Adaptive Heuristics in Stock Selection

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Abstract

We conduct AI-led, open-ended interviews with 1,540 investors across ten countries to understand how they decide which individual stocks to purchase. We find that investors use heuristics: simple rules that draw on cues, such as brand familiarity, to guide stock selection. We identify thirteen such heuristics that capture the reasoning of 95.2% of investors in our sample, with at most minor gaps. Investors are more likely to choose heuristics they perceive as more effective for the goals they prioritize; some place greater relative importance on high average returns, others on exceptional upside or stable performance. Notably, these perceptions align with historical performance: stocks associated with investors' chosen heuristics outperform those associated with unused heuristics on the goals investors prioritize; chosen heuristics underperform on the goals investors do not prioritize. These findings suggest that investors' reliance on simple rules is partly adaptive: they tend to choose rules suited to their priorities and local market conditions.

JEL Classification: G11, G12, G14, G40, G50

Keywords: Heuristics, Investor Decision Making, Field Interview, Large Language Models, Artificial Intelligence

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1. Introduction

Many retail investors directly purchase individual stocks rather than obtain all of their equity exposure through diversified funds. In the United States, for example, 21% of households directly held individual stocks in 2022, while 58% held stocks either directly or indirectly through funds and retirement accounts (Aladangady, Bricker, Chang, Goodman, Krimmel, Moore, Reber, Henriques Volz, and Windle 2023). Once investors decide to invest in individual stocks, they face a daunting task. There are thousands of securities to choose from, and assessing their future returns and risks requires processing substantial amounts of information. How do investors determine which stocks to purchase?

A large literature studies individual investor decision making through their trading records and portfolio holdings (e.g., Barber and Odean 2000, Grinblatt and Keloharju 2001, Barber and Odean 2008, Betermier, Calvet, and Sodini 2017). These studies provide valuable evidence on which stocks investors buy, when they trade, and how their investments perform. But they do not directly reveal the reasoning that leads an investor to purchase a particular stock.

To better understand the considerations behind investors' stock purchase decisions, researchers increasingly examine investors' own explanations. Some studies use surveys to elicit investors' views and motives (e.g., Choi and Robertson 2020, Bender, Choi, Dyson, and Robertson 2022, Chinco, Hartzmark, and Sussman 2022, Liu, Peng, Xiong, and Xiong 2022). Others analyze written accounts of why certain market participants favor particular stocks such as analyst reports or online stock-opinion posts (e.g., Chen, Hwang, and Peng 2025). These approaches help distinguish explanations that can generate similar trading patterns but rest on different assumptions about investor behavior.

In this paper, we conduct field interviews to study how investors determine which individual stocks to purchase. Interviews allow respondents to describe their approaches in their own words and permit follow-up questions that clarify how the considerations they mention guide their decisions. Recent advances in AI-led interviewing make it possible to conduct these conversations at scale while following a common protocol across countries and languages (Chopra and Haaland 2023, Geiecke and Jaravel 2024). In our setting, respondents receive a link to an online chat interface, where they exchange written messages with an AI interviewer. The interviewer begins with an open-ended question about how they select stocks, then uses their answers to formulate follow-up

questions within a researcher-designed protocol. These questions invite respondents to elaborate on the considerations they raise and explain how those considerations guide stock selection. At the end, the interviewer summarizes each respondent's approach and asks her to assess the summary's accuracy.

Using this approach, we interview 1,540 investors across ten countries. Our sample includes 280 investors from the United States and 140 each from Australia, Canada, France, Germany, India, Japan, South Korea, Singapore, and the United Kingdom. Within each country, more than half of the respondents have at least USD 500,000 in investable assets.

A brief example illustrates what these conversations can reveal. One respondent initially describes her stock selection as involving "A combination of factors including stability and dividends." Follow-up questions reveal that, to this respondent, "stability" means "it [the firm] will exist in 5 years" and that the respondent assesses this through product popularity: "do people I know use their products - ex, Apple with the I-Phone." This conversation reveals that the investor uses product popularity to identify companies she perceives as stable. Such connection would have been difficult to infer from her trades or holdings, or from her response to a survey question alone.

To systematically compare the interview transcripts, we use large language models (LLMs) to represent each transcript as an argument map, structured as a directed acyclic graph (Andre, Haaland, Roth, Wiederholt, and Wohlfart 2026). The maps record the considerations investors mention and the connections they draw among them. This common representation allows us to identify similar approaches even when respondents describe them in different terms.

Our analysis reveals that investors generally rely on heuristics. They use rules based on a limited set of cues to identify stocks they believe will serve their objectives. Some investors buy companies with strong fundamentals, others seek innovative firms, and still others favor familiar brands or stocks with strong recent returns.

We identify a total of thirteen recurrent heuristics, which, together, capture the reasoning of 95.2% of our investors. They are: *Authority-Follow*, *Blue-Chip Comfort*, *Buy-the-Dip*, *Confluence*, *Dividends*, *ESG/Values*, *Familiarity/Brand Affect*, *Fundamental Strength*, *Growth/Innovation*, *Momentum*, *Social-Copy*, *Technical Analysis*, and *Valuation/Mispricing*. We describe each heuristic in the main body of our paper. Briefly, *Authority-Follow* and *Social-Copy* follow professionals and peers, respectively; *Blue-Chip Comfort* favors large, established firms; *Buy-the-Dip* targets temporary price

declines; *Confluence* requires agreement across signals; *Dividends* seeks dividend income; *ESG/Values* emphasizes alignment with personal values; *Familiarity/Brand Affect* draws on product familiarity and experiences; *Fundamental Strength* emphasizes financial health; *Growth/Innovation* targets growth prospects; *Momentum* follows sustained price gains; *Technical Analysis* uses chart patterns; and *Valuation/Mispricing* compares market value to perceived fair value.

Fundamental Strength and *Growth/Innovation* are the most prevalent, contributing meaningfully to stock selection for 40.5% and 37.6% of investors, respectively. Other common approaches include *Familiarity/Brand Affect*, *Blue-Chip Comfort*, and *Momentum*. Most investors use several heuristics, with an average of 2.6 per investor. While many of these approaches have counterparts in existing research, our contribution is to document their prevalence and combinations within a common sample and measurement framework. We also show that while, in the aggregate, some heuristics are more widely used than others, there is substantial variation in heuristic use across investors. For example, nearly half of all investor pairs share no heuristic.

Heuristic use also varies substantially across countries. For example, 60.0% of Indian investors use *Fundamental Strength*, compared with only 30.0% of U.S. investors. Similarly, 43.6% of Japanese investors use *Familiarity/Brand Affect*, compared with only 19.3% of Singaporean investors. These patterns raise several questions: Why do investors choose heuristics, why does their use vary so much across investors and across countries, and how well do investors' chosen heuristics serve them?

One possible explanation for investors' choice of these simple rules is that they misjudge which information matters for stock selection. This view echoes common warnings in investment guides and financial commentary that heuristics can lead investors astray (e.g., Malkiel 1973, Bogle 1999, Ellis 2002). Yet, another possibility is that heuristic use is partly adaptive: These rules may be well suited to the outcomes investors seek and the markets in which they invest. For example, an investor who prioritizes stability may use a dividend-oriented rule because she recognizes that dividend-paying stocks tend to be unusually stable in her market.

The latter possibility follows from a longstanding view that decision rules should be evaluated in relation to the environments in which they are used (Simon 1955, 1956, Gigerenzer and Gaissmaier 2011). Estimating expected returns and risks for many securities is difficult, and estimation

error can undermine the benefits of more elaborate decision-making processes.[1] Simple rules can exploit stable features of the environment by focusing on a few cues that are informative about an investor's primary objective (e.g., DeMiguel, Garlappi, and Uppal 2009). Applied to our setting, this perspective suggests that investors could be adaptively simplifying stock selection in ways that preserve information useful for achieving their particular objectives.

We develop two hypotheses to examine this possibility. The first concerns heuristic choice. We conjecture that investors are more likely to use heuristics they perceive as more effective for the objectives they care more about. The second concerns adaptation. We distinguish between *semi-strong-form adaptation*, under which investors' perceived effectiveness contains information about actual historical effectiveness in their own markets, and *strong-form adaptation*, under which investors' chosen heuristics actually deliver better outcomes on their prioritized objectives than unused heuristics, which they could have used but chose not to.

To test these hypotheses, we conduct a personalized follow-up survey of 600 participants drawn from the original pool of 1,540 interviewees.[2] The follow-up sample is broadly similar to the original sample in observable investor characteristics and heuristic use. First, we ask how much importance respondents attach to consistently high returns, exceptional upside, and stability.[3] Our respondents differ considerably in their priorities: more than 80% rate at least one financial objective strictly above another.

Second, we elicit their perceptions of how effective they believe the approaches they use or have used are in achieving their key objectives. We then assess whether these perceptions contain information about actual historical effectiveness, which we estimate independently using global stock market data. Specifically, we map seven of the thirteen heuristics to observable firm characteristics (e.g., *Fundamental Strength* to various profitability measures) and examine, in each country over the decade preceding the interviews, how stocks with the characteristics a heuristic favors perform relative to stocks with the opposite characteristics. We measure effectiveness for average returns, upside, and stability using the CAPM alpha, the frequency of exceptionally high returns, and return

[1] Even when information is available, limited cognitive resources can make its evaluation imprecise, leaving decision makers uncertain about which choice best serves their objectives (Woodford 2020, Enke and Graeber 2023, Oprea and Woodford 2026).

[2] Funding constraints are the primary reason we do not survey all 1,540 interviewees again.

[3] We also ask about alignment with personal values. As discussed in Section 5.3, these values vary widely across investors. This heterogeneity, together with data limitations, prevents us from independently measuring how effectively each heuristic serves this objective.

volatility, respectively. For instance, we examine whether investors' assessment of *Fundamental Strength* as effective for achieving high average returns in a particular country corresponds to higher alphas for stocks with high profitability measures in that country.

Past outcomes provide a natural benchmark for assessing adaptation. A related question is whether chosen heuristics continue to serve investors' priorities after investors begin using them. A proper evaluation of this question would require several additional years of data after the interviews and follow-up survey. We discuss how such study could be designed and provide an auxiliary test based on start dates estimated from self-reported usage durations in Section 5.5.4.

Our results support the heuristic choice hypothesis. Investors are more likely to use heuristics they perceive as more effective for the objectives they care more about. The interaction between the importance assigned to an objective and perceived effectiveness is positive and statistically significant across all specifications. Investors' choices thus reflect how well they believe an approach serves their particular goals. Importantly, investors distinguish between a heuristic's effectiveness for different objectives: they often view an approach as well suited to one goal but less suited to another. Their assessments thus reflect perceived strengths and weaknesses across objectives rather than a single ranking of approaches from best to worst.

We next examine whether these beliefs correspond to actual historical effectiveness. We find that within investors, heuristics rated as more effective for a given objective were in fact more effective for that objective in their own markets over the decade preceding the interviews. The relation is positive and statistically significant overall. It is also positive for each of the three financial objectives. These findings are in line with semi-strong-form adaptation: investors' assessments contain information about independently measured actual historical performance.

Turning to strong-form adaptation, we examine whether investors' chosen heuristics historically deliver better outcomes on their prioritized financial objectives than a broad set of unused heuristics. Among the seven heuristics covered by our archival measures, we compare each investor's chosen approaches with equally sized sets of heuristics drawn randomly from those she does not use, evaluated in the same country and period. These unused heuristics include approaches she may have previously used and abandoned, but also those she may have never personally tried. Chosen heuristics outperform unused heuristics on the financial objectives investors prioritize. On objectives investors do not prioritize, however, chosen heuristics perform worse on average. Again, this contrast

suggests that investors select approaches whose relative strengths match their particular priorities, rather than approaches with broadly superior performance.

Overall, our interviews reveal that investors use a range of heuristics to select individual stocks. Our subsequent tests suggest that their choice of heuristics is at least partly adaptive. Investors favor approaches they believe serve their priorities. Critically, these beliefs contain information about actual historical effectiveness, and investors' chosen heuristics are more effective than unused heuristics on their prioritized objectives.

Our study makes three contributions. First, we contribute to a fundamental question in finance: how do investors decide which assets to hold? Understanding how preferences and beliefs translate into investment choices is important for both household finance and asset pricing (Gomes, Haliassos, and Ramadorai 2021, Koijen and Yogo 2019), and recent work calls for a richer account of how investors think about this decision (Campbell and Ramadorai 2026). A growing empirical literature uses surveys to study the considerations underlying investment decisions. Choi and Robertson (2020) and Bender, Choi, Dyson, and Robertson (2022) survey U.S. households and U.S. millionaires, respectively, to examine the factors they consider when deciding how much of their wealth to allocate to equities and their beliefs about the risks and returns of particular investment styles. Chinco, Hartzmark, and Sussman (2022) use survey experiments to test whether investors consider the correlation of stock returns with consumption growth, as consumption-based asset-pricing models predict. Liu, Peng, Xiong, and Xiong (2022) link survey responses to transaction data for Chinese retail investors and find that perceived information advantages and gambling preferences best explain why some Chinese investors trade more actively than others. Complementary work analyzes written buy recommendations to understand why investors favor stocks on the short legs of return anomalies (Chen, Hwang, and Peng 2025). We extend this literature by providing a systematic account of how investors select individual stocks, elicited in their own words. Our sample spans ten countries and includes substantial numbers of investors with large financial asset holdings, allowing us to compare stock-selection approaches across markets and wealth levels within a common measurement framework.

We find that investors largely rely on simple rules to select individual stocks: thirteen recurrent heuristics capture the reasoning of 95.2% of investors. We further show that investors' choices among these heuristics align with their financial objectives and with both perceived and measured

effectiveness. These findings motivate models in which heterogeneous objectives and beliefs about heuristic effectiveness jointly determine which heuristics investors choose and, in turn, which firm characteristics they favor.

Such models may help explain why average return differences tied to firm characteristics persist at equilibrium prices. Investors who place greater importance on stability or exceptional upside may prefer approaches that serve those objectives, even if they recognize that another heuristic identifies stocks with higher expected returns at prevailing prices. Even investors who prioritize high average returns may also care about risk, upside potential, or alignment with personal values. Capital may therefore flow toward a return-oriented approach only until its remaining expected-return advantage compensates investors for the trade-offs involved in increasing their positions. Price adjustment can thus reduce the return advantage of stocks associated with a heuristic without eliminating it. This mechanism offers a possible explanation for why seemingly anomalous performances exist and even persist post-publication (McLean and Pontiff 2016, Jacobs and Müller 2020, Chen 2021, Jensen, Kelly, and Pedersen 2023).

Second, we make a methodological contribution by combining AI-led interviews with LLM-based argument maps. Fixed survey questions offer limited scope to probe unexpected answers, while existing texts may leave important aspects of investors' reasoning unstated. Building on advances in AI-led interviewing (Chopra and Haaland 2023, Geiecke and Jaravel 2024), we allow investors to introduce considerations in their own words and use adaptive follow-up questions to clarify how those considerations guide stock selection. The interviews can thus uncover connections that an initial response or written account leaves ambiguous. LLM-based argument maps then organize these accounts into comparable representations, allowing us to identify common approaches even when respondents express similar ideas in different terms (Andre, Haaland, Roth, Wiederholt, and Wohlfart 2026). Together, these tools combine the depth of field interviews with the scale and consistency needed for systematic comparisons.

Finally, our findings provide empirical inputs for the growing literature using AI agents to model investors and financial markets. Recent studies examine under what conditions LLM-based agents behave similarly to real-world investors and whether markets populated by such agents can reproduce observed market regularities (Bhagwat, Cookson, Dim, and Niessner 2025, Bybee 2023, Henning, Ojha, Spoon, Han, and Camerer 2025, Lopez-Lira 2025). If sufficiently realistic, these

simulated markets could provide a setting for studying how changes in regulations or market design affect investor behavior and market outcomes. Building such markets requires specifying plausible objectives and decision rules that actual, real-world investors follow. It also requires evidence on how prevalent these objectives and rules are in the real world. Our study provides these empirical inputs within a common measurement framework across ten countries.

The remainder of the paper proceeds as follows. Section 2 develops our hypotheses. Section 3 describes the subject pool, interviews, transcript analysis, and follow-up survey. Section 4 presents descriptive evidence on heuristic use, and Section 5 tests the choice and adaptation hypotheses. We conclude in Section 6.

2. Hypothesis Development

2.1. Investor Objectives

We posit that investors differ in the objectives they prioritize when actively selecting individual stocks. Some prioritize consistently high returns: In a portfolio of five stocks, they would ideally want most or all to perform well. Others prioritize the possibility of exceptional gains: They may be satisfied with moderate returns on most holdings as long as one becomes a very large winner. Still others prioritize stable and predictable performance or alignment with personal values even at the expense of financial returns. These objectives are likely all important to investors and not mutually exclusive, but investors may still attach higher *relative* importance to some of the goals.

Data limitations, discussed in Section 5.3, prevent us from evaluating outcomes related to personal values alignment. Our hypothesis development therefore focuses on the three objectives related to a stock's future return distribution: consistently high returns, the possibility of exceptional gains, and low volatility. Let $g \in \mathcal{G} = \{\text{Returns}, \text{Upside}, \text{Stability}\}$ index these objectives, and let investor i be characterized by a vector of weights, $\theta_i = (\theta_{ig})_{g \in \mathcal{G}}$, where θ_{ig} captures the relative importance she assigns to objective g.

2.2. The Choice of Heuristics

Selecting stocks that deliver on an investor's prioritized objectives requires forming beliefs about return distributions for a large set of securities. We posit the reason investors use heuristics is to simplify this task.

Let $X_g(s)$ denote the realized outcome of stock s with respect to objective g, defined so that higher values indicate better performance on that objective. We define the true effectiveness of heuristic h in achieving objective g in country c as

$$\eta_{hgc} = \mathbf{E}\left[X_g(s) \mid s \text{ is selected by heuristic } h \text{ in country } c\right].$$

True effectiveness may vary across objectives and countries. For example, a dividend-oriented rule may identify stocks with consistently high returns in one country but stocks with particularly low volatility in another. Similarly, a growth-oriented rule may identify stocks with exceptional upside potential in some countries but provide little information about such outcomes in others.

We denote investor i's perceived effectiveness of heuristic h for objective g in country c by η^{P}_{ihgc}. A heuristic's perceived effectiveness need not be high across all objectives, that is, be uniformly strong. Investors may differentiate and rate a heuristic's effectiveness higher for some dimensions and weaker for others. We conjecture that conditional on active stock selection, investor i chooses a set of heuristics $\mathcal{H}_i$ based jointly on her weights θ_i and these perceptions η^{P}_{ihgc}. In our baseline hypothesis, we assume equal implementation costs across heuristics.[4]

Hypothesis 1 (Heuristic Choice)**.** Investor i's choice of heuristics $\mathcal{H}_i$ depends jointly on the weights θ_i she assigns to different objectives and the corresponding perceived effectiveness η^{P}_{ihgc}. Investors are more likely to choose heuristics they perceive as more effective for the objectives they care more about.

2.3. The Adaptiveness of Investors' Chosen Heuristics

We further conjecture that investors use heuristics *adaptively*. In our hypothesis, we distinguish between two forms of adaptation.

[4]Differences in implementation costs may lead investors to choose a less effective heuristic because it is less costly to implement, even when they correctly perceive the effectiveness of the alternatives.

Hypothesis 2 (Heuristic Adaptation)**.**

(a) *Semi-Strong-Form Adaptation.* Investor i's perceived effectiveness η^{P}_{ihgc} is positively related to the true effectiveness η_{hgc} of heuristic h for objective g in her country c.

(b) *Strong-Form Adaptation.* For objectives g to which investor i assigns relatively high weight θ_{ig}, stocks selected by her chosen heuristics $\mathcal{H}_i$ deliver higher average outcomes X_g than stocks selected by heuristics she does not use, evaluated in the same country and over the same period.

Our hypotheses and our empirical tests assess whether investors' beliefs and choices align with historical effectiveness. Separate analyses could explore whether these heuristics subsequently serve investors' priorities to more directly assess their practical effectiveness. Such analysis would require additional years of data. We discuss this point further in Section 5.5.4.

Together, our hypotheses propose that heuristics represent adaptive responses to a complex inference problem. Forming beliefs about expected returns, extreme outcomes, and risk for many securities requires estimating numerous parameters from noisy data. This task is both computationally demanding and subject to substantial estimation error. Simple rules may exploit stable features of the environment by focusing on a few cues that are informative about the objectives an investor prioritizes. Related theories of rational inattention and sparsity argue that agents facing complex decisions optimally concentrate on a limited set of payoff-relevant dimensions (Sims 2003, Gabaix 2019). Our hypotheses examine whether similar adaptive features help explain how investors determine which individual stocks to purchase.

We note one important caveat: Under the classical mean–variance framework with homogeneous beliefs and frictionless borrowing and lending, investors optimally hold combinations of the market portfolio and the risk-free asset. We do not challenge this benchmark. Rather, based on our interview evidence, we take as given that many investors want to actively select individual stocks and rely on heuristics to aid in their stock selection. Conditional on their doing so, we examine whether their choice of heuristics reflects systematic alignment between objectives, perceived effectiveness, and true effectiveness.

2.4. Empirical Implementation

Testing Hypotheses 1 and 2 requires four measures: (i) investor i's weights θ_{ig}; (ii) her perceived effectiveness η^{P}_{ihgc} of various heuristics; (iii) the corresponding true effectiveness η_{hgc}; and (iv) the set of heuristics $\mathcal{H}_i$ she ends up using.

As described in the next section, we can measure the weights, perceived effectiveness, and actual heuristic use directly from our survey and interview data. To construct empirical proxies for true effectiveness, we first map each heuristic to the firm characteristics it is likely to select on. We then compare the subsequent outcomes of stocks with the characteristics a heuristic favors relative to those of stocks with the opposite characteristics to construct country-specific measures of performance on each objective. Section 5.3 describes the characteristic mappings and the historical performance measures.

3. Sample and Methodology

3.1. Subject Pool

We recruit retail investors who invest on their own behalf and currently hold individual stocks through CoreData Research, a market research firm that conducts investor surveys for major financial institutions. The firm maintains a global panel of retail and institutional investors who have agreed to receive occasional survey invitations in exchange for monetary compensation and have obtained any required compliance clearance. These surveys generally concern market outlook and investment trends. For our study, CoreData Research informs participants that they will take part in an academic study involving an AI-led interview about how they select stocks. We design the interview protocol and web application and pay CoreData Research a lump sum to manage recruitment, participant compensation, and delivery of completed responses.

We impose quotas on investable assets to examine variation in stock-selection approaches across wealth levels and facilitate comparisons across countries. Our final sample comprises 1,540 investors across ten countries: 280 from the United States and 140 each from Australia, Canada, France, Germany, India, Japan, South Korea, Singapore, and the United Kingdom. In each country other than the United States, we recruit 40 investors with at least USD 1,000,000 in investable assets, 40

with USD 500,000–999,999, and 60 with USD 1,000–499,999. We double each quota for the United States, preserving the same proportions across wealth strata in all ten countries. The resulting samples are not nationally representative of stock investors. All interviews take place in July and August 2025.

Table 1 reports descriptive statistics for the full sample, and Table 2 reports demographic distributions by country. Participants vary widely in gender, age, education, self-reported investment knowledge, and attitudes toward risk. The country samples are broadly comparable in gender, age, and education, with two main exceptions: Japanese participants are predominantly male, while Indian participants are younger and almost all hold a university degree.

3.2. Step 1: The Initial Background Survey and the Interview

Step 1 comprises three stages: (i) the background survey stage, (ii) the main AI-led interview stage, and (iii) the summary and evaluation stage.

1. **Background survey:** CoreData Research sends investors a brief closed-ended (multiple-choice) survey to collect or confirm basic background information, including their country of residence, age, gender, educational background, personal investments (investment types held and total investable assets), frequency of changes to their investments, sources of wealth, perceived investment knowledge, and perceived risk appetite. We present the full questionnaire in Online Appendix A.[5]

   Respondents who report currently investing in individual stocks are directed to our web application for the AI-led interview: https://investment-ai-interview.streamlit.app/.

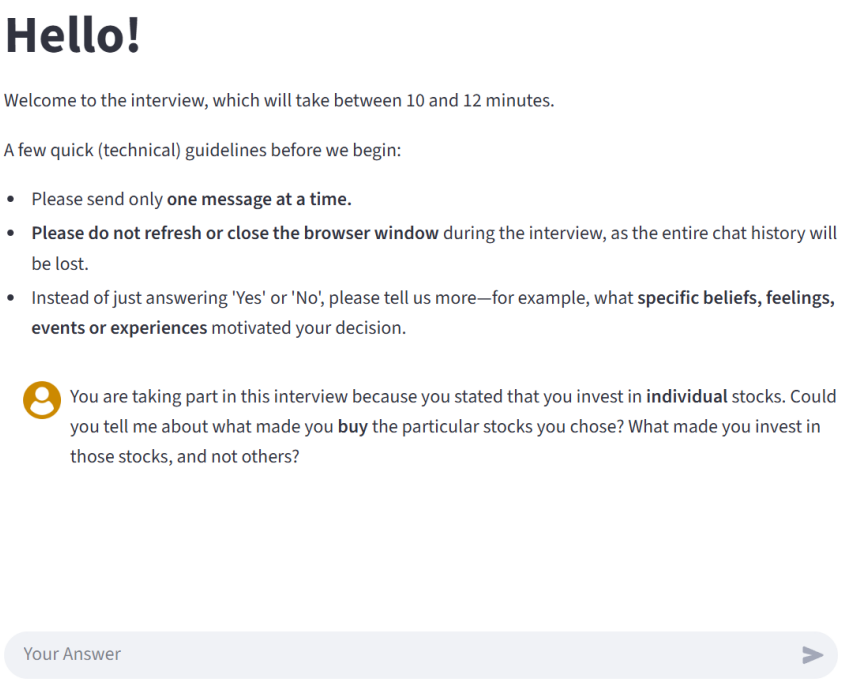
2. **AI-led interview:** Once participants open our app, they engage in a one-on-one interview with an AI agent. The AI agent runs on GPT-4.1, the most recent GPT model at the time we developed the AI-led interview. We describe our instructions to the AI agent in Online Appendix B. We design these instructions to follow best research practices and to mimic the training we would provide to a human interviewer.

   While each interview is unique in both content and line of questioning, reflecting its open-ended and adaptive nature, it adheres to a consistent structure:

[5]The Online Appendix is available at https://adaptive-heuristics.github.io/.

(2.a) Participants enter the unique ID they receive upon completing the background survey and select their preferred language: English, French, German, Japanese, or Korean. The AI agent conducts the remainder of the interview in that language.

(2.b) Participants receive a greeting and brief instructions, followed by the opening question shown below.



(2.c) The AI agent asks ten to fifteen adaptive follow-up questions to explore participants' reasons for buying particular stocks without directing them toward specific answers. It then asks a final "sweep" question, inviting participants to raise any considerations that have not yet been discussed. If participants introduce additional considerations, the agent asks two to three further questions to explore them (see Online Appendix B). The interview concludes with one fixed multiple-choice question asking whether participants continue to track the performance of stocks after selling them.

3. **Summary and evaluation:**

(3.a) The AI agent summarizes the key points from the interview and asks respondents to rate, on a four-point scale, the accuracy of the summary and the overall quality of the interview. The AI agent also asks respondents (1) whether they would prefer a human interviewer

over the AI interviewer and (2) whether they would prefer a single open-ended question over the AI-led conversation. Both preference questions include an option to express indifference. Online Appendix B provides the exact wording and response options.

(3.b) The AI agent closes the session with a brief thank-you note.

The average respondent spends approximately four minutes on the background survey and around nineteen minutes in the AI-led interview, summary, and evaluation stages. The interview duration is broadly similar across demographic groups, although it is approximately two and three minutes longer for male and older investors, respectively (Online Appendix Table G1).

Online Appendix Figures G1 and G2 report the responses to the five multiple-choice questions. Notably, most respondents continue to track the performance of stocks after selling them: 87% do so at least "sometimes," with 31% selecting "always" (Online Appendix Figure G1). More importantly in the context of this study, respondents generally rate the interview experience favorably (Online Appendix Figure G2). Most respondents (94%) rate the AI agent's summary of the key points from the interview as "good" or "very good," with 62% selecting "very good." Only 11% would prefer a human interviewer; 39% prefer the AI interviewer and 50% are indifferent. Despite the substantial time spent on the interview, only 15% would prefer a single open-ended question. Preference for the AI interviewer is broadly similar across demographic groups but somewhat stronger among younger investors, those with higher education, and respondents in Asian countries (Online Appendix Table G2). Together, these responses suggest that participants view the summaries as accurate representations of their approaches to stock selection and generally accept the AI-led conversational format despite its substantial time commitment.

3.3. Step 2: Extracting Heuristics From the Interview Transcripts

In Step 2, we analyze the 1,540 interview transcripts in four stages: (i) conversion of each transcript into an "argument map," (ii) identification of recurrent heuristics across transcripts, (iii) validation and refinement, and (iv) final scoring on how strongly each transcript loads on the recurrent heuristics. Step 2 uses GPT-5, the most recent GPT model available at the time of this part of our analysis. Online Appendix C summarizes the prompts for each stage.

1. **Constructing argument maps:** We convert each transcript into an investor-level argument

map, represented as a directed acyclic graph (DAG). We construct these maps from the reasoning expressed in each transcript in an entirely bottom-up, data-driven manner. Each map consists of (i) nodes, representing factors relevant to the stock-purchase decision (e.g., signals, beliefs, preferences, affect, constraints); (ii) directed edges, which trace the links between the nodes; and (iii) a node dictionary, providing short definitions for each node. The resulting maps summarize each investor's stated reasoning from initial cues to the final purchase decision.

Figure 1 illustrates the structure of argument maps with stylized examples. In Panel (a), an investor states that she purchases a company's stock because the company offers "innovative products." When the AI interviewer asks what these products signal to her, she explains that they indicate substantial growth potential. The DAG corresponding to this conversation consists of:

- a "node set" = {InnovativeProduct, GrowthPotential, BuyStock}
- a "directed edge set" = {(InnovativeProduct, GrowthPotential), (GrowthPotential, BuyStock)}
- a "node dictionary" that defines all three nodes.

In Panel (b), we show another example with a greater number of nodes and edges. These plots are stylized illustrations. In the analysis, LLMs produce DAGs as textual outputs.

[Figure 1 here]

2. **Identifying recurrent heuristics:** We examine the full set of 1,540 DAGs for pathways that share a common logic leading to stock purchases. We group related pathways into recurrent approaches, or "heuristics." For each heuristic, GPT-5 generates a concise description of its core logic, representative pathways, diagnostic edges that distinguish it from other heuristics, and recurrent cues that trigger its use.
3. **Validation and refinement:** We return to the investor-level maps and assess how fully the proposed heuristics capture each investor's stated decision process. If more than 5% of the investor-level maps contain substantial unexplained patterns, we refine the taxonomy by lightly broadening existing descriptions and, if necessary, adding at most one new heuristic based on the dominant residual pattern. We repeat the procedure until the residual share

falls below 5%. In our implementation, the cycle runs once, yielding thirteen heuristics that account for the reasoning of 95.2% of investors in our sample, leaving at most minor aspects of their rationale uncaptured (Online Appendix C.3.2).

4. **Final scoring:** We assign each transcript–heuristic pair a four-point score that captures how strongly the heuristic governs the reasoning of a particular investor, where 4 denotes a primary driver, 3 a meaningful contributor, 2 a fragmentary presence, and 1 absence. To reduce sensitivity to variation across model runs, we repeat the scoring procedure fifteen times and use the median score for each pair. This procedure yields a $1{,}540 \times 13$ matrix of heuristic scores.

3.4. Step 3: The Follow-Up Survey

In Step 3, we return to the original interviewees with a closed-ended follow-up survey.[6] As before, CoreData Research handles participant outreach and compensation, and respondents complete the survey in their preferred language. The survey runs for approximately one month, from mid-May through mid-June 2026. Our research budget allows for 600 completed responses, and we close the survey upon reaching this target.

Respondents span all ten countries and a broad range of investor characteristics (Online Appendix Tables G3 and G4). Response rates differ across countries, but respondents and nonrespondents exhibit broadly similar demographic characteristics. The 600 respondents are somewhat older, wealthier, and more likely to report advanced investment knowledge than the 940 nonrespondents (Online Appendix Table G5, Panel A). Respondents and nonrespondents spend essentially the same amount of time in the initial AI-led interview (18.5 versus 18.9 minutes) and use nearly identical numbers of heuristics on average (2.56 versus 2.57). Crucially for our analysis, the prevalence of each heuristic is similar between respondents and nonrespondents. For example, 39.3% of respondents and 41.2% of nonrespondents select stocks based on firms' fundamental strength; 28.7% of respondents and 28.3% of nonrespondents rely on familiarity or brand affect. Across all thirteen heuristics, the differences between the two groups are no larger than 3.4 percentage points (Online Appendix Table G5, Panel B).

[6] Online Appendix D presents the follow-up survey materials.

We personalize each follow-up questionnaire using the heuristics identified in the respondent's initial AI-led interview. The first question begins with: "In our previous interview, we discussed several approaches you use when deciding which stocks to buy. Below are the approaches we recorded for you. Please review them and answer the question that follows." Throughout the survey, we use the neutral term "approaches" rather than "heuristics" and we present each approach with a plain-language label and a one-sentence description.

Respondents first review the approaches identified in their initial interview and indicate, for each approach, whether they still use it and, if so, for how long. We then present the remaining heuristics, which were *not* identified for this particular respondent in their initial interview. For each of these remaining heuristics, we ask respondents whether they have heard of the approach and, if so, whether they have ever used it.

Two sets of questions are central to our analysis. First, we ask respondents to rate how important each of four objectives is to them personally. The following four goals appear verbatim in randomized order:

- **Consistent High Returns:** "I look for stocks that, in most cases, are likely to give me high total returns (from price gains or dividends). For example, if I hold five stocks, I would ideally want most or all of them to do well."
- **High Upside Focus:** "I look for stocks that could become major winners and deliver very large gains. For example, if I hold five stocks, it is OK if most deliver only moderate returns, as long as at least one becomes a very big winner."
- **Stable Performance:** "I look for stocks that I expect to give stable and predictable performance."
- **Personal Values Alignment:** "I invest in companies that match my personal values, even if it means lower financial returns."

Respondents rate each goal on a five-point slider ranging from 1 ("Not important at all") to 5 ("Extremely important"). We use these ratings to measure investor i's weights θ_{ig}.

Second, we ask respondents to assess how effective they believe a particular approach is at identifying stocks that meet a particular objective in their country's stock market. To keep the survey length manageable, we elicit these ratings only for the objectives the respondent rates as "important" or "extremely important" (4 or 5) and only for approaches the respondent describes in the initial

interview or, in the follow-up survey, reports as having used previously.[7] Perceived effectiveness is measured on a five-point scale ranging from 1 ("Not effective at all") to 5 ("Extremely effective"), with the order of objectives and approaches randomized. These ratings provide our measure of perceived effectiveness, η^{P}_{ihgc}.

The survey also collects information on respondents' investment allocations, including the share of their stockholdings invested in locally listed stocks, which we later use to assess the robustness of our findings.

4. Evidence: The Use of Heuristics in Stock Selection

We begin by describing the recurrent heuristics, their prevalence in the pooled sample, and how their use varies across countries and investor demographics.

4.1. Evidence in the Pooled Sample

Our procedure determines thirteen recurrent heuristics that, together, summarize how investors in our sample choose which individual stocks to purchase. Table 3 provides detailed descriptions based on the transcript analysis described in Section 3.3. The heuristics differ mainly in the cues investors use. *Fundamental Strength*, *Growth/Innovation*, and *Valuation/Mispricing* focus on financial performance, growth and R&D metrics, and valuation ratios, respectively, and *Dividends* targets high dividend income. *Familiarity/Brand Affect* draws on personal familiarity and product experiences, while *Blue-Chip Comfort* favors large, established firms. *Momentum*, *Buy-the-Dip*, and *Technical Analysis* rely on sustained price gains, temporary price declines, and chart patterns, respectively. *Authority-Follow* follows trusted professionals, *Social-Copy* follows friends and family, *Confluence* requires agreement across multiple signals, and *ESG/Values* screens firms on the investor's values.

Table 4 illustrates these heuristics through respondents' own descriptions of how they select stocks. For each heuristic, we present an excerpt from an investor for whom it is the sole "primary driver" of stock-purchase decisions. For example, an investor classified under *Fundamental Strength* explains: "I prioritize revenue growth, profit margins, return on equity (ROE), debt-to-equity ratio,

[7] If this combined set contains more than three approaches, respondents assess effectiveness only for the three they have used for the longest period. Otherwise, they rate all approaches in the set.

and cash flow generation, as these metrics provide insight into a company's financial health and sustainability." An investor classified under *Social-Copy* instead states: "I pay a lot of attention to what my parents buy. They simply have more experience than I do."[8]

In Figure 2, we display the proportion of transcripts in which each heuristic features prominently, based on the scoring procedure described in Section 3.3. The dark bars represent the share of transcripts in which a heuristic is a "primary driver" of the investor's stock selection. The light bars represent the share in which it is at least a "meaningful contributor."

Fundamental Strength and *Growth/Innovation* are the most prevalent, contributing meaningfully to stock selection for 40.5% and 37.6% of investors, respectively. *Familiarity/Brand Affect* (28.4%) and *Blue-Chip Comfort* (28.1%) follow. The remaining heuristics each contribute meaningfully for between 10.3% and 18.6% of investors, except *Technical Analysis*, which contributes meaningfully for 6.8%. These shares sum to more than 100% because most investors use multiple heuristics, with an average of 2.6 per investor.[9]

Many of these approaches have counterparts in existing research, including studies of momentum (Barberis, Shleifer, and Vishny 1998), familiarity (Frieder and Subrahmanyam 2005, Keloharju, Knüpfer, and Linnainmaa 2012), social influence (Han, Hirshleifer, and Walden 2022), and dividend preferences (Shefrin and Statman 1984, Hartzmark and Solomon 2019), among others. Our contribution is to document their prevalence within a common sample and measurement framework.

Although some heuristics are more prevalent than others in the pooled sample, investors differ substantially in the combinations they use. Nearly half of all investor pairs (49.1%) share no heuristic, despite investors using an average of 2.6 heuristics each. This heterogeneity is not simply a consequence of pooling investors from different countries: within individual countries, the share of pairs with no heuristic in common ranges from 34.5% in South Korea to 58.7% in Canada (Online Appendix Figure G5). Thus, even investors operating in the same national market often rely on entirely different sets of stock-selection cues.

[8] We translate this excerpt from German.

[9] Online Appendix Figure G3 shows that 34.7% of investors use two heuristics and 35.6% use three, whereas only 12.5% use one. Online Appendix Figure G4 shows the most common combinations and identifies pairs used together more or less often than would be expected if heuristic choices were independent, given each heuristic's unconditional prevalence.

4.2. Evidence Across Countries

Heuristic use also varies notably across countries. Figure 3 compares heuristic prevalence across the ten countries. In each radar chart, distance from the center represents the proportion of investors using a given heuristic. The dark region represents primary drivers, and the light region includes all heuristics that are at least meaningful contributors. Our discussion focuses on the light regions; the patterns are similar for the dark regions.

The charts reveal substantial cross-country variation. For example, 60.0% of Indian investors use *Fundamental Strength*, compared with 30.0% of U.S. investors. Similarly, *Familiarity/Brand Affect* contributes meaningfully to stock selection for 43.6% of Japanese investors, compared with 19.3% of investors in Singapore. Our sampling design holds the wealth composition fixed across countries, and the samples are broadly comparable along other demographic dimensions (Table 2), suggesting that our observed differences are not a mere artifact of differences in demographics.

To explore which countries are most similar to each other in their heuristic use, we conduct agglomerative hierarchical clustering based on the prevalence of the thirteen heuristics (Online Appendix Figure G6(a)). Three groups emerge at the reported cutoff. South Korea, India, and Singapore form a group in which fundamental and growth-oriented approaches are particularly prevalent. Japan stands apart through its use of *Dividends* and *Familiarity/Brand Affect*. Australia, Canada, France, Germany, the United Kingdom, and the United States form a group with more balanced profiles.[10] The pronounced differences across countries caution against broadly generalizing retail investor evidence from one country to other countries. At the same time, the agglomerative hierarchical clustering also indicates for which subsets of countries findings from one country may carry over to others.

What could explain the observed variation in heuristic use across some of the countries? One possible explanation is that investors in different countries place different weights on different investment objectives. Even for the same objective, differences in economic structure and the composition of listed firms may generate differences in the heuristics that best serve that objective.

[10]Clustering on the six Hofstede cultural dimensions (Hofstede, Hofstede, and Minkov 2010) produces nearly identical groups, with France the only country that changes groups (Online Appendix Figure G6(b)). This correspondence is consistent with cultural influences on heuristic use (Chui, Titman, and Wei 2010). It could also reflect similarities in economic structure across culturally similar countries, making the same heuristics effective in achieving a particular objective.

If investors use heuristics adaptively, their choices should reflect these differences. We formally test this proposition in Section 5.

4.3. Evidence Across Investor Demographics

We next examine how heuristic use varies across investor demographics. We divide investors into two groups along each of six dimensions: gender, age, education, wealth, self-reported investment knowledge, and self-reported risk attitude. Online Appendix Figure G7 presents the resulting twelve radar charts.

We find that heuristic use varies across demographic groups, but these differences are modest compared with those across countries. Male investors use *Fundamental Strength*, *Growth/Innovation*, and *Valuation/Mispricing* more frequently than female investors. Conservative investors use *Blue-Chip Comfort* more frequently than aggressive investors (34.9% versus 18.6%), while older investors use *Dividends* more frequently than younger investors (15.7% versus 9.1%). But even the largest demographic gap, the 16.3-percentage-point difference in *Blue-Chip Comfort* across risk attitudes, is only about half the 30-percentage-point difference in *Fundamental Strength* between India and the United States.

To examine country and demographic differences jointly, we estimate a separate logit regression for each heuristic, relating an indicator for its use to demographic characteristics and country indicators. Figure 4 presents the coefficient estimates in a bubble plot, with marker size indicating magnitude and filled markers denoting statistical significance. Again, several demographic characteristics predict heuristic use, but differences across countries are generally much larger than differences tied to demographics.

5. Testing the Choice and Adaptation Hypotheses

The evidence in Section 4 documents substantial variation in heuristic use. We now examine whether this variation is consistent with the adaptive view conjectured in Section 2. We first describe investors' relative priorities and construct measures of perceived and true heuristic effectiveness. We then test whether investors choose heuristics they perceive as more effective for the objectives they relatively care more about (Hypothesis 1). Turning to adaptation, we examine whether perceived

effectiveness tracks historical effectiveness in investors' local markets (Hypothesis 2(a)) and whether chosen heuristics outperform unused heuristics on investors' prioritized objectives (Hypothesis 2(b)).

5.1. Measuring Objectives Investors Prioritize

We measure the weights that investors attach to different objectives, θ_{ig}, using the five-point importance ratings elicited in the follow-up survey (Section 3.4).

Figure 5 reports the proportion of respondents assigning each objective a rating of 4 or 5 (light bars) and a rating of 5 (dark bars). Stability receives a rating of 4 or 5 from 77.0% of respondents, followed by returns at 71.2% and upside at 63.0%. The ranking is unchanged when we consider ratings of 5 only: the corresponding shares are 31.3%, 23.0%, and 18.0%. Each financial objective is therefore important to a majority of respondents, with stability receiving the strongest overall emphasis. Although not the focus of our later empirical analysis, the survey also asks about alignment with personal values. Personal values alignment receives a rating of 4 or 5 from 40.2% of respondents and a rating of 5 from 11.8%.

The broad importance of all three financial objectives does not mean that investors weight them equally. More than 80% of respondents rate at least one financial objective strictly higher than another. Our subsequent tests exploit this variation in investors' relative priorities.

Priorities also vary across countries (Online Appendix Table G4). Stability receives the largest share of ratings of 4 or 5 in most countries, but returns ranks first in India, Japan, and South Korea. Upside receives a rating of 4 or 5 from more than 75% of respondents in India, Singapore, and South Korea.[11]

5.2. Measuring Perceived Effectiveness

We measure perceived effectiveness, η^{P}_{ihgc}, using the five-point effectiveness ratings elicited in the follow-up survey (Section 3.4).

Our analysis focuses on differences in ratings within investors. For the regressions below, we standardize perceived effectiveness within investor across her ratings for the three financial

[11]The number of follow-up respondents varies across countries and is relatively small in some, so we interpret these country-level rankings as indicative.

objectives. This transformation expresses each rating relative to her other ratings and accounts for differences across investors in how they use the response scale.[12]

5.3. Estimating True Effectiveness

To assess whether investors' beliefs and choices align with true effectiveness, we estimate how well the stocks likely favored by a heuristic perform on each objective in each country. We construct these measures independently of the survey responses using the global stock data of Jensen, Kelly, and Pedersen (2023) (henceforth JKP).[13]

Step 1: Mapping heuristics to stocks. JKP examine the replicability of asset-pricing factors using a global dataset covering 93 countries, including all ten countries in our study. They construct 406 stock characteristics using a consistent methodology across markets. Their data therefore provide a natural basis for our international comparisons. Using established characteristic definitions and construction procedures also limits our discretion in building the underlying measures, facilitates replication, and helps ensure that any observed cross-country differences reflect differences in stock performance rather than differences in how we construct the characteristics.

We focus on seven heuristics that we believe we can map to observable firm characteristics: *Fundamental Strength*, *Growth/Innovation*, *Blue-Chip Comfort*, *Buy-the-Dip*, *Dividends*, *Momentum*, and *Valuation/Mispricing*. Our mapping is guided by the cues emphasized in the heuristic descriptions in Table 3. For each heuristic, we select three JKP characteristics that capture those cues and specify whether the heuristic favors high or low values. For example, we map *Fundamental Strength* to return on equity, operating margin, and gross profitability. These measures capture profits relative to shareholder equity, sales, and the firm's asset base, respectively. Similarly, we map *Buy-the-Dip* to low past one-, two-, and three-month returns, capturing recent price declines over different horizons. Table 5 reports the full mapping, including the direction of selection for each characteristic.

These mappings are meant to approximate the stocks each heuristic favors; they are not designed to reproduce every investor's implementation of that heuristic. We also acknowledge that a heuristic

[12] Fifty-six investors assign identical effectiveness ratings across all heuristic–financial-objective pairs they evaluate. We set their standardized ratings to zero. Excluding these investors increases the pooled coefficient in the historical belief–effectiveness regression from 0.137 to 0.152, with a p-value of 0.002 (untabulated).

[13] We exclude nano-cap stocks from the sample.

could plausibly be tied to additional firm characteristics beyond the three we select. To the extent that alternative proxies capture the same underlying attributes, we would expect them to correlate with our chosen measures and yield broadly similar patterns. In Online Appendix E, we assess this conjecture by repeating our main tests with 7,596 distinct alternative mappings built from the choices of LLMs that never see our mapping in Table 5.[14] Online Appendix E shows that our results are robust to these alternative mappings.

For the remaining six heuristics, a comparable mapping is substantially less straightforward. *Authority-Follow*, *Confluence*, and *Social-Copy* emphasize information sources or agreement among them rather than a consistent set of firm characteristics. *Familiarity/Brand Affect* directs investors toward particular firms, but measuring its effectiveness would require a proxy for familiarity and brand strength with broad stock coverage in each of the ten countries. We are not aware of any such data.[15] *Technical Analysis* encompasses many different trading rules, which need not favor stocks with the same characteristics. *ESG/Values* poses a similar challenge because the values respondents describe vary across investors and extend well beyond conventional ESG criteria. Some emphasize national interests, as in "I invested in French defense because I think it is important for the country," while others express social concerns, as in "I avoid AI completely its putting college graduates out of jobs so far."[16]

Step 2: Measuring performance on each objective. Our analysis focuses on the financial objectives: returns, upside, and stability. We cannot construct a common archival measure of performance on personal values alignment, as values encompass many diverse considerations that differ across investors. Personal values alignment also receives relatively low priority: only 3.8% of respondents rank it strictly above the financial objectives, and only 11.7% rank it among their two most important objectives.

To measure a heuristic's performance on each financial objective in a particular country, we

[14] In each call, we give an LLM the description of one heuristic from Table 3 and a list of candidate JKP characteristics with short definitions, and we ask it to act as a retail investor who uses that heuristic and to choose the one to three characteristics most relevant for selecting stocks. We make about 10,000 such independent individual calls and combine one response for each heuristic into a mapping in every possible way, which yields 7,596 distinct mappings. The detailed procedure is in Online Appendix E.

[15] Widely used brand-value sources, such as Interbrand's Best Global Brands rankings, primarily cover large, internationally established firms. Constructing a familiarity/brand affect measure from large-scale text data, such as social media posts, may be feasible but lies beyond the scope of this paper.

[16] We translate the first excerpt from French. The second excerpt is from an American investor.

first follow JKP and sort stocks each month within each country into terciles on each mapped characteristic, with cutoffs computed among non-micro firms. We compare the tercile favored by the heuristic with the opposite tercile, referring to these as the long and short legs, respectively.[17]

We then compute performance on returns, upside, and stability separately for each country–heuristic–firm characteristic combination (10 countries $\times$ 7 heuristics $\times$ 3 firm characteristics) using stock outcomes from July 2015 through June 2025, the ten years preceding the interviews. For returns, we estimate the CAPM alpha of the value-weighted long–short portfolio, formed at each month-end and held over the following month.[18] This procedure yields one alpha estimate for each country–heuristic–firm characteristic combination. The alpha adjusts for differences in local-market exposure between the two legs while retaining the performance associated with the characteristic. Because market performance varies widely across countries, using the alpha lets our measure better reflect the effectiveness of the stock-selection cue.

For upside, we calculate the fraction of stocks in each leg whose returns over the following month fall in the top 1% of the country-month cross-section, and subtract the short-leg fraction from the long-leg fraction. Research on lottery preferences emphasizes the appeal of earning an extraordinarily large gain even if the odds of winning are very low (Barberis and Huang 2008, Green and Hwang 2012, Conrad, Kapadia, and Xing 2014, Barberis, Jin, and Wang 2021). Our measure similarly focuses on exceptional outcomes and asks how frequently the stocks favored by a heuristic become extreme winners.

For stability, we calculate the value-weighted average return volatility of stocks in each leg over the following month. Volatility captures the fluctuations an investor experiences when holding a stock, corresponding closely to the stated objective of stable performance. We reverse the sign of the long-minus-short difference so that higher values indicate greater stability.[19]

Finally, we summarize the performance of a heuristic on each objective in a particular country by taking the average across the three characteristics assigned to that heuristic. Within each objective,

[17] For the three *Dividends* characteristics, we compute the upper-tercile cutoff among firms with positive payouts. The long leg consists of firms above this cutoff, and the short leg consists of firms with no positive payouts. Because many firms pay no dividends, this rule targets the highest payers.

[18] We winsorize monthly stock returns at the 0.5th and 99.5th percentiles of each country-month cross-section. The market return in the CAPM regression is the value-weighted average of these returns in each country. Our results are virtually unchanged without winsorization (untabulated).

[19] We use the JKP variable *rvol_21d*, the standard deviation of daily returns over the trailing 21 trading days, measured at the end of the month following portfolio formation.

we standardize the resulting measures by subtracting their mean across the seventy heuristic–country pairs and dividing by their standard deviation. This transformation expresses effectiveness relative to the average heuristic–country pair in standard-deviation units and places the three objectives on comparable scales. A positive standardized value therefore indicates above-average effectiveness. We denote the resulting standardized measures, which proxy for true effectiveness η_{hgc}, by η^{H}_{hgc} and refer to them as historical effectiveness.

5.4. Results: Heuristic Choice and Adaptation

5.4.1. Do Investors Choose Heuristics According to Their Priorities and Beliefs?

We first test Hypothesis 1, which predicts that heuristic choice depends jointly on investors' relative priorities and perceived effectiveness. We estimate a linear probability model in which the unit of observation is an investor–heuristic–objective combination:

$$D(\text{Chosen})_{ih} = \beta_1\left(\theta_{ig} \times \eta^{\mathrm{P}}_{ihgc}\right) + \beta_2 \eta^{\mathrm{P}}_{ihgc} + \beta_3 \theta_{ig} + \alpha_i + \varepsilon_{ihgc}. \tag{1}$$

$D(\text{Chosen})_{ih}$ equals one if heuristic h is at least a "meaningful contributor" to how investor i determines which individual stocks to purchase, as recorded in the initial interview, and zero otherwise. This indicator is the same across objectives for a given investor–heuristic pair. The weight θ_{ig} measures the importance investor i assigns to objective g, and η^{P}_{ihgc} measures how effective she believes heuristic h is at identifying stocks that achieve objective g in her country c.[20] The term α_i denotes investor fixed effects, and ε_{ihgc} is the error term. A positive interaction coefficient, β_1, implies that investors are more likely to choose heuristics they perceive as more effective for the objectives they care more about.

Table 6 reports the results from three specifications relating heuristic use to importance ratings, perceived effectiveness, and their interaction. Column (1) includes investor fixed effects. Column (2) replaces them with investor × objective fixed effects, which absorb the standalone importance rating. Column (3) additionally includes country × heuristic × objective fixed effects, absorbing differences in popularity and effectiveness for each heuristic–objective combination that are common

[20] We standardize θ_{ig} within investor across the three financial objectives and perceived effectiveness within investor (Section 5.2). We set standardized importance ratings to zero for the 104 investors who rate all three financial objectives identically. Excluding these investors does not change the results.

to investors in the same country. We cluster standard errors by investor.[21]

Consistent with Hypothesis 1, the interaction coefficient is positive and statistically significant at the 5% level in all three specifications. Investors are more likely to use approaches they perceive as more effective for objectives to which they assign greater weight. In the richest specification, a one-standard-deviation increase in the weight assigned to an objective strengthens the association between a one-standard-deviation increase in perceived effectiveness and the probability of choosing a heuristic by 3.5 percentage points. For comparison, the standard deviation of usage rates across the thirteen heuristics is 10.6 percentage points. Importantly, the standalone coefficients are all indistinguishable from zero, suggesting that investors differentiate a heuristic's effectiveness across dimensions and are more likely to choose a heuristic only if it is perceived to be effective for the particular objective investors care most about.

Online Appendix Figure G8 reports awareness and choice of each heuristic among follow-up respondents. The share of respondents who have at least heard of a heuristic ranges from 41% to 86% across the thirteen heuristics. Among respondents aware of a given heuristic, only about 10%–50% end up using it. For example, about 70% of respondents are aware of *Familiarity/Brand Affect*, and a similar share are aware of *Dividends*, but only 41% and 20% of those aware use these approaches, respectively. The gap between awareness and use indicates that knowing about an approach does not automatically translate into choosing it, leaving scope for investors' priorities and beliefs to shape their choices.

5.4.2. Do Beliefs Track Effectiveness?

We next test the semi-strong-form adaptation prediction in Hypothesis 2(a): perceived effectiveness is positively related to historical true effectiveness. We estimate the following pooled OLS regression:

$$\eta^{\mathrm{P}}_{ihgc} = \beta \eta^{\mathrm{H}}_{hgc} + \alpha_i + \lambda_g + \varepsilon_{ihgc}, \tag{2}$$

where η^{P}_{ihgc} measures how effective investor i believes heuristic h is at identifying stocks that achieve objective g in her country's stock market. Historical effectiveness, η^{H}_{hgc}, measures the performance of stocks associated with heuristic h on objective g in country c from July 2015 through June

[21] A fixed-effects logit yields similar results (Online Appendix Table G6). We use the linear specification as the baseline because of concerns about incidental-parameter bias in the logit with many fixed effects.

2025, as described in Section 5.3. Each observation pairs an investor's effectiveness rating with the corresponding historical effectiveness, which is common to investors evaluating the same heuristic and objective in the same country. The terms α_i and λ_g denote investor and objective fixed effects, respectively, and ε_{ihgc} is the error term. A positive β indicates that, after accounting for these fixed effects, investors assign higher effectiveness ratings to heuristic–objective pairs with stronger historical performance in their markets. We cluster standard errors by country and, given the small number of countries, base inference on wild-cluster bootstrap p-values (Cameron, Gelbach, and Miller 2008, MacKinnon, Nielsen, and Webb 2023).

Figure 6 presents binned scatterplots of perceived effectiveness against historical effectiveness, together with fitted regression lines. Both variables are net of the fixed effects in the corresponding specification, so the slope of each fitted line equals the corresponding estimate of β. Online Appendix Table G7 reports the regression coefficient estimates.

The pooled coefficient is positive at 0.137 ($p = 0.001$): a one-standard-deviation increase in historical effectiveness is associated with a 0.137-standard-deviation increase in perceived effectiveness. Investors thus assign higher ratings to approaches that have historically performed better on the corresponding objectives in their markets. The coefficients are also positive for each objective: 0.128 for returns, 0.147 for upside, and 0.209 for stability. The returns estimate is not statistically significant at conventional levels ($p = 0.102$), whereas the upside and stability estimates are significant at the 5% level. Overall, the results appear consistent with the semi-strong-form adaptation prediction in Hypothesis 2(a).

Our findings help interpret the heuristic choice results in Table 6. Because we elicit beliefs after recording heuristic use, investors may ex post rationalize approaches they already use as particularly effective for the objectives they prioritize. For example, an investor who prioritizes stability and uses *Blue-Chip Comfort* may rate that approach favorably simply to justify her existing choice. Such ex post rationalization could generate a positive interaction between priorities and perceived effectiveness even if those beliefs did not guide the original choice. The belief-accuracy results do not rule out this possibility, but they show that respondents' assessments contain information about independently measured performance. These results therefore weigh against an interpretation based solely on favorable but uninformative assessments of chosen approaches.

5.4.3. Do Chosen Heuristics Deliver on Investors' Priorities?

To keep the follow-up survey manageable, we ask investors to rate only heuristics they currently use or have used in the past. Our next test compares investors' chosen heuristics with unused alternatives across all seven heuristics, including approaches an investor has never directly tried herself. For example, if an investor prioritizes stability and uses *Blue-Chip Comfort* and *Dividends*, we first evaluate the historical effectiveness of these two chosen heuristics at identifying stable stocks in her country. We then compare these approaches with equally sized sets of other heuristics she does not use.

Evaluating the historical effectiveness of heuristics chosen by an investor. We define an objective as prioritized if an investor rates its importance strictly above her own average across returns, upside, and stability. The evaluation sample contains 427 investors who prioritize at least one financial objective and use between one and three of the seven covered heuristics.[22] The unit of analysis is an investor–objective pair. For each prioritized objective, we compute the average historical effectiveness of the investor's chosen heuristics:

$$\bar{\eta}^{\mathrm{H}}_{ig} = \frac{1}{|\mathcal{H}^{\mathrm{C}}_i|} \sum_{h \in \mathcal{H}^{\mathrm{C}}_i} \eta^{\mathrm{H}}_{hgc}, \tag{3}$$

where $\mathcal{H}^{\mathrm{C}}_i$ is the subset of investor i's chosen heuristics (those with $D(\mathrm{Chosen})_{ih} = 1$) covered by our archival measures, $|\mathcal{H}^{\mathrm{C}}_i|$ is the number of these heuristics, and η^{H}_{hgc} is the standardized historical effectiveness of heuristic h for objective g in her country c. We weight the heuristics equally because we do not observe how investors allocate capital across approaches.

For each objective, we average $\bar{\eta}^{\mathrm{H}}_{ig}$ across investors who prioritize it. For the overall measure, we first average across each investor's prioritized objectives and then across investors, giving each investor equal weight. Higher values indicate that investors use approaches with stronger historical effectiveness on the objectives they prioritize.

[22] We exclude investors who use four or more of the seven covered heuristics because they have too few unused heuristics to form an equally sized comparison set. The returns, upside, and stability comparisons include 210, 158, and 256 investors, respectively; an investor can prioritize more than one objective.

Evaluating the historical effectiveness of heuristics not chosen by an investor. Our main benchmark replaces each investor's chosen heuristics with an equally sized set drawn randomly, without replacement, from the heuristics she does not use. We refer to these draws as "unused heuristics." We evaluate the unused heuristics in her country on the same prioritized objectives and aggregate their historical effectiveness in the same way as for her chosen approaches. We repeat this procedure 10,000 times. The fraction of draws that perform at least as well as the investor's chosen heuristics gives the one-sided p-value. This comparison asks whether chosen approaches outperform the alternatives investors could have chosen but ended up not using.[23]

A second benchmark draws equally sized sets from all seven covered heuristics, including those the investor uses. We label these draws "randomly selected heuristics." This comparison asks whether observed choices outperform random selections from the full set of covered approaches.

Evidence. Figure 7 plots the distributions of historical effectiveness of unused heuristics across random draws, overall and separately for each objective, with dashed coral lines marking the historical effectiveness of investors' chosen heuristics. In every panel, chosen heuristics outperform unused heuristics in more than 99% of the 10,000 draws.

Table 7 reports the historical effectiveness of chosen heuristics alongside the two heuristic benchmarks. Overall, the historical effectiveness is +0.130 for chosen heuristics, compared with −0.076 for unused heuristics. Chosen heuristics outperform unused heuristics on all three prioritized objectives ($p < 0.001$), supporting the strong-form adaptation prediction in Hypothesis 2(b). Their advantage thus extends to a comparison set that includes approaches investors may never have tried. Chosen heuristics also outperform randomly selected heuristics on every prioritized objective ($p \leq 0.010$).

To assess whether the performance advantage is specific to investors' priorities, we repeat the comparison for the objectives investors do *not* prioritize. We define an objective as nonprioritized if the investor rates its importance strictly below her own average across returns, upside, and stability. Because every investor whose three ratings are not all equal has at least one objective above and at least one below her average, the comparison retains the same 427 investors, chosen heuristics, and

[23] Unused heuristics may include approaches investors have never heard of. Restricting the benchmark to covered heuristics respondents report being aware of in the follow-up survey preserves the overall historical performance advantage (Online Appendix Table G8).

historical effectiveness measures. We aggregate $\bar{\eta}_{ig}^{\mathrm{H}}$ in equation (3) across nonprioritized objectives and investors as in the main analysis. Both benchmarks follow the same procedure as in the main analysis and use the same 10,000 random draws, which we now evaluate on nonprioritized rather than prioritized objectives.

On these nonprioritized objectives, chosen heuristics perform worse than unused heuristics (−0.100 versus −0.026; Table 8), and only 0.6% of random draws of unused heuristics perform worse than the chosen heuristics. The advantage on prioritized objectives therefore does not extend to other dimensions of performance. This contrast suggests that investors favor approaches whose relative strengths correspond to their priorities, even when those approaches deliver weaker average outcomes on dimensions they consider less important.

5.5. Discussion and Additional Analyses

5.5.1. Adaptive Heuristics and Investor Mistakes

Our evidence of adaptive heuristic choice may appear at odds with research documenting mistakes in how investors interpret information and form return expectations. For instance, Tetlock (2011) finds evidence that individual investors overreact to stale news, suggesting that they do not fully account for information already reflected in prices. Similarly, Andre, Schirmer, and Wohlfart (2026) show that many investors associate favorable earnings news with higher expected returns without adequately accounting for the extent to which that news may already be reflected in prices. Related theoretical work shows how neglecting the information conveyed by prices can distort beliefs and generate excessive trading (Eyster, Rabin, and Vayanos 2019).

An incomplete understanding of price formation, however, need not preclude recognizing useful empirical patterns. Through experience, observation, or advice, an investor may learn that financially strong firms tend to offer higher average returns in her market without fully understanding why. Such knowledge can guide her choice of approach even if she sometimes misinterprets news or makes mistakes when applying it.

Indeed, a complementary strand of research documents informed trading by individual investors around earnings announcements (Kaniel, Liu, Saar, and Titman 2012), informed retail short sales (Kelley and Tetlock 2017), and favorable aggregate investment performance among Robinhood users

(Welch 2022). Our study adds to this more nuanced view of retail investor behavior and further qualifies it without implying full rationality.

Our findings also suggest we should distinguish underperformance relative to conventional, "rational" benchmarks from failure to achieve an investor's objectives. Prior research documents that individual investors underperform market benchmarks (Barber and Odean 2000, 2001). Our paper does not challenge these findings and their implications, but adds that conventional performance measures may not fully capture what investors seek from stock selection. For an investor who prioritizes exceptional upside, a low Sharpe ratio does not establish that her approach fails to serve that objective. Indeed, our finding that chosen heuristics outperform unused heuristics on prioritized objectives but underperform on nonprioritized objectives illustrates the importance of this distinction.

5.5.2. Additional Analysis: Global Views vs. Local Views

Another question is whether investors' beliefs reflect conditions in their local markets or views formed from evidence in other markets, especially the United States. Much of the research on stock-return anomalies uses U.S. data. Investors elsewhere might therefore generalize findings from the U.S. market to their own markets, even when the underlying relations differ. For example, evidence that profitability predicts returns in the United States might lead investors in other countries to expect a similar relation locally.

Drawing on evidence from other markets need not conflict with adaptation. Investors, including those who hold only local stocks, observe evidence from foreign markets through the financial press, professional advice, and other sources. Because the track record of any single market is noisy and the performance of stock characteristics is largely shared across markets (JKP), a Bayesian investor who wants to know how well a heuristic works in her own market would combine local evidence with evidence from other markets. Whether investors learn from local evidence, from global evidence, or from both is thus an empirical question, and each of these answers is consistent with adaptive heuristic choice.

Our survey evidence suggests that investors distinguish between these environments. To provide an illustration, U.S. respondents view *Fundamental Strength* as particularly effective at identifying

stocks with high returns, whereas this belief is much less pronounced among Japanese respondents.[24] Notably, this difference aligns with our measure of historical effectiveness and that of the international anomaly literature: the profitability anomaly is strong in the United States, yet almost non-existent in Japan (Fama and French 2017).[25] Although illustrative, this comparison suggests that investors' assessments reflect local conditions.

To examine this question more systematically, we decompose historical effectiveness into three parts,

$$\eta^{\mathrm{H}}_{hgc} = \tilde{\mu}_{hg} + \tilde{\delta}_{hgc} + \tilde{e}_{hgc}, \tag{4}$$

where the global component $\tilde{\mu}_{hg}$ captures how well heuristic h serves objective g across markets, the local component $\tilde{\delta}_{hgc}$ captures how its effectiveness in country c differs from this global level, and $\tilde{e}_{hgc}$ is estimation noise. We estimate the three parts in the empirical Bayes framework of JKP, using all 47 developed and emerging markets in their data. We then regress perceived effectiveness on the estimates of the global and local components, with investor × objective fixed effects.[26]

Online Appendix Table G9 reports the results. Perceived effectiveness is positively related to both components, with coefficients of 0.262 ($p = 0.018$) on the local component and 0.158 ($p = 0.003$) on the global component. The local coefficient is about two-thirds larger, although the difference is not statistically significant ($p = 0.168$). These results suggest that investors' beliefs reflect both evidence common across markets and a heuristic's relative local performance. Among investors outside the United States, the local coefficient is similar. We also add a U.S.-specific component that captures the portion of the U.S. local component not reflected in the investor's own market. This component enters positively and is marginally significant (0.215, $p = 0.069$). Overall, investors' beliefs appear to reflect both local and global evidence, with some additional association with U.S.-specific performance, consistent with adaptive heuristic use.

[24] U.S. respondents report a mean effectiveness rating of 4.1 for identifying stocks with high returns on the five-point scale, compared with 3.6 among Japanese respondents. The U.S.–Japan gap of approximately 0.5 points is about three times the average absolute gap of 0.15 points between the U.S. and each of the other nine countries for *Fundamental Strength* and the returns objective.

[25] For the returns objective, our historical effectiveness measure for *Fundamental Strength* is +0.91 in the United States and −0.81 in Japan.

[26] Using such estimates as regressors follows Chetty and Hendren (2018). A simpler approach would subtract the average across markets from each market's historical effectiveness. Part of this difference, however, reflects (researcher's) estimation noise rather than true local differences (which is a cleaner proxy for what investors observe), and noise in a regressor biases its coefficient toward zero. The empirical Bayes estimates avoid this problem by scaling down each market's difference more when it is measured less precisely.

5.5.3. Additional Analysis: Foreign Stock Holdings

A related concern is that respondents may hold substantial investments in foreign stocks. Historical effectiveness measured solely in their local market may therefore be an imperfect benchmark for assessing whether their chosen heuristics serve their priorities.[27] In Online Appendix F, we repeat the main analyses using historical effectiveness measures that account for each investor's foreign stock shares. Specifically, we combine historical effectiveness in local and foreign markets using each investor's reported share of local investment.[28] Because we do not observe how respondents allocate their foreign holdings across markets, we assume they invest across the other nine countries using either market-capitalization weights or resident portfolio weights, which follow the aggregate equity holdings of residents of the respondent's country in each foreign market as per the International Monetary Fund (IMF) Portfolio Investment Positions (PIP) by Counterpart Economy.[29] Our findings are similar under both weighting schemes (Online Appendix Figure F1 and Tables F2 and F3).

5.5.4. Future Research: Evaluating Adaptation over Time

Before concluding, we broach a possible direction for future research: evaluating whether investors' chosen heuristics remain effective and how investors adapt over time. Our historical tests document alignment between investors' priorities, beliefs, and heuristic performance, but they do not establish whether this alignment persists. We conducted the initial interviews in July–August 2025 and the follow-up survey in May–June 2026. Our available stock-return data end in December 2025. Evaluating subsequent performance therefore requires several additional years of data. Future work could examine whether heuristics that investors perceive as more effective subsequently perform better and whether their chosen heuristics continue to serve their priorities. Ideally, such work would also track changes in investors' priorities, perceived heuristic effectiveness, and heuristic use. These repeated observations would allow researchers to examine how investors adjust their heuristic choices as their priorities, beliefs, and heuristic performance evolve.

Tracking these adjustments would also connect our findings to research on reinforcement

[27] This concern applies less to our measure of *perceived* effectiveness, because the follow-up survey asks respondents how effective each heuristic is in their own country's stock market.

[28] Our follow-up survey asks respondents what share of their individual-stock holdings is in local stocks.

[29] This dataset was formerly known as the Coordinated Portfolio Investment Survey (CPIS). We report the weights in Online Appendix Table F1.

learning, in which decision makers repeat choices that have paid off (Erev and Roth 1998, Sutton and Barto 2018). In finance, Barberis and Jin (2023) model how investors adjust their stock market allocations in response to experienced returns. Empirical studies examine how past investment outcomes influence subsequent IPO subscriptions (Kaustia and Knüpfer 2008), saving decisions (Choi, Laibson, Madrian, and Metrick 2009), and repurchases of previously held stocks (Strahilevitz, Odean, and Barber 2011). Learning may also operate at the level of decision rules: Stahl (2000) finds that players in experimental games learn which rules to use from their past performance. Our interviews identify reusable stock-selection rules to which such learning could apply. A successful experience might reinforce an investor's tendency to "buy profitable firms," guiding subsequent purchases of stocks she has never held. Repeated observations could establish whether investors adjust their heuristic use in response to such experience.

As an auxiliary test, we examine whether chosen heuristics outperform unused heuristics on investors' prioritized objectives after the *estimated* dates on which investors began using them. We approximate these dates by counting backward from June 2026, when we elicit usage durations, using the lower bound of each reported duration category.[30] For example, if an investor reports having used a heuristic for one to three years, we assign a start date of June 2025 and evaluate its performance from July through December 2025. For reported usage of more than three years, we assign June 2023. Using the lower bounds places the start of use as late as the reported durations allow, excluding months that could precede it. The resulting evaluation periods average approximately 20 months per investor. Online Appendix Table G10 details the procedure and reports the results.

Chosen heuristics continue to outperform both heuristic benchmarks overall. This evidence is retrospective, however: start dates are approximate, and we must assume that reported priorities reasonably reflect those held during the evaluation period. It therefore complements, but cannot replace, a prospective study that tracks investors' choices, priorities, and beliefs alongside subsequent stock performance over time.

[30] Online Appendix Figure G9 reports usage durations for the approaches identified in the initial interviews.

6. Conclusion

Using AI-led, open-ended interviews with 1,540 investors across ten countries, we study how investors determine which individual stocks to purchase. Our interviews reveal that investors generally rely on heuristics. We identify thirteen such heuristics that together capture the reasoning of 95.2% of investors, and document their prevalence within a common sample and measurement framework.

We then develop and test a framework that helps explain investors' choice of heuristics. A follow-up survey of 600 original interviewees reveals that investors generally pursue multiple investment goals but differ in the relative importance they assign to them. Investors are more likely to choose heuristics they perceive as more effective for the objectives they prioritize. Crucially, these perceptions contain information about historical effectiveness in their own markets, measured independently using stock characteristics and returns. Moreover, their chosen heuristics historically outperform a broader set of unused heuristics on the objectives they prioritize, including approaches they may never have tried, but perform worse on average on objectives they do not prioritize. This contrast points to adaptation in the matching of approaches to priorities, rather than the selection of uniformly superior approaches.

Overall, our findings suggest that the use and choice of heuristics are partly adaptive: investors tend to choose approaches suited to their objectives and local market conditions. Adaptation need not imply optimality. Our evidence does not establish that selecting individual stocks using heuristics improves on diversified portfolio investment. It does, however, caution against the view that simple stock-selection rules merely lead investors astray. More broadly, our findings illustrate how listening directly to investors can reveal reasoning that is difficult to infer from their choices alone and enrich our understanding of their behavior.

References

Aladangady, Aditya, Jesse Bricker, Andrew C. Chang, Sarena Goodman, Jacob Krimmel, Kevin B. Moore, Sarah Reber, Alice Henriques Volz, and Richard A. Windle, 2023, Changes in U.S. family finances from 2019 to 2022: Evidence from the Survey of Consumer Finances, Discussion paper Board of Governors of the Federal Reserve System Washington, DC.

Andre, Peter, Ingar Haaland, Christopher Roth, Mirko Wiederholt, and Johannes Wohlfart, 2026, Narratives about the macroeconomy, *Review of Economic Studies* Advance access.

Andre, Peter, Philipp Schirmer, and Johannes Wohlfart, 2026, Mental models of the stock market, *The Quarterly Journal of Economics* 141, 2925–2978.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

——— , 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–292.

——— , 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *The Review of Financial Studies* 21, 785–818.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.

Barberis, Nicholas, Lawrence J. Jin, and Baolian Wang, 2021, Prospect Theory and Stock Market Anomalies, *The Journal of Finance* 76, 2639–2687.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Barberis, Nicholas C., and Lawrence J. Jin, 2023, Model-free and Model-based Learning as Joint Drivers of Investor Behavior, Working Paper 31081 National Bureau of Economic Research.

Bender, Svetlana, James J. Choi, Danielle Dyson, and Adriana Z. Robertson, 2022, Millionaires speak: What drives their personal investment decisions?, *Journal of Financial Economics* 146, 305–330.

Betermier, Sebastien, Laurent E. Calvet, and Paolo Sodini, 2017, Who Are the Value and Growth Investors?, *The Journal of Finance* 72, 5–46.

Bhagwat, Vineet, J Anthony Cookson, Chukwuma Dim, and Marina Niessner, 2025, The market's mirror: Revealing investor disagreement with LLMs, *FEB-RN Research Paper*.

Bogle, John C., 1999, *Common Sense on Mutual Funds* (Wiley).

Bybee, J Leland, 2023, The ghost in the machine: Generating beliefs with large language models, *arXiv preprint arXiv:2305.02823*.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, 2008, Bootstrap-based improvements for inference with clustered errors, *The Review of Economics and Statistics* 90, 414–427.

Campbell, John Y, and Tarun Ramadorai, 2026, Household finance in retrospect and prospect, Working Paper 34621 National Bureau of Economic Research.

Chen, Andrew Y, 2021, The limits of p-hacking: Some thought experiments, *The Journal of Finance* 76, 2447–2480.

Chen, Hailiang, Byoung-Hyoun Hwang, and Zhuozhen Peng, 2025, Why Do Investors Like Short-leg Securities?

Evidence from a Textual Analysis of Buy Recommendations, *The Review of Financial Studies* 38, 3729–3767.

Chetty, Raj, and Nathaniel Hendren, 2018, The impacts of neighborhoods on intergenerational mobility II: County-level estimates, *The Quarterly Journal of Economics* 133, 1163–1228.

Chinco, Alex, Samuel M. Hartzmark, and Abigail B. Sussman, 2022, A New Test of Risk Factor Relevance, *The Journal of Finance* 77, 2183–2238.

Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick, 2009, Reinforcement Learning and Savings Behavior, *The Journal of Finance* 64, 2515–2534.

Choi, James J., and Adriana Z. Robertson, 2020, What Matters to Individual Investors? Evidence from the Horse's Mouth, *The Journal of Finance* 75, 1965–2020.

Chopra, Felix, and Ingar Haaland, 2023, Conducting Qualitative Interviews with AI, *SSRN Working Paper*.

Chui, Andy CW, Sheridan Titman, and KC John Wei, 2010, Individualism and momentum around the world, *The Journal of Finance* 65, 361–392.

Conrad, Jennifer, Nishad Kapadia, and Yuhang Xing, 2014, Death and jackpot: Why do individual investors hold overpriced stocks?, *Journal of Financial Economics* 113, 455–475.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal, 2009, Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?, *Review of Financial Studies* 22, 1915–1953.

Ellis, Charles D., 2002, *Winning the Loser's Game* (McGraw-Hill).

Enke, Benjamin, and Thomas Graeber, 2023, Cognitive uncertainty, *The Quarterly Journal of Economics* 138, 2021–2067.

Erev, I., and A.E. Roth, 1998, Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria, *American Economic Review* 88, 848–881.

Eyster, Erik, Matthew Rabin, and Dimitri Vayanos, 2019, Financial markets where traders neglect the informational content of prices, *The Journal of Finance* 74, 371–399.

Fama, Eugene F., and Kenneth R. French, 2017, International tests of a five-factor asset pricing model, *Journal of Financial Economics* 123, 441–463.

Frieder, Laura, and Avanidhar Subrahmanyam, 2005, Brand perceptions and the market for common stock, *Journal of Financial and Quantitative Analysis* 40, 57–85.

Gabaix, Xavier, 2019, Chapter 4 - Behavioral inattention, in B. Douglas Bernheim, Stefano DellaVigna, and David Laibson, ed.: *Handbook of Behavioral Economics: Applications and Foundations 1, Volume 2*, pp. 261–343 (North-Holland).

Geiecke, Friedrich, and Xavier Jaravel, 2024, Conversations at Scale: Robust AI-led Interviews with a Simple Open-Source Platform, *SSRN Working Paper*.

Gigerenzer, Gerd, and Wolfgang Gaissmaier, 2011, Heuristic decision making, *Annual Review of Psychology* 62, 451–482.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, 2021, Household Finance, *Journal of Economic Literature* 59, 919–1000.

Green, T. Clifton, and Byoung-Hyoun Hwang, 2012, Initial public offerings as lotteries: Skewness preference and first-day returns, *Management Science* 58, 432–444.

Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade?, *The Journal of Finance* 56, 589–616.

Han, Bing, David Hirshleifer, and Johan Walden, 2022, Social Transmission Bias and Investor Behavior, *Journal of Financial and Quantitative Analysis* 57, 390–412.

Hartzmark, Samuel M, and David H Solomon, 2019, The dividend disconnect, *The Journal of Finance* 74, 2153–2199.

Henning, Thomas, Siddhartha M. Ojha, Ross Spoon, Jiatong Han, and Colin F. Camerer, 2025, LLM agents do not replicate human market traders: Evidence from experimental finance, *arXiv Working Paper*.

Hofstede, G., G.J. Hofstede, and M. Minkov, 2010, *Cultures and Organizations: Software of the Mind, Third Edition* (McGraw Hill LLC).

Jacobs, Heiko, and Sebastian Müller, 2020, Anomalies across the globe: Once public, no longer existent?, *Journal of Financial Economics* 135, 213–230.

Jensen, Theis Ingerslev, Bryan Kelly, and Lasse Heje Pedersen, 2023, Is There a Replication Crisis in Finance?, *The Journal of Finance* 78, 2465–2518.

Kaniel, Ron, Shuming Liu, Gideon Saar, and Sheridan Titman, 2012, Individual investor trading and return patterns around earnings announcements, *The Journal of Finance* 67, 639–680.

Kaustia, Markku, and Samuli Knüpfer, 2008, Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions, *The Journal of Finance* 63, 2679–2702.

Kelley, Eric K., and Paul C. Tetlock, 2017, Retail short selling and stock prices, *The Review of Financial Studies* 30, 801–834.

Keloharju, Matti, Samuli Knüpfer, and Juhani Linnainmaa, 2012, Do investors buy what they know? Product market choices and investment decisions, *The Review of Financial Studies* 25, 2921–2958.

Koijen, Ralph S. J., and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.

Liu, Hongqi, Cameron Peng, Wei A. Xiong, and Wei Xiong, 2022, Taming the bias zoo, *Journal of Financial Economics* 143, 716–741.

Lopez-Lira, Alejandro, 2025, Can Large Language Models Trade? Testing Financial Theories with LLM Agents in Market Simulations, *arXiv Working Paper*.

MacKinnon, James G, Morten Ørregaard Nielsen, and Matthew D Webb, 2023, Cluster-robust inference: A guide to empirical practice, *Journal of Econometrics* 232, 272–299.

Malkiel, Burton G., 1973, *A Random Walk Down Wall Street* (W. W. Norton).

McLean, R. David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *The Journal of Finance* 71, 5–32.

Oprea, Ryan, and Michael Woodford, 2026, Behavioral signatures of cognitive noise, *Annual Review of Economics, forthcoming*.

Shefrin, Hersh M, and Meir Statman, 1984, Explaining investor preference for cash dividends, *Journal of Financial Economics* 13, 253–282.

Simon, Herbert A., 1955, A behavioral model of rational choice, *The Quarterly Journal of Economics* 69, 99–118.

——— , 1956, Rational choice and the structure of the environment, *Psychological Review* 63, 129–138.

Sims, Christopher A., 2003, Implications of rational inattention, *Journal of Monetary Economics* 50, 665–690.

Stahl, Dale O., 2000, Rule learning in symmetric normal-form games: Theory and evidence, *Games and Economic Behavior* 32, 105–138.

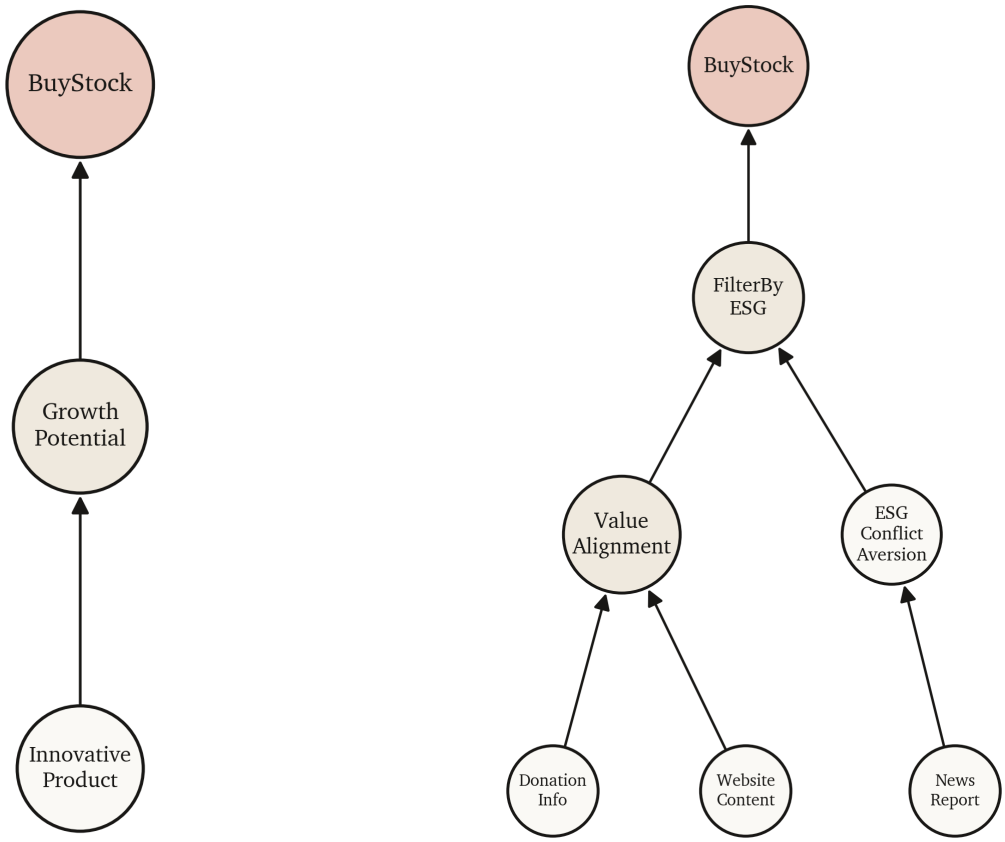
Strahilevitz, Michal Ann, Terrance Odean, and Brad M. Barber, 2011, Once burned, twice shy: How naive learning, counterfactuals, and regret affect the repurchase of stocks previously sold, *Journal of Marketing Research* 48, S102–S120.

Sutton, Richard S., and Andrew G. Barto, 2018, *Reinforcement Learning: An Introduction* (MIT Press: Cambridge, MA) 2nd edn.

Tetlock, Paul C., 2011, All the news that's fit to reprint: Do investors react to stale information?, *The Review of Financial Studies* 24, 1481–1512.

Welch, Ivo, 2022, The wisdom of the Robinhood crowd, *The Journal of Finance* 77, 1489–1527.

Woodford, Michael, 2020, Modeling imprecision in perception, valuation, and choice, *Annual Review of Economics* 12, 579–601.



(a) Example 1

(b) Example 2

Figure 1. DAG Examples

This figure shows two stylized examples of the investor-level argument maps, represented as directed acyclic graphs (DAGs), that we construct from the interview transcripts. Nodes represent factors relevant to the stock-purchase decision, directed edges represent the reasoning links respondents draw between them, and the terminal node, *BuyStock*, represents the decision to purchase the stock. Node shading is for illustration only.

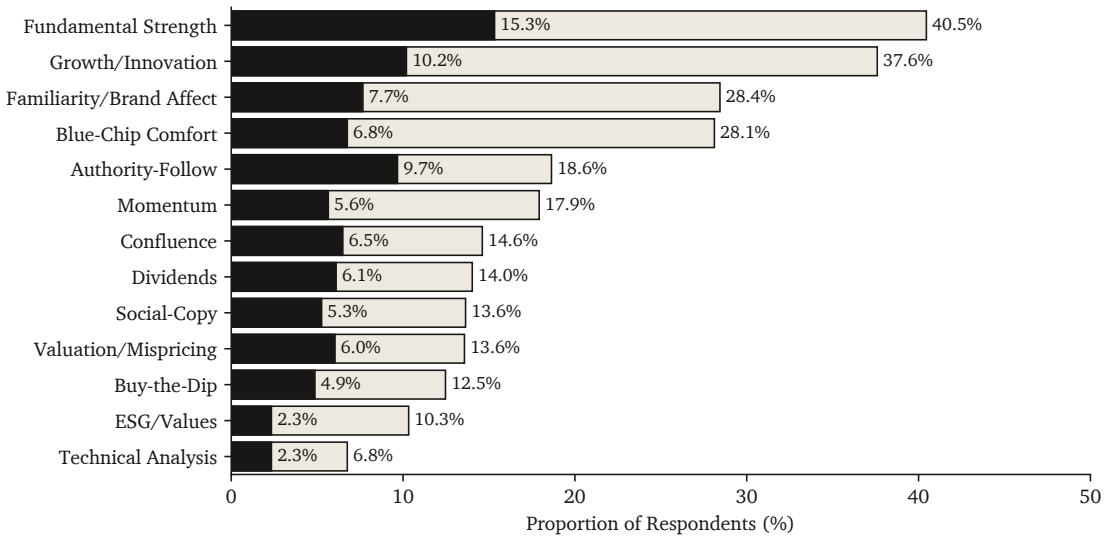


Figure 2. Proportion of Investors Using Each Heuristic

This figure shows the proportion of investors who use each of the thirteen recurrent heuristics. We assign each transcript–heuristic pair a four-point score that captures how strongly the heuristic governs the reasoning of the investor (4: "primary driver," 3: "meaningful contributor," 2: "fragmentary presence," 1: "absent"). Dark bars show the share of investors for whom the heuristic is a primary driver; light bars show the share for whom it is at least a meaningful contributor. The dark bars are nested within the light bars. Heuristics are ordered by decreasing share of investors for whom they are at least meaningful contributors.

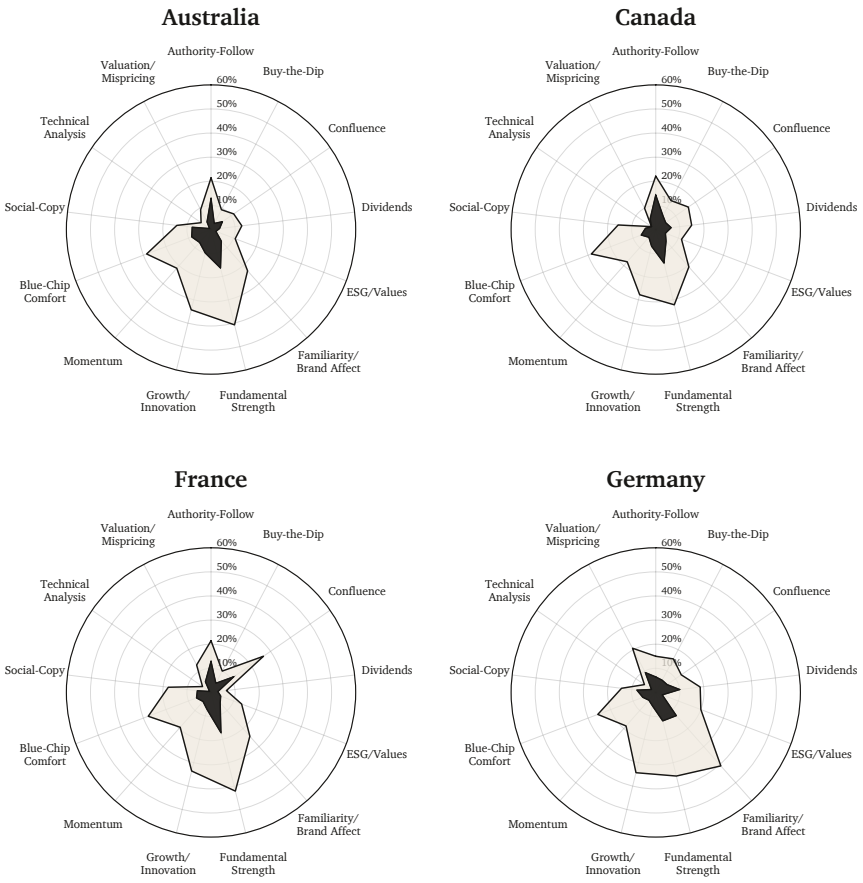


Figure 3. Heuristic Prevalence by Country

This figure shows, separately by country, the proportion of investors who use each of the thirteen recurrent heuristics. We assign each transcript–heuristic pair a four-point score that captures how strongly the heuristic governs the reasoning of the investor (4: "primary driver," 3: "meaningful contributor," 2: "fragmentary presence," 1: "absent"). We count a heuristic as used if it is at least a meaningful contributor to the investor's stock-selection process. Panels are ordered alphabetically by country. This page reports Australia, Canada, France, and Germany; the next page reports India, Japan, Singapore, South Korea, the U.K., and the U.S. Within each panel, the thirteen heuristics are arranged radially, with distance from the center indicating the share of investors in that country. The dark region shows the share for whom each heuristic is a primary driver; the light region shows the share for whom it is at least a meaningful contributor. The dark region is nested within the light region. The radial axis ranges from 0% at the center to 60% at the outer circle, with concentric circles at 10-percentage-point intervals.

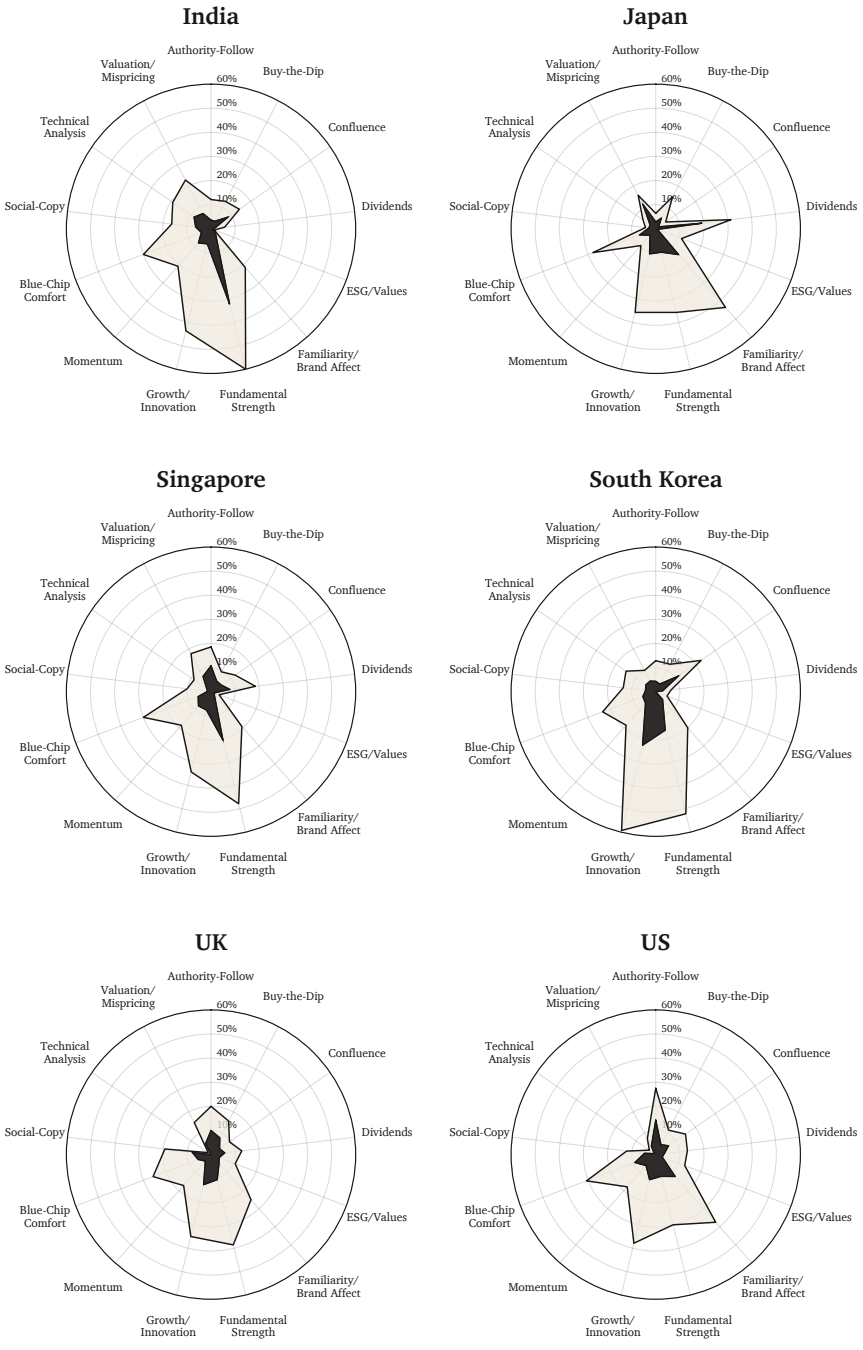


Figure 3. Heuristic Prevalence by Country (continued)

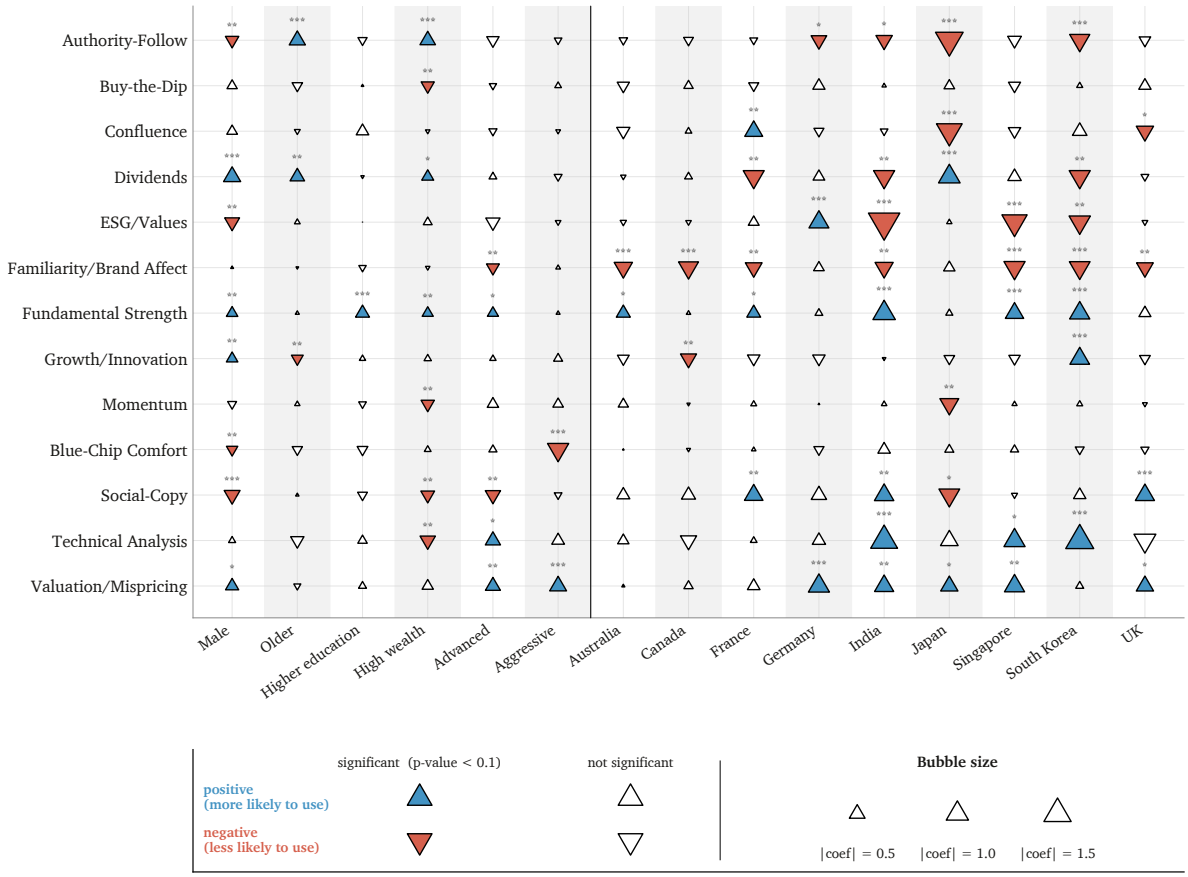


Figure 4. Demographic and Country Correlates of Heuristic Choice

This figure reports coefficient estimates from logistic regressions of heuristic choice on demographic and country indicators. For each of the thirteen heuristics h, we estimate a separate logistic regression:

$$\Pr(D(\text{Chosen})_{ih} = 1) = \Lambda\left(\alpha_h + \sum_d \beta_{hd} X_{id} + \sum_c \gamma_{hc} \mathbf{1}\{\text{Country}_i = c\}\right),$$

where $\Lambda(\cdot)$ is the logistic function and $D(\text{Chosen})_{ih}$ equals one if heuristic h is at least a meaningful contributor to investor i's stock-selection process, and zero otherwise. The six demographic indicators, X_{id}, are *Male*; *Older* (age $\geq$ 35); *Higher education* (bachelor's degree or above); *High wealth* (investable assets $\geq$ USD 500,000); *Advanced* (self-reported advanced or expert investment knowledge); and *Aggressive* (self-reported willingness to take above-average or substantial financial risks). Country indicators cover the nine countries other than the U.S., which serves as the reference group. Because only one investor reports "another gender," we exclude this investor. Rows correspond to heuristics and columns to regressors, with a vertical line separating demographic from country indicators. Each triangle marker represents an estimated coefficient in log-odds, pointing up for positive coefficients and down for negative coefficients. Marker size increases with the absolute value of the coefficient estimate, as shown in the legend. Filled markers indicate statistical significance at the 10% level (blue for positive coefficients and red for negative coefficients); hollow markers indicate insignificance. Standard errors are heteroskedasticity-robust. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

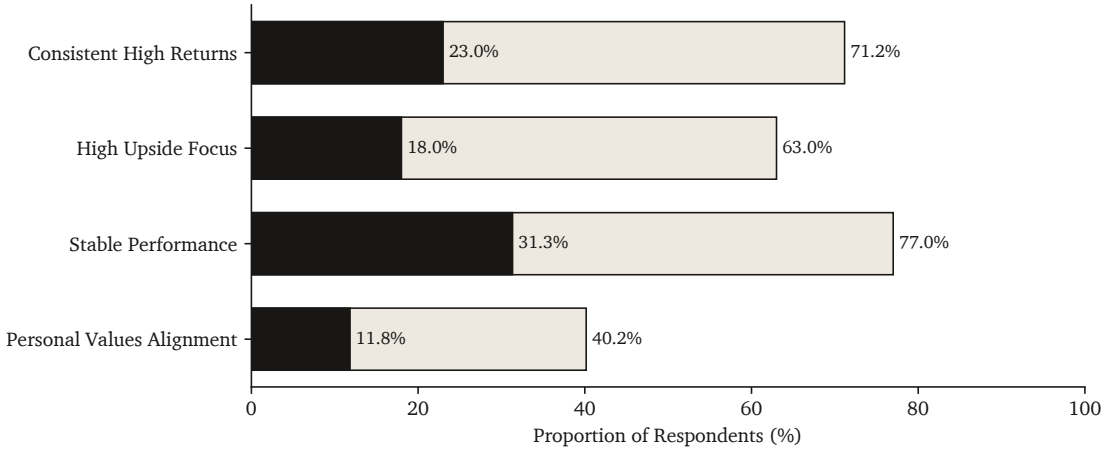


Figure 5. Importance of Investment Objectives

This figure shows the proportion of follow-up survey respondents who consider each of four investment objectives important. Respondents rate the importance of "consistent high returns," "high upside focus," "stable performance," and "personal values alignment," when selecting stocks on a five-point scale from 1 ("Not important at all") to 5 ("Extremely important"). These four objectives are presented to survey respondents in randomized order. Dark bars show the share of respondents assigning a rating of 5; light bars show the share assigning a rating of 4 or 5. Dark bars are nested within light bars.

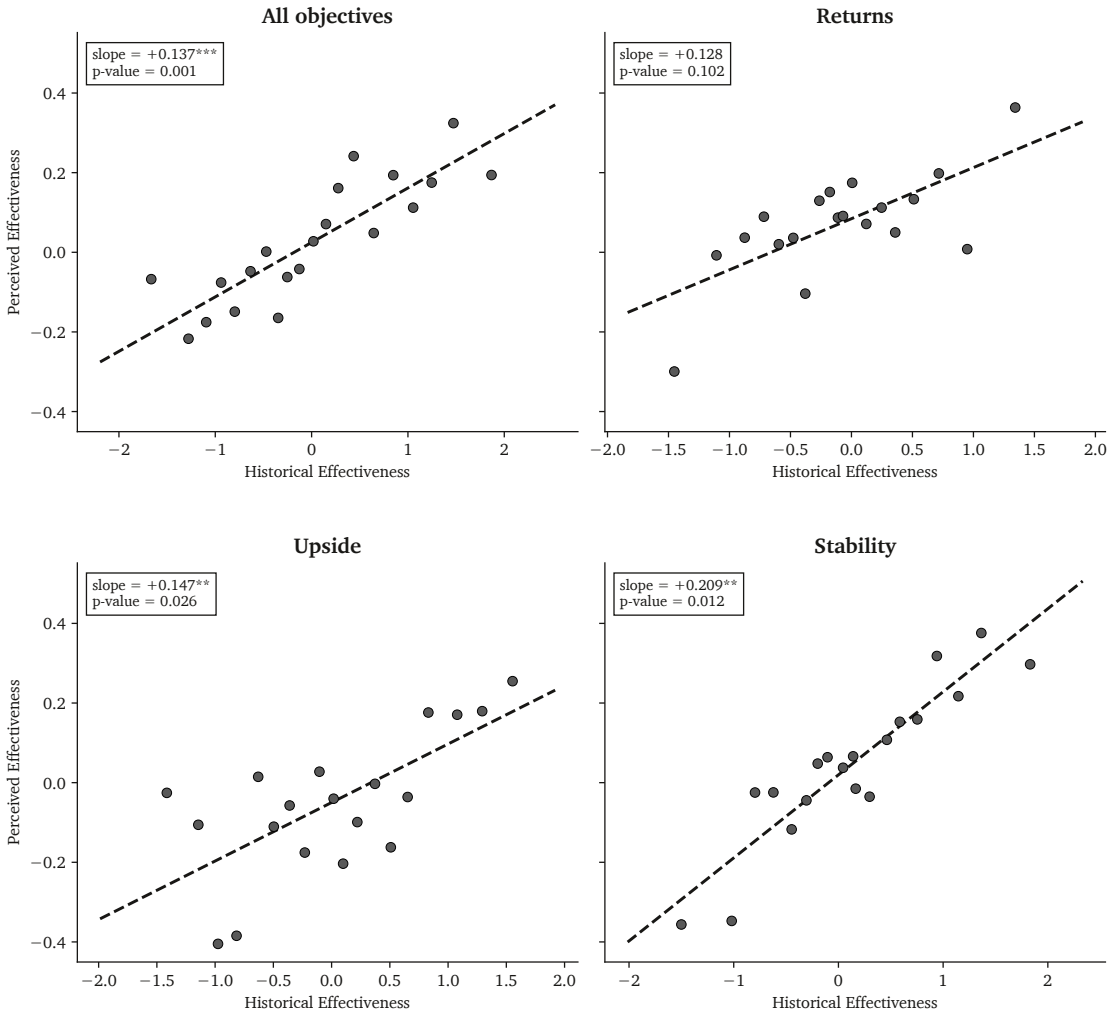


Figure 6. Relationship between Perceived and Historical Effectiveness

This figure shows binned scatterplots of perceived heuristic effectiveness against historical heuristic effectiveness. The top-left panel pools the three financial objectives (returns, upside, and stability), and the other panels show each objective separately. Perceived effectiveness is the investor's five-point heuristic effectiveness rating from the follow-up survey, standardized within each investor across her ratings of heuristics for the three financial objectives. Historical effectiveness measures the performance of stocks associated with a heuristic on a given objective in the investor's country from July 2015 through June 2025, standardized within objective across the seventy heuristic–country pairs. We control for investor and objective fixed effects in the pooled panel and for investor fixed effects in the objective-specific panels. We group observations into quantile bins of historical effectiveness, and each marker shows the within-bin means of the two variables. Dashed lines show ordinary least squares fits to the underlying unbinned data. The reported slopes are the estimates of β in regression equation (2), and p-values are based on a wild-cluster bootstrap by country using Webb six-point weights and 9,999 replications. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

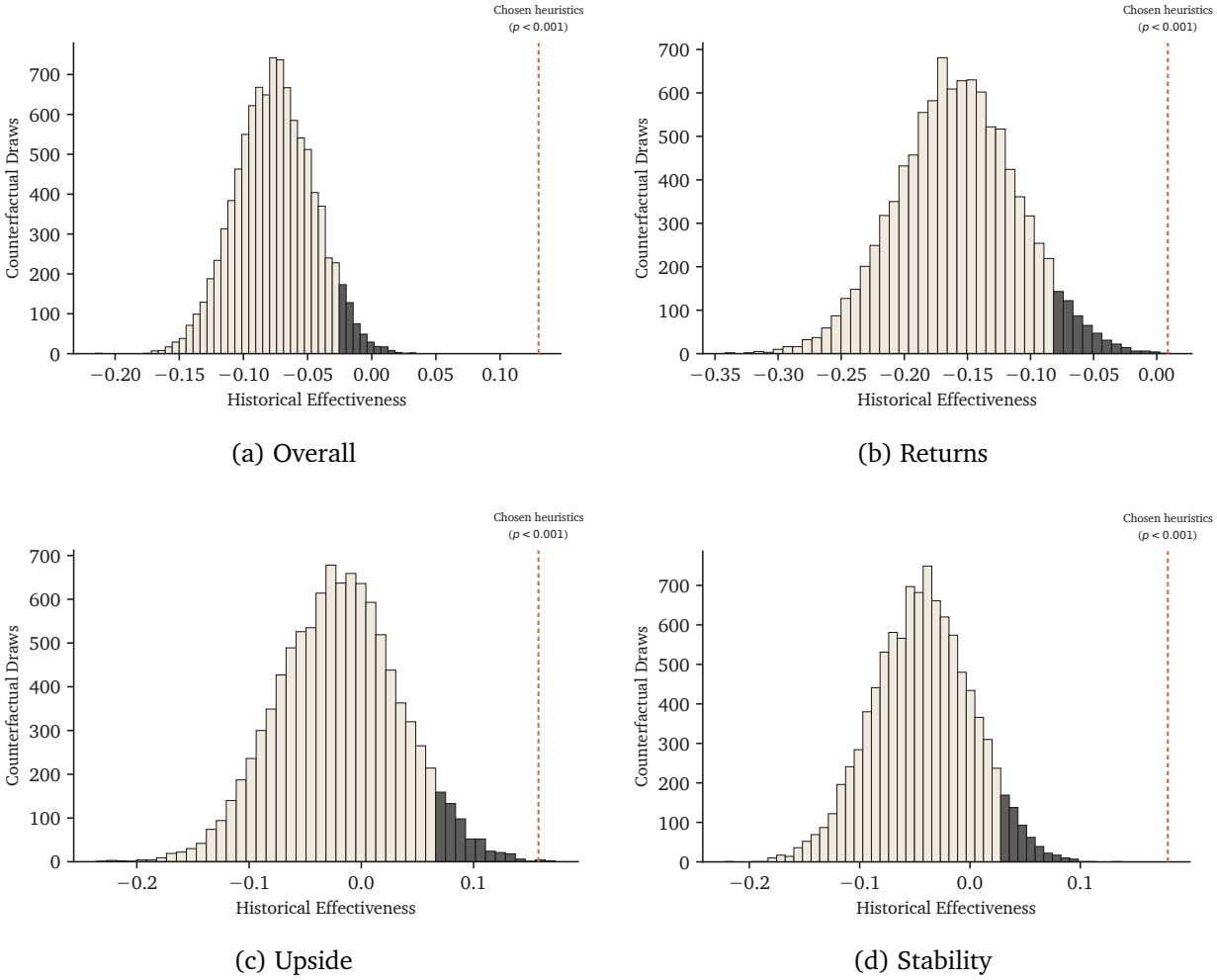


Figure 7. Historical Effectiveness of Chosen Heuristics versus Unused Heuristics

This figure compares the average historical effectiveness of investors' chosen heuristics on their prioritized objectives with counterfactual distributions based on random draws of unused heuristics. We focus on the seven heuristics covered by archival data (Section 5.3). Historical effectiveness measures the performance of stocks associated with a heuristic on a given objective in the investor's country from July 2015 through June 2025. We standardize it within objective across the seventy heuristic–country pairs, so the horizontal axis is expressed in within-objective standard deviations. An objective is prioritized if the investor rates its importance strictly above her own average across the three financial objectives (returns, upside, and stability). Chosen heuristics are those that are at least meaningful contributors to the investor's stock selection based on the interview. For each investor and prioritized objective, we average the historical effectiveness of her chosen heuristics in her country. Panel (a) first averages across each investor's prioritized objectives and then across investors, giving each investor equal weight. Panels (b) through (d) average across investors who prioritize returns, upside, and stability, respectively. In each panel, the dashed coral vertical line marks the average historical effectiveness of chosen heuristics. The histogram shows 10,000 draws replacing each investor's chosen heuristics with an equally sized set sampled randomly, without replacement, from the covered heuristics she does not use. We evaluate these sets on the same objectives in the same country and aggregate identically. The upper 5% tail of each distribution is shaded dark. Reported one-sided p-values are the fractions of draws that perform at least as well as the chosen heuristics, and values below 0.001 are shown as $p < 0.001$.

Table 1. Sample Demographics

This table reports descriptive statistics for the 1,540 interviewed investors. The first row covers the full sample; the remaining rows group investors by gender, age, education, investable assets, self-reported investment knowledge, and self-reported risk attitude, all elicited in the background survey. Columns (1) and (2) report the number of investors in each group and their share of the full sample. Columns (3) through (6) report the percentage of investors in each group who own individual stocks, mutual funds or exchange-traded funds, derivatives, and cryptocurrencies, respectively. Column (3) equals 100% by construction because ownership of individual stocks is required for participation in the interview.

			% Owning			
	N	% Sample	Stocks	Funds	Deriv.	Crypto
	(1)	(2)	(3)	(4)	(5)	(6)
Overall	1,540	100.0	100.0	61.6	14.7	38.6
Gender						
Female	514	33.4	100.0	58.4	11.7	29.0
Male	1,025	66.6	100.0	63.2	16.3	43.4
Other	1	0.1	100.0	0.0	0.0	0.0
Age						
21–24	64	4.2	100.0	57.8	17.2	59.4
25–34	322	20.9	100.0	66.8	22.0	54.0
35–44	404	26.2	100.0	65.3	22.0	46.8
45–54	312	20.3	100.0	60.9	11.2	38.5
55–64	213	13.8	100.0	56.3	5.6	22.5
65+	225	14.6	100.0	54.2	4.0	11.1
Education						
No degree	24	1.6	100.0	50.0	16.7	8.3
School diploma	268	17.4	100.0	49.3	7.8	36.9
Bachelor's	757	49.2	100.0	61.3	13.1	38.3
Master's	397	25.8	100.0	70.3	21.2	42.1
Doctorate	68	4.4	100.0	70.6	25.0	39.7
Other	26	1.7	100.0	50.0	7.7	34.6
Investable assets						
1K–10K	142	9.2	100.0	40.8	9.9	38.0
10K–25K	123	8.0	100.0	44.7	7.3	36.6
25K–50K	123	8.0	100.0	56.1	7.3	42.3
50K–100K	100	6.5	100.0	52.0	14.0	38.0
100K–250K	105	6.8	100.0	53.3	14.3	39.0
250K–500K	67	4.4	100.0	62.7	14.9	43.3
500K–1M	440	28.6	100.0	62.7	15.5	40.5
1M+	440	28.6	100.0	77.3	20.0	35.7
Investment knowledge						
Complete beginner	70	4.5	100.0	35.7	4.3	25.7
Rudimentary	345	22.4	100.0	45.5	5.8	25.5
Intermediate	762	49.5	100.0	62.5	12.5	37.5
Advanced	310	20.1	100.0	80.0	26.8	54.5
Expert	53	3.4	100.0	79.2	49.1	62.3
Risk attitude						
Conservative	87	5.6	100.0	40.2	9.2	23.0
Average	812	52.7	100.0	54.2	8.7	29.7
Aggressive	546	35.5	100.0	71.8	21.2	49.6
Very aggressive	95	6.2	100.0	85.3	33.7	65.3

Table 2. Sample Demographics by Country

This table reports demographic characteristics of the 1,540 interviewed investors by country of residence. The first row, *Overall*, covers the full sample; the remaining ten rows each correspond to one country. Column (1) reports the number of investors. Columns (2) through (5) report the percentage who are female, are aged 35 or above, hold at least a bachelor's degree, and report investable assets of at least USD 500,000, respectively. Column (5) equals 57.1% in every row by design: we stipulated to CoreData Research that in each country 57.1% of investors must have at least USD 500,000 in investable assets.

	N (1)	% Female (2)	% Age 35+ (3)	% Bachelor's+ (4)	% High Assets (5)
Overall	1,540	33.4	74.9	79.4	57.1
Australia	140	35.7	66.4	75.7	57.1
Canada	140	42.9	78.6	75.7	57.1
France	140	30.0	75.7	84.3	57.1
Germany	140	22.1	67.1	67.9	57.1
India	140	30.0	50.7	97.1	57.1
Japan	140	14.3	85.7	87.1	57.1
Singapore	140	33.6	75.7	81.4	57.1
South Korea	140	28.6	81.4	87.1	57.1
UK	140	28.6	75.7	75.7	57.1
US	280	50.7	83.6	70.4	57.1

Table 3. The Thirteen Recurrent Heuristics

This table describes the thirteen recurrent heuristics identified from the 1,540 interview transcripts. For each heuristic, we report its label, prevalence, and description. Labels and descriptions are based on the output of the data-driven process automated by GPT-5, as described in Section 3.3. We assign each transcript–heuristic pair a four-point score that captures how strongly the heuristic governs the reasoning of the investor (4: "primary driver," 3: "meaningful contributor," 2: "fragmentary presence," 1: "absent"). Prevalence is the share of investors for whom the heuristic is at least a meaningful contributor to the stock-selection process. Heuristics are ordered by decreasing prevalence.

Heuristic	Prevalence	Description
Fundamental Strength	40.5%	Investors purchase stocks when audited financial information, such as revenues, profitability, and balance-sheet strength, indicates robust current performance and attractive expected returns. This heuristic is historical-data-driven, grounded in verifiable accounting data.
Growth/Innovation	37.6%	Investors buy when they perceive a strong forward-looking growth runway, typically linked to product innovation, technological advantage, or structural demand expansion. The emphasis is on long-term upside potential rather than current fundamentals, and purchase decisions often precede earnings confirmation.
Familiarity/Brand Affect	28.4%	Investors act on personal familiarity, brand trust, or positive product experiences. These cues generate affective comfort and intuitive confidence, leading to rapid decisions that largely bypass detailed analysis. Diminished familiarity sharply reduces willingness to buy.
Blue-Chip Comfort	28.1%	Investors prefer large, stable firms that are perceived as safe and low risk. Signals of operating history, enduring consumer demand, and low volatility create a sense of security that can outweigh concerns about modest expected returns.
Authority-Follow	18.6%	Investors delegate stock selection to trusted professionals or platforms, such as advisors, brokers, financial experts, or investment apps. Source credibility substitutes for independent analysis, and perceived deterioration in that credibility substantially weakens buy intentions.
Momentum	17.9%	Investors buy when sustained price and volume trends reinforce beliefs in continued upward movement and predictable gains.
Confluence	14.6%	Investors require confirmation from multiple independent sources before acting. Expert opinions, online consensus, and other signals must align; conflicting information leads to inaction even when some indicators are favorable.
Dividends	14.0%	Investors purchase only when dividend yield and payout stability meet their income thresholds. A perceived decline in dividend safety sharply reduces buying even when yields rise.
Social-Copy	13.6%	Investors follow the stock choices of trusted peers or family members. Confidence derives from social trust and relational bonds rather than analytical verification, and repeated buys often trace to consistent social sources.
Valuation/Mispricing	13.6%	Investors buy when valuation metrics, such as low price-to-book ratios, discounted-cash-flow estimates, or NAV signals, indicate that the stock trades below intrinsic value. The heuristic requires a clear valuation gap rather than strong fundamentals alone.
Buy-the-Dip	12.5%	Investors interpret temporary price declines as opportunities to capitalize on expected mean reversion. Entry often occurs after evidence of stabilization or rebound, and the belief that the drop is transient is central.
ESG/Values	10.3%	Investors restrict purchases to firms aligned with their ethical or ESG standards. Values-based filters act as mandatory gates that can override otherwise attractive fundamentals, momentum, or valuation signals.
Technical Analysis	6.8%	Investors buy when specific technical patterns, such as breakouts, moving-average crossovers, or support bounces, generate predefined entry signals. Chart-based rules drive timing independent of broader narratives.

Table 4. Representative Interview Excerpts

This table presents interview excerpts illustrating each of the thirteen recurrent heuristics. Excerpts preserve respondents' original spelling and grammar. A bracketed ellipsis ([. . .]) joins answers given by the same respondent at different points in the interview. Excerpts marked with † are faithful English translations of passages from interviews conducted in other languages. The first column reports the heuristic that is the sole primary driver (score of 4) of the respondent's stock-purchase decisions, and the final column reports the respondent's country of residence, gender, and age bracket. Heuristics are ordered by decreasing prevalence, as in Table 3.

Primary driver	Excerpt	Respondent
Fundamental Strength	"I prioritize revenue growth, profit margins, return on equity (ROE), debt-to-equity ratio, and cash flow generation, as these metrics provide insight into a company's financial health and sustainability."	India, male, 25–34
Growth/Innovation	"I invested in the stocks of companies with large future growth engines. Some are companies that have high value now, but I try to pick companies to invest in by looking at their future growth potential."†	South Korea, female, 35–44
Familiarity/Brand Affect	"I like to eat at mcdonalds so that played a part in buying it's stock [. . .] My personal connection to the company usually outweighs the numbers and analyst ratings"	US, male, 55–64
Blue-Chip Comfort	"The reputation have to be good, and the company has to be well-established. Mainly, the ones I invest in have multiple facets to their business to keep them stable."	Singapore, female, 25–34
Authority-Follow	"I trust my sunlife advisor to choose my stocks. [. . .] He tells me what he does and asks me to agree or not. I haven't said no yet."	Canada, female, 45–54
Momentum	"Consistency is key. Stocks rise and fall but if I see that a stock consistently rises, I will buy it."	US, female, 45–54
Confluence	"I read expert opinions and ask AI [. . .] If they line up, I invest, if they differ I stay away"	Australia, male, 25–34
Dividends	"I often hesitate, but in the end I usually decide based on the yield. [. . .] As a rule, 4% or more."†	Japan, male, 45–54
Social-Copy	"I pay a lot of attention to what my parents buy. They simply have more experience than I do."†	Germany, male, 25–34
Valuation/Mispricing	"I think that they are undervalued and I can make some money out of them [. . .] If they are a sound business and the reason their share price is undervalued is due to market forces out of their control."	UK, male, 45–54
Buy-the-Dip	"At the time of purchase I believed that the share price had bottomed out and would soon rise again"	UK, male, 55–64
ESG/Values	"I do not invest in a company whose leader displays convictions that go against my own."†	France, female, 35–44
Technical Analysis	"First, I look for a clear pattern of higher highs and higher lows, with the stock trading above its 50- and 200-day moving averages. I want to see a breakout above a major resistance level, ideally with strong volume."	India, female, 21–24

Table 5. Mapping Heuristics to Firm Characteristics

This table maps seven of the thirteen recurrent heuristics to observable firm characteristics used to measure historical effectiveness, as described in Section 5.3. The firm characteristics are provided by Jensen, Kelly, and Pedersen (2023), whose data cover all ten countries in our study. For each heuristic, we select three characteristics that capture the stock-selection cues emphasized in its description in Table 3. The table reports each characteristic's identifier in Jensen, Kelly, and Pedersen (2023), its sign (in parentheses), and its definition. A positive (negative) sign indicates that we map the heuristic to stocks with high (low) values of the characteristic. For example, *Fundamental Strength* favors high return on equity, operating margin, and gross profitability, while *Buy-the-Dip* favors low past one-, two-, and three-month returns.

Heuristic	Characteristic (sign)	Definition
Fundamental Strength	*ni_be* (+)	Return on equity (net income / book equity)
	ebit_sale (+)	Operating margin (EBIT / sales)
	gp_at (+)	Gross profitability (gross profits / assets)
Growth/Innovation	*capx_gr1* (+)	Capital-expenditure growth (1 year)
	sale_gr1 (+)	Sales growth (1 year)
	rd_me (+)	R&D-to-market ratio (R&D expense / market equity)
Blue-Chip Comfort	*me* (+)	Market equity
	age (+)	Firm age
	rvol_21d (−)	Return volatility (21 days)
Buy-the-Dip	*ret_1_0* (−)	Past 1-month return
	ret_2_0 (−)	Past 2-month return
	ret_3_0 (−)	Past 3-month return
Dividends	*div6m_me* (+)	Dividend yield (trailing 6-month)
	div12m_me (+)	Dividend yield (trailing 12-month)
	eqnpo_me (+)	Net payout yield
Momentum	*ret_6_1* (+)	6-month momentum (return $t-6 \rightarrow t-1$)
	ret_9_1 (+)	9-month momentum (return $t-9 \rightarrow t-1$)
	ret_12_1 (+)	12-month momentum (return $t-12 \rightarrow t-1$)
Valuation/Mispricing	*be_me* (+)	Book-to-market ratio (book equity / market equity)
	ni_me (+)	Earnings-to-price ratio (net income / market equity)
	sale_me (+)	Sales-to-price ratio (sales / market equity)

Table 6. Heuristic Choice: Objective Importance and Perceived Effectiveness

This table reports linear probability regressions examining whether investors are more likely to choose heuristics they perceive as effective for objectives they consider important. The unit of observation is an investor–heuristic–objective combination. The dependent variable, $D(\text{Chosen})$, equals one if the heuristic is at least a meaningful contributor to the investor's stock-selection process in the initial interview, and zero otherwise. The key independent variable is *Objective importance* × *Perceived effectiveness*. *Objective importance* is the investor's five-point importance rating for the objective; *Perceived effectiveness* is her five-point rating of how effective she believes the heuristic is at identifying stocks that achieve that objective in her country's stock market. Both ratings come from the follow-up survey. We standardize importance within investor across the three financial objectives (returns, upside, and stability) and perceived effectiveness within investor across all ratings for these objectives. To keep the follow-up survey manageable, respondents evaluate only chosen heuristics or heuristics reported as previously used (but no longer in use). If this set exceeds three, they assess only the three longest-used heuristics. In addition, effectiveness ratings are elicited only for objectives assigned an importance rating of 4 or 5. Column (1) includes investor fixed effects. Column (2) replaces these with investor × objective fixed effects, which absorb the standalone importance rating. Column (3) additionally includes country × heuristic × objective fixed effects. Standard errors are clustered by investor and reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Dependent variable: $D(\text{Chosen})$			
	(1)	(2)	(3)
Objective importance × Perceived effectiveness	+0.033**	+0.036**	+0.035**
	(0.014)	(0.016)	(0.017)
Objective importance	-0.000		
	(0.001)		
Perceived effectiveness	-0.004	-0.005	-0.005
	(0.011)	(0.014)	(0.014)
Investor FE	✓	–	–
Investor × Objective FE	–	✓	✓
Country × Heuristic × Objective FE	–	–	✓
Observations	3,744	3,744	3,744
R^2	0.274	0.274	0.420

Table 7. Do Chosen Heuristics Deliver on the Objectives Investors Prioritize?

This table compares the historical effectiveness of investors' chosen heuristics on their prioritized objectives with two heuristic benchmarks (Section 5.4.3). The unit of observation is an investor–objective pair, restricted to objectives the investor prioritizes; an objective is prioritized if the investor rates its importance strictly above her own average across the three financial objectives (returns, upside, and stability). For investor i in country c, the historical effectiveness of her chosen heuristics on prioritized objective g is

$$\bar{\eta}^{\mathrm{H}}_{ig} = \frac{1}{|\mathcal{H}^{\mathrm{C}}_i|} \sum_{h \in \mathcal{H}^{\mathrm{C}}_i} \eta^{\mathrm{H}}_{hgc},$$

where $\mathcal{H}^{\mathrm{C}}_i$ is the set of the investor's chosen heuristics among the seven covered by archival data. η^{H}_{hgc} measures the performance of stocks associated with heuristic h on objective g in country c from July 2015 through June 2025, as described in Section 5.3. The row "Chosen heuristics" reports the average of $\bar{\eta}^{\mathrm{H}}_{ig}$. The "Overall" column first averages $\bar{\eta}^{\mathrm{H}}_{ig}$ across each investor's prioritized objectives and then across investors, giving each investor equal weight. The remaining columns average $\bar{\eta}^{\mathrm{H}}_{ig}$ across investors who prioritize the corresponding objective. The benchmark rows replace each investor's chosen heuristics with an equally sized set drawn randomly, without replacement, from either the covered heuristics she does not use ("Unused heuristics") or all seven covered heuristics ("Randomly selected heuristics"). We evaluate these sets on the same objectives in the same country and aggregate in the same way as for chosen heuristics. Each benchmark reports the mean across 10,000 draws, with the standard deviation across draws in parentheses. One-sided p-values, reported in brackets, are the fractions of draws that perform at least as well as the chosen heuristics. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively, using unrounded p-values.

Effectiveness, in standard deviations from the average heuristic–country pair				
	Overall (1)	Returns (2)	Upside (3)	Stability (4)
Chosen heuristics	+0.130	+0.009	+0.158	+0.179
Unused heuristics	-0.076	-0.158	-0.020	-0.043
Standard deviation across draws	(0.030)	(0.048)	(0.054)	(0.045)
p(Chosen ≤ unused heuristics)	[<0.001]***	[<0.001]***	[<0.001]***	[<0.001]***
Randomly selected heuristics	-0.035	-0.129	+0.021	-0.002
Standard deviation across draws	(0.032)	(0.050)	(0.058)	(0.048)
p(Chosen ≤ randomly selected heuristics)	[<0.001]***	[0.003]***	[0.010]***	[<0.001]***

Table 8. Do Chosen Heuristics Deliver on the Objectives Investors Do Not Prioritize?

This table repeats the analysis of Table 7 on objectives investors do *not* prioritize. An objective is nonprioritized if its importance rating is strictly below the investor's own average across the three financial objectives. Objectives rated exactly at this average are neither prioritized nor nonprioritized. Chosen heuristics are those identified in her interview among the seven covered by archival data (Table 5). We use historical effectiveness over July 2015 through June 2025. The row *Chosen heuristics* reports historical effectiveness on nonprioritized objectives in the investor's country. The column *Overall* first averages across each investor's nonprioritized objectives and then across investors. The other columns average across investors for whom the corresponding objective is nonprioritized. The two benchmarks replace the chosen heuristics with an equally sized random draw from covered heuristics she does not use (*Unused heuristics*) or all seven covered heuristics (*Randomly selected heuristics*). Both benchmarks use the same 10,000 draws as Table 7. Each benchmark reports the mean across these draws, with the standard deviation across draws in parentheses. Bracketed one-sided p-values report the fraction of draws that perform at least as well as the chosen heuristics. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively, using unrounded p-values.

Effectiveness, in standard deviations from the average heuristic–country pair				
	Overall (1)	Returns (2)	Upside (3)	Stability (4)
Chosen heuristics	-0.100	-0.078	-0.127	-0.091
Unused heuristics	-0.026	-0.124	+0.016	+0.017
Standard deviation across draws	(0.029)	(0.055)	(0.044)	(0.061)
p(Chosen ≤ unused heuristics)	[0.994]	[0.195]	[0.999]	[0.962]
Randomly selected heuristics	-0.050	-0.140	-0.014	-0.007
Standard deviation across draws	(0.032)	(0.057)	(0.047)	(0.063)
p(Chosen ≤ randomly selected heuristics)	[0.942]	[0.135]	[0.991]	[0.906]