Behavioral Limits to Complete Markets[*]

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Abstract

Standard economic theory predicts that complete markets maximize social welfare by allowing contingent claims for every possible state. Yet real financial markets remain incomplete, and the demand-side origins of this phenomenon are not well understood. We design a portfolio choice experiment in which participants choose between complete and incomplete markets after first experiencing both. Across treatments, only a minority prefers the complete market. We evaluate two mechanisms that could generate a preference for incompleteness: preference instability, which increases regret or temptation in complete markets, and cognitive costs, which rise with task dimensionality. Comparing homegrown and induced preference treatments, we find no support for explanations based on preference instability. Instead, participants make larger utility losses, spend substantially more time, and report higher perceived complexity and uncertainty in the complete market. Structural estimation of a complexity model confirms that the complete market is several times more complex than the incomplete one. Our findings provide direct experimental evidence that cognitive limitations can shape preferences over market structure, offering a behavioral foundation for market incompleteness.

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1 Introduction

Markets have evolved in many ways yet remain fundamentally distinct from the complete markets envisioned in economic theory, where claims contingent on every possible future state can be traded (Arrow, 1964; Debreu, 1959). Direct measurement of market completeness is difficult, but extensive evidence on limited risk-sharing indicates that real markets are highly incomplete (e.g. Cochrane, 1991). This disconnect raises a central question: If complete markets allow individuals to achieve optimal allocations under uncertainty, why have real markets not moved closer to that ideal?

Earlier works by Allen and Gale (1988, 1990, 1991) offered a partial answer by emphasizing the supply side: issuing and trading securities entails substantial transaction costs that limit the expansion of financial instruments. Much less is known about the demand side, which concerns the willingness and ability of investors to operate in a complete market even if such a market were available. Demand-side explanations have been proposed in the past, but they remain largely informal. Magill and Quinzii (2002, p.16) for example note: "A complete itemization of all possible events at each date, for an extended period into the future would involve far more contingencies than any individual (or computer) could possibly calculate or envision. The individual costs of time and effort involved in the use of contingent contracts become prohibitive." Despite its intuitive appeal, this idea has not been systematically examined.[1]

Two recent developments in economics make such an examination possible. One is the growing theoretical and empirical work on the complexity of choice environments, which provides a framework for assessing the cognitive demands that different market structures place on decision-makers (see for example Bossaerts and Murawski, 2017; Oprea, 2020, 2024; Gabaix and Graeber, 2024). The other is a body of research that models how individuals evaluate and compare different sets of options, such as markets, not only the options within them (e.g. Kreps, 1979; Dekel et al., 2001; Gul and Pesendorfer, 2001; Sarver, 2008).

Building on these frameworks, in this paper we ask whether investors prefer incomplete markets, and if so, what drives this preference. We study this question in a laboratory experiment where participants choose between complete and incomplete markets after first experiencing both. This design allows us to isolate the cognitive and preference-based forces that shape demand for market completeness.

Our analysis begins with a theoretical framework for individual portfolio choice under risk, which we use to characterize the demand for complete and incomplete markets. Each agent faces risk across a finite number S of states and allocates wealth through a set of securities with state-contingent payoffs.[2] We define a complete market as one offering a full set of Arrow-Debreu securities (i.e. one for each state), and an incomplete market as one

[1] On this point, Leijonhufvud (1993) observed: "There is by now a sizeable technical literature on missing markets, investigating the conditions under which people can or cannot get around imposed constraints not to transact in parts of the commodity space. What is less clear is why such clever people choose to labor under these constraints."

[2] While the general equilibrium formulation of a complete market involves the possibility to trade contingent on both time and state, we omit the time dimension for implementation reasons.

with only $J < S$ assets that span a coarser partition of the state space. By our design, all allocations feasible in the incomplete market are also feasible in the complete market, but not vice versa. A rational agent should therefore weakly prefer the complete market.

We then explore why agents might instead prefer incomplete markets. One class of explanations builds on preference instability, as in Dekel et al. (2001), Gul and Pesendorfer (2001), and Sarver (2008), where agents may choose smaller menus when future preferences are uncertain or inconsistent with ex-ante preferences. Applied to our setting, these models imply that complete markets can expose agents to greater regret or temptation. Using a tractable example with uncertainty between two possible utility functions (risk-neutral or maximally risk-averse), we show that anticipated regret can reverse the standard ranking, making the incomplete market welfare-superior when regret sensitivity is high.

A second explanation emphasizes cognitive limitations. Following Gabaix and Graeber (2024), we model decision making as subject to costly cognitive effort. Processing the parameters of the portfolio problem such as prices and endowments requires effort that increases cognitive precision but entails disutility. Complete markets involve a larger number of relevant dimensions, raising both cognitive costs and the losses from imprecision. When cognitive costs are sufficiently high, agents may therefore rationally prefer incomplete markets despite their lower potential utility frontier. Together, preference instability and cognitive costs provide distinct theoretical foundations for a demand for market incompleteness.

We design an experiment that implements this portfolio framework and tests whether subjects' choices conform to the predictions of rational choice, preference instability, or complexity-based models. Each participant completes three portfolio tasks, each involving 16 equiprobable states. In the first two rounds, participants face one complete market with 16 Arrow–Debreu securities and one incomplete market with two composite assets. In the third round, they choose which market to operate in, yielding an incentive-compatible measure of revealed preference.

Our main treatment dimension varies the source of preferences. In the homegrown treatment, payoffs depend on realized states, so participants' own risk attitudes affect outcomes. In the induced treatment, payoffs follow a deterministic CRRA expected-utility rule, removing preference instability (e.g., regret or temptation). Comparing choices across these treatments isolates the role of preference instability relative to cognitive complexity. Additional demo treatments provide example portfolios designed to lower cognitive costs, allowing us to test whether simplifying the task shifts behavior.

We begin by examining revealed preferences over market types. Fewer than one third of participants chose the complete market in their third portfolio task, indicating a robust revealed preference for incomplete markets and contradicting the benchmark rational model. Moreover, choices in the homegrown and induced treatments are statistically indistinguishable, providing no evidence that instability in risk preferences drives this behavior. These patterns point instead to complexity as the dominant mechanism behind the demand for market incompleteness. Providing example portfolios ("demos") modestly increased the share of participants selecting the complete market, but the effect is only marginally significant, suggesting that examples alone do not substantially reduce effective complexity.

We next analyze task-level data on portfolio choices and non-choice measures, including response time, self-reported complexity, and cognitive uncertainty. Losses relative to the optimal benchmark are consistently larger in complete markets than in incomplete ones, particularly in the induced-preferences treatments where utility is directly observable. Response times, which is our proxy for cognitive effort, are two to three times higher in complete markets, while subjective ratings confirm that participants perceive them as more complex and uncertain. Together, these findings indicate that greater market complexity induces higher effort but larger mistakes, thereby reducing net utility.

Finally, we use a structural estimation approach to assess whether the complexity model can quantitatively account for the observed behavior. We estimate the model using the generalized method of moments, focusing on moments related to effort, relative losses, and market choices in the induced-preferences treatment. The estimated model replicates the main empirical patterns: higher losses and higher effort in the complete market, and a preference for the incomplete market. While it slightly understates the effort differential between markets, the parameter estimates are highly significant and imply that the complete market is about seven times more complex than the incomplete one. Complexity increases more than proportionally with the number of parameters to process, which in each market are the prices and state endowments. The model also predicts that subjects allocate attention selectively, focusing on prices but largely ignoring endowments, which helps explain the non-linear scaling of complexity.

Our paper relates to three strands of literature: theories of market completeness, models of complexity and cognitive costs, and experimental studies of portfolio choice under complexity.

While it is well understood that, under standard assumptions, complete markets achieve the highest feasible level of social welfare, the theoretical literature surveyed in Magill and Quinzii (2002) has primarily examined how different forms of incompleteness affect welfare. A seminal result by Hart (1975) demonstrates that adding a new security can reduce welfare unless the security completes the market. Other relevant contributions include Malinvaud (1973), who shows that under certain conditions a Pareto-efficient allocation can be attained with fewer securities than required for full completeness, and Marin and Rahi (2000), who show that welfare may be higher in an incomplete market under asymmetric information. Allen and Gale (1988, 1990, 1991) endogenize the asset structure by considering supply-side frictions. While this literature provides many insights into the efficiency consequences of market completeness, it largely abstracts from how behavioral or cognitive constraints may shape the assets that investors demand or are willing to trade.

Our first contribution is to provide a behavioral foundation for theories of market incompleteness. Using experimental evidence, we show that cognitive costs can generate a preference for simpler, lower-dimensional market environments. This mechanism offers a complementary perspective to supply-side explanations and has implications for market design.

Our experiment also contributes to a growing literature on complexity in economics and finance in two ways. First, we operationalize complexity in a portfolio-choice environment. We adopt the notion of task complexity (Oprea, 2024), which focuses on descriptive features of the decision environment rather than the procedures used by subjects. Our setting is related to work measuring complexity through the number of states in a lottery (e.g. Bernheim and Sprenger, 2020; Puri, 2024), although in our experiment the state space is fixed across choice tasks.

Our notion of complexity is also connected to measures of cardinality such as the size of the choice set (e.g. Ortoleva, 2013), including the large literature on choice overload, partly reviewed in Chernev et al. (2015).[3] Unlike this literature, where alternatives are exogenous, subjects in our experiment endogenously construct lotteries over wealth, with the exogenous variation coming from the number of assets available for portfolio formation. In this respect, our environment fits naturally within the theoretical framework in Gabaix and Graeber (2024), which links complexity to the number and importance of problem dimensions.

Second, we quantify and show both theoretically and experimentally that complexity increases more than proportionally with problem dimensionality. Although it is natural to think of complexity as increasing with dimensionality, this perspective remains at a high level. We go beyond a purely dimensional view of complexity by estimating the theoretical model and quantifying the implied complexity of the complete- and incomplete-market tasks. This exercise highlights that complexity does not scale proportionally with the number of dimensions: increases in dimensionality translate into disproportionately larger cognitive demands. This property is central for interpreting behavior in high-dimensional portfolio problems and cautions against treating complexity as proportional to problem size.

Our third contribution is to provide new experimental evidence on how complexity shapes portfolio behavior and market choices. There is a growing experimental literature studying how complexity and cognitive limitations affect portfolio decisions (e.g. Baltussen and Post, 2011; Magnani et al., 2022). Recent papers such as Carvalho and Silverman (2024) and Halevy and Mayraz (2024) show that decision quality deteriorates as the number of assets increases, typically measured through violations of GARP. However, in these experiments all environments are complete markets, and subjects' behavior is examined only within the given market structures.

In contrast, our design introduces variation in market incompleteness and allows subjects to choose between incomplete and complete markets. This aspect enables us to study not only how complexity affects portfolio choice performance, but also how it shapes the demand for incomplete markets, an aspect that to our knowledge has not been examined experimentally. Our experiment therefore provides an empirical foundation for understanding how cognitive costs influence both behavior within markets and preferences over market structures.

The rest of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 discusses our experimental design and laboratory procedures. Sections 4 and 5 present the reduced-form results and the structural estimation, respectively. Section 6

[3]Other papers on choice overload include Iyengar and Kamenica (2010); Reutskaja et al. (2011); Besedeš et al. (2015); Reutskaja et al. (2018).

discusses the implications of our findings. The appendix includes details of the theoretical framework, supplementary data analysis, and a copy of the experiment instructions.

2 Theoretical Framework

2.1 Model Setup and Rational Benchmark

The economy is subject to uncertainty at date 1, represented by a finite number of states of nature $\{1, 2, \ldots, S\}$ with probability measure $Pr(1), Pr(2), \ldots, Pr(S)$. For simplicity we assume states are equiprobable: $Pr(s) = 1/S\ \forall s$. An agent has preferences over the distribution of final wealth across states, which we denote by: $\mathbf{x} = \{x_1, x_2, \ldots, x_S\}$. The agent has state-dependent endowments $\mathbf{e} = \{e_1, e_2, \ldots, e_S\}$. At date 0 the agent is also endowed with an initial budget e_0, that can be used to purchase assets which pay out at date 1.

The economy contains J securities. The assets prices are exogenous and denoted by: $p_1, p_2, \ldots, p_J$. One unit of asset j yields a payoff in state s denoted by y_s^j and we write the payoff matrix from all J assets as:

$$\mathbf{y}_{S\times J} = \begin{bmatrix} y_1^1 & y_1^2 & y_1^3 & \cdots & y_1^J \\ y_2^1 & y_2^2 & y_2^3 & \cdots & y_2^J \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_S^1 & y_S^2 & y_S^3 & \cdots & y_S^J \end{bmatrix}$$

The agent makes asset allocation decisions at date 0. We denote the agent's purchases of assets as $q_1, q_2, \ldots, q_J$. Asset purchases can be negative, as long as final wealth is greater than or equal to zero. Final wealth in state s is given by the endowment in that state and the payoffs from the asset holdings: $x_s = e_s + \sum_j y_s^j q_j$. Asset purchases are subject to the budget constraint: $\sum_j p_j q_j \leq e_0$.

The objective of the agent is to maximize his utility from date 1 consumption by choosing his asset holdings at date 0, subject to the constraints:

$$\begin{aligned} \max_{\{q_j\}_{j=1}^J} \quad & U(x_1, ..., x_S) \\ \text{subject to} \quad & x_s = e_s + \sum_j y_s^j q_j \text{ for } s = 1, ..., S \\ & \sum_j p_j q_j \leq e_0 \\ & x_s \geq 0 \text{ for } s = 1, ..., S \end{aligned}$$

We consider two asset structures: a complete market and an incomplete market. A market is complete if any final wealth profile can be replicated using a portfolio of the J assets (e.g. Ross, 1976). Let $\boldsymbol{q} = (q_1, q_2, ..., q_J)^\top$ be the portfolio quantities and $\mathbf{x} = (x_1, x_2, ..., x_S)^\top$ be an arbitrary final wealth profile. The market is complete if any possible

$\mathbf{x}$ can be constructed as a linear combination of the asset payoffs:

$$\mathbf{x} = \mathbf{y}\boldsymbol{q}$$

In other words, the market is complete if and only if the payoff matrix $\mathbf{y}$ has full row rank:

$$\text{rank}(\mathbf{y}) = S$$

A market that is not complete is called an incomplete market.

While there are many asset structures that can be either complete or incomplete, we focus on one simple structure in each class by imposing several assumptions. First, assets have binary payoffs: $y_s^j \in \{0, y\}$, for some $y > 0$. Second, we restrict the payoff structure so that the sets of states in which different assets pay off do not overlap. Third, we require that for every state, there exists at least one asset that delivers a nonzero payoff in that state.

The first two assumptions are aimed at simplifying the asset structure, which allows us to focus on the effect of increasing the number of assets, rather than other features such as the correlation of payoffs.[4] By imposing the third assumption we want to rule out cases where there is a state in which all assets become worthless, as this represents an unlikely extreme scenario. To sum up, the asset structure defines a partition of the state space into J subsets, $\{\mathcal{S}_1, ..., \mathcal{S}_J\}$, each representing the set of states where asset j pays out.

Given these assumptions, we have one specific asset structure for the complete market and one for an incomplete market with a given number of assets. First, our complete market has $J = S$ Arrow-Debreu securities, with payoffs:

$$y_s^j = \begin{cases} y, & \text{if } s = j \\ 0, & \text{otherwise} \end{cases}$$

Second, the incomplete market has $J < S$ securities with payoffs:

$$y_s^j = \begin{cases} y, & \text{if } s \in \mathcal{S}_j \\ 0, & \text{if } s \notin \mathcal{S}_j \end{cases}$$

where $\{\mathcal{S}_1, ..., \mathcal{S}_J\}$ is a partition of the state-space, with at least one block containing more than one state. In our experimental design we will require that each block of the partition contains the same number of states.

Finally, we focus on a pair of markets that are linked in the following way. We construct the prices of the assets in the incomplete market by summing up the underlying complete

[4]In our markets, the negative correlation among assets is highly transparent: when one security pays a positive amount, the others yield a zero payoff. A more general correlation structure could introduce additional behavioral considerations, since the literature suggests people do not perfectly perceive correlation (e.g. Baltussen and Post, 2011; Ungeheuer and Weber, 2021).

market state-prices:

$$p_j^{incomplete} = \sum_{s \in \mathcal{S}_j} p_s^{complete} \tag{1}$$

The pair of markets we have designed ensures that any final wealth profile that is feasible in the incomplete market can also be achieved in the complete market. However, the converse is not true. For instance, it is easy to see that full insurance is possible in the complete market but not in the incomplete market. Thus, at the optimal portfolio choice, an agent's utility cannot be lower in the complete market than in the incomplete market:

$$U(\mathbf{x}^*_{complete}) \geq U(\mathbf{x}^*_{incomplete})$$

where $\mathbf{x}^*$ denotes the optimal final wealth profile. Rational agents should always (weakly) prefer the complete market over the incomplete market.

What could lead agents to prefer the incomplete market? In the next two sections we consider two potential explanations, based on preferences and complexity, respectively.

2.2 Preference Instability

Agents may prefer an incomplete market to a complete market because it minimizes regret or temptation. A number of decision theory models predict a preference for smaller menus over larger ones (Dekel et al., 2001; Gul and Pesendorfer, 2001; Sarver, 2008). In Gul and Pesendorfer (2001), smaller menus act as a commitment device that limits self-control costs by removing tempting alternatives. In Sarver (2008), smaller menus reduce the likelihood that the choice made ex-ante will turn out to be suboptimal once the decision-maker's true preferences are fully revealed. In this vein, complete markets expand the choice set and thereby increase the scope for regret or temptation.

We adapt the regret framework of Sarver (2008) to our portfolio environment. When the agent selects a portfolio, he may not yet know his true risk-preference. We represent this uncertainty as a probability measure μ over a set of possible ex-post utility functions $\mathcal{U}$. After the portfolio is chosen, but before the payoff state is realized, the agent's true utility function is revealed. Ex-post utility is therefore $U(\mathbf{x})$, where $\mathbf{x}$ is the profile of final wealth across states and $U(\cdot) \in \mathcal{U}$.

Because the choice is made prior to the revelation of preferences, the selected portfolio may not be the optimal once the true preference is known. The agent experiences regret about the choice (not about the realized payoff). Regret is proportional to the utility gap relative to the best portfolio that would have been chosen under the now-revealed preference:

$$R(M, U, \mathbf{x}) = K \times [U(\mathbf{x}^*) - U(\mathbf{x})] \tag{2}$$

where M is the set of feasible allocations determined by the market structure, $\mathbf{x}^* \equiv \max_{\mathbf{x} \in M} U(\mathbf{x})$ is the ex-post optimal choice, and $K \geq 0$ measures the sensitivity to regret. The ex-ante optimal portfolio is chosen to maximize the expectation of utility net of regret over the possible realizations of the agent's preferences:

$$\mathcal{W} = \max_{\mathbf{x} \in M} \int_{\mathcal{U}} \left[U(\mathbf{x}) - R(M, U, \mathbf{x}) \right] \mu(dU) \tag{3}$$

The welfare of the agent, $\mathcal{W}$, depends on the market structure M. A complete market has a larger set of feasible allocations, and a higher utility frontier. For the same reason, however, a higher maximum attainable ex-post utility also makes regret $U(x^*) - U(x)$ larger in the complete market. Thus, depending on the sensitivity to regret, a complete market may lead to a lower welfare.

To illustrate this mechanism, we consider a simple numerical example aligned with the parameters of our experiment. The agent is uncertain about his own risk preferences: with probability 0.5 he is risk-neutral, $U(\mathbf{x}) = \frac{1}{S} \sum x_s$, and with probability 0.5 he is maximally risk-averse, $U(\mathbf{x}) = \min_s x_s$. As we show in Appendix B.1, under our parametrization of the market, the ex-ante optimal strategy is to maximize the minimum final wealth.[5] This strategy is optimal also ex-post if the agent turns out to be risk-averse. However, if the agent learns that he is risk-neutral, the ex-post optimal policy is to buy only the cheapest security while selling others to achieve a higher mean wealth.[6]

We derive the agent's welfare $\mathcal{W}$ as a decreasing function of regret sensitivity K and plot it under each market structure in Figure 1. For sufficiently high K, the incomplete market becomes preferable because it limits the utility gap between the ex-post optimal and the ex-ante chosen portfolios. Agents who are uncertain about their preferences and sensitive to regret favor incomplete markets.

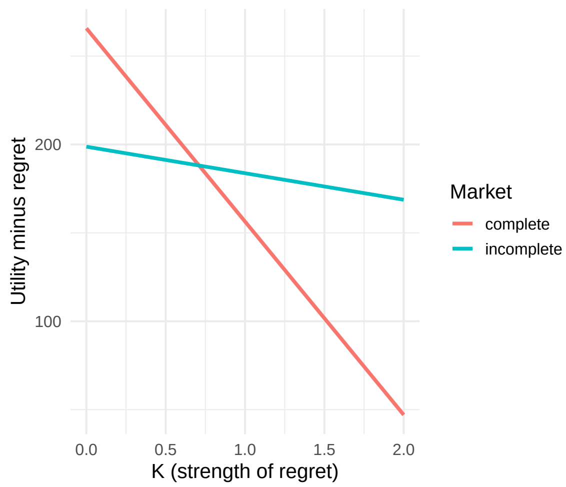


Figure 1: Market Completeness and Regret

[5]The ex-ante optimal strategy yields a constant wealth across states in the complete market. In the incomplete market, the ex-ante optimal portfolio equalizes wealth across the lowest-endowment states within each partition block. Therefore the incomplete market leads to a lower minimum but a higher mean wealth relatively to the complete market.

[6]The ex-post optimal policy is to sell all securities whose price exceeds the minimum price and use the proceeds (plus the initial budget) to buy the cheapest security(ies) in the complete market. However, in the incomplete market, sales of any asset j are bounded by the lowest endowment in the block of states linked to asset j.

A similar conclusion arises in Gul and Pesendorfer (2001), where the concern is not regret but temptation. For example, in our setting, an agent may be tempted to choose a more risk-seeking portfolio than he prefers ex-ante. Both Sarver (2008) and Gul and Pesendorfer (2001) assume dynamic changes in the agents' preferences, either due to the resolution of uncertainty about own preferences or to dynamic inconsistency in preferences.

In both models, the key aspect is that market completeness increases the potential divergence between ex-ante and ex-post optimal choices. Thus, both anticipated-regret and temptation frameworks yield the prediction that preference instability can generate a demand for incomplete markets.

2.3 Complexity

An alternative explanation of why agents may prefer incomplete markets is cognitive limitations. Participating in a complete market requires processing a larger set of asset prices, which raises cognitive demands. When cognitive effort is costly, agents optimally trade off the welfare gains from greater precision against the cost of exerting effort, which can make them favor a simpler, incomplete market.

To formalize this intuition, we adapt the complexity model of Gabaix and Graeber (2024) to our context. In this model, the agent incurs cognitive effort to process the relevant parameters of the decision problem. Let $z_1, ..., z_{\mathcal{I}}$ denote the parameters that require mental processing, which we assume to be the asset prices and state-contingent endowments (so $\mathcal{I} = J + S$).[7] The agent does not directly perceive the true parameters z_i, but instead obtains cognitive cues $\tilde{z}_i$ that combine the true parameters with a default. Each cue has an endogenous precision $m_i \in [0, 1]$, which reflects how much the agent adjusts away from the default by exerting cognitive effort. When $m_i = 1$, the parameter is correctly perceived: $\tilde{z}_i = z_i$. At the other extreme, when $m_i = 0$, the parameter is perceived to be equal to the default value: $\tilde{z}_i = z_i^d$.

We assume that the default price is the mean price, and the default endowment is equal to the mean endowment. We are thus modeling an agent who, when exerting no effort, can perceive the average price and average endowment, but perceives no differences across assets and states. The default thus implies a portfolio choice heuristic consisting of holding equal quantities of each asset. Such default strategy is unlikely to be optimal given the actual parameters z_i, and so it involves a loss relative to the highest attainable utility. A higher precision makes the portfolio choice closer to optimal.

The precision m_i is endogenously produced through cognitive effort L_i according to an increasing and concave production function: $m_i = f(L_i)$, with $f' \geq 0$ and $f'' \leq 0$. This assumption allows Gabaix and Graeber (2024) to define a complexity index computed as the increase in total effort required to marginally raise utility. In this model, complexity depends on the structure of the decision problem (including the number of dimensions), the utility

[7] We focus on parameters that drive the optimal allocation across assets, rather than the initial budget e_0. As discussed in Gabaix (2014), failures in processing the available budget are immaterial when the budget constraint must bind. The budget constraint is binding at the optimum in our model and it is mechanically enforced in our experiment, as explained later.

function and the cognitive production function.

Finally, each unit of effort reduces utility by w, so that the agent allocates effort across $i = 1, \ldots, \mathcal{I}$ dimensions to maximize the expected value of utility net of cognitive costs:

$$\mathcal{W} = \max_{L_1,\ldots,L_{\mathcal{I}}} U^* - \underbrace{\sum_{i=1}^{\mathcal{I}} V_i\big[1 - f(L_i)\big]}_{\text{losses from limited precision}} - \underbrace{w \sum_{i=1}^{\mathcal{I}} L_i}_{\text{cognitive effort cost}} \tag{4}$$

The first two terms in equation (4) are obtained from an approximation of utility around the default (see Appendix B.2 for details). U^* is the maximum attainable utility under full precision. V_i measures the marginal value of improving precision in dimension i and $V_i\big[1 - f(L_i)\big]$ represents the utility losses from limited precision. The last term is total cognitive effort costs.

Although a complete market expands the attainable utility frontier, it can nevertheless reduce welfare $\mathcal{W}$ once cognitive costs are taken into account. A complete market involves a larger number of relevant dimensions ($\mathcal{I}$), requiring agents to distribute effort more thinly across them. This dispersion lowers precision in each dimension and may increase total effort costs. Formally, moving from an incomplete to a complete market raises U^* and the V_i terms, but it can reduce net welfare through two channels: (i) lower effort L_i per dimension, which decreases precision m_i and increases utility losses, and (ii) higher total effort costs $w \sum_i L_i$.

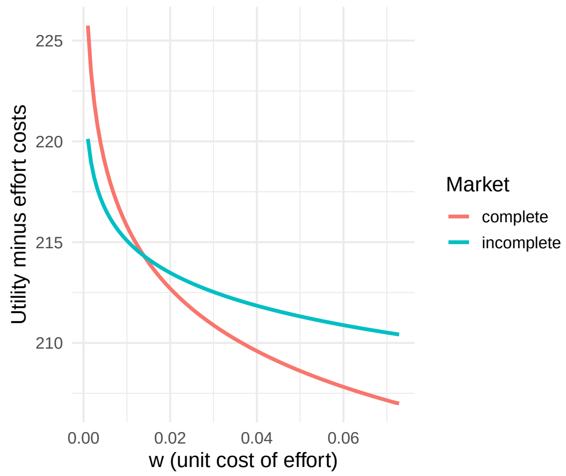


Figure 2: Market Completeness and Utility under Cognitive Costs

We solve the model numerically using the portfolio choice problem employed in the experiment, a CRRA utility function (the same we induce in one of the experiment's treatments) and the parameters of the model we estimate from our data (as discussed in Section 5). The results, illustrated in Figure 2, show that the net effect depends on the unit cost of effort w. For sufficiently high values of w, the complexity of the complete market can lead the decision maker to prefer the incomplete market.

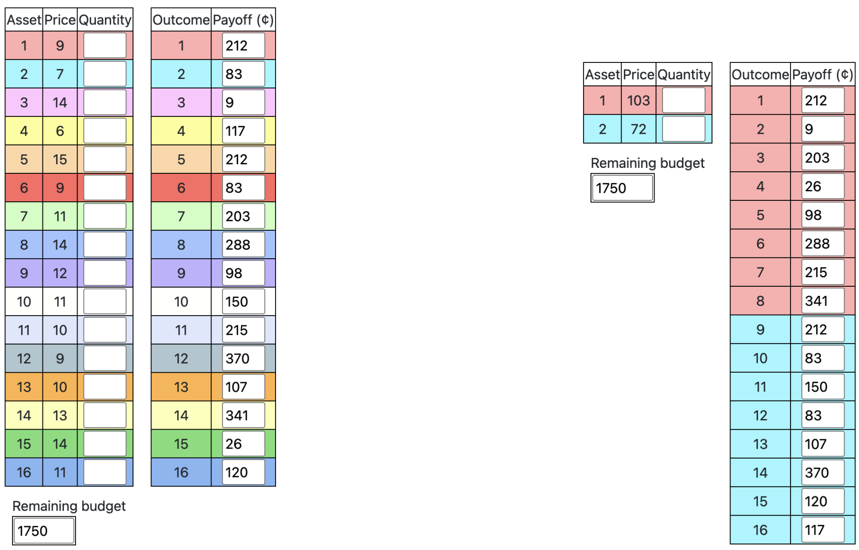
This framework formalizes complexity aversion as a structural form of bounded rationality (Simon, 1955): agents remain fully optimizing, but subject to internal cognitive constraints. The mechanism is conceptually related to rational inattention (Sims, 2003), though here cognitive costs arise from effort-based precision rather than from information-processing limits. Across these frameworks, greater complexity can rationally induce simplification, and in our setting, a preference for the incomplete market.

3 Experimental Design

3.1 Portfolio Choice Task

Our experiment consists of several variations of a baseline portfolio choice task, both within-subject and between-subject. In each task, the number of states is $S = 16$ and the states are equiprobable. Different portfolio choice tasks vary by the other parameters, like budget, endowments and asset structures.[8]

As in our theoretical framework, there are two possible asset structures. The complete market has $J = 16 = S$ Arrow-Debreu securities, while the incomplete market has $J = 2 < S$ securities. Thus the asset structure of the incomplete market induces a partition of the state-space $\{\mathcal{S}_1, \mathcal{S}_2\}$, where each block $\mathcal{S}_j$ contains 8 states. We choose to have two securities in the incomplete market to distinguish it as much as possible from the complete market, while ensuring the participant still faces a meaningful portfolio choice (that would not be the case with $J = 1$). The two markets are linked in the way described in the theory section: the prices of the assets in the incomplete market are obtained by summing up the underlying complete market state-prices within each block of the partition $\{\mathcal{S}_1, \mathcal{S}_2\}$. The assignment of the states to the two blocks was determined randomly (and was the same for all participants).



(a) Complete market (b) Incomplete market

Figure 3: Interface

Each participant makes his portfolio choice using an interface illustrated in Figure 3. The interface lists all the states (called outcomes), state-contingent final wealth levels (called payoffs), the available assets and their prices. The states in which an asset j pays off are

[8] Appendix E provides the full experimental instructions and interface.

displayed in the same color as the asset to help participants easily identify the asset structure. At the start of each task, the payoff column lists the state-endowments, i.e. the state-contingent final wealth participants obtain if they do not engage in any trading. The initial budget is displayed below the asset table.

Participants can choose the quantity of each asset to buy or sell either by typing a number in the corresponding input box or by adjusting the quantity in increments of 0.1 using the up and down arrow keys on their keyboard. As participants make their quantity choices, payoffs and the remaining budget are updated in real time.

Participants can submit the task only if the following conditions are met: 1) all quantities are filled out, 2) no final wealth is below zero, 3) the remaining budget is between 0 and a small value $b > 0$ (specified below). This budget constraint allows us to focus on the type of decision errors most relevant to our analysis, namely mistakes in portfolio allocation across assets rather than failures to spend the available budget. Because any unspent budget is lost, such mistakes could be trivially corrected by increasing the purchase of any asset. For this reason, participants are required to use nearly all of their budget. A small budget surplus is permitted, however, since asset quantities in the interface can only be adjusted in increments of 0.1, making it impossible in some cases to reach a remaining budget of exactly zero.

3.2 Rounds, Subjective Ratings and Market Choice

Each session of our experiment consists of three portfolio tasks, called rounds, as illustrated in Figure 4.

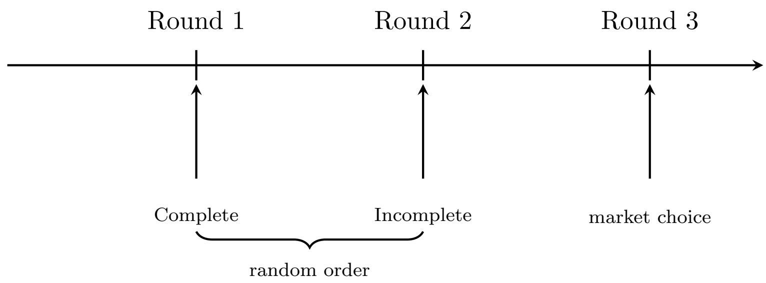


Figure 4: Basic Design

The portfolio tasks in the first two rounds have the same budget and state-contingent endowments. The only difference between the first two rounds is that in one the participant faces a complete market and in the other the participant faces an incomplete market, with the order of the two markets randomized at the participant level. No feedback on the realized state is provided between rounds.

Immediately after each of the first two portfolio choice tasks, we collect the cognitive uncertainty measure of Enke and Graeber (2023) and a subjective measure of complexity (based on the experiment of Gabaix and Graeber, 2024). Specifically, participants were asked to answer the following two questions on a scale from 0 to 100 using a slider: 1) “How certain are you that your chosen budget allocation is the best possible option for you?” and 2) “How complex did you find this task?”

In the third round, participants complete another portfolio task. Before doing so, they choose whether the task will take place in a complete or an incomplete market. This choice is incentive-compatible and therefore reveals each participant's (weakly) preferred market type.[9]

At the time of market choice, participants are informed that the third portfolio task will be similar, but not identical, to those encountered previously. Specifically, they are told that the number of states and their probabilities remain fixed, while prices, budgets, and initial payoffs are randomly drawn from the same distributions used in earlier rounds (discussed further below). This procedure prevents the repetition of an identical portfolio problem, which could otherwise affect behavior by reducing uncertainty about one's risk preferences or by lowering cognitive demands. At the same time, it allows participants to base their decision on prior experience with each market type. To facilitate their choice, participants are shown a summary of key statistics from their previous two rounds, including the expected value and range of their wealth profiles, their self-reported cognitive uncertainty and perceived complexity, and the time spent on each task. Again, no feedback about the realized state in any task is provided until after the experiment, when final payments are determined.

3.3 Treatments

Our main between-subject treatment design varies whether portfolio choices are driven by subjects' own risk-preferences or by a preference that we induce in the lab. The goal of the induced-preference treatment is to remove scope for dynamic changes in subjects' risk-preferences that could lead to a preference for incomplete markets, leaving complexity as the residual explanation.

In the homegrown-preferences (*HOM*) treatment, the subject's payment in each task is equal to the final wealth in a randomly selected state (all states are equiprobable). Participants therefore face actual risk, exactly as in the original portfolio problem. In this treatment, a preference for the incomplete market may arise either because dynamic changes in risk-preferences (as in Section 2.2) or complexity (as in Section 2.3).

In the induced-preferences (*IND*) treatment, the subject's payment in each task is given by a deterministic function of the final wealth profile. Specifically, the final payment is:

$$\left[\frac{1}{16}\sum_{s=1}^{16}(x_s)^{0.8}\right]^{1/0.8} \tag{5}$$

where x_s is the final wealth in state s. This payment rule induces CRRA expected utility preferences with relative risk aversion $\gamma = 0.2$, thereby inducing a known and stable preference over final-wealth profiles. Participants were informed of the utility function, and the interface displayed the realized utility associated with their current portfolio in real time.

[9] We did not elicit a cardinal measure of preferences over market types, such as the willingness to pay to switch from an incomplete to a complete market. Doing so would have required a multiple-price list and made the experiment more complex and time-consuming.

Since the deterministic payment rule implies a unique payoff-maximizing portfolio, changes in the subject's homegrown preferences cannot generate regret or temptation. This removes preference instability as a source of differences between complete and incomplete markets. In this setting, the only remaining channel that could make participants prefer the incomplete market is the cognitive cost of handling a more complex environment.

By comparing revealed choices in *HOM* and *IND*, we can therefore assess the importance of preference instability relative to complexity. If significantly more participants select the complete market in *IND*, this would indicate that regret or temptation plays a substantial role in the preference for incomplete markets. If instead the choice rates are similar across the two treatments, preference-based explanations are unlikely to be the main driver, leaving cognitive costs of complexity as the dominant mechanism.

Besides our main treatments, we also implemented two additional versions of the experiment, referred to as the *DEMO* treatments, designed to lower cognitive costs and to provide robustness for our findings. These treatments are identical to those described above except that participants are shown three example portfolios. The first example is the optimal portfolio for an expected-utility maximizing agent with constant relative risk aversion $\gamma = 0.5$ (note that this differs from the utility induced in the *IND* treatment). The second example is the optimal portfolio for a maximally risk-averse agent with utility $\min_s x_s$. The third example is a randomly selected feasible portfolio, which is the same for all subjects within a task.

Subjects can view and edit thes examples by clicking a button labeled "Click for an example choice" in the portfolio choice interface. Each click reveals the next example, looping back to the first example after the third. Importantly, participants retain full freedom to adjust asset quantities at any time, regardless of whether they have viewed the examples. We introduce demos in both the *HOM* and *IND* treatments, leading to two new treatments called *HOM-DEMO* and *IND-DEMO*. To the extent that these demos reduce the cost of cognitive effort, we expect these treatments to decrease effort, losses, complexity, cognitive uncertainty and the proportion of participants choosing the incomplete market.

3.4 Parametrization

In this section, we describe how we set the parameters of the portfolio choice tasks in the first two rounds of the experiment, which provided the main source of data for our empirical analysis, in both the *HOM* and *IND* treatment. The third portfolio task follows a similar parametrization. Our objectives are twofold. First, we express asset prices, payoffs, induced utility in the *IND* treatment and budgets directly in dollars in order to save the participants' effort to convert units. Second, we aim to generate average subject's payoffs that are similar across the two treatments, as well as comparable complete market gains across two treatments. We set the asset dividend equal to $y = 10$ in all market types and treatments.

In the *HOM* treatment, asset prices and state endowments were pre-drawn from a random distributions and remained fixed across subjects within each task. Asset prices in the complete market are integers drawn from a uniform distribution between 6 and 16. State endowments are integers drawn from a uniform distribution between 0 and 400. The budget was determined after drawing the prices, to ensure that participants could purchase around 10 units of each asset, so that they could increase their state endowment by a sure payoff of around 100 (cents). The budget in each of the first two rounds of the *HOM* treatment was $e_0 = 1750$. The maximum unspent budget allowed was 100 (the opportunity cost of a budget surplus of 100 is equivalent to a sure increase in final wealth of around 5 cents).

This parametrization implies a specific distribution of final wealth, and therefore of participant payments. Although we do not observe individual risk preferences, we compute summary statistics for the distribution of final wealth implied by several portfolio strategies. Table 1 reports these values. Consider first a risk-neutral subject who maximizes expected final wealth (MaxEV strategy). This strategy yields an average wealth of 484 cents in the complete market and 288 cents in the incomplete market. It therefore provides a clear incentives to choose the complete market. The MaxEV strategy also produces a distribution with substantial positive skewness in the complete market. The maximum wealth is 7750 cents in the complete market compared with 626 cents in the incomplete market. These features suggest that participants who value skewness, for example under prospect theory or rank dependent utility, also have strong incentives to choose the complete market.

Next we consider a maximally risk-averse subject who maximizes the minimum possible wealth (MaxMin strategy). Such a subject would achieve a sure wealth of 266 in the complete market, and a minimum wealth of only 139 in the incomplete market. Again, utility is significantly higher (almost doubled) in the complete market than in the incomplete market.

Finally, we report the outcome of the default portfolio strategy, which we define as purchasing the same quantity of each asset. Although this strategy is not likely to be the optimal strategy for any preference (as it ignores both prices and endowments), it is a heuristic that plays an important role in the complexity model, as discussed below. The default strategy results in an expected wealth of 265 in both markets.

Table 1: Final Wealth from Portfolio Choices in the HOM Treatment

		Market Structure	
Strategy	**Statistic**	**Complete**	**Incomplete**
MaxEV	Max wealth	7750	626
	Expected wealth	484	288
	min wealth	0	0
MaxMin	Max wealth	266	471
	Expected wealth	266	258
	Min wealth	266	139
Default	Max wealth	470	470
	Expected wealth	265	265
	Min wealth	109	109

Note. All values are rounded to the nearest integer. The three portfolio strategies shown in the table are: MaxEV - maximization of the expected value of final wealth; MaxMin - maximization of the minimum final wealth; Default - purchasing the same amount of each asset (around 10 units of each asset).

In the *IND* treatment, we parametrized the first two portfolio tasks to achieve payoff levels comparable to those in the *HOM* treatment. This ensures similar monetary incentives across treatments. Achieving this requires choosing an induced utility function jointly with the other parameters. Asset prices in the complete market are integers drawn from a uniform distribution between 1 and 10. State endowments are integers drawn from a uniform distribution between 0 and 200. As in the *HOM* treatment, we set the budget after observing prices so that participants could purchase roughly 10 units of each asset. The budget in each of the first two rounds of the *IND* treatment was $e_0 = 870$. The maximum unspent budget allowed was 50, to ensure a similar opportunity cost as in the *HOM* treatment. In this treatment, the optimal portfolio strategy is uniquely defined.

Table 2 summarizes the resulting utilities. The optimal portfolio strategy leads to a utility of 412 cents in the complete market and 288 cents in the incomplete market, which generates incentives to choose the complete market similar in magnitude to those in the *HOM* treatment. The default strategy of purchasing equal quantities of each asset yields a utility of 207 cents.

Table 2: Induced Utility from Portfolio Choices in the IND Treatment

	Market Structure	
Strategy	**Complete**	**Incomplete**
Optimal	412	288
Default	207	207

Note. These are payoffs computed using the induced utility function. All values are rounded to the nearest integer. The default portfolio strategy involves purchasing the same amount of each asset (around 10 units of each asset).

3.5 Other Details

Our experiment was conducted on Prolific in June 2025. 120 subjects participated in each treatment, for a total of 480 subjects. The experiment lasted 20 minutes on average. After reading the instructions, participants completed a quiz. All participants received a base payment of $4. In addition, a bonus payment was implemented: for one quarter of the participants, a randomly selected task was chosen for payment. The final wealth or utility realized in that task was converted directly in dollar cents and added to the base payment. The experiment was preregistered at AsPredicted, with id 232198.

4 Results

Our empirical analysis focuses on the behavior of participants who answered at least three out of four comprehension questions correctly, as pre-registered. This restriction leaves 80% of the original participants: 106 subjects in the *HOM* treatment, 86 subjects in *IND*, 96 subjects in *HOM-DEMO* and 96 subjects in *IND-DEMO*. We use portfolio choice data from the first two rounds and market choices made at the beginning of the third round of the experiment.

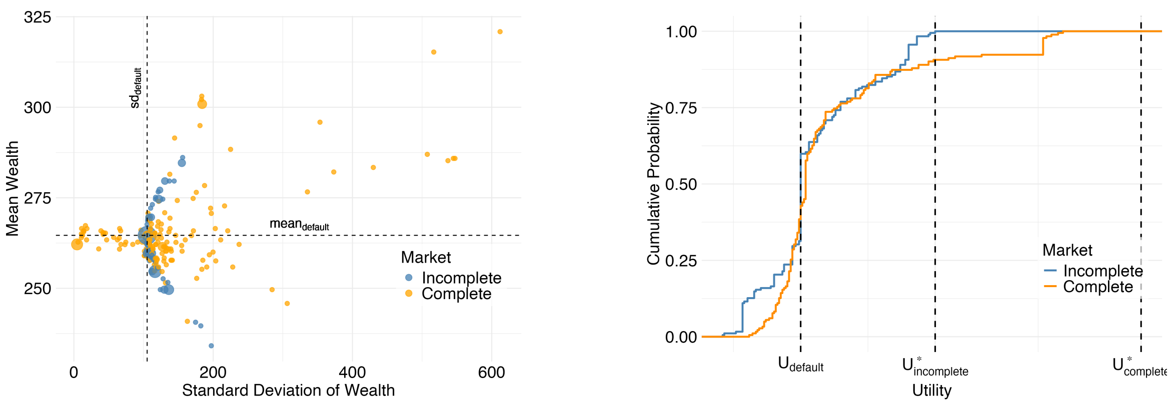
All main analysis results are very similar when using the full sample rather instead of the pre-registered filtered sample, indicating that the results are not sensitive to this exclusion rule. Appendix A reports these robustness checks. In most of our analysis, we break down the results into the four treatments, but in some figures and tables we pool together observations from experiments with and without demos within each preference treatment, and we refer to the resulting two samples as *HOM-All* and *IND-All*.

4.1 Descriptive Analysis of Portfolio Choices

Subjects construct a variety of portfolios across our experiments. To highlight the main characteristics, we begin by examining the outcomes of the chosen portfolios for final wealth and utility.

For each portfolio choice in the *HOM-All* treatments, we compute the mean and standard deviation of final wealth. Figure 5a plots these values, with point size indicating the number of observations at each mean–standard deviation combination. Two salient patterns emerge. First, there is substantial heterogeneity across individuals, which may reflect differences in risk-preferences, differences in skill or both. Importantly, because we do not assume that subjects evaluate portfolios solely through mean–variance considerations, the figure should not be interpreted as implying that low-mean, high-variance portfolios are necessarily mistakes. We assess efficiency later using a first-order stochastic dominance criterion.

Second, although the two markets generate visibly different sets of outcomes, observations in both markets are centered around a common strategy close to the default equal-quantities portfolio. In the incomplete market (blue), the data trace out the familiar parabola that represents the efficient frontier with two negatively correlated assets. In the complete market (orange), portfolios are spread out more widely. As designed, the complete market expands the feasible set in mean–standard-deviation space and some subjects take advantage of this added flexibility. For instance, several choose relatively safe portfolios that lie to the left of the default allocation, while others construct more risk-seeking portfolios with high means and high standard deviations.



(a) *HOM-All*: Mean and SD of Wealth

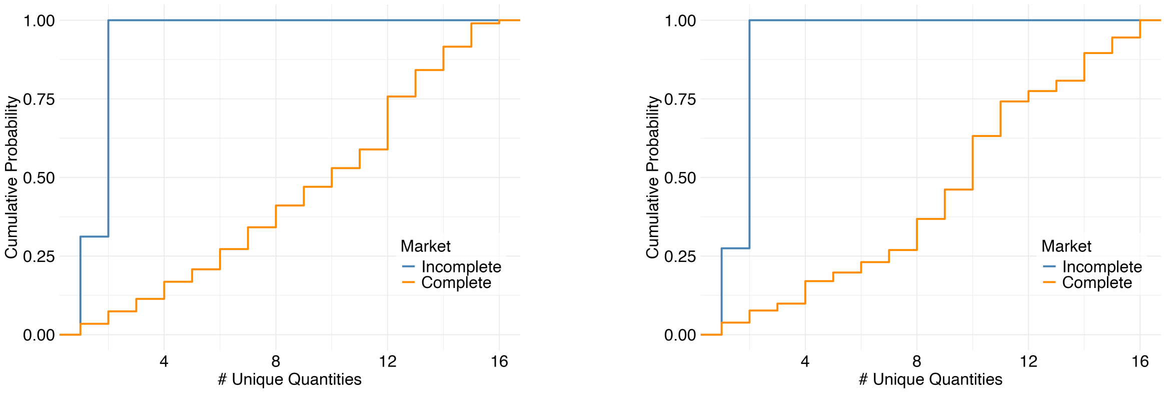
(b) *IND-All*: Utility

Figure 5: Final Wealth and Utility

In the *IND-All* treatments, each portfolio maps directly to a utility level. We therefore examine the distribution of realized utility. Figure 5b shows that median utility under both market structures is close to the utility of the default strategy (defined as allocating equal quantities across assets). The utility distributions are nearly identical over the interquartile range. The main differences appear in the tails: in both the upper and lower quartiles, utility in the complete market exceeds that in the incomplete market. Only a small share of participants come close to the maximum achievable utility in either market structure.

As a behavioral measure of the sophistication of portfolio choices, we use the number of distinct purchase quantities. This metric captures the extent to which subjects fine-tune their allocations across assets versus relying on coarse decisions or heuristics. Divergence in this measure across market structures provides evidence on the role of cognitive effort in portfolio selection.

Figure 6a and Figure 6b show that in both treatments, portfolios in the incomplete market (blue) involve relatively few distinct purchase quantities, which is expected given that only two asset quantities must be chosen. By contrast, in the complete market (orange), portfolio choices display much greater dispersion: roughly half of participants use more than 10 distinct quantities, while about one-quarter use only around 4, despite variation in prices and endowments. This divergence suggests that some subjects invest effort to explore the enlarged choice set, whereas others rely on simplifying heuristics to avoid the cognitive cost of evaluating many prices and payoffs.



(a) *HOM-All* treatments (b) *IND-All* treatments

Figure 6: Unique Quantities in Portfolios

4.2 Market Choice

Next we examine the subjects' revealed preference for complete markets. Table 3 shows that only 23% to 32% of participants select the complete market in their third portfolio task, and for every treatment this proportion is significantly below 50%. The preference for the incomplete market is therefore both strong and remarkably consistent, running counter to the rational benchmark in Section 2.1.

To compare market choices across treatments, we conduct a set of two-sample proportion tests, summarized in Table 4. Our first comparison is between the *HOM* and *IND* treatments. If preference instability (i.e. anticipate regret or temptation) is a driver of the demand for

Table 3: Proportion Choosing the Complete Market by Treatment

Treatment	Market choice Complete (%)	p-value
HOM	28.30	0.0000***
IND	23.26	0.0000***
HOM-DEMO	31.25	0.0003***
IND-DEMO	32.29	0.0007***

Note: P-values are from two-sided binomial tests assessing whether the proportion choosing market 16 is significantly different from 50%. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

incomplete markets, once a stable risk-preference is induced, a higher percentage of subjects should choose the complete market. The test shows that the difference is not statistically significant (p-value = 0.7346). This suggests that the dynamic changes in risk-preferences underlying preference-based explanations have a limited role. In fact, participants seem to be more likely to choose the complete market in *HOM* treatment (28%) than in the *IND* treatment (23%). Similarly, the proportion of subjects choosing the complete market is essentially indistinguishable between treatments *IND-DEMO* and *HOM-DEMO*. Even pooling them into *HOM-All* and *IND-All* yields no statistically significant difference.

Second, we examine the effect of the demo treatments. While the demo treatments tend to raise the preference for the complete market, the increase is not statistically significant. The effect approaches the 10% level when comparing *IND* with *IND-DEMO* or when pooling the baseline and demo treatments. Notably, the demo effect becomes significant in the full sample (p-value = 0.0430 for *IND* and p-value = 0.0957 for the pooled comparison; See Table A3).

Table 4: Pairwise Comparisons of Market Choice Across Treatments

Treatment1	Market choice Complete (%)	Treatment2	Market choice Complete (%)	p-value
HOM	28.30	IND	23.26	0.7346
HOM-DEMO	31.25	IND-DEMO	32.29	0.5000
HOM-All	29.70	IND-All	28.02	0.5987
HOM	28.30	HOM-DEMO	31.25	0.3807
IND	23.26	IND-DEMO	32.29	0.1171
NO-DEMO	26.04	DEMO	31.77	0.1301

1. P-values are from one-sided proportional tests assessing whether the proportion choosing market 16 is significantly greater in Treatment 2 than in Treatment 1.
2. "HOM-All" denotes the pooled sample of HOM and HOM-DEMO treatments.
3. "IND-All" denotes the pooled sample of IND and IND-DEMO treatments.
4. "NO-DEMO" pools HOM and IND treatments.
5. "DEMO" pools HOM-DEMO and IND-DEMO treatments.
6. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Taken together, the evidence suggests that: 1) there is a consistent and strong preference for incomplete markets, 2) dynamic changes in preferences like those assumed in models of regret and temptation are not the main drivers of this preference. Thus, complexity emerges as a central mechanism. While the demo treatments may attenuate cognitive costs, the reduction does not appear large enough to reach the tipping point at which a significant number of participants would switch to the complete market choice.

Complexity also appears central in subjects' feedback. Many explain their choice of the incomplete market by emphasizing its simplicity or lower complexity, while those choosing the complete market often cite higher payoff, flexibility, or diversification. A detailed summary of the subjects' feedback is presented in Appendix D. These comments support our conclusion preferences over markets reflect a trade-off between flexibility and complexity.

4.3 Correlates of Market Complexity

We then check how utility losses and non-choice measures that proxy for complexity differ across market structures. The model of Gabaix and Graeber (2024) suggests that, if the complete market is more complex, we should expect systematic differences in several behavioral and subjective measures across market structures. We show in Appendix B.2.2 that, under the assumptions of their framework, this logic leads to four testable predictions for our setting:

Prediction 1 (Utility losses): The difference between maximum attainable utility and realized utility should be larger in the complete market.

Prediction 2 (Response time): Participants are expected to exert greater effort, measured by response time, in the complete market.

Prediction 3 (Cognitive uncertainty): The complete market should lead to lower precision in cognitive cues, and therefore higher cognitive uncertainty.

Prediction 4 (Subjective complexity): Subjective ratings of complexity will be higher for the complete market.

To test these predictions, we compare the medians of each correlate of complexity between market structures. Table 5 reports the results. The last column reports p-values from Wilcoxon signed-rank tests comparing complete markets vs. incomplete markets.

First, we examine the effect of market completeness on utility losses. In the *IND-All* treatments, we know the utility function so we quantify utility losses as follows:

$$loss_{IND} = U(\mathbf{x}^*) - U(\tilde{\mathbf{x}}) \tag{6}$$

where $\mathbf{x}^*$ is the optimal wealth profile for the induced utility function $U(\cdot)$ and $\tilde{\mathbf{x}}$ is the final wealth profile resulting from the actual portfolio choice of the subject.

In the *HOM-All* treatments, however, we do not know the utility of the subjects nor the optimal choice. We thus resort to a measure of first-order stochastic dominance efficiency loss proposed by Kuosmanen (2004) for generic portfolio problems (see also Kopa and Post (2009)). This measure is given by:

$$loss_{HOM} = E(\hat{\mathbf{x}}) - E(\tilde{\mathbf{x}}) \tag{7}$$

where $\hat{\mathbf{x}}$ is the wealth profile that maximizes the expected value of final wealth among the

Table 5: Median Outcomes by Market Structure

Variable	Market Structure Incomplete	Complete	p-value
	HOM		
Loss	0	52	0.0000***
Response Time	42	159	0.0000***
Complexity	53	66	0.0000***
Uncertainty	28	28	0.0524*
	IND		
Loss	81	205	0.0000***
Response Time	59	155	0.0000***
Complexity	55	66	0.0000***
Uncertainty	21	29	0.0003***
	HOM-DEMO		
Loss	2	43	0.0000***
Response Time	34	97	0.0000***
Complexity	40	59	0.0000***
Uncertainty	23	28	0.0007***
	IND-DEMO		
Loss	81	202	0.0000***
Response Time	50	101	0.0000***
Complexity	50	57	0.0206**
Uncertainty	19	18	0.2520

1.P-values are from within-subject Wilcoxon signed-rank tests comparing outcomes across the two market structures.
2. Median of each variable is reported and rounded to the nearest integer (exact loss in *HOM*–incomplete is 0.34).
3. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

feasible profiles that first order stochastic dominate $\tilde{\mathbf{x}}$. This measure can be computed solving a mixed integer linear programming problem. $loss_{HOM}$ represents the maximum increase in mean wealth over $\tilde{\mathbf{x}}$ obtainable without aggravating the risk exposure of the portfolio, where risk is measured in terms of first-order stochastic dominance. This is a lower bound on the utility loss from mistakes (expressed in monetary terms).[10] Clearly, our loss measures for the homegrown- and induced-preference treatments are not comparable. However this is not a problem because we are interested in comparing losses between markets within each treatment.

As shown in Table 5, we find that losses are positive on average across treatments and markets.[11] It means that, on average, participants are not choosing fully optimal portfolios, and are leaving some payoff (or utility) "on the table". It implies that the optimal choice

[10]The actual utility loss may be larger that this in some cases. For example, in the complete market, full insurance is not first order stochastically dominated by any other feasible allocation, and so it results in $loss_{HOM} = 0$, but it leads to a utility loss of 218 if the subject is risk-neutral, see Table 1.

[11]Loss values are rounded to the nearest integer. For example, the exact median loss in the *HOM* in incomplete market is 0.34.

process is not frictionless. Losses are systematically larger in the complete market than in the incomplete market. In the *HOM* and *HOM-DEMO* treatments, losses in the incomplete markets are between 0-2, meaning the median portfolio is close to first-order stochastic dominance. In the complete markets, participants incur a loss of about 43–52, implying a guaranteed 50 cents gain in expected payoff without worsening the payoff distribution by switching to a different portfolio.

In the *IND* and *IND-DEMO* treatments, the complete market leads to losses more than twice as large as in the incomplete market. Participants' losses on average are comparable to 28% of the maximum utility in the incomplete market, and 49% of the maximum utility in the complete market. These patterns are consistent with the complexity-based model: participants make larger mistakes in the complete market, while performance is markedly better in the simpler incomplete market.

Second, we find that response time is systematically higher in the complete markets than in the incomplete markets. Without demos, subjects spend around 155–159 second on the complete market task, but only 42–59 seconds on the incomplete market task. In the *DEMO* treatments, response time is somewhat lower overall, yet participants still spend substantially more time in the complete market. Interpreting response time as a proxy for effort, these differences are consistent with the cognitive cost mechanism that solving the complete market requires considerably more cognitive processing and chosen effort increases with task complexity given some parametric assumptions.[12]

Third, subjective complexity (which we measure on a scale from 0 to 100) is significantly higher in the complete market than the incomplete market across treatments. This suggests that participants can introspectively assess complexity to some extent, a notion supported by experimental evidence in Gabaix and Graeber (2024), although from a different context related to intertemporal choice tasks.

Finally, we consider cognitive uncertainty, which we measure using a 0–100 rating scale, following the approach in Enke and Graeber (2023). Cognitive uncertainty may also reflect uncertainty about preferences in the *HOM* treatment, but not in the *IND* treatment where preferences are induced. We find that cognitive uncertainty is significantly higher in the complete market for treatments *IND* and *HOM-DEMO*, and marginally higher in *HOM* (at the 10% significance level). Moreover, average levels of cognitive uncertainty are similar across homegrown-preferences and induced-preferences treatments, again confirming that instability in risk-preferences is not the main mechanism.

Overall, the above evidence shows that participants, on average, put more effort in the complete market task than the incomplete market task, but end up making worse decisions and with stronger feelings of complexity and uncertainty (in most treatments). These patterns align with the correlates of complexity identified by Gabaix and Graeber (2024), indicating that the complete market task is indeed more complex. This adds support to a

[12] Although the complete market interface requires subjects to enter 16 values instead of 2, this mechanical difference can be handled within a few seconds using arrow keys, as practiced during the instructions. Thus, the observed gap in response times is unlikely to be driven by data entry alone and instead reflects additional cognitive processing.

complexity-based explanation for participants' revealed preference for incomplete markets.

Table 6: Differences Between Complete-Market and Incomplete-Market Choosers

	Market Choice					
	Complete		**Incomplete**			
Market Structure	*Com*	*Inc*	*Com*	*Inc*	ΔCom	ΔInc
			HOM-All			
Loss	48	1	50	0.5	0.5827	0.0315**
Response Time	115	50	125	37	0.4624	0.3470
Complexity	60	47	64	50	0.5255	0.9098
Uncertainty	24	28	30	25	0.7102	0.1717
			IND-All			
Loss	197	81	205	81	0.0006***	0.0386**
Response Time	111	80	133	45	0.8021	0.0097***
Complexity	55	50	64	52	0.0375**	0.5044
Uncertainty	20	20	22	20	0.6767	0.6615

Notes: Columns 2–3 report medians for observations with *Market Choice* = Complete; within those, the subcolumns show outcomes under the Complete and Incomplete *market structures*, respectively. Columns 4–5 analogously report medians for observations with *Market Choice* = Incomplete. Columns 6 and 7 report Wilcoxon rank-sum p-values comparing, respectively, MC=Complete vs. MC=Incomplete within the Complete and Incomplete market structures for each variable.

4.4 Complexity Correlates and Market Choice

We further evaluate the complexity-based explanation by examining whether the correlates of complexity are related to individual market choices. Because variation across subjects reflects a mix of cognitive costs and idiosyncratic factors, individual-level patterns are naturally noisier than the cross-market comparisons above. We study these patterns in two ways.

First, we compare the distribution of each complexity correlate between subjects who choose the complete market and those who choose the incomplete market. Table 6 reports the median value of each complexity correlate by market choice, along with the p-values from non-parametric tests. In the *HOM-All* treatments, we find no significant differences in effort, performance, or perceived complexity, aside from slightly higher losses in the incomplete task among complete-market choosers.

Clearer differences emerge in the *IND-All* treatments. Participants who prefer the complete market tend to incur lower losses in both tasks, spend more time on the incomplete market task, and rate the complete market task as less complex than those who prefer the incomplete market.

Second, we examine whether within-subject differences in complexity correlates help explain market choice. We regress the probability of choosing the complete market on the difference between a participant's performance and perceptions in the complete- and incomplete-market tasks. We estimate a linear probability model separately for the *HOM-All* and *IND-All* datasets, and report the results in Table 7. In the homegrown-preference treatments, participants are significantly less likely to select the complete market when they

Table 7: Market Choice and Within-Subject Differences in Complexity Correlates

	Pr(Market Choice = Complete)	
	HOM-All	IND-All
Δ Loss	-0.0009	-0.0030***
	(0.0012)	(0.0009)
Δ Response time	-0.0002	0.0001
	(0.0001)	(0.0002)
Δ Complexity	-0.0005	-0.0013
	(0.0012)	(0.0014)
Δ Uncertainty	-0.0043**	-0.0012
	(0.0014)	(0.0018)
Constant	0.3785***	0.6278***
	(0.0637)	(0.1128)
Observations	202	182
Adjusted R^2	0.0287	0.0658

Notes: ΔX denotes the within-subject difference between the complete and incomplete markets, defined as $\Delta X = X_{\text{com}} - X_{\text{inc}}$. Positive values indicate higher levels in the complete market. Estimates are from a linear probability model and fitted values fall outside $[0, 1]$ for only about 2% of observations. Robust standard errors are reported. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

report higher cognitive uncertainty in that environment. In the induced-preference treatments, they are significantly less likely to choose the complete market when they experience larger utility losses in it. The estimated regression intercepts suggest that, if there were no differences in complexity correlates between markets, the most likely choice under induced preferences would be the complete market, consistent with the complexity model. This is not the case in the *HOM-All* treatments, where the predicted probability of choosing the complete market remains below 50% even if there were no differences in complexity correlates.

The complexity model implies that individuals who experience greater cognitive demands or larger performance shortfalls in the complete market should be less inclined to select it. The individual-level evidence therefore provides an indirect check on the mechanism. In the *IND-All* treatments, the patterns are broadly consistent with this logic: subjects who incur larger losses or face greater subjective difficulty in the complete market are systematically less likely to choose it. In contrast, the *HOM-All* treatments display weaker and noisier associations (aside from cognitive uncertainty), because homegrown preferences introduce additional sources of variation.[13] Controlling for a stochastic-dominance measure of losses in the *HOM-All* analysis only partially mitigates this issue, as the measure is an imperfect proxy for true utility differences.

In sum, the individual-level patterns complement the market-level evidence and align with the complexity-based explanation, especially in the *IND-All* treatments where variation

[13]Under homegrown preferences, the net evaluation of the complete market reflects both cognitive costs and heterogeneous risk preferences, making individual choice inherently more variable.

in market choice primarily reflects differences in cognitive costs across individuals rather than unobserved preference heterogeneity.

5 Structural Estimation

The previous sections have shown that both the market-level results and the individual-level evidence exhibit systematic patterns in effort, utility losses, subjective ratings and market choices that align with the complexity model in Section 2.3. These findings support the view that the complete market is more complex than the incomplete one. What is still missing, however, is a precise quantification of how much more complex the complete market is.

To do this, we now turn to a structural estimation of the complexity model. This approach serves two additional purposes. First, it enables us to evaluate whether the model can quantitatively account for the patterns observed in the data. Second, it allows us to recover deep parameters, such as the curvature of the cognitive production function and effort costs, which can serve as inputs for calibrating models of financial markets and general equilibrium environments.

Our structural approach focuses on estimating the parameters that are directly related to the production of cognitive effort. Solving the model requires a number of auxiliary inputs, including the agent's risk-preferences. To make the estimation feasible, we exploit the fact that the utility function is known in the *IND* treatment and restrict the analysis to this subset of the data.

The model also requires values for the budget, asset prices and endowments. We calibrate these parameters directly to the values used in the experiment. The variances of prices and endowments are set to the values used to generate them, as described in Section 3.4. The model further requires specifying a default. As before, we assume that all securities have the same price and all states have the same endowment at the default. Under the CRRA utility induced in the lab, the corresponding default portfolio assigns equal quantities to each asset. This is consistent with the data, since the median realized payoffs are close to those generated by such default strategy (Figure 5b).

Next, we specify the parameters of the model described in section 2.3. The cognitive production function follows Gabaix and Graeber (2024):[14]

$$m_i = \max\left\{1 - \left(\frac{L_i}{c} + \phi\right)^{1-\alpha}, 0\right\} \tag{8}$$

with $\alpha > 1$, $c > 0$ and $\phi \geq 0$. Here, α measures the degree of diminishing marginal product of effort, c captures the exogenous micro-complexity of thinking about a single parameter, and ϕ is a shift in the production function.[15]

[14]Gabaix and Graeber (2024) propose two alternative formulations of the cognitive production function, one with $\alpha \in [0, 1]$ and one with $\alpha > 1$. We choose the latter because the first specification rules out that effort is increasing in complexity (Proposition 7 in Gabaix and Graeber, 2024), a key stylized fact of our data.

[15]We assume that all dimensions of the choice problem, namely prices and endowments, have the same micro-complexity $c_i = c, \forall i$ (though different dimensions have different importance weights V_i).

To match the observed variation in market choices and effort across subjects, we introduce individual heterogeneity in the parameters of the model. In principle individuals may differ in any of the model parameters, for example it is conceivable that the micro-complexity c could have an individual-specific component. For tractability and consistency with the analysis in section 2.3, we limit heterogeneity to cognitive effort costs w. We assume the effort cost follows a log-normal distribution across subjects:

$$w \sim LogNormal(\mu_w, \sigma_w^2) \tag{9}$$

where μ_w and σ_w are the mean and standard deviation of $\log(w)$ in our subject pool. Thus, the parameters of the model are $\Theta = \{\alpha, c, \phi, \mu_w, \sigma_w\}$.

We estimate the parameters Θ by the simulated method of moments (McFadden, 1989; Pakes and Pollard, 1989). This technique selects parameter values that minimize the distance between the moments produced by the model ($\Psi^M(\Theta)$) and their corresponding empirical values (Ψ^E):

$$\hat{\Theta} = \arg\min_{\Theta} \left[\Psi^E - \Psi^M(\Theta)\right]' \hat{W} \left[\Psi^E - \Psi^M(\Theta)\right] \tag{10}$$

in which $\hat{W}$ is a positive definite matrix that converges in probability to a deterministic positive definite matrix W. We set the weighting matrix $\hat{W}$ equal to the inverse of the diagonal elements of the variance-covariance matrix of the data moments (Appendix C for details).

To estimate the parameters of the model, we use six moments. The first two moments are the mean effort levels in each of the two markets, L_{com}, L_{inc}. The empirical counterparts are the average response times in those two tasks (measured in seconds). The second two moments are the mean utility losses ℓ_{com}, ℓ_{inc}. The empirical counterparts are average utility losses. The last two moments are the standard deviation of effort (i.e. response time) in the complete market σ_L and the proportion of subjects who choose the complete market χ.

Table 8: SMM Estimates

	α	c	ϕ	μ_w	σ_w
Estimate	1.040	1.800	0.310	-3.860	0.840
Std. Error	0.004	0.387	0.144	0.087	0.011

Table 9: Moments and Moment Conditions

	L_{com}	L_{inc}	ℓ_{com}	ℓ_{inc}	σ_L	χ
Empirical	230.02	90.72	196.57	74.83	229.21	0.23
Theoretical	212.31	113.17	198.80	73.02	213.17	0.19
p-value	0.23	0.96	0.53	0.22	0.31	0.19

Tables 8 and 9 show the estimation results. Estimated parameters are statistically significant at the 1% level, with the exception of ϕ which is significant only at the 5%

level.[16] The model fits the data fairly well, as shown in Table 9: we cannot reject that the predicted moments are statistically indistinguishable from the empirical moments at standard significance levels. Although the model predicts a smaller difference in effort levels across the two markets than in reality, it correctly predicts the complete market will lead to a higher effort level and higher losses than the incomplete market. It also matches the loss levels and the preference for the incomplete market observed in the experiment.

Using the estimated model, we draw three main implications that cannot be obtained from the reduced-form evidence alone. First, the model provides a quantitative measure of complexity. Following Gabaix and Graeber (2024), we construct a macro-complexity measure C that summarizes the overall cognitive difficulty of the portfolio choice problem. Specifically, we derive macro-complexity C as an inverse total factor productivity term, which is given by:

$$C \equiv c \times \left(\sum_{i \in \Omega} s_i^{\frac{1}{\alpha}} \right)^{-\frac{\alpha}{1-\alpha}} \tag{11}$$

where Ω is the set of dimensions with $L_i > 0$, and $s_i = \frac{V_i}{\sum_j^{\mathcal{I}} V_j}$ is the relative importance of dimension i.

Using our estimates of α, c, ϕ and the mean w, we compute the model-based complexity for the two markets and obtain: $C_{\text{complete}} \approx 21$ and $C_{\text{incomplete}} \approx 3$. Thus, the complete market is around seven times more complex than the incomplete market. The increase is far larger than the proportional increase in dimensionality (the number of prices and endowments), which rises from $\mathcal{I} = 18$ in the incomplete market to $\mathcal{I} = 32$ in the complete market. This result highlights that complexity should not be proxied simply by counting the number of dimensions an agent must process.

Second, the model allows us to recover how cognitive effort is allocated across dimensions. We compute the values $\{L_i\}_{i=1}^{\mathcal{I}}$ and find that the subjects devote positive effort to thinking about prices in both markets, but the precision m_i with which each price is processed falls sharply as dimensionality increases (from 11 percent to 6 percent). By contrast, the model predicts zero effort devoted to endowments in both markets: subjects behave as if endowments are constant. This element explains why complexity rises more than proportionally with dimensionality: when all attention is focused solely on prices, then moving from 2 prices to 16 prices represents a dramatic increase in cognitive demands.

Finally, the structural model enables a welfare analysis of different degrees of market completeness. We consider three agents with α, c, ϕ equal to the estimated parameters and with w set to the mean, 5th percentile, and 95th percentile of the estimated distribution of effort costs. Using the parametrization of the two main rounds of our experiment, we vary the number of assets in $J \in \{1, 2, 4, 8, 16\}$ and compute welfare for each type in each market.

As shown in Figure 7, all three types achieve higher welfare in markets with fewer than 16 assets, but extremely coarse structures (one or two assets) are also inefficient. Although

[16] When the shift ϕ is equal to zero, the cognitive production function features a range of effort levels $0 < L_i < c$ such that effort yields no improvement in precision. Thus, a ϕ close to zero strengthens the agent's incentives to put no effort at all in thinking about some dimensions of the problem.

agents with low cognitive effort costs discount the coarsest market structures more steeply than those with higher costs, the welfare-maximizing number of assets remains 4 for all three types. Overall, the structural model indicates that the preference for incomplete markets documented in our experiment is robust across the distribution of cognitive effort costs.

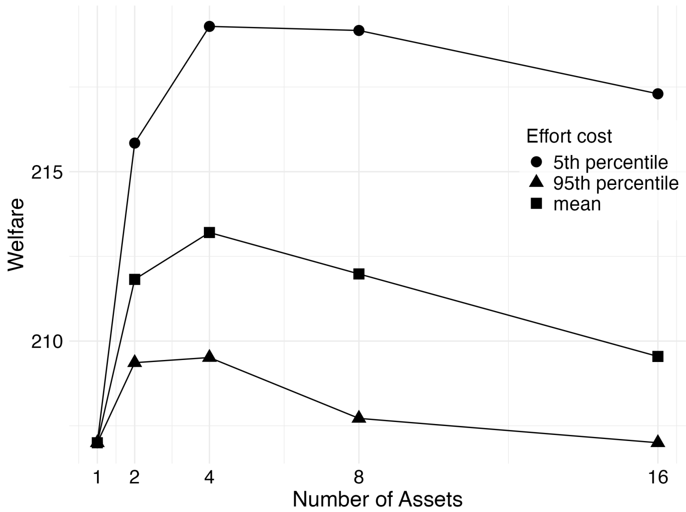


Figure 7: Market Incompleteness and Welfare

6 Conclusion

Our study provides a cognitive foundation for understanding why real-world financial markets remain incomplete even though complete markets are theoretically welfare superior. In a portfolio choice experiment that exposes participants to both complete and incomplete markets, only a minority preferred the complete one. The pattern cannot be explained by regret, temptation, or preference instability. Instead, larger mistakes, longer decision times, higher perceived complexity, and structural estimates all point to cognitive costs as the central mechanism generating a systematic preference for market incompleteness.

Our results point to the role of cognitive costs in shaping the evolution of financial market structure. If investors systematically avoid high-dimensional environments, then security exchanges that compete for participation have limited incentives to offer increasingly complex sets of assets. Market incompleteness may therefore arise as an equilibrium outcome of supply adapting to the cognitive constraints of demand. Our evidence points to a theoretical avenue where competition among exchanges internalizes investors' dislike of complexity, in a way that parallels how firm competition internalizes complexity-averse consumer preferences for sticky prices in Gabaix (2025).

Second, our results suggest that, even within the same market, many investors do not fully exploit the available securities. Only a small share of participants in our experiment take advantage of the additional flexibility offered by the complete-market task—for example, by constructing portfolios that achieve risk–return profiles unattainable in the incomplete market. Most participants instead choose wealth allocations that are nearly identical across the two settings. This pattern indicates that only investors with low cognitive costs are able to capitalize on the full set of available financial opportunities. Such cognitive heterogeneity may widen return dispersion and amplify wealth inequality, even when investors face the same financial technologies and hold similar risk preferences, consistent with empirical evidence (e.g. Fagereng et al., 2020).

Finally, our results also have implications for the design of new markets, such as prediction markets. In prediction markets, participants trade in contracts whose payoff depends on unknown future events, and whose prices aggregate and reveal information about those events (Wolfers and Zitzewitz, 2004). One issue in designing such markets is how to partition the state space into assets. While complete markets are theoretically better at revealing information (as supported by recent experiments like Corgnet et al. (2023), though see Bossaerts et al. (2024) for a counterexample), our experiment suggests that as the number of state-contingent contracts grows, cognitive demands rise sharply and participation may decline. Designers therefore face a trade-off between informational richness and market thickness. As in auction and matching markets design (Li, 2024), simplicity is likely to be an important principle for structuring prediction markets.

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Online Appendix

Behavioral Limits to Complete Markets

This online appendix contains the following sections:

- A Additional Tables and Figures
  - A1 Summary Statistics for Main Rounds by Market Structures
  - A2 Proportion Choosing the Complete Market by Treatment - Full Sample
  - A3 Pairwise Comparisons of Market Choice Across Treatments - Full Sample
  - A4 Median Outcomes by Market Structure - Full Sample
- B Details of the Theoretical Models
  - B.1 Regret Model
  - B.2 Complexity Model
- C Details of the Structural Estimation
- D Analysis of Participants' Written Feedback
- E Experimental Instructions

A Additional Tables and Figures

Table A1: Summary Statistics for Main Rounds by Market Structures

Panel A: 2-Asset Market

Variable	Min	p25	p50	p75	Max	Mean	SD	*N*
Response time	4	27	44	85	867	75	99	384
Complexity	0	23	50	72	100	48	28	384
Uncertainty	0	8	22	40	100	27	25	384
Unspent budget	0	0	6	30	95	18	22	384
Mean wealth	169	208	255	265	312	242	32	384
SD of wealth	54	68	105	117	246	102	38	384
Distinct quantities	1	1	2	2	2	2	0	384

Panel B: 16-Asset Market

Variable	Min	p25	p50	p75	Max	Mean	SD	*N*
Response time	4	71	125	201	2242	167	184	384
Complexity	0	46	62	81	100	59	28	384
Uncertainty	0	11	25	48	100	32	27	384
Unspent budget	0	1	11	45	100	24	27	384
Mean wealth	185	211	260	265	407	252	44	384
SD of wealth	0	67	109	148	1107	143	160	384
Distinct quantities	1	6	10	12	16	9	4	384

Notes: All summary statistics round values to the nearest integer and are computed across participants within each market in the main rounds. 18 participants spent 10 seconds or less, with 16 of these from demo treatments where some subjects may have clicked through rapidly.

Table A2: Proportion Choosing the Complete Market by Treatment - Full Sample

Treatment	**Market choice Complete (%)**	**p-value**
HOM	28.33	0.0000***
IND	21.85	0.0000***
HOM-DEMO	29.51	0.0000***
IND-DEMO	32.23	0.0001***

Notes: This table replicates Table 3 using all participants rather than applying the pre-registered quiz-performance filter. p-values are from two-sided binomial tests assessing whether the proportion choosing market 16 is significantly different from 50%. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Pairwise Comparisons of Market Choice Across Treatments - Full Sample

Treatment1	**Market choice Complete (%)**	**Treatment2**	**Market choice Complete (%)**	**p-value**
HOM	28.33	IND	21.85	0.8430
HOM-DEMO	29.51	IND-DEMO	32.23	0.3743
HOM-All	28.93	IND-All	27.08	0.6364
HOM	28.33	HOM-DEMO	29.51	0.4762
IND	21.85	IND-DEMO	32.23	0.0480**
NO-DEMO	25.10	DEMO	30.86	0.0957*

1. This table replicates Table 4 using all participants rather than applying the pre-registered quiz-performance filter.
2. p-values are from one-sided proportional tests assessing whether the proportion choosing market 16 is significantly greater in Treatment 2 than in Treatment 1.
3. "HOM-All" denotes the pooled sample of HOM and HOM-DEMO treatments.
4. "IND-All" denotes the pooled sample of IND and IND-DEMO treatments.
5. "NO-DEMO" pools HOM and IND treatments.
6. "DEMO" pools HOM-DEMO and IND-DEMO treatments.
7. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Median Outcomes by Market Structure - Full Sample

Variable	**Market Structure** Incomplete	Complete	**p-value**
	HOM		
Loss	0	53	0.0000***
Response Time	43	148	0.0000***
Complexity	54	66	0.0000***
Uncertainty	29	30	0.0280**
	IND		
Loss	81	206	0.0000***
Response Time	48	142	0.0000***
Complexity	56	67	0.0000***
Uncertainty	21	26	0.0000***
	HOM-DEMO		
Loss	2	42	0.0000***
Response Time	31	87	0.0000***
Complexity	50	62	0.0000***
Uncertainty	24	29	0.0044***
	IND-DEMO		
Loss	81	202	0.0000***
Response Time	48	85	0.0000***
Complexity	50	53	0.0581*
Uncertainty	20	20	0.0844*

1. This table replicates Table 5 using all participants rather than applying the pre-registered quiz-performance filter.
2. p-values are from within-subject Wilcoxon signed-rank tests comparing outcomes across the two market structures.
3. Median of each variable is reported and rounded to the nearest integer (exact loss in *HOM*–incomplete is 0.35).
4. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B Details of the Theoretical Models

B.1 Regret Model

In this appendix, we provide details on the numerical solution of the regret model.

First, we repeat the main assumptions. The agent is uncertain about his own risk preferences: with probability 0.5 he is risk-neutral, $U_n(\mathbf{x}) = \frac{1}{S}\sum x_s$, and with probability 0.5 he is maximally risk-averse, $U_a(\mathbf{x}) = \min_s x_s$. Regret is given by:

$$R(M, U, \mathbf{x}) = K \times [U(\mathbf{x}^*) - U(\mathbf{x})]$$

where M is the set of feasible allocations determined by the market structure, $K \geq 0$ and

$$\mathbf{x}^* \equiv \max_{\mathbf{x} \in M} U(\mathbf{x})$$

is the ex-post optimal choice. The ex-ante optimal portfolio solves:

$$\mathcal{W}(M) = \max_{\mathbf{x} \in M} \{0.5 \left[U_n(\mathbf{x}) - R(M, U_n, \mathbf{x})\right] + 0.5 \left[U_a(\mathbf{x}) - R(M, U_a, \mathbf{x})\right]\}$$

Second, we note that the ex-ante optimal choice is either the profile that maximizes U_a or the profile that maximizes U_n. In other words, the ex-ante optimal choice is one of the two ex-post optimal strategies. This holds in both the complete market and the incomplete market. The reason for this is that we can rewrite $\mathcal{W}(M)$ as a linear function of the $\{x_s\}_s^S$ and of an auxiliary variable $m \equiv \min_s x_s$. The ex-ante optimal portfolio choice problem then becomes a linear programming problem in $m, x_1, ..., x_S$. In our parametrization, the agent's ex-ante optimal portfolio strategy is to maximize the minimum of the final wealth profile in both the complete and incomplete markets.

Third, we compute $\mathcal{W}$ under the complete market. The agent's ex-ante optimal portfolio strategy is to maximize the minimum of the final wealth profile policy. This involves full insurance, that is a constant level of final wealth across states, equal to 266. Thus, this strategy yields an ex-post utility $U_a = 266$ when the agent is risk-averse and $U_n = 266$ when he is risk-neutral. The ex-ante optimal strategy is also optimal ex-post if the agent learns that he is in fact risk-averse. If the agent turns out to be risk-neutral, however, the ex-post optimal policy is to sell all securities whose price exceeds the minimum price and use the proceeds (plus the initial budget) to buy the cheapest security(ies). This strategy yields a utility of $U_n = 484$ to a risk-neutral agent. So, the agent's ex-ante optimal portfolio strategy results in a regret of $K \times (484 - 266) = 218K$ if the agent eventually learns he is risk-neutral. Total utility is then:

$$\mathcal{W}(M_{complete}) = 266 - 0.5 \times 218K = 266 - 109K$$

Next, we compute $\mathcal{W}$ under the incomplete market. As before, using the numerical values for the parameters of our incomplete market, we find that the agent's ex-ante optimal portfolio strategy is to maximize the minimum final wealth. The agent achieves this by equalizing wealth across states with the lowest endowment in each block of the partition. This strategy yields an ex-post utility $U_a = 134$ when the agent is risk-averse and $U_n = 258$ when he is risk-neutral. The difference between the two values is due to the fact that there are several states with final wealth above the minimum. As before, this strategy is optimal also ex-post if the agent turns out to be risk-averse. If instead the agents learns that he is risk-neutral, the ex-post optimal policy is again to buy only the cheapest security and sell all others. However, sales of any asset j are now bounded by the lowest endowment in the block of states linked to asset j. As a result, the ex-post optimal policy of a risk-neutral agent only yields $U_n = 288$. Regret in this case is thus $K \times (288 - 258) = 30K$. Total utility is then:

$$\mathcal{W}(M_{incomplete}) = 0.5 \times 134 + 0.5 \times 258 - 0.5 \times 30K = 198 - 15K$$

B.2 Complexity Model

In this appendix, we provide more details on the complexity model. This model is an application of Gabaix (2014) and Gabaix and Graeber (2024).

B.2.1 Formulating the Model

We start by restating the portfolio choice problem:

$$\begin{aligned}
\max_{\{q_j\}_{j=1}^{J}} \quad & U(x_1, ..., x_S) \\
\text{subject to} \quad & x_s = e_s + \sum_j y_s^j q_j \text{ for } s = 1, ..., S \\
& \sum_j p_j q_j \leq e_0 \\
& x_s \geq 0 \text{ for } s = 1, ..., S
\end{aligned}$$

We now focus on an expected utility agent with $U(\mathbf{x}) = \frac{1}{S}\sum_s^S u(x_s)$. We further assume that $\lim_{x\to 0} u'(x) = \infty$, like in our CRRA implementation, so that the non-negativity constraints are always satisfied (with strict inequality) at an optimal choice.

We denote by $\mathbf{z}$ the $\mathcal{I}$ parameters that require mental processing, which we assume to be the asset prices and state-contingent endowments. So, $\mathcal{I} = J + S$. Denote by $U(\mathbf{q}, \mathbf{z})$ expected utility as a function of asset quantities $\mathbf{q}$ and parameters $\mathbf{z}$, obtained after substituting the constraint $x_s = e_s + \sum_j y_s^j q_j$ for each state s. The rational portfolio choice is:

$$\mathbf{q}^r(\mathbf{z}) \equiv \arg\max_{\mathbf{q}} U(\mathbf{q}, \mathbf{z}) \text{ s.t. } \sum_j p_j q_j \leq e_0$$

Parameter z_i is assumed to be drawn from a distribution with variance σ_i^2 and mean z_i^d (the default value). As in Gabaix and Graeber (2024), the parameters are perceived to be independent. We additionally assume that all prices have the same default value and all state endowments have the same default value (as in our experimental design). As in Gabaix and Graeber (2024), the agent does not directly perceive the true parameters z_i, but instead obtains cognitive cues $\tilde{z}_i$ given by:

$$\tilde{z}_i = m_z z_i + (1 - m_i) z_i^d + \sqrt{m_i(1 - m_i)}\varepsilon_i$$

where $m_i \in [0, 1]$ is the endogenous precision of the cognitive cue and ε_i is a mean-zero noise with variance σ_i^2 (in turn, this assumption can be motivated with a model of Bayesian updating). Using the cognitive cues about the parameters, the agent then chooses a portfolio

$$\tilde{\mathbf{q}}(\mathbf{z}) \equiv \arg\max_{\mathbf{q}} U(\mathbf{q}, \tilde{\mathbf{z}}) \text{ s.t. } \sum_j p_j q_j \leq e_0$$

Following Gabaix and Graeber (2024), a second order Taylor expansion gives:

$$E_z[U(\tilde{\mathbf{q}}(\mathbf{z}), \mathbf{z})] \approx U^* - \sum_i V_i(1 - m_i)$$

where $U^* \equiv E_z[U(\mathbf{q}^r(\mathbf{z}), \mathbf{z})]$ and the V_i terms are discussed below.

As in Gabaix and Graeber (2024), the precision m_i is endogenously produced through cognitive effort L_i according to the function:

$$m_i = \max\left\{1 - \left(\frac{L_i}{c} + \phi\right)^{1-\alpha}, 0\right\}$$

with $\alpha > 1$, $c > 0$ and $\phi \geq 0$.

As in Gabaix and Graeber (2024), each unit of effort is assumed to reduce utility by w, so that the agent allocates effort across $i = 1, \ldots, \mathcal{I}$ dimensions to maximize the expected value of utility net of cognitive costs:

$$\mathcal{W} = \max_{L_1, \ldots, L_{\mathcal{I}}} U^* - \sum_{i=1}^{\mathcal{I}} V_i\big(1 - f(L_i)\big) \; - \; w \sum_{i=1}^{\mathcal{I}} L_i$$

B.2.2 Model-Predicted Correlates of Complexity

In this section we show that model-defined complexity predicts several behavioral and subjective outcomes. Gabaix and Graeber (2024)'s model offers an index of complexity C. Here, we assume the complete market has a higher complexity index, $C_{\text{complete}} > C_{\text{incomplete}}$(consistent with our structural estimation of the index), and derive four predictions.

Prediction 1: utility losses will be higher in the complete market
Proposition 7 in Gabaix and Graeber (2024) shows that a higher C decreases performance $Q(L) \equiv \frac{U(L)-U^d}{U^r-U^d}$, where $U(L)$ is realized utility at given total effort L, U^d is utility at default strategy and U^r is (rational) max utility. So, $Q_{\text{complete}} < Q_{\text{incomplete}}$. Utility losses are given by: $loss = (1 - Q) \times (U^r - U^d)$. We have that $U^r_{\text{complete}} > U^r_{\text{incomplete}}$ and $U^d_{\text{complete}} = U^d_{\text{incomplete}}$. Then it follows that $loss_{\text{complete}} > loss_{\text{incomplete}}$.

Prediction 2: effort will be higher in the complete market
Total effort is denoted by L and measured by response time. Proposition 7 in Gabaix and

Graeber (2024) shows that at the optimal solution of the problem $\max_L pQ(L) - wL$, a higher C increases L, under the assumption $\alpha > 1$. The same proposition also shows that L is increasing in the marginal benefit of effort p. The marginal benefit of effort is given by $U^r - U^d$. As before, $U^r_{\text{complete}} > U^r_{\text{incomplete}}$ and $U^d_{\text{complete}} = U^d_{\text{incomplete}}$. Thus, the complete market has not only a higher C, but also a higher marginal benefit of effort. So, assuming $\alpha > 1$, $L_{\text{complete}} > L_{\text{incomplete}}$.

Prediction 3: cognitive uncertainty will be higher in the complete market
This prediction derives from Proposition 6 in Gabaix and Graeber (2024), under our assumption about market complexity.

Prediction 4: subjective ratings of complexity will be higher in the complete market
This prediction derives from Proposition 6 in Gabaix and Graeber (2024), under our assumption about market complexity.

B.2.3 Computation of the Model's Auxiliary Parameters

To compute the V_i terms in our numerical exercises, we use the formula provided in Gabaix (2014) for problems with a budget constraint:

$$V_i \equiv -\frac{1}{2}\mathbf{q}'_{z_i}\mathscr{L}_{qq}\mathbf{q}_{z_i}\sigma_i^2$$

where $\mathscr{L}$ is the Lagrangian:

$$\mathscr{L} \equiv U(\mathbf{q}, \tilde{\mathbf{z}}) + \lambda^d \times \left(e_0 - \sum_j p_j q_j\right)$$

where λ^d is the Lagrange multiplier at the default, and the derivatives $\mathbf{q}_{z_i}$ are computed as:

$$\mathbf{q}_{z_i} = -\mathscr{L}_{qq}^{-1} \cdot \mathscr{L}_{qz_i}$$

All the derivatives are evaluated at the default. To compute the different terms in the V_i expression, we use the utility function we induce in the experiment:

$$U(\mathbf{x}) = \left[\frac{1}{S}\sum_{s=1}^{S}(x_s)^{1-\gamma}\right]^{\frac{1}{1-\gamma}}$$

(in the experiment parametrization $\gamma = 0.2$). Since $U(\mathbf{x})$ is not strictly concave at the default point, in order to compute the derivatives $\mathbf{q}_{z_i}$, we use the rescaled function $\hat{U}(\mathbf{x})$:

$$\hat{U}(\mathbf{x}) \equiv \frac{1}{S}\sum_{s=1}^{S}(x_s)^{1-\gamma}$$

and

$$\hat{\mathscr{L}} \equiv \hat{U}(\mathbf{q}, \tilde{\mathbf{z}}) + \hat{\lambda}^d \times \left(e_0 - \sum_j p_j q_j \right)$$

Then:

$$\mathbf{q}_{z_i} = -\hat{\mathscr{L}}_{qq}^{-1} \cdot \hat{\mathscr{L}}_{qz_i}$$

First, we reproduce the expressions for the complete market. In this case we have the following:

$$(\mathscr{L}_{qq})_{ij} = \begin{cases} (1-S)\frac{y^2}{S^2}\gamma\frac{1}{x^d}, & \text{if } i = j, \\ \frac{y^2}{S^2}\gamma\frac{1}{x^d}, & \text{if } i \neq j. \end{cases}$$

where $x^d = e^d + y\frac{e_0}{S}\frac{1}{p^d}$.

$$(\hat{\mathscr{L}}_{qq}^{-1})_{ij} = \begin{cases} \frac{-S(x^d)^{\gamma+1}}{\gamma(1-\gamma)y^2}, & \text{if } i = j, \\ 0, & \text{if } i \neq j. \end{cases}$$

$$(\hat{\mathscr{L}}_{qp_i})_j = \begin{cases} -\frac{(1-\gamma)(x^d)^{-\gamma}y}{Sp^d}, & \text{if } j = i, \\ 0, & \text{if } j \neq i. \end{cases}$$

$$(\hat{\mathscr{L}}_{qe_i})_j = \begin{cases} -\frac{\gamma(1-\gamma)(x^d)^{-\gamma-1}y}{S}, & \text{if } j = i, \\ 0, & \text{if } j \neq i. \end{cases}$$

Second, we reproduce the expressions for the incomplete market. In this case, the J assets induce a partition $\{\mathcal{S}_1, ..., \mathcal{S}_J\}$ of the state-space. We assume each block $\mathcal{S}_j$ contains the same number M of states (in the experiment $J = 2, M = 8$). Then, we have the following:

$$(\mathscr{L}_{qq})_{ij} = \begin{cases} \frac{M}{S}\left(\frac{M}{S} - 1\right)\frac{y^2\gamma}{x^d}, & \text{if } i = j, \\ \frac{M^2}{S^2}\frac{y^2\gamma}{x^d}, & \text{if } i \neq j. \end{cases}$$

$$(\hat{\mathscr{L}}_{qq}^{-1})_{ij} = \begin{cases} \frac{-S(x^d)^{\gamma+1}}{M\gamma(1-\gamma)y^2}, & \text{if } i = j, \\ 0, & \text{if } i \neq j. \end{cases}$$

$$(\hat{\mathscr{L}}_{qp_i})_j = \begin{cases} -\frac{M(1-\gamma)(x^d)^{-\gamma}y}{Sp^d}, & \text{if } j = i, \\ 0, & \text{if } j \neq i. \end{cases}$$

$$(\hat{\mathscr{L}}_{qe_i})_j = \begin{cases} -\frac{\gamma(1-\gamma)(x^d)^{-\gamma-1}y}{S}, & \text{if } i \in \mathcal{S}_j, \\ 0, & \text{if } i \notin \mathcal{S}_j. \end{cases}$$

C Details of the Structural Estimation

We estimate the parameters $\Theta = \{\alpha, c, \phi, \mu_w, \sigma_w\}$ of the model by the simulated method of moments (McFadden, 1989; Pakes and Pollard, 1989):

$$\hat{\Theta} = \arg\min_{\Theta} \left[\Psi^E - \Psi^M(\Theta)\right]' \hat{W} \left[\Psi^E - \Psi^M(\Theta)\right] \tag{B1}$$

where $\Psi^M(\Theta)$ are the moments produced by model simulation, Ψ^E are their corresponding empirical values , and $\hat{W}$ is a positive definite matrix that converges in probability to a deterministic positive definite matrix W. We set the weighting matrix $\hat{W}$ equal to the inverse of the diagonal elements of the variance-covariance matrix of the data moments, estimated by bootstrapping.

We solve the minimization problem numerically using the simulated annealing method, a probabilistic search method. At a given set of parameter values, we compute the simulated moments for $K = 10$ simulations,[17] each with N simulated individuals, where N equals the number of subjects in our data. The simulated moments are then averaged across the K simulations. Before starting the optimization algorithm, we generate random variables that determines the variation in w (the cost of effort) across the simulated individuals. For each simulation $k = 1, \ldots, K$, we construct a vector Q_k of N independent standard uniform random draws. This vector is held constant for all subsequent estimation steps. The w assigned to simulated individual i in simulation k is then given by: $w_{i,k} = \exp\{\mu_w + \sigma_w \Phi^{-1}[(Q_k)_i]\}$.

Under standard conditions $\hat{\Theta}$ is consistent and asymptotically normal:

$$\sqrt{N}\,(\hat{\Theta} - \Theta) \xrightarrow{d} \mathcal{N}\left(0,\ \frac{1+K}{K}\left(G'WG\right)^{-1}\ G'W\,\Omega\,WG\ \left(G'WG\right)^{-1}\right),$$

where $G = \frac{\partial\ \Psi^M(\Theta)}{\partial\Theta}$ is also computed numerically, and Ω is the variance-covariance matrix of sample moments (estimated by bootstrapping).

[17]Michaelides and Ng (2000) find that $K \geq 10$ delivers good finite-sample performance.

D Analysis of Participants' Written Feedback

(a) Market choice: Incomplete

(b) Market choice: Complete

Figure A1: Word Clouds from Participants' Feedback

At the end of the experiment, participants were given an optional open-ended question asking them to briefly explain why they chose either the 2-asset or the 16-asset market in the final choice stage. The exact instruction shown to participants was:

"If you'd like, you can leave a short comment about the study in the box below (optional, max 400 characters). We are particularly interested in why you chose one task instead of the other."

The 400-character limit applies to characters (including spaces) and corresponds approximately to a short sentence in English. Participants were free to answer in their own words, and responses were not incentivized. A total of 171 non-empty comments were collected. Figure A1 gives a visualization of the language participants use, by participants' market choices.[18] The resulting word clouds indicate that participants who chose the 2-asset market frequently describe it as "easier", "less complex", "simpler", and "quicker", and they also mention budgeting and time. In contrast, participants who chose the 16-asset market more often mention "higher" , "potential" and "payoff", as well as words related to complexity and engagement such as "complexity", "engaging", and "enjoyed".

We also conduct a structured thematic analysis to classify the content of these explanations into interpretable categories. The goal of this exercise is to document the reasoning patterns participants articulate when describing their market choice. We identify 12 themes, shown in Table A5. We split the subjects into two groups based on their market choice and we report the percentage of explanations consistent with each theme within a given group.

Among subjects who choose the incomplete market, the two most frequently mentioned motives are *simplicity* and *enjoyment*. Many participants stated that the 2-asset task was

[18] We remove experiment specific words that carry little information, such as "asset", "task", "study", "option", "choose", and polite closings such as "thank" or "thanks". We then count word frequencies and retain words that appear at least twice.

Table A5: Percentage of Participants' Written Explanations Falling Into Each Theme

Theme	**Description**	**Market Choice** **2 assets**	**16 assets**
Simplicity	Easier, simpler, less complex, manageable	0.36	0.11
Complexity avoidance	Mentions complexity as burden: too complex, difficult, avoided complex option	0.05	0.04
Complexity preference	Mentions complexity as positive challenge or engagement	0.01	0.04
Complexity neutral	Mentions complex/challenging without expressing avoidance or preference	0.09	0.09
Payoff considerations	Higher potential payoff, returns, bonus	0.13	0.27
Time considerations	Time-saving, quicker	0.10	0.07
Risk mentions	Any reference to risk or risky outcomes	0.02	0.04
Control / flexibility	Control, flexibility, diversification	0.02	0.13
Confusion / overwhelm	Confusion or difficulty understanding	0.03	0.02
Budget reasoning	Budget clarity, ease of allocation	0.10	0.02
Enjoyment	Expressions of fun, interest, engagement	0.29	0.29
Preference instability	Mentions regret, temptation, limiting options, smaller menu preference	0.00	0.00

"easier," "simpler," or "less complex," while others described the task as "interesting," "fun," or "engaging."

While subjects who choose the complete market are also likely to mention *enjoyment*, the *simplicity* theme is less prevalent than in the incomplete market choice group. Instead, subjects who choose the complete market are more likely to reference the potential payoff of the task relative to the other and the degree of control or flexibility afforded by the number of assets. Conversely, subjects who choose the incomplete market mention budget clarity and ease of allocation more frequently than those who choose the complete market.

Several other motives appear, although less frequently. Some subjects mention complexity, and in the table we distinguish between complexity avoidance (indicating that the unchosen market was "too complex", "overwhelming", or "difficult"), complexity preference (statements where participants explicitly valued the challenge or engagement of the more complex task) and complexity neutral stances (comments mentioning complexity without expressing either avoidance or preference). Mentions of risk are relatively rare, and importantly, no participant provided explanations consistent with regret avoidance or preference instability (such as limiting one's future temptation or reducing the size of the choice menu).

Overall, the qualitative evidence suggests that subjects' explanations center on perceived simplicity, complexity, enjoyment of the task, and expected payoff, rather than concerns related to commitment or self-control. That said, preference instability may reflect latent motives which individuals reveal in behavior rather than verbalize.

E Experimental Instructions

This appendix reproduces the complete set of interactive instructions used in the *HOM* treatment. The instructions required participants to actively fill in responses as prompted before proceeding to the next section. For the *IND-DEMO* treatment, only the pages containing modified text are shown.

Instruction

HOM Treatment

This study consists of the following parts:

- Instructions
- Comprehension questions
- Three **decision tasks**

If you complete the study, you will receive a guaranteed payment of around $4.

In addition, one out of every four participants will receive a **bonus payment**. The amount of the bonus payment depends on your choices in the decision tasks.

Instructions 1/13

In each decision task, you will receive a budget to trade a specific set of assets.

Your bonus payment will be based on the payoffs you obtain in the decision tasks.

Below, you can see what the decision screen will look like:

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

On the next pages, we'll walk you through each part of the decision screen, step by step.

Instructions 2/13

In each task, you will receive a budget to buy and sell different assets. How much each asset is worth depends on which outcome happens. The possible **OUTCOMES** are highlighted in the example below:

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 3/13

Your screen will show the **PAYOFFS** you can earn in each possible outcome:

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Payoffs are shown in cents. Example: if the payoff for Outcome 5 is 150, this means you will receive 1.5 dollars if Outcome 5 occurs.

When you start a new task, the payoff column shows you the payoff you earn if you do not buy or sell any assets.

Instructions 4/13

In each round, you can trade **ASSETS**. Available assets are displayed to the left of the outcome table on your decision screen as shown below.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 5/13

You can choose a **QUANTITY** you wish to buy or sell for each asset by **typing a number in its box**. You can also increase (or decrease) the quantity of an asset in increments of 0.1 by **pressing the up arrow (or down arrow)** on your keyboard.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 6/13

Each asset is linked to one or more outcomes.

If any of its **LINKED OUTCOMES** occurs, the asset pays a fixed **10 cents per unit**.

On your screen, each asset and its linked outcomes are shown in the **same color**, so you can easily see the connections.

Try changing the quantity of one asset at a time to see how it affects your payoffs in the linked outcomes.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 7/13

In each task, you can buy or sell assets at the **PRICES** shown in the asset table. Prices are per unit and displayed in cents.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 8/13

In each task, you have an initial **BUDGET** to allocate across the available assets. At any time, your remaining budget will be shown below the asset table.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 9/13

To **BUY AN ASSET**, **type a positive number** in its box. You will pay the asset's price multiplied by the quantity you buy, and this amount will be **subtracted from your budget**. Buying an asset **increases your payoff** in the outcomes it is linked to.

To move on from this screen please:

- buy 11 units of Asset 1
- buy 10 units of Asset 2
- buy 9.5 units of Asset 3

Watch how your payoffs change across outcomes and how your remaining budget is updated.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 10/13

To **SELL AN ASSET**, **type a negative number** in its box (for example, -1). You will earn the asset's price multiplied by the quantity you sell, and this amount will be **added to your budget**. Selling an asset **reduces your payoff** in the outcomes it is linked to.

To move on from this screen please:

- buy 62 units of Asset 1
- sell 10 unit of Asset 2
- sell 2.6 units of Asset 3

Watch how your payoffs change across outcomes and how your remaining budget is updated.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Instructions 11/13

SELLING LIMITS: there is a limit to how much you can sell because you cannot have a **negative payoff** in any outcome. So, once you've reached a zero payoff in at least one of an asset's linked outcomes, you **can't sell more** units of that asset.

In the example below, you are selling 3 units of each asset. If you click the Next button, you'll see an error message because your payoffs are below zero.

To continue, **reduce the number of units you're selling** (click on the box and press the up arrow on your keyboard), or **switch to buying** by entering positive numbers. Make sure all your payoffs stay above zero.

Asset	Price	Quantity
1	40	-3
2	53	-3
3	82	-3

Remaining budget

2275.0

Outcome	Payoff (¢)
1	-21
2	173
3	77
4	71
5	120
6	-4

Instructions 12/13

There are three important **BUDGET RULES** to keep in mind:

- **You cannot finish the task with a negative budget.**
- **You cannot finish the task if you have more than 100 left in your budget.**
- You can finish the task if your remaining budget is between 0 and 100.
  However, **any money you don't spend will be lost and won't count toward your payoff.**

In the example below, you are buying 15 units of each asset. If you click the Next button, you'll see an error message because your budget is below zero.

To continue, **reduce your purchases** so that your remaining budget is positive (but close to zero).

Asset	Price	Quantity
1	40	15
2	53	15
3	82	15

Remaining budget

-875.0

Outcome	Payoff (¢)
1	159
2	353
3	257
4	251
5	300
6	176

Instructions 13/13

To compute your **FINAL PAYOFF** in a task, the computer will randomly select **ONE of the possible outcomes**.

Each outcome has the same chance of being selected.

Below, you can see how the computer determines the final payoff by clicking the "Click for a random payoff" button.

Asset	Price	Quantity
1	40	
2	53	
3	82	

Remaining budget

1750

Outcome	Payoff (¢)
1	9
2	203
3	107
4	101
5	150
6	26

Click for a random payoff

Final payoff (¢)

In the real decision tasks, the computer will select the random outcome immediately after you have clicked the "Next" button. You will not see the selected outcome and final payoff until you have completed all tasks.

Your bonus payment will be equal to the final payoff from one of the tasks.

Comprehension questions 1/2

Before continuing with the experiment, please answer the following questions. If you answer all the questions correctly, we will add an extra $1 to your bonus payment.

1. **What happens to your budget when you buy more units of an asset?**

   Your answer:

   ----

2. **What happens to your payoff in the linked outcomes when you buy more units of an asset?**

   Your answer:

   ----

3. **If you have any unspent budget after your asset purchases, what will happen to it when you submit your choice?**

   Your answer:

   ----

4. **How will your bonus payment depend on the payoffs in the round selected for payment?**

   Your answer:

Comprehension questions 2/2

Here are the quiz results.

1. **What happens to your budget when you buy more units of an asset?**

   You answered: A) It decreases. Your answer is right!

2. **What happens to your payoff in the linked outcomes when you buy more units of an asset?**

   You answered: A) It decreases. Your answer is **WRONG** .

   The right answer is: **B) It increases**

3. **If you have any unspent budget after your asset purchases, what will happen to it when you submit your choice?**

   You answered: A) It will be added to your final payoff. Your answer is **WRONG** .

   The right answer is: **C) It will not carry over and will be lost**

4. **How will your bonus payment depend on the payoffs in the task selected for payment?**

   You answered: A) The bonus is equal to a kind of average of the payoffs across all outcomes . Your answer is **WRONG** .

   The right answer is: **B) The bonus is equal to the payoff in one random outcome**

Next, you will complete **three decision tasks**.

At the end, your bonus will be based on one outcome from one of the tasks, both chosen at random.

Each task includes **16 OUTCOMES** and either **2 or 16 assets**.

Decision task 1/3 - Make Your Choices

Asset	Price	Quantity
1	9	
2	7	
3	14	
4	6	
5	15	
6	9	
7	11	
8	14	
9	12	
10	11	
11	10	
12	9	
13	10	
14	13	
15	14	
16	11	

Outcome	Payoff (¢)
1	212
2	83
3	9
4	117
5	212
6	83
7	203
8	288
9	98
10	150
11	215
12	370
13	107
14	341
15	26
16	120

Remaining budget

1750

Decision task 1/3

How CERTAIN are you that your chosen budget allocation is the BEST possible option for you?

(0 = very uncertain, 100 = very certain, click the blue bar to reveal the slider)

0 100

How COMPLEX did you find this task?

(0 = very easy, 100 = very complex, click the blue bar to reveal the slider)

0 100

Next

Decision task 2/3 - Make Your Choices

Asset	Price	Quantity
1	103	
2	72	

Remaining budget

1750

Outcome	Payoff (¢)
1	212
2	9
3	203
4	26
5	98
6	288
7	215
8	341
9	212
10	83
11	150
12	83
13	107
14	370
15	120
16	117

Decision task 2/3

How CERTAIN are you that your chosen budget allocation is the BEST possible option for you?

(0 = very uncertain, 100 = very certain, click the blue bar to reveal the slider)

0 100

Your value: **0**

How COMPLEX did you find this task?

(0 = very easy, 100 = very complex, click the blue bar to reveal the slider)

0 100

Decision task 3/3

The next and final task will be similar—but not identical—to one you've encountered before. Specifically, the number of outcomes will remain the same, while prices, budget and initial payoffs will be randomly drawn from the same probability distribution.

Before proceeding, you must choose the type of decision task for the next page: either one involving 2 assets or 16 assets. To facilitate your choice here is a **summary of the previous two tasks**:

Assets	**16**	**2**
How certain you felt	4	8
How complex it felt	11	5
Time spent (in seconds)	41	44
Lowest possible payoff (¢)	109	103
Highest possible payoff (¢)	470	491
Average payoff (¢)	265	250

Please **CHOOSE THE NEXT TASK**:

Decision task 3/3 - Make Your Choices

Asset	Price	Quantity
1	99	
2	80	

Remaining budget

1790.0

Outcome	Payoff (¢)
1	20
2	174
3	304
4	285
5	220
6	319
7	3
8	341
9	313
10	298
11	216
12	102
13	295
14	138
15	125
16	90

Below are your final payoffs in each task. If you are eligible for a bonus payment, one of the tasks will be randomly selected for payment.

Task	Number of assets	Final payoff (¢)
1	16	207
2	2	491
3	2	385

If you'd like, you can leave a short comment about the study in the box below (optional, max 400 characters).

We are particularly interested in why you chose one task instead of the other.

Feedback

IND-DEMO Treatment

Instructions 13/14

In each decision task, you will see three **EXAMPLE CHOICES**.

These examples show different ways you could distribute your budget across the assets.

You can view an example choice by clicking the "Click for an example choice" button.

Each time you click it, you will see the next example, looping back to the first one after the last.

You can always change the asset quantities yourself, even after trying an example choice.

Asset	Price	Quantity
1	12	-4
2	21	5
3	54	15

Remaining budget

3.0

Outcome	Payoff (¢)
1	92
2	142
3	194
4	223
5	176
6	302

Click for example choices

Instructions 14/14

Your **FINAL PAYOFF** is equal to a special kind of **average of the payoffs** across all outcomes. The formula is:

{1 / (number of outcomes) × [(payoff in outcome 1)$^{4/5}$ + (payoff in outcome 2)$^{4/5}$ + ... + (payoff in last outcome)$^{4/5}$]}$^{5/4}$

Overall, **your final payoff increases when your payoff improves in any outcome**.

As you change your choices, your final payoff will be automatically updated and shown at the bottom of the screen.

Asset	Price	Quantity
1	12	
2	21	
3	54	

Remaining budget

870

Outcome	Payoff (¢)
1	132
2	182
3	144
4	173
5	26
6	152

Final payoff (¢)

Your bonus payment will be equal to the final payoff from one of the tasks.

Decision task 3/3

The next and final task will be similar—but not identical—to one you've encountered before. Specifically, the number of outcome will remain the same, while prices, budget and initial payoffs will be randomly drawn from the same probability distribution.

Before proceeding, you must choose the type of decision task for the next page: either one involving 2 assets or 16 assets. T facilitate your choice here is a **summary of the previous two tasks**:

Assets	**16**	**2**
How certain you felt	9	7
How complex it felt	8	6
Time spent (in seconds)	26	2
Your payoff (¢)	353	172

Please **CHOOSE THE NEXT TASK**:

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