MENTAL CAPABILITIES, HETEROGENEOUS TRADING BEHAVIOUR AND PERFORMANCE IN AN EXPERIMENTAL ASSET MARKET

MENTAL CAPABILITIES, TRADING AND PERFORMANCE

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Abstract

We study how variations in two mental capabilities – analytical capability (quantitative reasoning) and mentalizing (assessing others' behaviour) – drive heterogeneity in evaluations of identical information about an asset's fundamental value and past prices. Our mental framework aligns with regularities observed in experimental asset markets, providing a cognitive basis for heterogeneous trading behaviour. Applied to an experimental market, it predicts that trading, performance and bubble-crash patterns depend crucially on mental capability differences. Traders proficient in both capabilities succeed most, while performance otherwise is non-monotonically in capabilities. Experimental results support these predictions, highlighting the important role of mental capabilities in asset markets.

Key words: Mental Capabilities; Mentalizing; Analytical Capability; Trader Types; Price Bubbles; Asset Markets

JEL-Codes: G41, D91, C91

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1 Introduction

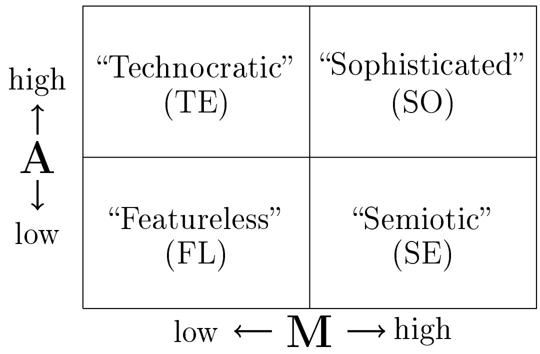
Most of conventional economics has been developed under the presumption that there is no difference between the objectively given information and its mental representation by decision-makers. The assumption of such a homogeneous "all-seeing eye" has been challenged by recent evidence from neuroscience and psychology, showing that there is substantial variation in human perceptions of a given information set (see, e.g., Felin *et al.*, 2017; Chater *et al.*, 2018). In this paper we show that accounting for the cognitive causes of such variations can provide a novel explanation for well-known regularities observed in experimental asset markets: Heterogeneous trading behaviour and transitory exuberant prices.

To develop our framework, we consider a market with a single asset, where traders base their valuations on information about the fundamental value and past prices. The key distinction between fundamental value and past prices motivating our cognitive approach is that the latter are also a consequence of market participants' individual intentions to trade, while the former reflects, e.g., the discounted stream of future earnings, and thus is unaffected by actual trading decisions. Our main proposition is that the same public data may induce heterogeneous behaviour across traders who differ only in two separate mental capabilities: *analytical capability* and *mentalizing*.

Our conjecture is based on research showing that, in general, two different mental traits affect how information with quantitative, logical content is processed, as opposed to information with intentional content. As for the first, we posit that someone's analytical capability ("A"-dimension) affects how information about the evolution of the fundamental value is evaluated. As for the second, people have a known tendency to personify financial markets by attributing intentionality to the market price. Because mentalizing ("M"-dimension) captures how well a person can predict future behaviour from observed intentional behaviour, we surmise that someones mentalizing capability affects how observed price dynamics are evaluated.

Consistent with psychometric research, the two mental capabilities enter our framework as independent cognitive traits. Their intensities determine separately how sensitively a trader's valuation responds to observed changes in fundamental value and price, respectively. According to this *sensitivity property*, a lower capability means a less sensitive response, much like a listener with a weaker hearing capability responds less to finer tones in hearing tests. Using a "low-high"-split for each mental capability, we obtain four *mental types*, each characterized by a specific mental profile (Figure 1). "Sophisticated" types respond sensitively to changes in fundamental value

Figure 1: The four mental types



and price because this type masters the analytical challenges of a problem, and can also detect intentionality in observed behaviour. By contrast, "Technocratic" types score lower in mentalizing, and thus respond less to observed price changes, while "Semiotic" types are lower in analytical capability, and respond less to changes in the fundamental value.[1] Finally, "Featureless" types respond less to changes in both observables.

To isolate the effects of cognitive heterogeneity for trading behaviour and aggregate market outcome, we suppose that differences in mental capabilities, given by the four mental types in Figure 1, are the sole source of trader heterogeneity. In particular, we study a complete information setting where all traders receive identical information about fundamental value and past asset prices. For such a setting our framework predicts the four mental types to exert distinguishable trading dynamics

[1]The name "semiotic" is meant to express the figurative fact that such types predominantly base their choices on "reading intentions" from observed human behaviour.

when fundamental value and market price change their patterns over different market phases.

To make this evident, we consider a Smith *et al.* (1988) (SSW) type of market featuring a constantly falling fundamental value and a bubble-crash pattern of the market price. Such a market has two natural phases, defined by the changing price dynamics. The *pre-peak phase* is characterized by a falling fundamental value paired with an increasing market price. The sensitivity property then implies that technocratic types divest while semiotic types accumulate shares during this phase: Technocratic types are sensitive to the falling fundamental value, but not to the increasing price, while the opposite holds for semiotic types. Sophisticated types respond sensitively to both dynamics, which offsets each other, while featureless types are insensitive to both. Therefore, the valuations of technocratic (semiotic) types must decrease (increase) most relative to the other types, making them net sellers (buyers). A similar rationale shows that sophisticated types divest while featureless types accumulate shares during the *post-peak phase*, featuring a falling price and fundamental value.

The differences in trading behaviour also imply that trading gains can be ranked: Sophisticated types exert the best market timing and achieve the highest trading gains, while semiotic types incur the highest trading losses; technocratic and featureless types range in between. The comparison between featureless and semiotic types entails a striking *non-monotonicity* between mental capabilities and performance: Not being strong in mentalizing is better if one is analytically weak.

Our framework has implications for aggregate market outcome as well. We exemplify, by means of a standard simulation platform, that the characteristic trading behaviour induced by the differential valuations of the four mental types culminates in an endogenous bubble-crash pattern in a market with a falling fundamental value. Beyond explaining trader heterogeneity, our framework thus also offers a cognitive rationale for why price bubbles in SSW experiments are persistently observed, despite that all traders obtain the same market information. Further, magnitude and shape of the price bubble reflect the type composition in a market: If the fraction of traders with high mentalizing capability is increased, a larger bubble with a more extreme crash pattern results; if the fraction of traders with high analytical capability is increased, smaller bubbles result. These findings may help to understand why previous experimental studies have found smaller bubbles in markets featuring more analytically able traders or a less complex dividend structure.

We conduct a laboratory experiment to validate our predictions about type-specific trading and performance. The laboratory gives us the possibility to measure mental capabilities independently from trading behaviour, and offers the necessary control over the decision environment. This allows us to largely isolate the effects of heterogeneous mental capabilities, ensuring that differences in trading behaviour result from asymmetric information processing, and not from asymmetric information or disparities in other characteristics as risk attitudes. The experimental design consists of two independent phases. In the screening phase, we elicit subjects' mental capabilities with separate, incentivized tasks. We use those choices to classify subjects into the four mental types, independent of their later performance in the asset market. In the trading phase, we observe participants' trading decisions in a call market version of SSW.

Our hypotheses could be falsified in several ways. First, we could fail to observe behavioural differences between the four mental types. Such a finding would be consistent with the "all-seeing eye" tradition of economics, where different mental representations of the same information set are irrelevant for choice behaviour. Second, if only a single mental capability matters for choices, or capabilities can substitute each other, then at least two mental types should display an indistinguishable behaviour. For example, if mentalizing plays no role, then we could only distinguish two types along the vertical axis in Figure 1; technocratic and sophisticated as well as featureless and semiotic types should behave identically. The data from our experiment allows us to reject the above two possibilities: We find clear evidence for a distinguishable behaviour of all four mental types, consistent with our theoretical predictions.

The remaining article is structured as follows. Section 2 points out our contribution relative to the literature. Section 3 presents our mental framework and derives its core predictions. We explain our experimental design in Section 4, and present empirical results in Section 5. Section 6 provides a concluding discussion.

2 Related Literature

Exploring the role of mental capabilities in asset markets is a new area of research. Our subsequent discussion focuses on literature related to analytical and mentalizing capabilities.[2] Most studies focus on *analytical capability*, often assessed via IQ scores or Cognitive Reflection Tests. Findings indicate that higher scores correlate with active stock market participation, diversified portfolios, better Sharpe ratios, and higher trading profits.[3] While *mentalizing* – the ability to ascribe intentional behaviour via recognition of behavioural patterns – is considered an important trait for decision-making (Singer and Fehr, 2005), research on its effects is still sparse in economics and finance (Bossaerts *et al.*, 2019; Bosch-Rosa and Corgnet, 2022). However, Bruguier *et al.* (2010); De Martino *et al.* (2013); Corgnet *et al.* (2022); Rotaru *et al.* (2021) show that "Theory of Mind" (ToM) is correlated with the ability to forecast prices by detecting intentionality in human behaviour.

In an experimental study, Corgnet *et al.* (2018) explore how analytical capabilities and ToM affect trader performance in an asset market due to Plott and Sunder (1988).[4] Their findings, demonstrating that the most successful traders excel on both mental dimensions, resonate with our results, indicating a robust complementarity between these capabilities. However, our study departs from theirs in critical ways.

[2]Bosch-Rosa and Corgnet (2022) survey the implications of other cognitive traits for financial markets. See Palan (2013) or Powell and Shestakova (2016) for general surveys on experimental asset markets.

[3]See, e.g., Korniotis and Kumar (2010); Bailey *et al.* (2011); Grinblatt *et al.* (2011, 2012); Corgnet *et al.* (2014); Li *et al.* (2015); Noussair *et al.* (2016); Luik and Steinhardt (2016).

[4]Our conceptualization of mentalizing includes the capacity to interpret and predict intentional behaviour. Consequently, our empirical evaluation encompasses the Heider-Simmel task, whereas Corgnet *et al.* (2018) focus exclusively on the 'Reading the Mind in the Eyes' test.

In Plott and Sunder (1988), traders infer the fundamental value from both private signals and observed market prices, where prices typically gravitate towards the true fundamental value (Corgnet *et al.*, 2021). By contrast, our study requires a setting where all traders obtain identical market information and the price dynamics are non-monotonic. This distinction is pivotal for our objective to dissect trading behaviours across different mental types. If prices approach the fundamental value from below, technocratic types (TE) likely follow this trend by acquiring assets, not for the trend's sake but because they infer a higher fundamental value from it. Conversely, SE traders may perceive the same trend as reflecting a positive market sentiment, leading to similar decisions. This convergence in behaviour between TE and SE contrasts with the divergent pattern our framework predicts in the complete information setting we study. Moreover, while Corgnet *et al.* (2018) explicitly suggest that stronger ToM enhances trading performance, we identify a more nuanced, ambivalent effect of stronger mentalizing capabilities.

Our framework sheds new light on previous empirical findings, particularly regarding the complex interplay between mental capabilities and trading performance. For instance, the non-monotonic relationship we establish between mental capabilities and performance offers insights into why studies sometimes report a null effect of mentalizing on performance (Corgnet *et al.*, 2020; Farago *et al.*, 2022). Our data would also indicate such a null effect if we did not account for heterogeneous analytical capability. Furthermore, our approach can explain the variations in price dynamics observed in prior studies when market complexity or type composition changes. Lei *et al.* (2001) and Kirchler *et al.* (2012) link mispricing to subject confusion due to market complexity or specific design features like a falling fundamental value. Similarly, studies by Bosch-Rosa *et al.* (2015), Breaban and Noussair (2015), Hanaki *et al.* (2015), and Akiyama *et al.* (2017) find that price volatility diminishes in markets populated by more analytically capable subjects. These findings are consistent with our framework, which predicts that a greater proportion of analytically skilled traders tends to mitigate the bubble dynamics.

Overall, our paper presents the first framework and experimental evaluation examining how heterogeneity in mentalizing and analytical capabilities influences trading behaviour, performance, and market outcomes through differential mental information processing. Diverging from previous studies that categorized trader types ex-post based on trading data, our methodology allows for an independent classification of mental types and out-of-sample tests of our main predictions.

Predicted Trader Types Our paper differs from previous explanations of disequilibria phenomena by offering a unified mental framework that yields a cognitive rationale for heterogeneous trading behaviour. Nevertheless, it is notable that some of our predictions resemble those exogenously attributed to various trader types.

Our sophisticated type (SO) aligns with the "rational-speculators" as introduced in De Long *et al.* (1990); Haruvy and Noussair (2006); Baghestanian *et al.* (2015), known for their strategic, profitable sales in response to a shifting price momentum. In Haruvy and Noussair (2006), such speculators are distinguished by their unique capacity to form rational expectations about future prices. In contrast, our approach differentiates SO not by an exclusive trait, but through a common mental model of the asset market, where variations arise solely from differences in mental capabilities. The "bubble-riding" behaviour of SO occurs because this is the only mental type to react comparably sensitively to fundamental value and market price.

Technocratic types (TE) are net sellers during the pre-peak phase of the market we study, reminiscent of "fundamentalists" or "passive investors" in Haruvy and Noussair (2006) or Baghestanian *et al.* (2015). However, unlike these predefined trader types, where selling is an exogenous response to prices exceeding fundamental values, TE's early exit is driven by their subdued sensitivity to price momentum. This behaviour reflects TE's limited mentalizing ability, making them less adept at recognizing and reacting to behavioural price trends.

Semiotic types (SE) show a trading style akin to "feedback-" or "momentum-traders" as described by De Long *et al.* (1990); Haruvy and Noussair (2006), known for their trend-chasing behaviours. This tendency of SE emerges because their mentalizing ability allows them to detect the price momentum fueled by other traders' behaviour while their weaker analytical skills blind SE to changes in fundamental value.[5]

The Featureless type (FL) is distinguished by minimal responsiveness to both price and fundamental value changes. Rather than trading erratically, FL types tend to accumulate shares in the post-peak phase. This behaviour resembles the one of "noise traders" (Black, 1986; Baghestanian *et al.*, 2015), who act as liquidity providers during sell-offs. Nevertheless, the rationale behind FL's behaviour differs significantly. Whereas noise traders follow predefined trading patterns, the behaviour of FL reflects that this type has the least sensitive valuations among all mental types.

3 Mental Calibrations and Trading Behaviour

In this section, we lay out our mental framework, focusing on its implications for asset trading, performance, and market outcomes. Section 3.1 details the relationship between mental capabilities and individual asset valuations. Subsequently, Section 3.2 formulates our core hypotheses about the behaviour and performance of the four mental types from Figure 1. Section 3.3 demonstrates that the interaction of these mental types can lead to the formation of price bubbles, including an exploration of how variations in type composition affect the market dynamics.

3.1 Mental Framework

Consider a market for a single asset, freely tradable over a series $t = 1, 2, ...$ of trading periods. The asset is defined by an objective, exogenously determined fundamental value F_t. Further, P_{t-1} denotes the last observed price (i.e., P_{t-1} is the market-clearing price from period $t-1$). To capture market dynamics, we define $\Delta F_t \equiv F_t - F_{t-1}$ and $\Delta P_{t-1} \equiv P_{t-1} - P_{t-2}$ as the recent changes in these two key observables. Consequently, the pair $(\Delta F_t, \Delta P_{t-1})$ encapsulates the latest market data available in

[5]SE types resemble technical analysts in their focus on price momentum. However, technical analysts often employ sophisticated analytical tools such as long-run moving averages or Bollinger bands to deduce fundamental values. We are grateful to an anonymous referee for this insightful remark.

period t.[6] Throughout our analysis we assume that this data is equally accessible by all traders.

3.1.1 Mental Capabilities and Valuations

At the outset of each trading period t, each trader i develops a conjecture V^i_{t+1} regarding the asset's future valuation, based on the latest market data $(\Delta F_t, \Delta P_{t-1})$. The key novelty of our model is that traders' valuations respond differentially sensitively to changes in fundamental value and last price. This is premised on the idea that ΔF_t and ΔP_{t-1} encapsulate different types of information, necessitating distinct mental capabilities for processing: *Analytical Capability* (A) and *Mentalizing* (M).

Firstly, ΔF_t reflects changes in the asset's objective, intrinsic value and is independent of market participants' trading behaviours. Accurately assessing ΔF_t requires analytical and quantitative processing, like analyzing business reports or financial statements.[7] Prior research has demonstrated that analytical capability is a critical and variably distributed human trait essential for tasks involving quantitative processing, logical reasoning, and stochastic analysis (see e.g. Baghestanian *et al.*, 2015; Corgnet *et al.*, 2018; Bosch-Rosa and Corgnet, 2022). Consequently, we propose that a trader's *analytical capability* determines how the valuation V^i_{t+1} depends on ΔF_t.

Secondly, the evolution of the market price ΔP_{t-1} reflects the collective evaluations of all market participants. Previous research indicated that traders often perceive market prices as representing an intentional agent, encapsulating the "market sentiments" of all traders (Bossaerts *et al.*, 2019).[8] In light of such personification, we conjecture that a trader's reaction to ΔP_{t-1} is related to her ability to predict intentional behaviour. This ability is understood to depend on two sub-traits: i) recognizing and identifying others' intentions ("perspective-aking"), and ii) developing a working model of the ensuing behaviour ("online simulation"); see e.g. Reniers *et al.*

[6] The significance of $(\Delta F_t, \Delta P_{t-1})$ in trading decisions is well-established; see e.g. Hellwig (1980); Kyle (1985, 1989).

[7] In the experiment, subjects needed to deduce F_t from the dividend structure of the asset.

[8] This tendency aligns with a broader human pattern of attributing intentions, such as desires, preferences, or beliefs, to entities that may actually lack them (Dennett, 1987).

(2011); Quesque and Rossetti (2020); Schurz *et al.* (2021).[9] Combining these insights, we posit that a trader's *mentalizing capability*, encompassing these sub-traits, determines her reactions to observed price changes.[10]

3.1.2 Sensitivity and Stimulus Response

We conceptualize the above discussion by proposing that the valuation V_{t+1}^i of a trader endowed with stronger analytical (mentalizing) capability responds more sensitively to changes in the fundamental value (the market price), much like listeners respond to finer tones the better their hearing capacities. This *sensitivity property* implies that valuations are capability-depending calibrations of a common mental model. Operationalizing this notion, we posit that A and M determine separately how traders' valuations deviate from a common market assessment $\bar{V}_t$. This deviation is modulated by an update function λ_t^i, such that $V_{t+1}^i = \bar{V}_t + \lambda_t^i$. The update function is

$$\lambda_t^i = \varphi_P(\Delta P_{t-1}, c_M^i) + \varphi_F(\Delta F_t, c_A^i) + \varepsilon^i, \tag{1}$$

where $c_A^i, c_M^i > 0$ represent the analytical and mentalizing capability of trader i, respectively, and ε^i is an iid zero-mean error term.[11] The functions φ_P, φ_F quantify how traders with different capabilities update their valuations following changes in price or fundamental value. We normalize these functions by requiring that they map through the origin ($\varphi_F(0, c_A) = \varphi_P(0, c_M) = 0$); zero changes induce zero updates. How sensitively a trader updates her valuation following a change in fundamental value or price is captured by the *stimulus-response coefficients*, amounting to the

[9]The social cognition literature uses various terms related to our concept of mentalizing, such as Theory of Mind or Empathy; see the discussion in Section 4.1 and the survey by Schurz *et al.* (2021).

[10]Also see Bruguier *et al.* (2010) or Corgnet *et al.* (2022) who observe that Theory of Mind measures correlate with forecasting errors about market prices. Further, Bruguier *et al.* (2010) document that analytical capability is not related to the ability to correctly predict asset prices, and Janssen *et al.* (2015) find no correlation between "Cognitive Reflection" and behaviour in a speculation task.

[11]Consistent with the stochastic nature of mental representations (Wei and Stocker, 2015), we consider updates λ_t^i as random variables, with ε^i accounting for possible non-capability-related effects. Only the systematic part of λ_t^i, defined by the φ-functions, will matter for our predictions. Further, we restrict attention to the latest changes in price or fundamental for simplicity (longer lags turn out to be insignificant).

first derivatives[12]

$$\alpha_F^i \equiv \frac{\partial \varphi_F(\Delta F_t, c_A^i)}{\partial F_t}, \qquad \alpha_P^i \equiv \frac{\partial \varphi_P(\Delta P_{t-1}, c_M^i)}{\partial P_{t-1}}. \tag{2}$$

Our central assumption – the *sensitivity property* – posits that these coefficients are *increasing* with the respective mental capability:[13]

$$\frac{\partial \alpha_F(\Delta F_t, c_A)}{\partial c_A} > 0, \qquad \frac{\partial \alpha_P(\Delta P_{t-1}, c_M)}{\partial c_M} > 0. \tag{3}$$

This implies that, e.g., traders with higher mentalizing capabilities exhibit stronger reactions to shifts in P_{t-1}, ceteris paribus (i.e., for given P_{t-2}). The main consequence of the sensitivity property is that the response functions φ_P, φ_F must be ordered by capability levels, as exemplified in Figure 2.[14] The intuitive concept of the sensitivity property finds theoretical support in models of imperfect information processing: Utilizing signal extraction theory, detailed in Appendix A.1, we demonstrate that enhanced mental capabilities lead to more sensitive responses as in (3). This foundation not only substantiates the sensitivity property, aligning with our illustrative hearing analogy, but also guides the functional form of the φ-functions as conditional expectations that embody all our proposed properties.[15]

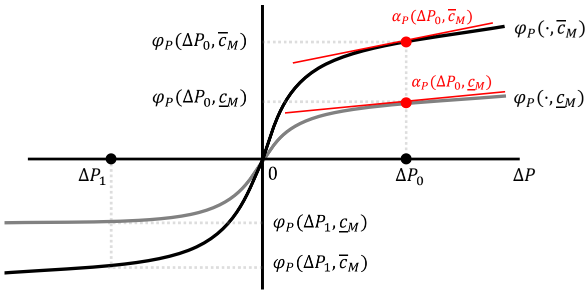


Figure 2: Updating Function φ_P for different mentalizing capability
A lower mentalizing capability $\underline{c}_M < \bar{c}_M$ leads to a clock-wise rotation of the updating function φ_P around zero. The single-crossing property at zero follows from the sensitivity property (3) and $\varphi_P(0, c_M) = 0$.

[12] Note that $\frac{\partial \varphi_F(\Delta F_t, c_A^i)}{\partial F_t} = \frac{\partial \varphi_F(\Delta F_t, c_A^i)}{\partial \Delta F_t}$ by the rules of differentiation (similarly for α_P^i).

[13] Equivalently, φ_F, φ_p are strictly supermodular in $(\Delta F, c_A)$ and $(\Delta P, c_M)$.

[14] The assumptions on the φ-functions have asymptotic implications. The function $\varphi_P(\Delta_P, c_M)$ asymptotically approaches a limit function $\hat{\varphi}_P(\Delta P)$ as $c_M \to \infty$; see Appendix A.1. We interpret this limit as an "ideal update" from a hypothetical infinitely capable brain that represents the best mental calibration resulting from observing many iterations of one and the same asset market.

[15] Our model implies that it is optimal to listen less carefully to information that is harder to comprehend, given the available mental capability. This perspective aligns with recent literature exploring how various behavioural patterns can be explained through models of limited information processing, see e.g., Wiederholt (2010); Gabaix (2018); Hefti *et al.* (2022).

3.2 Asset Trading and Performance: Main Predictions

We derive our hypothesis about trading behaviour and performance within the context of a complete information setting, assuming that traders differ only in their mental capabilities. To make the implications of heterogeneous capabilities most salient, we distinguish between two capability levels ("low" and "high"), denoted as $c_H \in \{\underline{c}_H, \bar{c_H}\}$ with $\underline{c}_H < \bar{c_H}$ for $H \in \{A, M\}$. Then, the four combinations of (c_A, c_M) yield the four mental types from Table 1: $(\underline{c}_A, \underline{c}_M)$ FL (featureless), $(\underline{c}_A, \bar{c}_M)$ SE (semiotic), $(\bar{c}_A, \underline{c}_M)$ TE (technocratic), $(\bar{c}_A, \bar{c}_M)$ SO (sophisticate).

3.2.1 Stimulus Response

By (3), each of the four mental types θ has a unique pair of stimulus-response coefficients $(\alpha_F^\theta, \alpha_P^\theta)$, aligned with their respective "low" and "high" capability levels. The "off-diagonal" types TE and SE, shown in Table 1, each share one capability level with SO, while TE and SE display the most disparate response patterns. This leads to our Stimulus-Response Hypothesis.[16]

($\mathbf{H_{SR}}$) Stimulus-Response Hypothesis

a) $\alpha_F^{TE} = \alpha_F^{SO}$ and $\alpha_P^{SE} = \alpha_P^{SO}$.

b) $\alpha_F^{TE} > \alpha_F^{SE}$ and $\alpha_P^{SE} > \alpha_P^{TE}$.

3.2.2 Asset Accumulation and Exit Timing

Trading in each period t reflects differences in valuations V_{t+1}^i across traders, where those with the highest (lowest) average valuations typically become net buyers (sellers). Over time, even small, systematic valuation differences among mental types can result in significant divergences in portfolios during certain market phases. This divergence becomes most evident in markets exhibiting bubble-crash dynamics, as these are marked by distinct market phases with characteristic patterns of $(\Delta F_t, \Delta P_{t-1})$. A key example is the experimental asset market with a constantly falling fundamental

[16]Our hypotheses also hold under the milder condition that mental capabilities are not overly substitutable for producing mental evaluations; see Appendix A.2.

value, pioneered by Smith *et al.* (1988) (SSW). We base our main predictions for the four mental types on this well-studied setting.[17]

Trading in the two Market Phases A market with a price bubble and a falling fundamental value can be divided into two market phases, split by the price peak (the period with the highest price). The characteristic patterns of $(\Delta F_t, \Delta P_{t-1})$ within these phases have specific implications for the type-wise portfolio dynamics.

In the *pre-peak phase*, marked by a falling fundamental jointly with a rising price, TE and SE display contrasting trading patterns. TE, primarily influenced by the fundamental value, obtain the lowest valuations because SO and SE are also sensitive to the increasing price, while FL does not account for the falling fundamental value. Likewise, SE becomes the net buying type, because SE is the only type sensitive to the increasing price but not to the declining fundamental value. In the *post-peak phase*, characterized by both falling price and fundamental value, all types experience decreasing valuations. SO, being most responsive to both factors, is most likely to sell, while FL, the least responsive, residually emerges as the net buying type.

This leads to a hypothesis of *mutually reversed accumulation patterns*: TE and SE show opposite behaviours in the pre-peak phase, and FL and SO in the post-peak phase. We summarize this observation in the following hypothesis, where A^θ denotes the amount of assets held by a type θ.[18]

($\mathbf{H_A}$) Asset Accumulation Hypothesis *The type-wise asset holding evolves according to Table 1.*

Market phase	A^{FL}	A^{SE}	A^{TE}	A^{SO}
pre-peak	-	$\uparrow$	$\downarrow$	-
post-peak	$\uparrow$	-	-	$\downarrow$

Table 1: Type-wise asset accumulation hypothesis
The "-" in Table 1 mean that our framework does not yield a definite prediction about asset accumulation of the corresponding type.

[17] See Palan, 2013 for a comprehensive survey. While our analysis focuses on the SSW setting, our framework's applicability extends beyond it, as illustrated in Appendix A.2.

[18] Appendix A.3 derives these claims formally.

Exit Timing Based on the above analysis, we anticipate SO to demonstrate the best exit timing, initiating sales when the asset's overpricing relative to its fundamental value is at its highest. The overpricing is maximal at the *bubble peak* – the period with the largest difference between market price and fundamental value.[19] To see the rationale behind SO's superior market timing, recall that TE are net sellers during the pre-peak phase, and thus divest prematurely. As the price nears its peak, ΔP_{t-1} approaches zero and gradually turns negative towards the bubble peak. During this transition, the falling fundamental value emerges as the dominant factor influencing selling decisions, which is recognised by SO, but not by FL and SE. Therefore, valuations of SO become lower than those of SE and FL, prompting SO to initiate a sell-out around the bubble peak.

($\mathbf{H_T}$) Exit Timing Hypothesis *SO have the best exit timing of all four types.*

3.2.3 Mental Capabilities and Performance: A non-monotonic Ranking

The divergent trading patterns of the four types have significant implications for the distribution of the trading gains. SO achieves the best exit timing and thus is anticipated to earn the highest trading gains among all types. Conversely, FL, being least sensitive to market information, might be expected to incur the most significant losses. However, our framework reveals a more intricate, non-monotonic relationship between mental capabilities and trading performance.

To see this, note that TE earns less than SO due to their premature divestment in the pre-peak phase. Their reduced price sensitivity, while limiting gains, also protects them from substantial trading losses as they do not buy shares once prices rise above the fundamental value in the pre-peak phase. By contrast, SE's higher price sensitivity, combined with lower responsiveness to ΔF_t, results in trading losses: SE accumulates shares in the pre-peak phase, which either cannot be sold later, or only at significant losses.

The comparison between SE and TE underscores that strengths in one mental

[19] With a constantly falling fundamental value, the bubble peak occurs after the price peak.

dimension cannot offset weaknesses in the other in the SSW setting we study. In fact, mental capabilities and performance are non-monotonically related, as the predicted behaviour of FL indicates. In particular, FL incurs less losses than SE because FL is less prone to purchasing those overpriced shares during the pre-peak phase, which SE cannot later sell profitably However, FL tends to forgo some trading gains relative to TE, because FL is less likely to sell shares during the pre-peak phase, but also tends to buy shares post-peak, with prices possibly still above the fundamental value.

In sum, the comparison of SE and FL demonstrates that a lack of mentalizing can be advantageous if analytical capabilities are also limited. Conversely, strong mentalizing capabilities are beneficial when complemented by strong analytical skills, as the comparison between TE and SO reveals.

($\mathbf{H_G}$) Trading Gains *SO makes the highest trading gains, and SE incurs the highest trading losses. In addition, TE does not incur trading losses, and FL realizes less trading gains than TE.*

3.3 Endogenous Price Dynamics

Besides offering differential trading patterns, the behaviour of the four mental types contributes to understanding the progression of the bubble-crash pattern within the market setting we study. To substantiate this, we integrate our mental framework into a pre-established call market simulation (Baghestanian *et al.*, 2015). Our main change is to replace the three exogenously defined trader types – "speculator", "fundamentalist" and "noise trader" – by Baghestanian *et al.* (2015) with the valuations of our four mental types. Specifically, we implement a linear updating function (1),

$$\lambda_t^\theta = \alpha_F^\theta \Delta F_t + \alpha_P^\theta \Delta P_t \tag{4}$$

for $\theta \in \{TE, SE, SO, FL\}$.[20] Systematic trader heterogeneity in our simulation is exclusively determined by the *stimulus-response coefficients* $\alpha_F^\theta, \alpha_P^\theta < 1$, as specified

[20]A linear specification matches with the regression framework we use in Section 5.1, and is implied by the signal-extraction model we study in Appendix A.1.

in (4) and aligned with the ordinal requirements of $\mathbf{H_{SR}}$.[21] Without this heterogeneity, traders would become stochastic clones of a single mental type, precluding the formation of price bubbles.[22] While $\alpha_F^\theta, \alpha_P^\theta$ might exhibit variation among real traders, we decided to keep them constant across all simulated traders. This approach aims to reduce stochastic noise in the simulation, thereby allowing a focused examination of the core dynamics specific to each mental type.

Each simulated trader i is one of the four types, and trades according to her valuation V_{t+1}^i. To allow for trading of multiple units, we follow Baghestanian *et al.* (2015) and split each period t into $S = 4$ consecutive *trading rounds*. In each trading round, traders can submit a buy and a sell order for a single unit of the asset. To obtain these orders, we generate bid-ask-spreads for each trader based on her period valuation V_{t+1}^i. We span these spreads around V_{t+1}^i with a standard inventory cost approach that calculates the value of acquiring or selling an additional unit of the asset. If trader i holds q_{ts}^i units of the asset and cash c_{ts}^i (both non-negative) at the beginning of a trading round s of period t, the simulated orders are as follows: If $c_{ts}^i > 0$, trader i places a buy order $B_{ts}^i = \min\{V_{t+1}^i - \delta(q_{ts}+1)^2, c_{ts}^i\}$ corresponding to the lesser of her willingness to pay or her current cash c_{ts}^i. If $q_{ts}^i > 0$, she issues a sell order $A_{ts}^i = V_{t+1}^i - \delta(q_{ts}-1)^2$ corresponding to her willingness to accept an additional unit of the asset.[23] The parameter $\delta > 0$ determines the size of the bid-ask-spread and can be interpreted as sensitivity to portfolio risk.[24] The call market price P_{t-1} at the end of period $t-1$ is obtained from the simulated bids and asks as in Baghestanian *et al.* (2015), and represents the average price over the four trading rounds in period $t-1$ (see Appendix A.4 for details).

Consistent with our experimental design, we simulate markets with 16 traders over 15 periods. Each trader is initially endowed with a random portfolio of shares and

[21]The constraint $\alpha_F^\theta, \alpha_P^\theta < 1$ is implied by the optimal information processing framework (see Appendix A.1) and prevents positive feedback loops and runaway dynamics.

[22]For example, a static no-trade equilibrium ensues when the error term ε^i in (1) is set to.

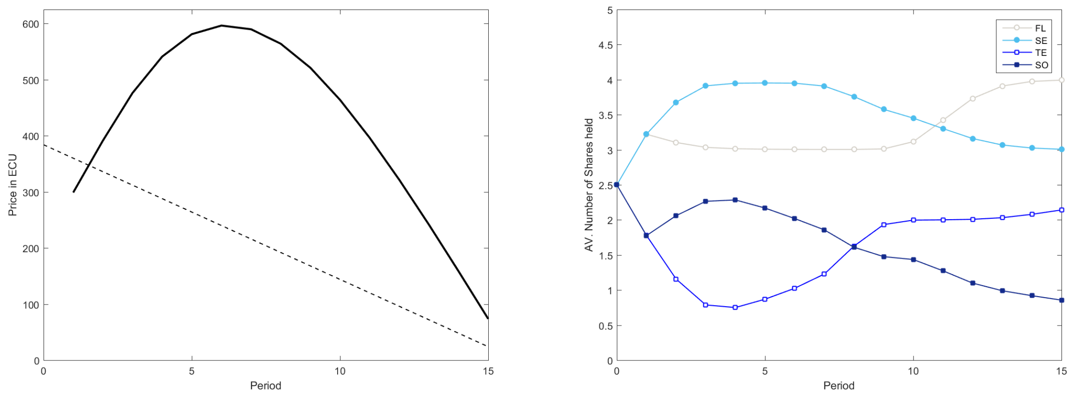
[23]Note that buy orders are feasible as traders cannot bid more than their available cash. Similarly, short selling and debt-financed purchases are excluded by setting $A_{ts}^i = \infty$ for $q_{ts} = 0$ and $B_{ts}^i = -\infty$ if $c_{ts}^i = 0$. These assumptions are consistent with the trading rules of our experimental asset market.

[24]See, e.g., Glosten and Harris (1988); Biais *et al.* (2005). The quadratic formulation reflects increasing risk with more assets held and smoothens trading and price curves in the simulation.

cash.[25] Figure 3 depicts a simulated outcome featuring equal representation of all four mental types, corresponding to the empirically relevant scenario in our study.[26] Beyond the evident Bubble-Crash pattern, the portfolio dynamics also display the

Figure 3: Call Market Simulation with all four mental types

(a) Price Bubble with four mental types (b) Portfolio Dynamics



Average of 10,000 simulated outcomes. LEFT: market price (solid line) and fundamental value (dashed line). RIGHT: average portfolio dynamics of the four types. This specific simulation was parametrized as follows: $\alpha_F^{TE} = \alpha_F^{SO} = 0.95$, $\alpha_F^{SE} = \alpha_F^{FL} = 0.05$, $\alpha_P^{SE} = \alpha_P^{SO} = 0.60$, $\alpha_P^{TE} = \alpha_P^{FL} = 0.45$, $\delta = 2.5$, $\varepsilon_i \sim U(-6, 6)$ and $V_{t+1}^i = \bar{V}_t + \lambda_t^i$ with $\bar{V}_t = 0.9P_t + 0.35F_t$.

variations qualitatively predicted by $\mathbf{H_A}$. Notably, during the pre-peak phase, TE and SE exhibit a striking divergence in portfolios, contrasting with the more stable dynamics of SO and FL.

The Bubble-Crash pattern in Figure 3 is driven by the distinct responses of various mental types. This pattern remains qualitatively consistent across different parametrizations, as the following argument elucidates. SE traders, not fully accounting for a declining fundamental value, extrapolate an initial price increase ($\Delta P_1 > 0$). This leads them to acquire shares, which further escalates market prices.[27] However,

[25]Four distinct portfolios were assigned to four traders each, ensuring 40 shares in total circulation: 1 share and 2228 cash; 2 shares and 1956 cash; 3 shares and 1684 cash; 4 shares and 1412 cash. The portfolios were randomly allocated to participants and hence independent of mental types. Every trading period ends with a randomly chosen dividend payment per asset unit from $\{0, 8, 28, 60\}$.

[26]Trading starts at $t = 1$, and the simulation begins with the following initial conditions: We set pre-trading values $\Delta F_1 = \Delta P_0 = 0$, where the latter reflects the absence of an a priori expectation for a systematic price trend, a phenomenon experimentally verified by (Palan, 2013). Further, P_1 is an iid draw from $U(0, 450)$ for each trader. This assures: i) the simulation is not biased by a commonly shared initial price, and ii) the possibility for some traders to expect an initial price higher than the average dividend ($= 360$).

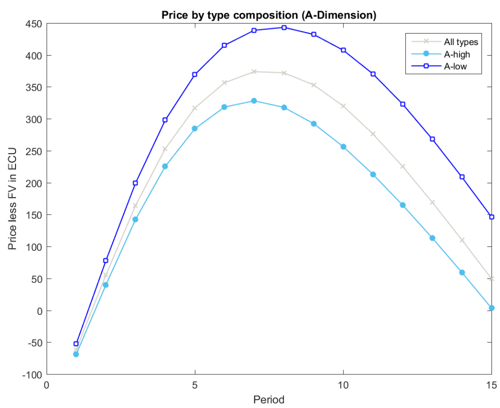
[27]The initial price rise is attributed to shared pre-trading beliefs regarding ΔF_1 and ΔP_0 in our simulation.

the valuation increase for SE is moderated ($\alpha_P^{SE} < 1$), leading to a gradual deceleration of the price increases. Unlike SE, SO are also sensitive to the negative trend in ΔF_t. Therefore, the slowdown in the price increase eventually leads SO to sell, which reverses the price trend and culminates in the Bubble-Crash pattern.[28]

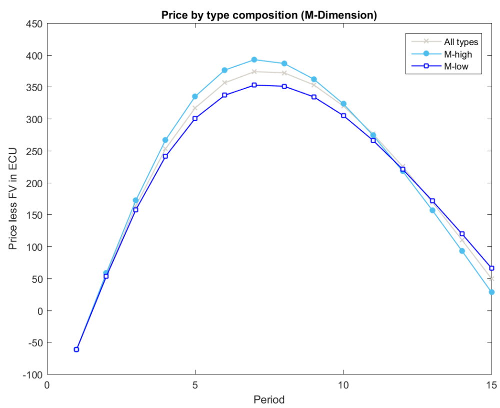
Market Composition Effects Figure 3 shows the price trajectory in the benchmark case where all four mental types are present in equal proportions. Nevertheless, the price dynamics, resulting from the collective valuation trajectories of all traders, are likely to be influenced by the composition of mental types in the market. Markets with a higher proportion of the analytically high types TE and SO tend to be more responsive to changes in fundamental value and less prone to the "trend-chasing" behaviour typical of SE traders. This suggests a smaller price bubble that bursts earlier compared to markets with a balanced mix of all four types. Conversely, markets dominated by traders with high mentalizing capabilities (SE and SO) are more sensitive to price trends, potentially leading to sharper rise-crash patterns.

Figure 4: Bubble formation by type composition

(a) Split along the A-Dimension



(b) Split along the M-Dimension



Average bubble component (= market price less the fundamental value), for 10'000 simulations, using the same parametrization as Figure 3. Gray lines represent cases where all four mental types are equally present. LEFT: A-high markets (light blue) feature mainly TE and SO types, while A-low (dark blue) feature mainly SE and FL types. RIGHT: M-high markets (light blue) feature mainly SE and SO types, while M-low (dark blue) feature mainly TE and FL types.

[28]The falling fundamental value matters as the bursting of the bubble is contingent on increased selling pressure. This becomes predominant once the positive price trend subsides. Further, variations in the stimulus-response coefficients' magnitudes affect the exact quantitative trajectories in the simulated dynamics. Specifically, decreasing the high-low difference in both coefficients tends to harmonize the portfolio dynamics across all four mental types.

Our simulation framework can visualize these intuitive patterns. Panel (a) of Figure 4 shows how the price bubble (i.e., price minus fundamental value) changes if we increase the number of the analytical high types TE and SO from 4 to 7 traders each (light blue curve), such that there are only 1 SE and 1 FL type in the market (maintaining a total of 16 traders). By contrast, the dark blue line is the price path if we increase the number of analytical low types SE and FL to 7 traders each. The figure shows that reducing the amount of analytical high types in a market amplifies the bubble, relative to a balanced market (gray line). This observation aligns with prior empirical research indicating that greater analytical capability in a market correlates with smaller bubbles and reduced price volatility (see e.g. Bosch-Rosa *et al.*, 2015; Breaban and Noussair, 2015; Hanaki *et al.*, 2015; Akiyama *et al.*, 2017). Panel (b) of Figure 4 examines the role of mentalizing. A reduction in the fraction of traders with high mentalizing capability (SE and SO) mitigates the bubble. By contrast, an increased presence of these types results in a larger bubble and a more pronounced crash, as evidenced by the intersections of the respective curves.

4 Experimental Design

We conduct a laboratory experiment to test the core predictions about the type-specific trading patterns. For this purpose, we developed an experimental design that allows us to measure mental capabilities independent from asset market behaviour. In Phase 1, participants complete incentivized tasks to independently measure their analytical and mentalizing capabilities. In Phase 2, we randomly divide participants into groups of 16 subjects, where each group plays a call-market version of Smith *et al.* (1988).

The experimental approach gives us the necessary degree of control to test our hypotheses. Firstly, our design confines decision-making to a single asset whose fundamental value we control, and also ensures uniform information access for all subjects. This is key to our framework's complete information premise. Secondly, it enables us to create out-of-sample forecasts about the behaviour of mental types in the asset market by assigning these types independently from market behaviour. This approach, distinct from those calibrating trading types based on market data (e.g., Haruvy and Noussair (2006); Baghestanian *et al.* (2015)), is recognised for yielding more reliable forecasting results (Tashman, 2000). Thirdly, monetary incentives align participants' objectives towards maximizing end-of-period cash holdings. Fourthly, we can elicit idiosyncratic variables like risk attitudes and gender, enhancing statistical robustness of the empirical analysis.

We conducted 8 sessions with 32 participants each at the experimental lab, University of Zurich.[29] We outline the two experimental phases in the following sections. Additional details, including experimental instructions, are available online.

4.1 Phase 1: Measuring Mental Capabilities

From a psychometric viewpoint, analytical and mentalizing capabilities are independent latent constructs, each comprising multiple sub-traits sharing a common variance. A well-known example is intelligence ("g-factor"), characterized by sub-traits like verbal, numerical, and logical reasoning. Our paper focuses on the implications of variations in these two mental capabilities for trading behaviour. Hence, we aim for holistic measures that approximate these latent constructs.[30] To this end, we adopt an integrative approach, deriving two separate measures from individual responses to various tasks targeting the known sub-traits of these cognitive abilities.

4.1.1 Analytical Capability

Analytical capability have multiple sub-traits (Gottfredson, 1997; Murphy and Davidshofer, 2004; Legg and Hutter, 2007) with the "g factor" (general intelligence factor) underlying each (Spearman, 1928), and further specializations for different branches

[29]Participants were recruited using hroot (Bock *et al.*, 2014) and the experiments were conducted using ztree (Fischbacher, 2007). Students of psychology and economics were excluded.

[30]See Bruguier *et al.* (2010); De Martino *et al.* (2013); Corgnet *et al.* (2018) or Farago *et al.* (2022) for an impact analysis of certain sub-task in context of financial decisions.

of intelligence (Carroll, 1997). We constructed our measure of someone's analytical capability from observing individual behaviour in the following three sub-tasks.

Raven's progressive matrices measures non-verbal intelligence, and is known to show a strong association with the g-factor (Jensen, 1998; Deary and Smith, 2004; Gignac, 2015). Participants see eight different patterns and have to choose the correct ninth pattern from a list of potential answers. We used a version that consisted of 12 items, with an overall time restriction of 12 minutes, and recorded the number of correct answers for each subject.

The **Game of Nim** requires backward-inductive reasoning (McKinney Jr and Van Huyck, 2006), a skill important to multi-period games and financial decision-making (Chari and Kehoe, 1990; Riedel, 2009; Bosch-Rosa and Corgnet, 2022).[31] In Nim, players alternately remove stones from any row on a board with varying stone counts. The goal is to remove the last stone. Subjects played five rounds against a computer, with each subsequent board increasing in complexity. Given the first move, subjects could win each round through optimal backward induction. We recorded the number of games each subject won, without imposing time limits on decision-making.

Finally, we administered seven **word problems** as in Bruguier *et al.* (2010). These problems are taken from a standard assessment-center test in the financial industry, and differentiate subjects according to their mathematical, quantitative and probabilistic reasoning (similar to the SAT). For each question, subjects had 60 seconds to answer, and we recorded the number of correct answers for each subject.

4.1.2 Mentalizing

A recent meta-analysis by Schurz *et al.* (2021) supports a hierarchical model of social cognition, with two primary sub-traits: i) reading intentions or goal-direction of others ("perspective taking"), and ii) forecasting behaviour of others from such data

[31] Nim is a combinatorial game similar to race games like "Race to 100", used in studies to assess strategic skills (Gneezy *et al.*, 2010; Levitt *et al.*, 2011; Bosch-Rosa *et al.*, 2015).

("online simulation").[32] These sub-traits align with our concept of mentalizing, and we measure them by two standard tasks: the "Reading the Mind in the Eyes Test" for perspective taking, and the Heider-Simmel test for online simulation. Following Bruguier *et al.* (2010), we employ incentivized versions of these tasks to construct our mentalizing measure.

The **Reading the Mind in the Eyes Test** (Baron-Cohen *et al.*, 1997) was designed to measure someone's perspective-taking capability (see Schurz *et al.*, 2021). This test extracts how well someone can attribute the true mental state of another person based on photos of human eyes expressing emotions like concern or happiness.[33] In our version, subjects needed to select the accurate mental state from four options, without time constraints, and we tracked the number of correct answers.

The **Heider-Simmel Prediction Task**, used in financial decision contexts by Bruguier *et al.* (2010), evaluates the ability to predict intentional behaviour from observed actions (Heider and Simmel, 1944). It uses video clips of geometric figures mimicking social interactions.[34] The task extracts the capacity of subjects to use so called online simulations (Reniers *et al.*, 2011) for understanding others' intentions. The more accurately a subject can interpret the intentionality behind the figures' movements, such as by constructing adequate narratives for the clips, the better she can predict the future movements of the figures. We paused each video every five seconds, asking subjects to predict the relative positions of two shapes within a five-second response window, and recorded the number of correct answers.[35]

4.1.3 Sorting into Mental Types

As our main interest is in the latent constructs of the two mental dimensions, we consolidated the results of all sub-tasks into a single performance measure for each

[32] Also see Premack and Woodruff (1978); Frith and Singer (2008); Van Overwalle and Baetens (2009); Reniers *et al.* (2011).

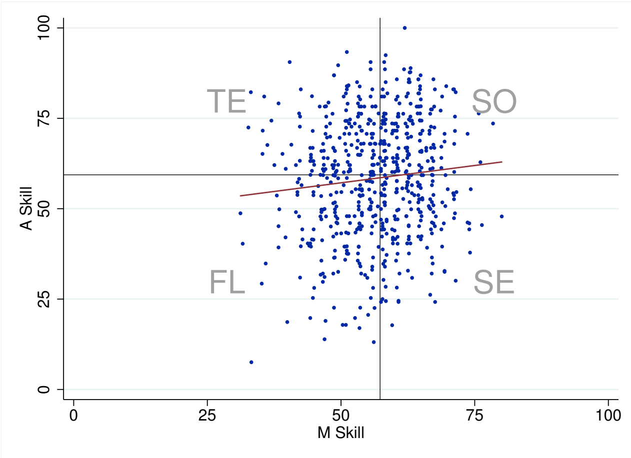
[33] While originally designed to detect disorders like autism, characterized by impaired perspective-taking (Dziobek *et al.*, 2008), the test was also linked to empathy (Quesque and Rossetti, 2020), which correlates with perspective-taking (Reniers *et al.*, 2011; Schurz *et al.*, 2021).

[34] The clips are accessible online at `https://www.youtube.com/watch?v=VTNmLt7QX8E`.

[35] Originally, this task involved free-form verbal responses to assess participants' anthropomorphizations of the shapes, and how they theorize about their "intentions".

dimension. Specifically, we averaged each subject's percentage of successes in every sub-task to obtain a composite score for each mental dimension. Figure 5 displays the empirical distribution of these composite measures; basic summary statistics by mental type are detailed in Appendix A.5, and the correlation matrix for the measures is in Appendix A.6. The scatterplot reveals a fairly broad dispersion of

Figure 5: Empirical Distribution of the two Performance Measures



Dots represent individual subjects, plotted against their performance in mentalizing (horizontal axis) and analytical (vertical axis) dimensions. The pattern of dots indicates little to no correlation between the two measures, the red line is the best linear fit. The medians, marked by black lines, are 59.4 for analytical and 57.3 for mentalizing dimensions.

mental capabilities, underscored by the very weak correlation ($\rho = 0.099$) between the measures.[36] This supports that mentalizing and analytical capability are distinct cognitive traits. Additionally, a factor analysis confirms that the five sub-tasks can be grouped into two similarly valued factors, aligning with the analytical and mentalizing sub-tasks, further confirming their separability (see Appendix A.7).

Figure 5 shows a balanced distribution of mental capabilities, indicating that randomly sampled markets are likely to reflect this balance. Accordingly, we categorized the four mental types using simple median splits, as illustrated by the quadrants in Figure 5.[37] This method preserves the balanced distribution of capabilities and enables a straightforward assessment of the impact of mental capabilities on trad-

[36]A strong correlation would have imposed an empirical challenge, although our framework's assumptions might still hold; see Appendix A.2.

[37]To strengthen the statistical reliability of our type sorting, we estimated the medians by using data from 20 experimental sessions, 12 of which featured a different task in Phase 2, thereby leveraging the Law of Large Numbers.

ing decisions. Should these capabilities prove to be irrelevant, we could not detect significant statistical differences in the trading patterns among the categorized types.

4.1.4 Mental Capabilities and other Characteristics

We cross-correlated the subjects in each quadrant with the additional controls *Risk Attitudes*, *Age* and *Gender* elicited during phase one (see Appendix A.5). Given the stochastic nature of the asset's dividend (see below) and conventional views relating trader heterogeneity to risk preferences, controlling for risk attitudes is fairly warranted.[38] Omitting risk preferences could create spurious correlations if these are strongly linked to mental capabilities.[39] We elicit risk attitudes with a standard incentivized task (Holt and Laury, 2002), and find these to be uncorrelated with mental capabilities (we cannot reject the null of no contingency: χ^2 test, $p = 0.214$).

Further, subjects are statistically similar in age across quadrants (mean $\cong$ 23 years); we cannot reject the null of no contingency (χ^2 test, $p = 0.207$). Gender distribution is less balanced (χ^2 test, $p < 0.01$), reflecting different performances in the A-dimension between men and women.[40] Finally, we analysed response times to exclude that bored or lazy subjects were misclassified as FL types.[41]

4.2 Phase 2: Experimental Asset Market

To test our hypotheses we implemented a call market version of Smith *et al.* (1988) (SSW) from the GIMS program (Palan, 2015). Despite criticisms of SSW's stylized features, like a deterministically falling fundamental value (Kirchler *et al.*, 2012),

[38]E.g., Cochrane (2009); Dohmen *et al.* (2010); Frey *et al.* (2017); Pedroni *et al.* (2017); Mata *et al.* (2018); Farago *et al.* (2022).

[39]The relationship between mental capabilities and risk preferences is debated (Frederick, 2005; Dohmen *et al.*, 2010, 2018; Lilleholt, 2019; Andersson *et al.*, 2016; Olschewski *et al.*, 2018; Amador-Hidalgo *et al.*, 2021; Mechera-Ostrovsky *et al.*, 2022).

[40]Women average 54 points and men 63 points in the A-dimension (t-test, $p < 0.01$), while women score slightly higher in the M-dimension (t-test, $p = 0.05$). Gender differences in cognitive abilities are well-documented (Reilly, 2012; Baron-Cohen *et al.*, 1997). Cueva and Rustichini (2015) also noted relevant gender effects in trading behaviour.

[41]Although all tasks are incentivized, one might be concerned that success rate in these tasks could be affected by participants' (dis-)interest or laziness. In particular, a disinterested participant would score low on all mental measurement tasks and hence be classified as FL type. Appendix A.8 analyses response time as a proxy for the effort invested in the tasks, where we did not find any significant difference between FL and the other types.

these aspects enable clear experimental testing of our predictions. In particular, the design ensures public observability of $(\Delta F_t, \Delta P_{t-1})$, and incorporates a consistently falling fundamental value. This setup is known to reliably generate bubble-crash patterns among both lay investors and professionals (Ackert *et al.*, 2001; Palan, 2013) that yield the two market phases we need to separate the behaviour of the four mental types. Alternative designs, such as the private information setting by Plott and Sunder (1988) (see Section 2) or a flat fundamental value (discussed in Appendix A.2) may not provide such differentiation.[42]

In each market, the 16 participants were initially endowed with varying combinations of cash and asset shares.[43] The asset market consisted of 15 periods, where each period started with an active trading phase followed by a passive dividend phase. In the latter the asset paid a uniformly random dividend from $\{0, 8, 28, 60\}$ per share. With shares expiring post-experiment, the asset's fundamental value F_t corresponded to its expected future dividends.[44] A subject's final payoff was the amount of cash held by the end of period 15.

During the trading phase, subjects could trade shares by submitting buy and sell orders. A buy order specified the maximum price $p_{\max}$ a subject was willing to pay per share and the quantity of shares she wished to buy at or below $p_{\max}$. Likewise, a sell order included the minimum price $p_{\min}$ a subject was willing to accept per share and the quantity of shares she was ready to sell at or above $p_{\min}$. Subjects could opt out of trading by not submitting any orders, preventing forced transactions that could skew results. Additionally, orders that breached individual budget constraints,

[42]We chose a call market rather than a double auction for two reasons. Firstly, it minimizes the impact of individual traders on market prices, reducing the likelihood of manipulative orders in a 16-subject market (Baghestanian *et al.*, 2014; Guler *et al.*, 2021). Secondly, call markets typically exhibit less financial exuberance and price volatility, adhere more closely to fundamental values, and are simpler for subjects to understand, offering a more conservative test for our hypotheses (Powell and Shestakova, 2016).

[43]The market had 40 shares in total, with each participant randomly receiving one of four portfolios: 1 share and 2228 Rappen; 2 shares and 1956 Rappen; 3 shares and 1684 Rappen; or 4 shares and 1412 Rappen. 100 Rappen equals 1 Swiss Franc (approximately USD 0.98 at the experiment time).

[44]These features imply that the fundamental value is deterministic and time-collinear. Comprehending these facts requires analytical processing, consistent with our presumption. An interesting extension could consider more complex structures of the fundamental value.

such as buying on credit or short selling, were automatically rejected.

Market Price Buy and sell orders in each period t were aggregated to determine the market-clearing price P_t. Figure 6 depicts the evolution of the average market price alongside with the fundamental value; graphs of individual markets, market-wise type compositions and other characteristics are in Appendix A.9. The price dynamics display the characteristic pattern seen in SSW markets (Palan, 2013): initially aligning closely with the fundamental value, the price then rises and eventually exceeds the fundamental value by over 200 Rappen at the price peak, followed by a rapid decline.

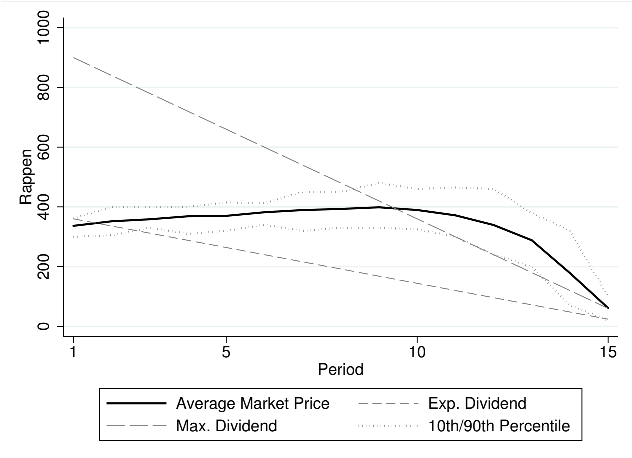


Figure 6: Average Market Price

Average (black solid line) and 10th/90th percentiles (gray dotted lines) of the market price across the 16 markets. The gray long dashed line represents the period-specific fundamental value of the share (number of remaining periods times 24 Rappen per share) and the gray short dashed line the maximum possible value of a share (60 Rappen per share and number of remaining periods), i.e., the best-case scenario for keeping one share until the end of the asset market.

4.3 Experimental Protocol

In each of the 8 sessions, subjects were randomly assigned to computer terminals. In Phase 1, instructions for each task were directly presented on subjects' computer screens. No performance feedback was given, except in the Game of Nim. In Phase 2, the 32 subjects were randomly split into two equally large asset markets, receiving detailed instructions and answering comprehension questions about trading rules, dividend payments and the payoff determination before the trading task began. We implemented two payoff-irrelevant practice periods to familiarize subjects with the interface. After Phase 2, a standard questionnaire was completed, and cash payouts were distributed.[45]

5 Empirical results

This section presents the experimental results, organized in alignment with our hypotheses.

5.1 Stimulus Response

To evaluate whether valuations respond to changes in price and fundamental value as proposed by $\mathbf{H}_{\mathrm{SR}}$, we estimate a linear update function with constant type-specific stimulus-response coefficients (2), like the one we simulated in 4. We use each trader's asset holdings as a proxy for her unobservable valuations.[46] Results in Table 2 are presented without and with controlling for risk aversion (M1 and M2, respectively).

The upper part of Table 2 reports the baseline regression results where, consistent with (2), the variables of interest are the interactions of the last price (P_{t-1}) and the fundamental value with type dummies. Figure 7 visualizes the estimated stimulus-response coefficients, and suggests notable differences between the four types.

The claims in $\mathbf{H}_{\mathrm{SR}}$ are tested based on the reported regression in the lower part of Table 2, which lists the pairwise comparisons of the interaction variables, together with p-values for standard two-sided tests. Consistent with our prediction, the most

[45]Earnings consisted of Phase 1 task earnings (CHF 0.30 per correct answer), cash holdings at the end of the 15th period in the asset market, and a CHF 10 show-up fee, averaging about CHF 70 per subject (ranging from CHF 23 to CHF 121). The entire session lasted approximately 2.5 hours.

[46]According to our framework, a trader's asset holdings are immediately tied to her valuations. We use the number of shares, rather than the changes in shares, because we want to estimate how sensitive valuations respond to prices, amounting to the derivative conditions in (2). We considered, but decided against, using bids and asks or their interpolation as proxies for valuations, for several reasons. Firstly, subjects were not forced to enter bids or asks (see Section 4.2), leading to frequent missing data or extreme values intended to guarantee order execution. Secondly, bids and asks do not capture the intent to trade multiple units, a factor likely tied to individual valuations a"nd inherently considered in asset holdings. Thirdly, our simulations suggest small variance in bids and asks across mental types, potentially making empirical detection challenging. Lastly, recent studies show a more complex relationship between valuations and the willingness to pay or accept, even in simple tasks like lotteries (Chapman *et al.*, 2021).

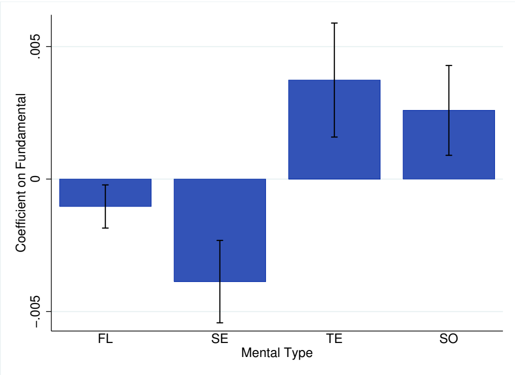
Table 2: Stimulus response regression, across types

	M1	M2
Semiotic (SE)	0.908**	0.906**
	(0.428)	(0.429)
Technocratic (TE)	0.728	0.728
	(1.256)	(1.256)
Sophisticated (SO)	-1.851**	-1.851**
	(0.747)	(0.747)
Fundamental	-0.001	-0.001
	(0.001)	(0.001)
SE×Fundamental	-0.003*	-0.003*
	(0.002)	(0.002)
TE×Fundamental	0.005**	0.005**
	(0.002)	(0.002)
SO×Fundamental	0.004**	0.004**
	(0.002)	(0.002)
Market Price$_{t-1}$	0.0002	0.0002
	(0.001)	(0.001)
SE×Price$_{t-1}$	0.001	0.001
	(0.001)	(0.001)
TE×Price$_{t-1}$	-0.005	-0.004
	(0.003)	(0.003)
SO×Price$_{t-1}$	0.002	0.002
	(0.003)	(0.003)
Market Price$_{t-2}$	0.0004	0.0004
	(0.0002)	(0.0002)
# Lottery choices		0.002
		(0.023)
Constant	2.414***	2.437***
	(0.306)	(0.471)
overall R^2	0.029	0.03
N	3088	3088
Clusters	16	16
Comparisons Fundamental:		
SE×Fun.=TE×Fun.	$\chi^2 = 13.76$***	$\chi^2 = 13.75$***
	$p = 0.0002$	$p = 0.0002$
SO×Fun.=TE×Fun.	$\chi^2 = 0.20$	$\chi^2 = 0.20$
	$p = 0.658$	$p = 0.658$
SO×Fun.=SE×Fun.	$\chi^2 = 8.24$***	$\chi^2 = 8.24$***
	$p = 0.004$	$p = 0.004$
Comparisons Price:		
SE×Price$_{t-1}$ =TE×Price$_{t-1}$	$\chi^2 = 2.83$*	$\chi^2 = 2.84$*
	$p = 0.092$	$p = 0.092$
SO×Price$_{t-1}$ =TE×Price$_{t-1}$	$\chi^2 = 2.40$	$\chi^2 = 2.40$
	$p = 0.122$	$p = 0.122$
SO×Price$_{t-1}$ =SE×Price$_{t-1}$	$\chi^2 = 0.29$	$\chi^2 = 0.29$
	$p = 0.588$	$p = 0.588$

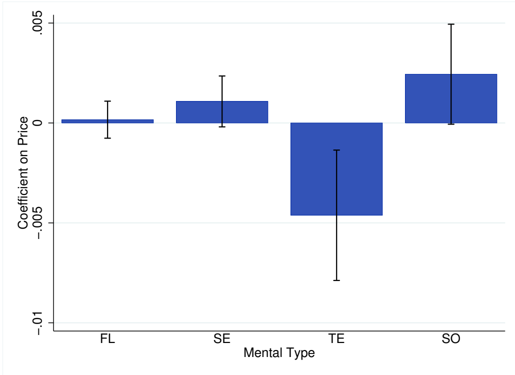
Random effects panel regressions, standard errors adjusted for clustering at the market level. Unit of observation: participant-period.
Significance levels for a two sided test: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Shares held at end of period.
Independent variables: SE, TE, SO: dummies for mental type; # Lottery choices: number of times a participant chose the lottery over the certain amount in the Holt-Laury task.

Figure 7: Marginal effects of fundamental and last price on asset holdings

(a) Marginal effects of fundamental



(b) Marginal effects of previous price



The graphs show the type-wise marginal effects of fundamental value (left) and previous market price (right) on shares held from regression M1 in table 2. Error bars represent the cluster-robust standard errors of the mean. Sophisticated types react positively to both the fundamental and the last price; semiotic types only respond positively to the last price, technocratic types only positively to the fundamental.

evident difference occurs for how the "off-diagnoal" types TE and SE respond to the two observables. The differences in the estimated response coefficients of these two types is highly significant for the fundamental value ($p = 0.001$), and at least weakly significant for the price ($p = 0.092$).[47] This pattern is consistent with the prediction that TE and SE should display strictly ranked response coefficients. Further, the response coefficients of SO and TE to the fundamental value do not differ statistically (p-value 0.658), while SO and SE respond similarly to the last price (p-value 0.588). In addition, we observe that the response coefficient for SO to the fundamental value is different from that of SE ($p = 0.004$). Finally, Table 2 shows that including risk attitudes does not alter the estimated coefficients, which will be a common pattern in all our regressions.[48] In conclusion, we interpret these findings as supporting $\mathbf{H}_{\text{SR}}$.

Result 1 (Stimulus-response). *Semiotic (Technocratic) and sophisticated types respond similarly to changes in last price (fundamental value), while the response coefficients of technocratic and semiotic types to both observables are ranked as in* $\mathbf{H}_{SR}$.

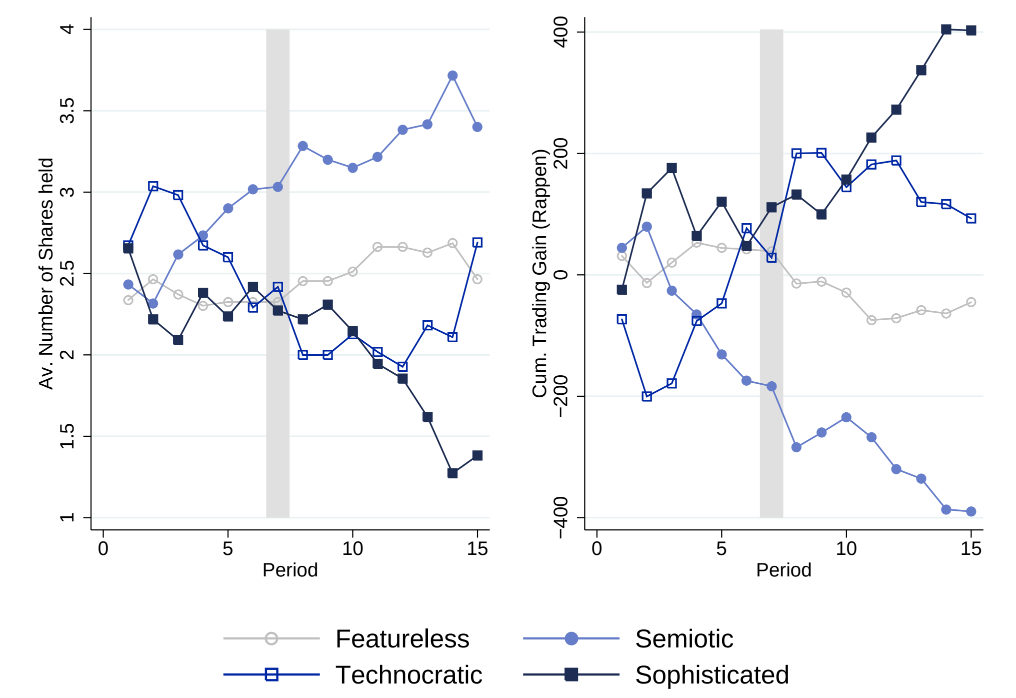
[47]As $\mathbf{H}_{\text{SR}}$ is a directional hypothesis, using one-sided p-values is appropriate. Consequently, the reported two-sided p-values could be halved, underscoring the strength of the statistical evidence.

[48]Including the variables "highest market price", "largest bubble component" and "peak period" as additional controls that account for the dynamic structure of the market does not significantly alter our main findings.

5.2 Asset Accumulation

We now examine the type-specific asset accumulation across the two market phases. Conventional theory does not distinguish between objective information and its subjective mental representation. This implies that behavioural difference across mental types should not arise in the complete information setting we study. Figure 8 displays the average asset holdings (left panel) and cumulative trading gains (right panel) by mental type, along with the two market phases separated by the price peak.[49] Given our random sampling process's tendency towards balanced markets, Figure 8 can be seen as approximating a fully balanced market scenario.

Figure 8: Asset holdings and trading gains over time, by type.



Left panel: Asset holdings of the four types over time. Right panel: Cumulative trading gains by period. The vertical gray bar indicates the average price peak, occurring around Period 7.

Both figures reveal substantial differences across mental types. Moreover, the accumulation patterns seem to align with those predicted by $\mathbf{H}_A$: SE tend to accumulate shares pre-peak, while TE divest. Post-peak, SO divest, while FL accumulate. While

[49] The price peak is the period with the highest market price. The average mean of all price peaks in our sample is calculated at 6.88 (SD = 3.1).

the empirical patterns share these central tendencies with their simulated counterparts in Figure 3(b), the two figures are not identical. In comparing these figures, it is important to consider various confounding factors that are inherent in our real-world data but absent in our stylized simulation environment, assuming constant stimulus-response coefficients and fully balanced markets. Firstly, our random sampling achieves balanced markets only on average; see Appendix A.9 for a decomposition by market. Variations in the markets' type compositions affect the price trajectories, as our simulations exemplified, and perturb the type-specific portfolio dynamics. Thus, the dynamics averaged across markets that are balanced only on average may not entirely mirror those from a fully balanced market. Secondly, our sorting by medians effectively distinguishes between high and low mental capability levels, but cannot quantify the capability differences across individual traders. These differences ought to affect the high-low differences in the stimulus-response coefficients pertaining to a mental capability, thereby indicating a potential sample dependence, while we exogenously imposed these differences in our simulation. Thirdly, the coarse nature of our dual capability classification, along with potential measurement noise and idiosyncrasy in individual traders' response coefficients may further contribute to discrepancies between observed and simulated dynamics. In light of these considerations, we interpret the evidence in Figure 8 as indicative of more nuanced variations in trader behaviour than what our stylized simulation in Figure 3(b) captures.

To reliably assess $\mathbf{H}_A$, we examine the portfolio dynamics of the four mental types during the pre- and the post-peak market phase with a panel regression framework, where the price peak is determined for each market separately. The regression output and the relevant statistical tests are in Table 3.[50] During the pre-peak phase, SE significantly increase their asset holdings by $0.017 + 0.158 = 0.175$ shares per period on average ($\chi^2 = 25.33$, $p < 0.001$). Similar calculations show that TE divest

[50] As in Section 5.1, including "highest market price", "largest bubble component" and "peak period" do not significantly alter our main findings. Table A.6 in Appendix A.5 contains the descriptive statistics of the 16 markets.

Table 3: Regression analysis of # shares held over time

	pre-peak	post-peak
Period	0.017	0.054***
	(0.060)	(0.017)
Semiotic (SE)	-0.505	1.379**
	(0.323)	(0.574)
Technocratic (TE)	1.259**	0.300
	(0.494)	(0.636)
SO	-0.171	1.165
	(0.603)	(0.896)
TE×Period	-0.225*	-0.050
	(0.116)	(0.053)
SE×Period	0.158**	-0.042
	(0.075)	(0.042)
SO×Period	-0.024	-0.161***
	(0.115)	(0.055)
Constant	2.382***	1.883***
	(0.238)	(0.300)
overall R^2	0.020	0.036
N	1312	2272
Clusters	16	16
Shares change over time?		
Period + SE×Period = 0	$\chi^2 = 25.33$***	$\chi^2 = 0.15$
	$p < 0.001$	$p = 0.703$
Period + TE×Period = 0	$\chi^2 = 6.29$**	$\chi^2 = 0.00$
	$p = 0.012$	$p = 0.945$
Period + SO×Period = 0	$\chi^2 = 0.01$	$\chi^2 = 5.04$**
	$p = 0.913$	$p = 0.025$

Random effects panel regressions, standard errors adjusted for clustering at the session level. Unit of observation: participant-period.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Shares held at end of period.
Independent variables: Constant: SE, SO, TE: dummies for mental type, Period.

($p = 0.012$), while FL and SO do not statistically change their asset holdings during this phase. In the post-peak phase, we estimate that FL acquire shares ($p < 0.01$), SO divest ($p = 0.025$), while SE and TE do not statistically change their portfolios.[51] In conclusion, the regression evidence is favorable to hypothesis $\mathbf{H}_A$.

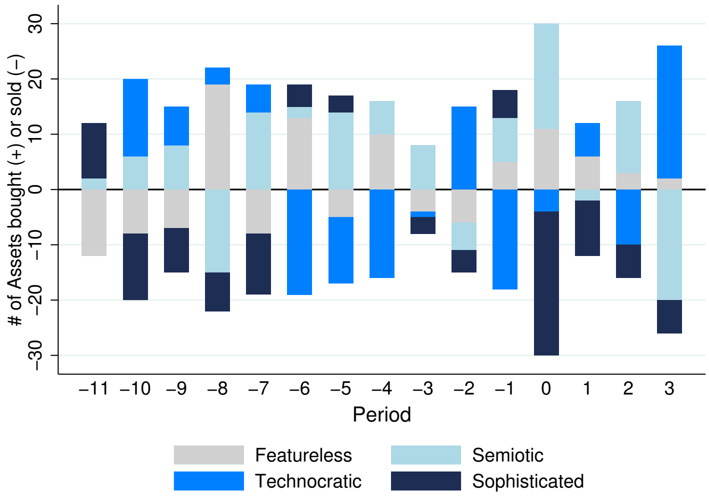
Result 2 (Asset Dynamics)**.** *During the pre-peak phase, semiotic types are the only types to increase their asset position, while technocratic types are the only types to divest. Likewise, sophisticated types are the only ones who divest in the post-peak phase, while featureless types are the only ones to buy during this phase. These type-wise trading patterns are consistent with* $\mathbf{H}_A$.

[51] One might note the coefficient of 0.054 for FL in the post-peak phase, while significant, indicates a comparably moderate change in shares held. This seems intuitive in view of the refractory trading style implied by the mental profile of FL, as FL appear as net buyers during the post-peak phase only because their valuations respond least sensitively among all mental types (see Section 3.2.2).

5.3 Exit Timing

Hypothesis $\mathbf{H}_T$ predicts that SO should have the best exit timing of all four types. Specifically, SO should be the dominant net seller at the *bubble peak*, i.e., at the period with the maximal over-pricing of the asset relative to its fundamental value. Figure 9

Figure 9: Net transactions, centered at the bubble peak



The graph shows the order of the exit timing centered at the bubble peak. TE exit first, several periods before the bubble peak; SO exit right at the bubble peak; SE miss the exit and divest once prices have collapsed, while FL acquire shares after the peak.

compares net sales and purchases across mental types, with periods normalized such that the bubble peak is period 0 in each market (the bubble peak occurred between period 11 and 12 on average). The figure evidently suggests that SO have the best (and SE the worst) exit timing. Moreover, the largest turnover occurs at the bubble peak, where most shares are sold from SO to SE. To test whether SO have the best exit timing, we investigate how portfolios change once the future bubble component (= market price less fundamental value) diminishes. Specifically, we derive the mean changes in asset holdings of all four types once the bubble component starts to decrease (see Table A.12 in Appendix A.10). Consistent with Figure 9 and $\mathbf{H}_T$, we find that SO is the only type to significantly reduce the assets held in anticipation of a decreasing bubble component ($p = 0.01$).

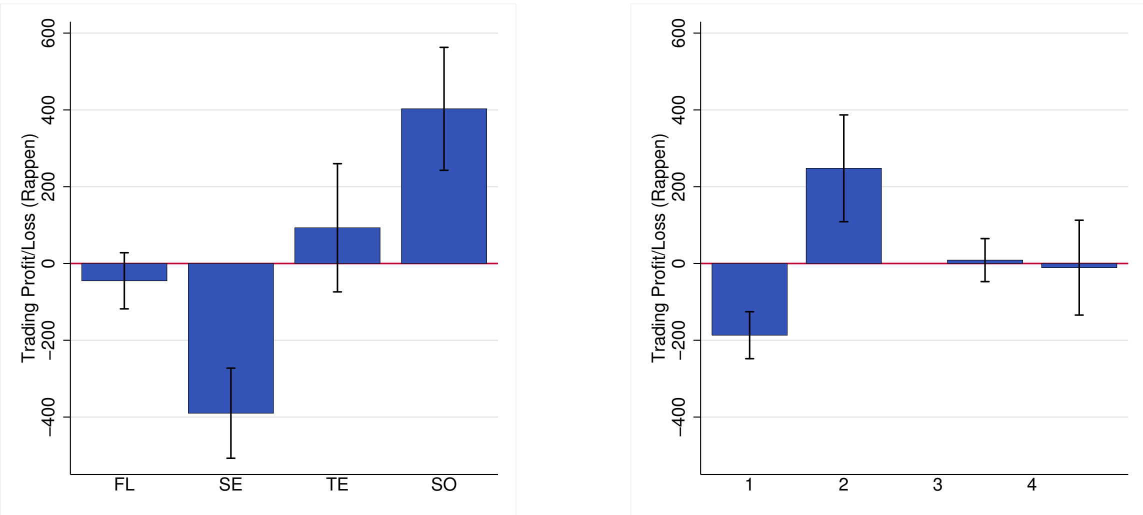
Result 3 (Exit Timing)**.** *Sophisticates have the best market timing, showing the* *largest net sale of shares among all types around the bubble peak.*

5.4 Trading Gains and Total Income

We now ask whether the ranking of trading gains is as predicted by Hypothesis $\mathbf{H}_G$. Panel 10a displays the distribution of the average cumulative trading gains by the end of the experiment. On visual inspection, trading gains indeed seem to adopt the predicted ranking, with SO earning most and SE losing most. As trading gains only are a part of the final income, and subjects were incentivized to maximize their total income at the end of the asset market, we also consider the distribution of total income. We find that total income shows the same ranking (Figure A.12, Appendix A.11).[52]

Figure 10: Trading gains across mental capability types.

(a) Trading gains across all four types (b) Trading gains one-dimension split



Panel 10a shows trading gains across all four mental types, while Panel 10b shows trading gains split along the A and M dimension separately. Error bars represent cluster-robust standard errors of means.

We subject the visual impression from Panel 10a to statistical testing in Table 4. The upper half of that table reports the results of OLS regressions of the two outcome

[52]Cash at the end of a period t comes from three different sources: initial cash, cumulative dividends from periods 1 to t, and cumulative trading gains from sales and purchases in periods 1 to t. Cumulative trading gain in a period is the residual from subtracting initial cash and cumulative dividend income from current cash. A further earnings measure of interest, suggested by an anonymous reviewer to us, is to offset trading gains with *expected* dividends from holding the asset. This measure (not reported) shows the same ranking as in Figure 10.

measures – trading gains and total income – on type dummies.[53] The lower half of Table 4 reports pairwise type comparisons. All pairwise comparisons are as predicted,

Table 4: Regression analysis of asset market outcomes across mental types

	Trading Gain	Total Income
Semiotic	-349.796***	-169.426*
	(117.449)	(97.706)
Technocratic	136.603	30.592
	(171.702)	(65.960)
Sophisticated	447.873***	188.896**
	(160.94)	(81.269)
# Lottery choices	-5.656	-0.249
	(15.342)	(10.192)
Constant	22.535	2840.468***
	(201.214)	(112.799)
adj. R^2	0.037	0.011
N	256	256
Clusters	16	16
Type comparisons:		
SE=TE	$\chi^2 = 6.08$**	$\chi^2 = 3.59$*
	$p = 0.014$	$p = 0.058$
SO=TE	$\chi^2 = 2.95$*	$\chi^2 = 2.76$*
	$p = 0.086$	$p = 0.097$
SO=SE	$\chi^2 = 23.23$**	$\chi^2 = 14.03$***
	$p < 0.001$	$p < 0.001$

OLS regressions, bootstrapped standard errors in parentheses, 1000 repetitions, adjusted for clustering at the session level. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01, two-sided tests.
Dependent variables: Total income and trading gains after period 15, in Rappen.
Independent variables: Constant: Featureless type. "Semiotic," "Technocratic," "Sophisticated": dummies for mental type; # Lottery choices: number of times a participant chose the lottery over the certain amount in the Holt-Laury task.

and statistically significant, except for the difference between TE and FL ($p = 0.426$). SO outperforms all three other types in terms of trading gains (first column) and total income (second column). Total income of SO is 189 Rappen higher than of FL ($p = 0.02$), with trading gains higher by 448 Rappen ($p = 0.005$). Conversely, SE perform worse than all other types, with total income 169 Rappen lower than FL ($p = 0.083$), and trading gains 350 Rappen lower ($p = 0.003$). SE and TE differ statistically in total income ($p = 0.058$) and trading gains ($p = 0.014$), as shown in the lower part of Table 4. Further, SO and TE differ in trading gains ($p = 0.086$) and total income ($p = 0.097$). While the difference between TE and SO is only marginally significant according to two-sided testing, it is economically highly relevant: The difference between SO and FL is more than five times larger

[53]We obtain similar results when excluding ambiguous subjects who score close to the medians of the two mental dimensions.

than between TE and FL for income, and more than three times larger for trading gains.[54] In sum, the statistical evidence largely corroborates our prediction about the performance ranking.

Result 4 (Trading Gains and Total Income)**.** *Sophisticated types realise the highest trading gains and overall income, semiotic types the highest trading losses and lowest overall income. By pairwise comparison, all mental types earn statistically different total trading gains and total income as predicted by* $\mathbf{H}_G$*, except that the difference between technocratic and featureless types is not significant.*

Non-Monotonicity The previous analysis confirms that the four mental types display different trading behaviours and performances. Ignoring one mental dimension therefore would lead to a mis-attribution of skills to profitability. In particular, we could miss the non-monotonic relation between performance and mental capabilities from Section 3.2.3. Panel 10b illustrates the distribution of trading gains if subjects were sorted only along one capability dimension: If mentalizing is ignored, we would erroneously conclude that high analytical capability *per se* assures higher gains.[55] Such an attribution is misleading according to Panel 10a, which reveals that this result is crucially influenced by the mentalizing dimension (the high earnings of SO versus the large losses of SE). Similarly, if analytical capability is ignored, we would wrongly infer that mentalizing is entirely irrelevant (because gains and losses of SO and SE offset each other). In particular, one would miss that mentalizing capability is responsible for both the highest gains and the largest losses.

6 Conclusion

A common approach for explaining heterogeneous behaviour and the occurrence of price bubbles in asset markets is to presume the existence of different, exogenously

[54] All results are robust to using within-markets income or trading gains ranking of a subject or within-markets standardized income or trading gains.

[55] A regression analysis analogous to Table 4 but including only one dimension confirms the visual impression conveyed by Panel 10b.

given trader types. By separately linking the two traits *analytical capability* and *mentalizing* to the evaluation of the market observables "fundamental value" and "asset price", respectively, this paper proposes a cognitive rationale why heterogeneous trading and exuberant price dynamics can arise.

We test our hypotheses on how mental capabilities influence trading behaviour and performance with an experimental asset market due to Smith *et al.* (1988). To ascertain that observed behavioural differences are likely to reflect disparities in individual information processing, as predicted by heterogeneous capabilities, our experimental approach assures that all subjects obtain exactly the same market information, and also controls for heterogeneous risk attitudes and other characteristics. In addition, we elicit mental capabilities independently from behaviour in the asset market, which yields out-of-sample forecasts for the effects of mental capabilities on trading. The asset market data of our experiment is consistent with our predictions, corroborating that heterogeneity in the two mental capabilities also leads to behavioural heterogeneity.

Our framework predicts a non-monotonic effect of mental capabilities on performance ("more is not always better"), also confirmed by the data. One consequence of this observation is that approaches relying on one-dimensional measures of mental capabilities can reach biased conclusions about what causes successful trading. For example, considering only analytical capability would produce the erroneous conclusion that high analytical capability are sufficient (rather than necessary) for achieving the highest trading income. Likewise, ignoring heterogeneity in analytical capability would yield the mistaken conclusion that mentalizing is entirely irrelevant, while differences in the latter effectively are decisive for the best and worst performances.

These observations may shed some new light on findings related to "strategic sophistication" (Bosch-Rosa and Corgnet, 2022). In experiments, strategic sophistication is commonly measured by the distance between the winning number and the individual bid in Beauty Contest tasks. By our mental framework, making a winning bid seems to require mentalizing *and* analytical capabilities: Understanding the logic of the game requires analytical thinking (most notably: backward induction), but successful bidding also requires to appropriately anticipate the behaviour of other subjects.[56] Someone scoring high on strategic sophistication according to play in a Beauty Contest therefore is likely to be a sophisticated type in our sense. Accordingly, our results may help to understand why strategic sophisticates tend to earn higher profits (Levine *et al.*, 2015), and why markets with more strategic sophisticates yield smaller bubbles (Bosch-Rosa *et al.*, 2015). Nevertheless, some of the heterogeneity we detect for lower capability levels remains obscured with sophistication measures derived from the bid distance in Beauty Contests, because the latter cannot independently discern between analytical and mentalizing capabilities.

Our cognitive approach can be extended in various directions. In our experiment subjects were randomly sampled into markets of 16 traders. As mental capabilities are virtually uncorrelated, our procedure lead to relatively balanced markets in terms of mental types, which we deem a reasonable starting point for testing our theory. In reality, however, traders may self-select into markets. Future research could therefore attempt to study whether certain markets, or certain asset classes, tend to dis-proportionally attract certain mental types. Another possibility is to apply our mental framework to private information settings. Additional distortions may arise if some market information is private rather than public, and our findings could work as a benchmark for those.

The mental framework could be resourceful beyond asset markets. In the last two decades, behavioural approaches studied the importance of mistakes in people's choices (McKelvey and Palfrey, 1995), while others assumed that choices are optimal but based on flawed beliefs (Stahl and Wilson, 1995; Camerer *et al.*, 2004; Eyster and Rabin, 2005; Toplak *et al.*, 2014). Our paper proposes and tests a specific cognitive foundation about diverging behaviour, which could give a new edge on explanations based on assuming exogenous behavioural types. For example, future empirical re-

[56]See Carpenter *et al.* (2013). Coricelli and Nagel (2009) observe that strategic sophisticates display higher activation in a brain region associated with Theory of Mind, and Gill and Prowse (2016) find that more cognitively able subjects choose numbers closer to equilibrium play.

search could try to elicit the concretions between our two mental capabilities and existing notions of limited rationality as in Stanovich (2012). As specific question, one could ask whether subjects scoring low in analytical capabilities also tend to show inconsistencies with respect to optimizing behaviour, or whether types low on mentalizing have flawed beliefs about other players.[57] The mental framework may also offer a new perspective on learning in games by separating between the analytical-conceptual and the mentalizing aspects of interactive decision. For example, one could attempt to study whether it is possible to learn or train a certain capability, or how behaviour changes if the complexity in one mental dimension is altered. Finally, our framework may offer some guidance for thinking about new interventions to limit exuberant prices. For example, adjustments in the presentation format of asset prices could mitigate the effects that differences in mentalizing play for trading outcome.[58] Further research can provide a deeper understanding of the interaction of such framing effects with cognitive abilities.

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[57]We are grateful to an anonymous referee for pointing this out to us.

[58]Corgnet *et al.* (2022) report that if the displayed information format eases pattern recognition, mentalizing capability have a greater impact on forecasting performance, or Glaser *et al.* (2019) observe that showing participants the same information as return charts instead of price charts affect individual price expectations.

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A Online Appendix

A.1 Mental Capabilities and Optimal Stimulus Response

In this section we provide a foundation for the positive association between mental capabilities and stimulus response we described intuitively in Section 3. In particular, we show that the sensitivity property emerges in a model of cognitive information processing. Suppose that a trader seeks to calibrate its mental model around the asset's valuation, where update function (1) is of the linear form

$$\lambda_t^i = \gamma_P \Delta P_{t-1} + \gamma_F \Delta F_t, \tag{A.1}$$

with parameters γ_P and γ_F. Obtaining a mental representation of the market information $(\Delta F_t, \Delta P_{t-1})$ requires mental processing, and as such cognitive effort. To elaborate this idea, we follow the literature on optimal information processing (see, e.g., Wiederholt, 2010; Hefti and Heinke, 2015) by assuming that the mental impression $(\Delta \tilde{F}_t, \Delta \tilde{P}_{t-1})$ of a trader is a noisy version of the true market data $(\Delta F_t, \Delta P_{t-1})$. Specifically, let

$$\begin{aligned} \Delta \tilde{P}_{t-1} &= \Delta P_{t-1} + \varepsilon_M, \qquad & \varepsilon_M &\sim N(0, \eta_M), \\ \Delta \tilde{F}_t &= \Delta F_t + \varepsilon_A, \qquad & \varepsilon_A &\sim N(0, \eta_A), \end{aligned}$$

where $\varepsilon_M, \varepsilon_A$ are independently and normally distributed zero-mean errors with *precision* η_M, η_A.[59] Then, obtaining the calibration of (A.1) requires to chose the precision of the estimates $\Delta \tilde{P}_{t-1}$, $\Delta \tilde{F}_t$, as well as *decision functions* $\pi_P(\Delta \tilde{P}_{t-1})$, $\pi_F(\Delta \tilde{F}_t)$ that capture how the various possible realizations of $\Delta \tilde{P}_{t-1}$, $\Delta \tilde{F}_t$ enter (A.1). Intuitively, one can think of the decision functions as the mental imprints caused by the realizations of $\Delta \tilde{P}_{t-1}, \Delta \tilde{F}_t$. A calibrated model thus is of the form

$$\tilde{\lambda}_t = \gamma_P \pi_P(\Delta \tilde{P}_{t-1} = \Delta p_{t-1}) + \gamma_F \pi_F(\Delta \tilde{F}_t = \Delta f_t), \tag{A.2}$$

where Δf_t and Δp_{t-1} denote particular realization of the random variables $\Delta \tilde{F}_t$ and $\Delta \tilde{P}_{t-1}$. We suppose that optimal decision functions π_P, π_F and signal precision η_M, η_A minimize the average mean squared error pertaining to (A.2), subject to processing costs $C(\cdot)$ (omitting period index t):

$$\min_{\substack{\pi_P, \pi_F \\ \eta_M, \eta_A}} \gamma_P E\left[(\Delta P - \Delta \tilde{P})^2 | \Delta \tilde{P} = \Delta p\right] + \gamma_F E\left[(\Delta F - \Delta \tilde{F})^2 | \tilde{\Delta} F = \Delta f\right] + C(\cdot) \tag{A.3}$$

Analytical and mentalizing capability, respectively, determine how efficient the given information about ΔP and ΔF can be processed, which we capture in the processing cost function

$$C(\cdot) = H_M(\eta_M, c_M) + H_A(\eta_A, c_A). \tag{A.4}$$

[59] $\eta_j \equiv Var(\varepsilon_j)^{-1}$, $j \in \{A, M\}$.

For $j \in \{A, M\}$, the function $H_j(\cdot)$ represents effort costs associated with an aspired levels of precision η_j, $j \in \{A, M\}$, where we impose that $\frac{\partial H_j}{\partial \eta_j} > 0$ and $\frac{\partial^2 H_j}{\partial \eta_j^2} \geq 0$. The latter two requirements capture that obtaining more precise representations is costly.[60] For each $j \in \{A, M\}$ we let $\frac{\partial^2 H_j}{\partial \eta_j c_j} < 0$, meaning that, say, a higher mentalizing capability c_M reduces the marginal costs associated with any aspired level of precision η_M about $\Delta\tilde{P}$, and likewise for analytical capability.[61]

Given these assumptions, what is the optimal solution to (A.3)? First, the *posterior means* $E[\Delta P_{t-1} | \Delta\tilde{P}_{t-1} = \Delta p_{t-1}] \equiv \mu_P(\Delta p_{t-1}, \eta_M)$ and $E[\Delta F_t | \Delta\tilde{F}_t = \Delta f_t] \equiv \mu_F(\Delta f_t, \eta_A)$ are the optimal choice of decision functions for any given level of precision η_M, η_A.[62] Thus, (A.2) becomes

$$\tilde{\lambda}_t = \gamma_P \mu_P(\Delta p_{t-1}, \eta_M) + \gamma_F \mu_F(\Delta f_t, \eta_A). \tag{A.5}$$

Update function (A.5) can be seen as a special form of (1), where the response functions φ_P, φ_F are given by *conditional expectations.* This further implies that the expected mean squared errors in (A.3) are conditional variances, such that (A.3) reduces to

$$\min_{\eta_M, \eta_A} \quad \gamma_P Var\left[\Delta P_{t-1} | \Delta p_{t-1}; \eta_M\right] + \gamma_F Var\left[\Delta F_t | \Delta f_t; \eta_A\right] + H_M(\eta_M, c_M) + H_A(\eta_A, c_A) \tag{A.6}$$

Restricting attention to interior solutions of (A.6), the optimal choices of the precisions η_M^*, η_A^* are characterized by

$$-\gamma_P \frac{\partial Var\left[\Delta P_{t-1} | \Delta p_{t-1}; \eta_M\right]}{\partial \eta_M} = \frac{\partial H_M(\eta_M, c_M)}{\partial \eta_M}, \quad -\gamma_F \frac{\partial Var\left[\Delta F_t | \Delta f_t; \eta_A\right]}{\partial \eta_A} = \frac{\partial H_A(\eta_A, c_A)}{\partial \eta_A}. \tag{A.7}$$

To illustrate the properties of the solution determined by (A.7), and its implications for stimulus response coefficients (3), let $\Delta P_{t-1} \sim N(0, \eta_P)$ and $\Delta F_t \sim N(0, \eta_F)$.[63] Standard algebra yields $Var\left[\Delta P_{t-1} | \Delta p_{t-1}; \eta_M\right] = (\eta_M + \eta_P)^{-1}$ and $Var\left[\Delta F_t | \Delta f_t; \eta_A\right] = (\eta_A + \eta_F)^{-1}$, such that (A.7) evaluates to

$$\frac{\gamma_P}{(\eta_M + \eta_P)^2} = \frac{\partial H_M(\eta_M, c_M)}{\partial \eta_M}, \qquad \frac{\gamma_F}{(\eta_A + \eta_F)^2} = \frac{\partial H_A(\eta_A, c_A)}{\partial \eta_A}.$$

By the Implicit Function Theorem $\eta_M'(c_M) > 0$ and $\eta_A'(c_A) > 0$, showing that aspired precision and the corresponding mental capability are positively related. Further, the

[60] These cognitive costs might manifest as a depletion of metabolic energy or entail certain opportunity costs, as discussed in Hefti and Lareida (2022).

[61] A simple class of examples is given by $H_j = \eta_j^\beta / c_j$, $\beta \geq 1$. Another class is obtained if, say, the H_M-functions is related to the Fisher information between ΔP and $\Delta\tilde{P}$, which is a known formulation in models of costly information acquisition (see, e.g., Sims, 2003; Caplin and Dean, 2015.

[62] This is an established result in mathematical statistics, see, e.g. Hogg *et al.*, 2005.

[63] The Gaussian case is a key benchmark in the literature on optimal information processing, also due to its great tractability; see Sims (2003); Wiederholt (2010). Our main insights also apply for other distributions, although we typically must rely on numerical evaluations.

posterior means evaluate to

$$\mu_P(\Delta p_{t-1};\eta_M) = \frac{\eta_M}{\eta_M+\eta_P}\Delta p_{t-1}, \qquad \mu_F(\Delta f_t;\eta_A) = \frac{\eta_A}{\eta_A+\eta_F}\Delta f_t, \tag{A.8}$$

such that the stimulus response coefficients (3) are constant and given by

$$\alpha_P(\Delta p_{t-1}, c_M) = \frac{\eta_M}{\eta_M+\eta_P}\gamma_P, \qquad \alpha_F(\Delta f_t, c_A) = \frac{\eta_A}{\eta_A+\eta_F}\gamma_F, \tag{A.9}$$

which together with $\eta'_M(c_M) > 0$ and $\eta'_A(c_A) > 0$ implies the positive relations $\frac{\partial \alpha_P}{\partial c_M}, \frac{\partial \alpha_F}{\partial c_A} > 0$ from the main text.[64]

These results are highly intuitive. A higher precision, say, in η_M means a lower decision uncertainty in terms of a lower conditional variance $Var\left[\Delta P_{t-1}|\Delta p_{t-1};\eta_M\right]$. Then, if a stronger mental capability is associated with a more efficient production of precision η_M, which condition $\frac{\partial^2 H_M}{\partial \eta_M c_M} < 0$ assures, it is optimal to aspire for more precision η_M whenever c_M is larger, ceteris paribus. A larger precision η_M, in turn, means that the corresponding mental evaluation of ΔP_{t-1} is more reliable, which therefore increases the sensitivity to ceteris paribus changes in p_{t-1} as captured by a larger stimulus response coefficient α_P.

A.2 Comments on the Model

On Non-Convertibility of Mental Capabilities One of our main assumptions is that mentalizing c^i_M affects valuations V^i_{t+1} only via price changes, while analytical capability c^i_A affects V^i_{t+1} only via changes in fundamental value. Thus, we impose that these two capabilities have a non-convertible effect on the respective observable. We now review the implications of this assumption for our hypotheses in greater detail.

Note first that none of the predictions in Section 3.2 remain valid if mental capabilities do not affect valuations, as predicted by conventional theory ignoring the possibility of heterogeneous mental representations despite identical information.[65] Further, if mental capabilities enter valuations in a strongly convertible manner, violating the separable structure of (1), then we could not predict the fourfold pattern of trading behaviour. For example, if only average capabilities $(c_A + c_M)/2$ or maximal capabilities $\max\{c_A, c_M\}$ matter for how sensitively valuations respond to changes in ΔP_t and ΔF_t, then TE and SE obtain the same stimulus-response coefficients, and therefore are predicted to display an indistinguishable trading behaviour. Likewise,

[64] If $\lim\limits_{c_j\to\infty} H_j(\eta_j, c_j) = 0$ for $j \in \{A, M\}$, stating that someone with infinite capacity can obtain perfect estimates at zero effort costs, (A.8) evaluates to $\mu_P = \Delta p_{t-1}$, $\mu_F = \Delta f_t$. This shows that the ideal updates are $\hat{\varphi}_P(\Delta p_{t-1}) = \gamma_P \Delta p_{t-1}$ and $\hat{\varphi}_F(\Delta f_t) = \gamma_F \Delta f_t$, such that γ_P and γ_F must amount to the ideal stimulus response coefficients in the current model.

[65] In such a case, the update function (1) would collapse to a zero-mean iid random variable $\lambda^i_t = \varepsilon^i$, such that all traders are stochastic clones of each other.

if one capability is entirely irrelevant for valuations, then at least two types should be indistinguishable. E.g., if only c_A but not c_M enters the two φ-functions in (1), then our model could distinguish at most between two types, as the analytically high types (TE,SO) jointly form a type as do the analytically low types (SE,FL).

Nevertheless, our main predictions about trading behaviour and performance ($\mathrm{H_A}$ and $\mathrm{H_G}$) remain valid even if non-convertibility is violated in its strict form. What we essentially require is that analytical capability are the dominating determinant of how ΔF_t affects V^i_{t+1}, while mentalizing is the dominating determinant of how ΔP_t affects V^i_{t+1}. That is, while e.g. SE and SO may not have a perfectly identical φ_P-function, the two functions should still remain fairly close to each other in Figure 2 if c_A plays a minor role as opposed to c_M. If a similar property holds for all four mental types and both mental capabilities, Hypotheses $\mathrm{H_A}$ and $\mathrm{H_G}$ remain valid.[66]

The above arguments clarify that the data could quite easily falsify our mental framework if our main supposition about how mental capabilities affect valuations is empirically inadequate. By contrast, if mental capabilities matter as predicted by our framework, a *one-dimensional* measure of mental capabilities could not account for the fourfold pattern of trading dynamics and trading gains our framework predicts, because such a measure cannot span the orthogonal type space we predict. Any such attempt would necessarily mix certain types, and produce biased estimates of how mental capabilities affect trading behaviour.

Correlated Capabilities There is another, more subtle, reason why we could empirically fail to distinguish between the trading behaviours of certain mental types, despite the potential validity of non-convertibility. This may happen if mental capabilities are strongly correlated *at the population level.* To see this, consider the extreme where c_A and c_M are perfectly correlated. In this case only two instead of four mental profiles would exist. More generally, correlation implies that if someone "gets it right", say, in the analytical dimension, this is also predictive of whether she gets it right in the mentalizing dimension. In this sense, high analytical capability may spuriously affect valuations via observed changes in prices, despite the validity of non-convertibility, simply because having high analytical capability is strongly predictive for having high mentalizing capapbilities, too. Our empirical approach allows us to estimate the correlation between the two mental dimensions, where we uncover at most a very weak positive correlation ($\rho = 0.01$). This fortunately makes correlated capabilities an empirically irrelevant concern.

[66] To illustrate, note that for $dF < 0$ and $dP > 0$ TE types then still are the ones to obtain the lowest valuations, making this the net selling type during the pre-peak phase.

Flat Markets Our mental framework could be applied beyond the type of SSW market we study theoretically and experimentally in this paper. In other settings, however, the four mental types may not exert a differential behaviour. As an example, consider a market with a prolonged phase of stagnation where $\Delta F_t \approx 0$. In such a case, differences in analytical capability would have no (or a close to negligible) effect on valuations, meaning that, if at all, only differences in mentalizing could produce distinct trading patterns according to our framework. More generally, our framework would not predict the systematic occurrence of a significant price bubble with a constant fundamental value, as opposed to the SSW market we study.[67]

A.3 Derivation of Hypothesis $\mathbf{H_A}$

Let V_{t+1}^{θ} denote the valuation for a mental type $\theta \in \{FL, SE, SO, TE\}$ from Section 3.1. Define $\bar{V}_{t+1}^{\theta} \equiv E[V_{t+1}^{\theta}]$ as the average valuation of a type θ in period t. Note that $\bar{V}_{t+1}^{\theta} > \bar{V}_{t+1}^{\theta'}$ iff θ obtains a higher average update than θ', i.e., $\bar{\lambda}_t^{\theta} > \bar{\lambda}_t^{\theta'}$. By (1), the latter inequality is determined by the two φ-functions characterizing the types θ, θ' jointly with the signs of ΔF_t and ΔP_{t-1}. In particular, the single-crossing property of the φ-functions (see Figure 2), reflecting the sensitivity property of mental capabilities, then determines which type has the highest (lowest) average valuation $\bar{V}_{t+1}^{\theta}$ during a given market phase, and thus is the net buying (selling) type in that phase.

If $\Delta F_t < 0$ and $\Delta P_t > 0$, as in the pre-peak phase, the single-crossing property of φ_F and φ_P at zero directly imply that $\bar{V}_{t+1}^{SE} > \bar{V}_{t+1}^{\theta'}$ for $\theta' \neq SE$, and $\bar{V}_{t+1}^{TE} < \bar{V}_{t+1}^{\theta'}$ for $\theta' \neq TE$. This shows that SE (TE) is the net buying (selling) type during the pre-peak phase. By contrast, if $\Delta F_t, \Delta P_t < 0$ (post-peak phase), then $\bar{V}_{t+1}^{FL} > \bar{V}_{t+1}^{\theta'}$ for $\theta' \neq FL$, and $\bar{V}_{t+1}^{SO} < \bar{V}_{t+1}^{\theta'}$ for $\theta' \neq SO$. Thus, FL (SO) is the net buying (selling) type during the post-peak phase. Given that F_t decreases persistently over time while P_t increases in the pre-peak and decreases in the post-peak phase, the above sorting of average valuations imply the divergence of portfolios from Hypothesis $\mathrm{H_A}$, even if valuation differences in any single period t are small.

A.4 Call Market Price Determination

Given the buy and sell orders issued by the simulated traders, the call market price is determined as in Baghestanian *et al.* (2015). The main steps of the algorithm are

[67] This follows by the logic of Figure 2, as $\Delta F_t = 0$ implies a zero effect of analytical capability on valuations for all types. In particular, this means that even if a small price spike $\Delta P_t > 0$ were to (randomly) occur at some point, the valuations will not diverge much, because TE types fail to display a decreasing williginess-to-pay due to the constant fundamental, in strong contrast to what happens in the SSW market with its falling fundamental value. Accordingly, such price spikes flatten out swiftly, rather than aggregating into the persistent tendency that marks the rise of a bubble.

as follows.

1. In any given trading round of a period t, the simulation generates the market-level demand (supply) schedules by sorting all issued buy (sell) orders from highest (lowest) to lowest (highest).

2. The price of the current trading round is the price that equates the demand and suppy schedules. If no such price exists, but demand is above supply, the market price corresponds to the maximal buy order (see Section 3.1 in Baghestanian *et al.* (2015)).

3. Once the price for the current trading round has been determined, all corresponding trades are executed, and portfolios are updated accordingly.

4. The same process is repeated for each of the S trading rounds in period t. After the last trading round in a period, the asset pays its random dividend in cash, which is added to individual cash holdings.

The *call market price* is the average price of all trading rounds in a given period. As in the main text, we denote the call market price determined at the end of period $t-1$ by P_{t-1}.[68]

A.5 Summary Statistics

Table A.5 presents a summary of the socio-economic variables collected during phase one in relation to the four mental types. To maximize statistical reliability, we present results for a total of 20 sessions with 32 participants each. This includes the 8 sessions pertinent to this paper, while the remaining 12 sessions involved a different task in their second phase. We elicited risk attitudes with a standard Holt and Laury (2002) task, where subjects had to choose between a lottery that yields either CHF 30 or CHF 0 with equal probability and a certain payment moved upward from CHF 0 in increments of CHF 1.

Table A.6 provides the descriptive statistics for participants in the 16 markets relevant for this paper, as well as for the market outcomes themselves.

[68] The market price of the separate trading rounds and the traded quantities are *not* revealed to simulated traders, capturing that trading behaviour can only be updated according to the call market price determined in the previous period, consistent with our framework and experiment.

Table A.5: Summary Statistics by Mental Type (N=640)

Mental Type	Participants	Women (%)	Age (years)	Av. risky choices
Featureless (FL)	166	59.6	23.5	11.6
Semiotic (SE)	155	66.5	23.4	11.1
Technocratic (TE)	155	29.7	22.8	12.1
Sophisticated (SO)	164	43.3	23.0	12.3
Total	640	49.8	23.1	11.8

Age and risk attitude are similar across mental types. Men tend to score higher in the A dimension, resulting in a gender imbalance across skill types.

Table A.6: Descriptive Statistics (N=259)

Variable	Mean/Median	Min/Max	Std. Dev.
Female	.51/1	0/1	.5
Age	23.29/23	18/39	3.28
Av. risky choices	11.69/11	0/20	3.85
Cash	2349.83/2488	8/5182	807.54
Assets	2.5/2	0/18	2.71
Total Trading Income	0/360.5	-4808/1750	1186.73
Total Dividend Income	1025/850	0/4716	857.92
Final Cash	2845/2814	678/5182	739
Price	332.53/350	20/500	104.12
Price Peak Period	6.88/7.5	1/12	1.32
Bubble Peak Period	11.5/12	9/14	1.32
Price Peak	413.69/400	350/500	44.62
Bubble Peak	269.81/264	184/404	56.39

Descriptive statistics for participants in the 16 markets relevant to this paper.

A.6 Correlation Matrix of the measures

Table A.7: Correlation Matrix for individual mental measures (normalized by z-scores)

	Raven's Test	Game of Nim	Word Problems	Eye Gaze	Heider Simmel Task	Av. risky choices	A-Measure
Game of Nim	0.3034***	-	-	-	-	-	-
Word Problems	0.3485***	0.352***	-	-	-	-	-
Eye Gaze	-0.016	-0.002	0.011	-	-	-	-
Heider Simmel Task	0.039	0.028	0.017	0.061***	-	-	-
Av. risky choices	0.0151	0.107*	0.140***	0.019	-0.062	-	-
A-Measure	0.688***	0.769***	0.775***	-0.005	0.037	0.124**	-
M-Measure	0.063***	0.082**	0.0562***	0.488***	0.756***	0.008	0.099**

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

A.7 Factor Analysis

A principal component analysis revealed that there are two factors with an Eigenvalue above 1 (Kaiser criterion) explaining 33.5% and 21.2% of the variation, respectively. A parallel analysis (Dinno *et al.*, 2009) shows that the data can be explained by these two factors, so these two components were retained for rotation. Using the varimax approach to orthogonalize the factors, the rotated pattern matrix and inter correlations between the two factors are displayed in Table A.8. Only the sub-tasks we implemented to measure analytical capability load with a similar size to the first factor. Likewise, only those sub-tasks aimed at mentalizing load with a similar size to the second factor. This is consistent with the notion of two separable latent constructs for our two mental capabilities discussed in Section 4.1 in that the first factor represents the common capability on the analytical dimension, and the second factor the one on the mentalizing dimension. In addition, the aggregation by taking the average of correct answers seems appropriate in view of the similar load sizes.

Table A.8: Factor loadings

	Factor 1	Factor 2
Game of Nim	0.5668	0.0125
Word Problems	0.5695	-0.0061
Raven's Test	0.5939	-0.0067
Eye Gaze	-0.0290	0.7150
Heider Simmel Task	0.0303	0.6990

A.8 Differences in Participants Efforts?

While we used monetary incentives to assure that participants have a genuine interest to optimize their performance in the asset markets, we also took a closer look at motivation and engagement of the participants. One possible concern is that our results could reflect subjects' laziness or disinterest to some extent. For example, a subject who simply does not care about earning money is likely to score low on the mental sub-tasks we implemented, and hence be classified as FL. Further, a bored subject who does not trade at all could resemble FL in that the subject outperforms SE types as a consequence of our derivations about performance in Section 3.2.3.

An unmotivated participant is likely to spend less effort on the various tasks, meaning that such a participant may just randomizes responses to save on time. We therefore consider response times as a possible indicator for the subjects' efforts in the tasks. For mental capability measures we look at the response time for the word problems (A-dimension) and the eye gaze test (M-dimension).[69] In the asset market, we also looked at the response times, as well as at the number of offers made over the whole 15 periods.

Table A.9: Response Time in Seconds

Task	Mentaltype	Mean	SD	Min/Max
Word Problems	FL	21.61	6.36	1/33
	SE	20.88	6.27	8/35
	TE	21.27	6.22	6/41
	SO	21.75	5.20	12/34
Reading the mind in the eye test	FL	7.12	4.15	3/31
	SE	7.00	2.78	3/18
	TE	8.95	5.19	2/28
	SO	8.79	4.42	2/21

This table reports the average response time per item measured in seconds.

The summary statistics in Table A.9 shows at most minor differences in the mean of the response times, and comparing the mean of FL against the rest (t-tests) shows no significant differences in mean response time for the word problems (p-value=0.69) and a weakly significant differences for reading the mind in the eye test (p-value=0.054); the same holds true if one only compares SE with FL: word problems: p-value=0.89; reading the mind in the eye test: p-value=0.025. Even tough the latter difference is statistically significant, the effect size is clearly negligible.

For asset market participation, Table A.10 reports the number of periods a buy or sell offer was made. While the average number of buy-offers looks similar, a t-test reveals that featureless types place on average significantly fewer buy offers than the rest ($p < 0.001$). For sell-offers, we detect no significant difference between FL and the rest ($p = 0.976$). Apart from a weakly faster response time for FL's sell-offers (mean: 39s) compared to the rest (mean: 42s, $p = 0.002$), there are no significant differences in response times for FL's buy-offers (mean: 45s) and the rest (mean: 46s, $p = 0.173$), nor when comparing FL to SE for buy- ($p = 0.186$) and sell-offers ($p = 0.111$). Together with very low correlation coefficients of the above variables, we conclude that, while some individual subjects may have provided less effort in

[69]In the word-problem-task participants had to answer each question within 60s and the eye gaze test had no time restrictions, thus the response time to each question can be seen as independent of each other. This is different for the Raven's Test, were participants had 12min overall to solve all questions and the Heider-Simmel Task, were each question was time restricted by 5s, which might be to short to measure any differences. In each round of the game of Nim the participant chooses how many stones to pick from one row, alternating with the computer, which makes analysing response times tricky.

Table A.10: Number of periods an offer was made

Task	Mentaltype	Mean	SD	Min/Max	<5
Buy Offers	FL	11.41	3.54	0/15	6
	SE	12.08	3.06	2/15	2
	TE	12.56	3.06	3/15	1
	SO	12.38	2.58	6/15	0
Sell Offers	FL	9.12	4.17	1/15	16
	SE	10.87	3.90	1/15	5
	TE	8.35	4.46	1/15	15
	SO	7.96	4.34	1/15	15

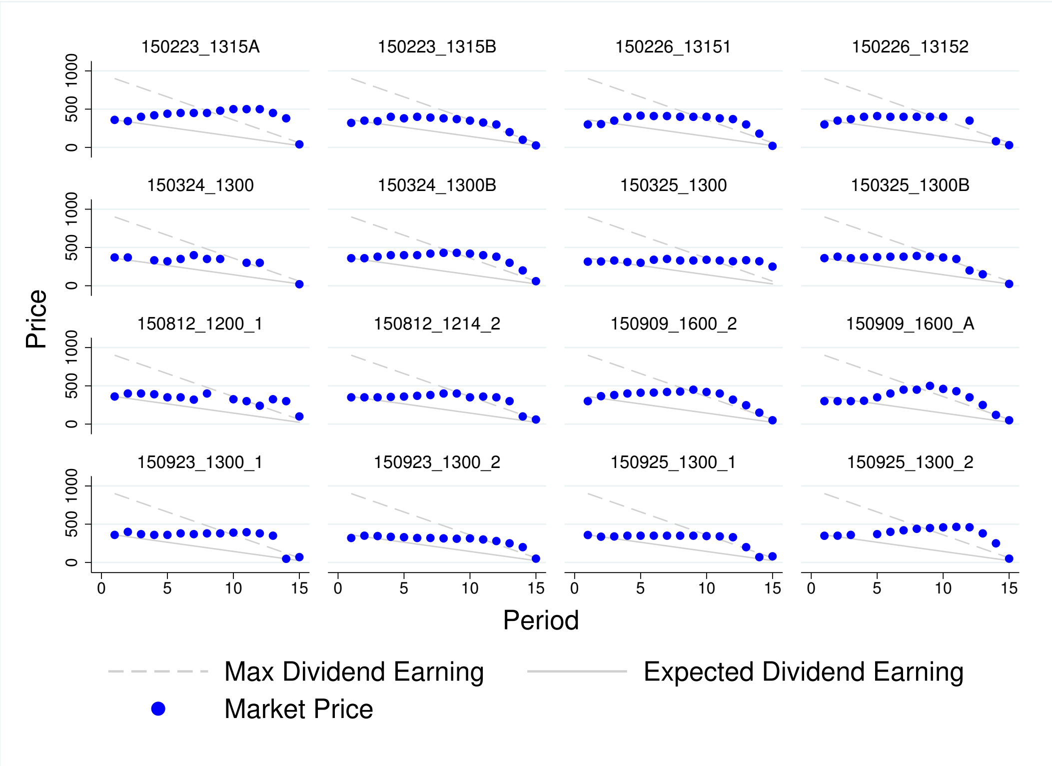
This table reports the number of buy- or sell-offers made(rounded figures). Buy- and sell offers with a price or volume of zero, where counted as no-offer made, since these are offers that are without success at the first place. For the same reason, we also interpreted sell-offers that are made at unrealistic prices of above 1000 Rappen as no-offer. "<5": Less then 5 periods with an offer.

certain tasks, this seems to have a small to negligible correlation with FL or the other mental types.[70]

[70]Correlation coefficients range between -0.024 and -0.061; detailed results are available upon request.

A.9 Experimental markets overview

Figure A.11: Experimental markets



Market prices (blue dots) for each of the 16 markets. The numbers indicate the session, e.g. 150223_1315A means it is the first market (A) in the session that started in February, 23rd in 2015 at 13:15. Some asset markets experienced periods without a market price, in which case the blue dot is missing. Every market experienced periods with the market price above the fundamental value.

Table A.11: # Types and Aggregated Market Outcome

Session	**# Types**	**Price Peak**	**Bubble Peak**
YYYY/MM/DD hh:mm Market	FL/SE/TE/SO	Period/Price	Period/ Bubble Component
2015/02/23 13:15 A	5/2/4/5	12/500	12/404
2015/02/23 13:15 B	6/5/3/2	6/400	10/206
2015/02/26 13:15 A	6/4/3/3	5/415	12/274
2015/02/26 13:15 B	4/3/5/4	5/410	10/256
2015/03/24 13:00 A	4/3/7/2	7/400	12/204
2015/03/24 13:00 B	7/2/5/2	9/430	12/284
2015/03/25 13:00 A	5/3/2/6	7/350	14/272
2015/03/25 13:00 B	6/3/2/5	8/390	11/230
2015/08/12 12:00 A	6/4/4/2	8/400	13/253
2015/08/12 12:00 B	6/7/0/3	9/400	12/254
2015/09/09 16:00 A	8/4/3/1	9/500	9/332
2015/09/09 16:00 B	4/4/5/3	9/450	9/282
2015/09/23 13:00 A	7/2/3/4	2/400	12/284
2015/09/23 13:00 B	6/5/3/2	2/350	12/184
2015/09/25 13:00 A	4/4/3/5	1/359	12/234
2015/09/25 13:00 B	2/5/3/6	11/465	12/364

A.10 Exit Timing

Table A.12 presents the regression evidence about the mean changes in portfolios of all for mental types once the bubble component starts to decrease. Specifically, we regress the changes in asset holdings of all four types for those periods t where the future bubble component in $t+1$ is smaller than in t (which includes the bubble peak). Consistent with the exit timing hypothesis, we find that SO is the only type to lower asset holdings significantly (by -0.34) in anticipation of a decreasing bubble component. Moreover, the data rejects the null of no differences between SO and the other three types (SE, TE: $p < 0.001$, FL: $p = 0.04$).

Table A.12: Regression analysis of changes in # shares held from one period to the next, once the bubble decreases

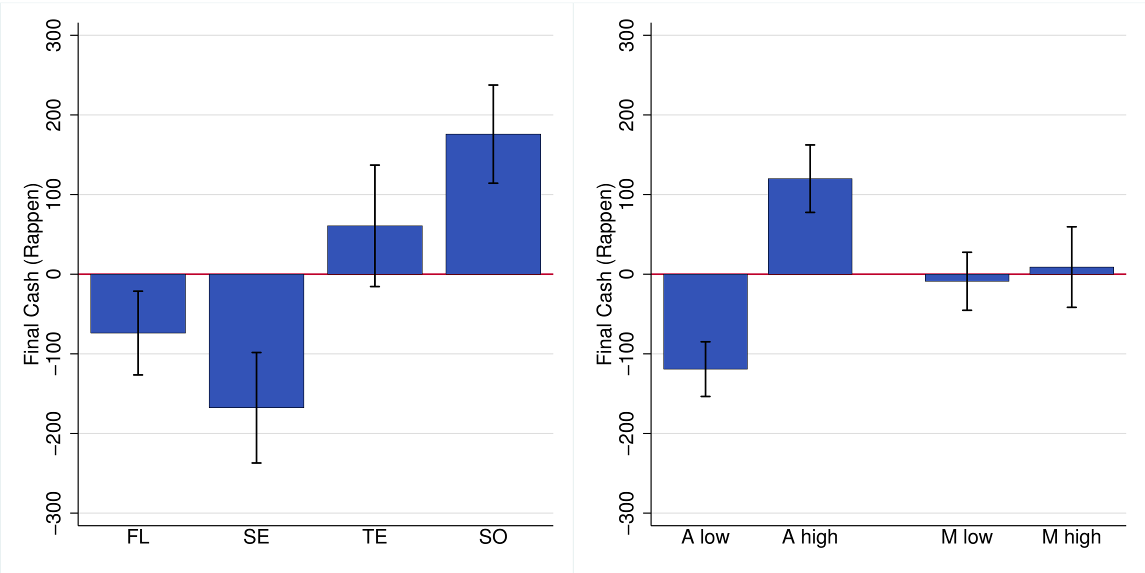
Semiotic (SE)	0.131
	(0.085)
Technocratic (TE)	-0.050
	(0.113)
Sophisticated	-0.340**
	(0.132)
Constant	0.026
	(0.056)
overall R^2	0.0165
N	960
Clusters	16
Comparison with SO	
FL=SO	$\chi^2 = 4.08$**
	$p = 0.04$
SE=SO	$\chi^2 = 14.99$***
	$p = 0.0001$
TE=SO	$\chi^2 = 8.46$***
	$p = 0.004$

Random effects panel regressions, standard errors adjusted for clustering at the session level.
Unit of observation: participant-period.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Changes in shares held at end of period.
Independent variables: Constant: FL. SE, SO, TE: dummies for mental type.
Bubble decreases in Period(t+1) means that the bubble component becomes smaller from Period(t) to Period(t+1).

A.11 Total Income Across Mental Capability types

Figure A.12: Total income across mental capability types.

(a) Total income across all four types (b) Total income one-dimension split



Panel A.12a shows total income across all four mental types, while Panel A.12b shows total income split along the A and M dimension separately. Error bars represent cluster-robust standard errors of means.

A.12 Stated Trading Strategy Analysis

This section contains an explorative analysis of the stated trading strategies in the asset market, as well as some anecdotal evidence.

Stated Strategy Analysis. In the exit questionnaire we asked participants to state their trading strategy in a free form statement:

"In the last part of this study, you could trade an asset on an asset market. Please explain briefly your considerations how you aimed to make profits through trading."

We analysed the participant's statements in the following way: First, the authors made a list of potential statements that reflect one or the other dimension, or a particular trading type. In a second step, four independent coders received 50 randomly selected participant statements. Their task was to decide whether the statements made by the subjects were well reflected by the list. Once all coders went through their first 50 statements, we met and discussed whether the original list needed to be adjusted. We made sure that the coders where not aware of our mental framework. The result is the list of statements in Table A.13. Next, we independently mapped each statement to one dimension as well as to mental types. We kept only those relations, where an agreement had occurred. An "x" in Table A.13 indicates that this statement characterizes the dimension or mental type and a "$-$" reflects a negative relation. In a final step, all coders went through all 256 participant statements and dummy-coded if the statement issued were similar to one of the statements of the final list. We measured the reliability of agreement using Fleiss-Kappa (Gwet, 2014), last column of Table A.13. According to Landis and Koch (1977), a number below zero can be interpreted as poor agreement, between $0.01 - 0.2$ as slight agreement, $0.21-0.4$ as fair agreement, $0.41-0.6$ as moderate agreement, $0.61-0.8$ as substantial agreement and everything above 0.8 as strong agreement. The median Fleiss-Kappa for all statements is 0.56 indicating that there existed only a moderate agreement among the coders. The Fleiss-Kappa for the A-dimension statements is 0.59, while for the statements related to the M-Dimension it is 0.36. This indicates that it was easier to classify statements along the A-dimension compared to the M-dimension.

For the final analysis we calculated the mean of all dummy-coded strategies for each statement and participant. Then, we used the mapping from Table A.13 and calculated points for the A- and M-dimension, as well as for each mental type. A summary statistics can be found in the bottom of Table A.13. Table A.14 displays the regression of these type points on the mental capabilities of each subject from the screening phase. This regression detected a significant effect between the coded points and our mental classification for the A-dimension (or the technocratic type), but not for the M-dimension.

We draw the following conclusion from this analysis. While using "free" verbal statements offers a largely unrestricted glimpse on what subjects perhaps were thinking in the experiment, the usage of such data for a quantitative analysis as intended by this article is limited. In particular, in case of the M-dimension our coders showed a non-negligible disagreement in their assignments of the statements, leading to a rather noisy measure. This raises the general concern that questionnaires may not produce a reliable way of differentiating between different mental capabilities, as opposed to our incentivized approach in the screening phase. Nevertheless, it is interesting that we found a correlation between the coded statements and the A-dimension. One possibility why we did not detect a similar correlation for the M-dimension, is that our "model statements" may not have sufficiently expressed verbally the sentiments pertaining to differences in that dimension. Future research may seek to analyse, what type of "statements" or "views" differentially express best the sentiments of subjects with different mentalizing capabilities.

Table A.13: Classification of Statements and Coders Agreement

Statement	**A-Dim.**	**M-Dim.**	**FL**	**SE**	**TE**	**SO**	**Fleiss-Kappa**
Mention Fundamental Value, Expected Value/Dividend Earnings, Correctly Calculated Expected Value	x				x		0.60
Anticipate The Value Of The Asset Will Be Zero At Period 15	x				x	x	0.21
Earn Dividends	x				x		0.69
Buy Below The Expected value	x				x		0.75
Sell Above Expected Value	x				x		0.66
Buy/Sell Random Or By Luck	(-)x		x				0.57
Did Not Get it, Mention To Be Confused	(-)x		x				0.43
Had Difficulties To Calculate Expected Value	(-)x		(-)x		x		-0.01
Mention Market Price	x	x		x	x	x	0.59
Mention Behaviour Intentions Of Other Traders Market Sentiment		x		x		x	0.36
Sell Higher Than Bought. Ride The Bubble		x		x		x	0.55
Sold When They Thought Market Price Would Be Highest		x				x	0.36
Buy Early And Sell Late, Buy Early And Hold		x		x		x	0.71
Hold And Sell At The End		x				x	0.21
Mention Turning Point For Selling, Mention Period 6-10 As Exit Point		x				x	0.55
Exiting The Market For Selling All Assets		x				x	0.14
Could Not Sell Their Assets At The End		x		x			0.61
Buy Low			x	x	x		0.58
Do not remember							0.83
Conservative safe trading							0.71
Changed Strategy							0.38
Sell Early And Buy Late							0.40
Mean	1.31	1.79	0.23	1.34	1.49	1.96	0.50
Median	1.00	1.75	0.00	1.25	1.25	1.75	0.56
SD	1.34	1.26	0.34	0.92	1.27	1.40	0.22
Min	-1.25	0.00	0.00	0.00	-0.25	0.00	-0.01
Max	6.25	5.50	1.50	3.75	6.25	6.00	0.83

Table A.14: Mental Types and Stated Trading Strategy

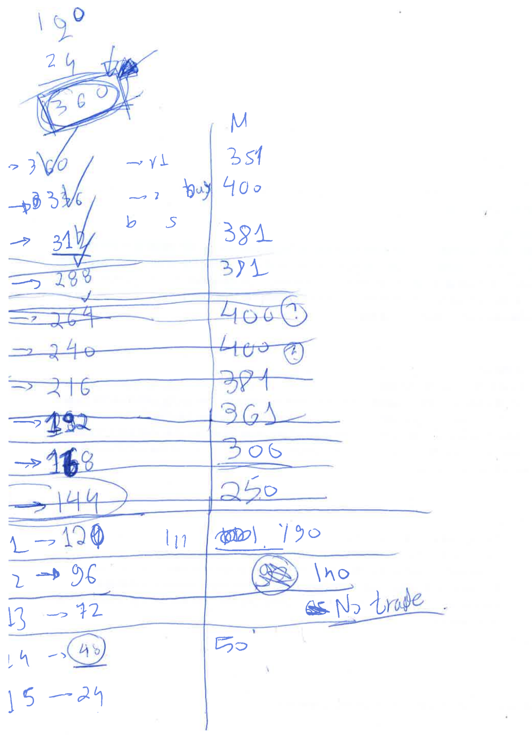
	Dependent variable:					
	Apoints	Mpoints	FLpoints	SEpoints	TEpoints	SOpoints
	(1)	(2)	(3)	(4)	(5)	(6)
M-high	−0.085	0.112	0.031	0.120	−0.051	0.112
	(0.213)	(0.211)	(0.056)	(0.153)	(0.203)	(0.236)
A-high	0.883***	0.053	−0.079	0.051	0.802***	−0.010
	(0.221)	(0.219)	(0.058)	(0.159)	(0.211)	(0.244)
A-high X M-high	−0.012	−0.167	−0.077	−0.272	−0.097	−0.167
	(0.325)	(0.323)	(0.085)	(0.234)	(0.310)	(0.360)
Constant	0.983***	1.753***	0.264***	1.319***	1.198***	1.954***
	(0.137)	(0.136)	(0.036)	(0.099)	(0.131)	(0.151)
Observations	256	256	256	256	256	256
R^2	0.104	0.001	0.031	0.007	0.087	0.002
Adjusted R^2	0.093	−0.011	0.020	−0.005	0.076	−0.010
Residual Std. Error (df = 252)	1.277	1.266	0.335	0.919	1.218	1.411
F Statistic (df = 3; 252)	9.754***	0.117	2.719**	0.587	8.009***	0.161

Note: Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01, two-sided tests.
Dependent variables: Average points for each dimension or type according to Table A.13.
Independent variables: Constant: Featureless type. "Semiotic," "Technocratic," "Sophisticated": dummies for mental type.

Subjects Note.

By incident we became aware of a subjects note, documented in Fig. A.13, while cleaning the laboratory after the experiment. We kept it for illustrative purpose, since it nicely shows that this participant wrote down the fundamental value as well as the market price per period. What makes this note interesting are the question marks after for period 5 and 6, where the market price peaked and the difference between price and fundamental value was largest. This underlines at first, that the market price and the fundamental value are taken into account, at least by this particular subject. Secondly, while some subjects tracked the market price, they could not always make sense of it.

Figure A.13: Subjects Note



This note was incidentally left on the table, and we kept it for illustrative purpose.