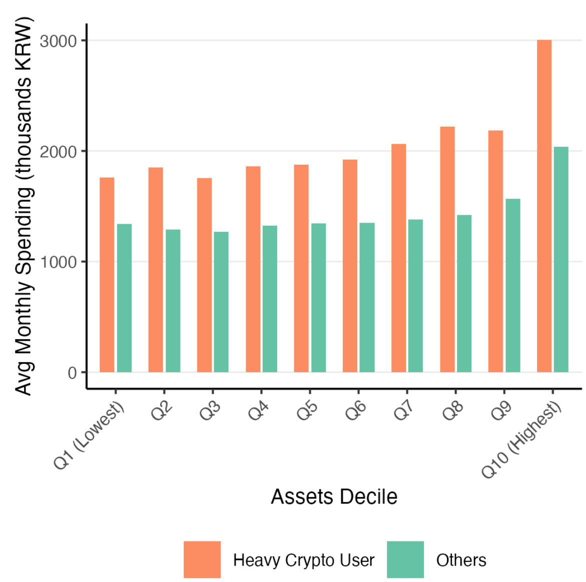
(a) Ages 20–29

(b) Ages 30–39

(c) Ages 40–49



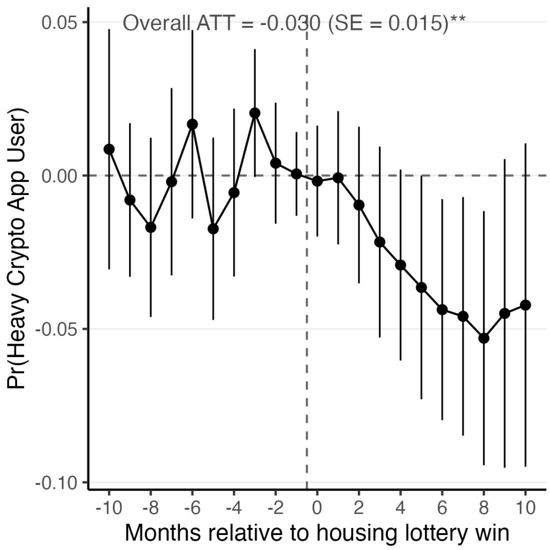
(d) Ages 50 and above



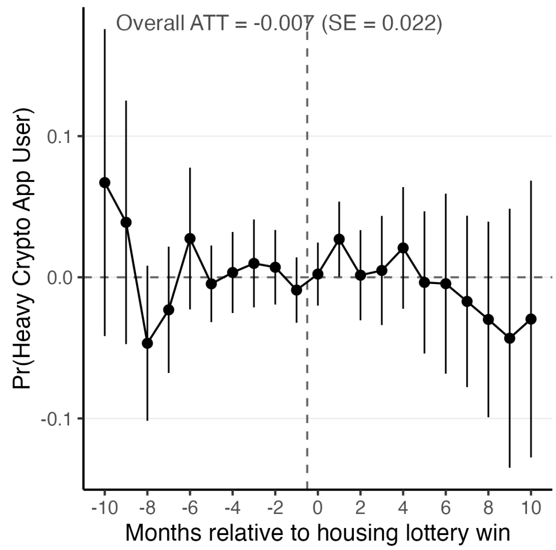
Notes: Figure shows average monthly spending by asset decile, separately for heavy crypto users and others, for each age group and for the full sample. Net assets are in deciles. Spending is measured in thousands of KRW. All variables are measured as of July 2021. Source: KCB and SKT.

Figure F.9: Change in Cryptocurrency Use Around a Housing Lottery Win: Sudogwon

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

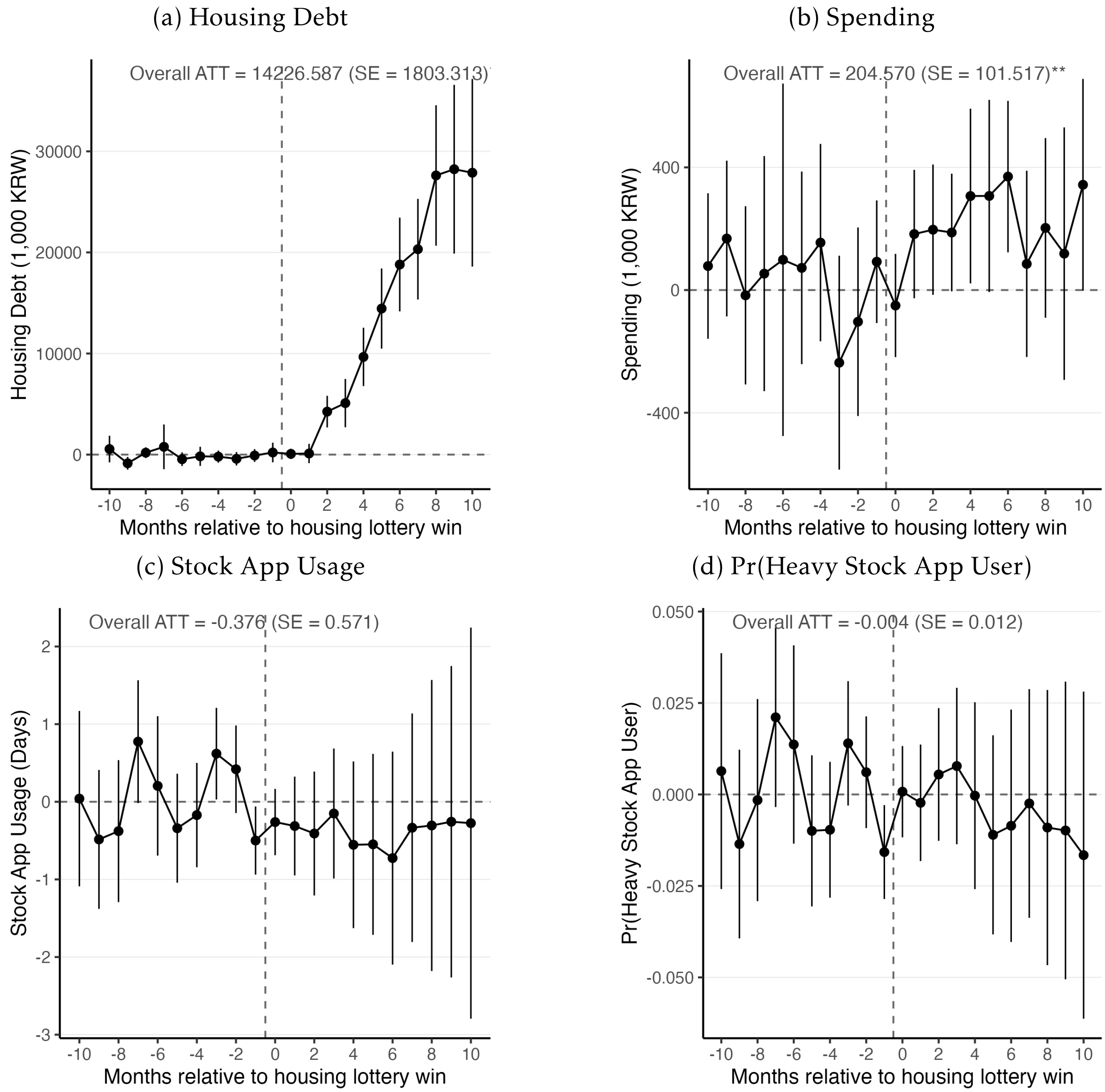


(b) Pr(Heavy Crypto App User) in Non-Sudogwon



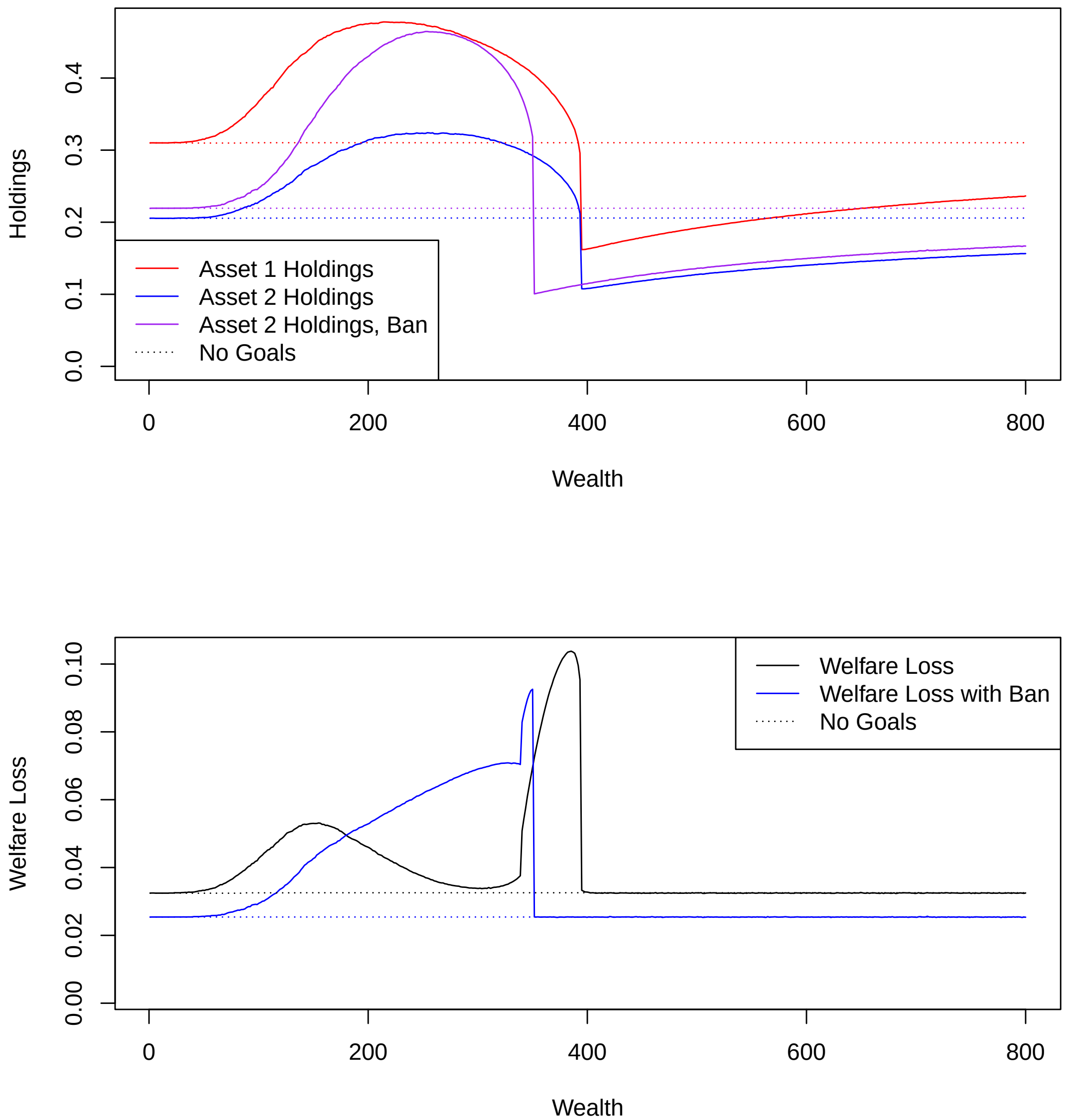
Notes: Figure plots difference-in-differences estimates of the effect of winning a housing lottery on various outcomes, relative to the contract date. Panel (a) shows the probability of being a heavy crypto app user among winners in the Sudogwon region. Panel (b) shows the probability of being a heavy 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 F.10: Change in Additional Outcomes Around a Housing Lottery Win



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 F.11: Asset Spillover



Notes: Figure shows the results of the simulations described in Section 7. The top panel plots the optimal allocation of wealth to Asset 1 and Asset 2 as a function of net worth. The solid black and blue lines show the allocations for optimistic agents with and without goal-driven gambling motives, respectively. The bottom panel plots the welfare losses relative to the corresponding "rational" agent.

G Additional Tables

Table G.1: Representativeness of Data

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

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

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

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

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

	Non-Crypto Users	All Crypto Users	Heavy Crypto Users
KCB: Share with Loan by Type			
Credit loan	0.23	0.37	0.47
House loan	0.12	0.15	0.18
Auto loan	0.07	0.08	0.10
KCB: Median Loan Balance Among Non-Zero			
Credit loan (1,000 KRW)	16,290	27,040	30,905
House loan (1,000 KRW)	89,250	112,850	116,930
Auto loan (1,000 KRW)	11,415	12,290	12,530
KCB: Other			
Average Annual Income (1,000 KRW)	37,001.33 (20,248.30)	43,619.76 (24,748.65)	47,232.13 (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 (295,628.81)	255,102.18 (274,786.37)	254,124.85 (279,982.43)
Average Monthly Card Spending (1,000 KRW)	1,397.47 (2,119.30)	1,799.85 (2,388.25)	2,036.77 (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 (376.61)	93.34 (439.19)	103.04 (413.39)
Total Spending (1,000 KRW)	974.36 (1,726.54)	1,207.69 (1,987.33)	1,327.60 (1,860.49)
Medical Spending (1,000 KRW)	84.77 (363.77)	88.90 (379.17)	98.42 (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 G.3: 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 G.4: 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 G.5: 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.