Portfolio Choice with Non-Fungible Brokerage Cash

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Abstract

Standard portfolio-choice models treat cash as fungible. Using positions and transfer records for 46,016 Chinese investors, we show that brokerage cash is non-fungible and that cash-source effects refresh and decay. We label inflows from savings transfers as "cold" and trading-recycled funds as "hot," and construct a cash-temperature measure tracking these dynamics. Investors allocate colder cash to safer stocks, controlling for gains and losses, trading intensity, and rebalancing. Quasi-experimental variation from China's 2016 IPO reform supports a causal interpretation. A pre-registered experiment links cold framing to loss aversion; a model with temperature-dependent sensitivity to gains and losses rationalizes the evidence.

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I. Introduction

Fungibility of cash—the idea that each dollar is interchangeable with any other—is often taken for granted. Reflecting this benchmark, standard portfolio-choice models treat an investor's total liquid wealth as the sufficient statistic for investment decisions, abstracting from how that liquidity was obtained. We study whether this assumption holds within brokerage accounts: do equity investors treat otherwise identical brokerage cash differently depending on its provenance, and does such perceived non-fungibility shape stock selection?

We answer these questions using both observational and experimental evidence. Our observational analysis uses a novel dataset that matches daily portfolio holdings to daily bank–brokerage cash transfer records for 46,016 individual investors in the Chinese stock market. Observing cash transfers allows us to measure, for each investor on each day, the composition of brokerage cash by source. We find a clear pattern: investors behave more cautiously when trading with cash that has recently been transferred into the brokerage account from stable sources than with cash that is routinely recycled through prior trading activity. We refer to the former as "cold cash" and the latter as "hot cash."

To summarize this composition in a single state variable, we use a "temperature" analogy. Cash that arrives from a savings account or a similarly stable source is "cold," whereas cash generated by selling stocks or other risky assets is "hot." We define an investor's *cash temperature* as a number on $[0, 1]$ that captures how hot the investor's available brokerage cash is at the time of purchase. Intuitively, temperature is the decay-adjusted share of available cash that is hot: it is refreshed by new cash-source events, shifts as money enters, exits, and is recycled within the brokerage account, and attenuates over inactive time in the absence of further relabeling.

Because temperature is shaped by recent trading history, our setting admits several related interpretations. We therefore use the term *cash temperature* to emphasize a distinct object: an investor's state-dependent attitude toward an otherwise identical unit of brokerage cash that evolves with its *source* and with the *time since it entered or was recycled within* the brokerage account. This focus differs from three prominent mechanisms that also link recent trading history to risk taking. First, *house money* and related gain–loss mechanisms operate through prior investment outcomes, whereas temperature is anchored in the provenance and aging of liquid funds. Second, *mental account rollover* and mechanical *rebalancing* can tie sales proceeds to subsequent purchases even absent any change in how investors value cash. To isolate a more persistent cash-composition channel, we exclude rollover purchases and implement rebalancing-related filters and controls. Third, time-varying *investor style* can generate predictable shifts in both trading-generated cash and portfolio risk (e.g., periods of heightened activity or speculative attention), potentially inducing spurious correlation with temperature. We therefore implement targeted controls and sample restrictions to distinguish cash temperature from these alternatives.

The cash-temperature framework builds on mental accounting, but it shifts attention from one-time labeling to repeated relabeling of recycled funds in an economically meaningful, high-stakes investment environment. Since Thaler (1985, 1990), a large literature has documented how individuals "organize, evaluate, and keep track of financial activities" (Thaler (1999)), often producing violations of fungibility in consumption and budgeting settings. A common feature of these applications is that labeled funds are typically spent once and then leave the accounting system. In contrast, brokerage cash can recycle frequently and in large amounts due to active trading by individual investors (Barber and Odean (2000)). This repeated cycling creates a natural environment in which labels attenuate over time and are refreshed as cash is recycled—a dynamic prediction that is central to our cash-temperature framework.

Many studies in finance extend mental accounting to stocks or asset classes rather than to money itself. Investors may open separate mental accounts to book gains and losses at the security level, helping explain the disposition effect (see Shefrin and Statman (1985), Barberis and Xiong (2009), and Barberis and Xiong (2012)) and risk attitudes (see Barberis and Huang (2001), Imas (2016), and Frydman, Hartzmark, and Solomon (2018)). Our findings are distinct from Imas (2016), who shows that paper (realized) losses are followed by higher (lower) risk taking in subsequent purchases. In our setting, realized trading proceeds (whether gains or losses) are classified as hot inflows and are associated with *more* risk taking rather than less. More broadly, while the stock-level literature emphasizes how gains and losses are carried across risky positions, we focus on how the composition and "aging" of liquid brokerage cash shapes stock selection.

We operationalize cash temperature by constructing an account-day measure $\theta_{i,t} \in [0, 1]$ from observed inflows and outflows. Its construction requires a rule for how cold and hot inflows are tracked and how mixed cash is allocated when an outflow occurs. We propose two extreme bookkeeping rules that bracket a broad set of plausible behaviors: Algorithm A1 assumes proportional mixing of cold and hot balances, while Algorithm A2 assumes a pecking order that matches cash type to purpose. We report results under both rules; the qualitative patterns are similar.

The resulting effects are economically meaningful. In Table 3, moving from fully cold cash ($\theta_{i,t} = 0$) to fully hot cash ($\theta_{i,t} = 1$) increases the riskiness of purchased stocks by about three cross-sectional percentiles. This effect is roughly three times as large as the mental account rollover effect documented in Frydman et al. (2018). In Internet Appendix Table 12, the same change in $\theta_{i,t}$ is associated with a roughly 3.4-percentile increase in momentum, a 1.2-percentile decrease in subsequent one-month returns, and a 3.4-percentile increase in abnormal trading volume. These magnitudes help anchor the behavioral interpretation: temperature shifts stock selection along several dimensions commonly associated with "cautious" versus "risk-on" investment behavior.

Because temperature is constructed from observed cash flows, a natural concern is endogeneity: investors may raise hot cash precisely when they plan to buy certain kinds of stocks, or unobserved investor-day shocks may move both cash flows and choices. We address these concerns in two complementary ways. First, within the algorithm-based approach, the temperature coefficient remains stable as we sequentially enrich the baseline specification with more comprehensive gain/loss controls, an interaction that captures the attenuation of temperature over time, rebalancing-related filters, trading-intensity controls, and conservative alternative cash definitions (Table 5 and related Internet Appendix tables). Second, and more importantly, we develop an algorithm-free identification strategy that addresses reverse-causality concerns and does not rely on any particular bookkeeping convention.

Our identification strategy exploits China's IPO lottery reform on January 1, 2016. During our identification window (June 17, 2014 to December 31, 2016), IPO stocks were severely underpriced due to a strictly enforced regulatory cap of 23 on the IPO price-to-earnings (PE) ratio, and first-day returns mechanically hit the 44% upper limit.[1]

[1]Maximum (minimum) daily returns of every stock listed in the Shanghai and Shenzhen stock exchanges

Participating in IPO lotteries was therefore widely perceived as signing up for a near-sure gain. Under the pre-reform regime, eligible investors submitted a cash deposit of the full application amount; the deposit was frozen in an IPO cash pool for two trading days and then largely refunded. Under the post-reform regime, no deposit was required and no refund occurred. This institutional change creates quasi-exogenous variation in whether funds pass through the frozen IPO cash pool. Using a Difference-in-Differences (DiD) design on IPO-result days, we show that cooled refunds under the old regime lead investors to select stocks more cautiously than the same refund share under the new regime, consistent with a causal cash-temperature effect.

After establishing the effect in the field, we probe mechanisms in a pre-registered experiment ($N = 405$) on Prolific. Participants are endowed with both a savings account and a brokerage account. After reviewing information about the two accounts, they are randomly assigned to use one of them to make a risky stock choice. The experimental results provide complementary causal evidence that cash source matters and that loss sensitivity is a plausible channel.

To formalize this mechanism and its equilibrium implications, we study a portfolio-choice model in which sensitivity to future gains and losses is decreasing in cash temperature. Intuitively, losses become less painful—and gains less exciting—when an investor uses hotter cash. In both myopic and dynamic settings, the model predicts higher equilibrium prices, lower expected returns, and greater risk taking when cash temperature is higher. The dynamic setting also generates the temperature smoothing pattern for investors who internalize the effect of risky investment today on cash temperature tomorrow.

are limited to 44% (-44%) on the first trading day after IPO and 10% (-10%) on any day after that.

The paper's central contribution is to show that the non-fungibility of brokerage cash is inherently dynamic: source-based cash labels are refreshed as funds enter, exit, and are recycled within the account, and attenuate over time absent further salient activity. Beyond this central insight, the paper contributes in two additional ways. First, standard portfolio-choice problems have three core elements: beliefs (expectations under uncertainty), preferences (the utility function), and amount of cash (the budget constraint). The non-fungibility of brokerage cash adds a fourth element: the *source* of cash. We incorporate this element in Section VI. Second, the model offers a unified perspective on several stylized facts emphasized in the literature, including the coexistence of limited market participation (Mankiw and Zeldes (1991), Campbell (2006), and Choukhmane and de Silva (2021)) and overtrading (Barber and Odean (2000)), overreaction to shocks (De Bondt and Thaler (1985)), and price fluctuations not driven by fundamental changes (Shiller (1992)).

The rest of the paper is organized as follows. Section II formalizes the temperature framework and describes the data. Section III introduces Algorithms A1 and A2, presents algorithm-based evidence, and discusses alternative mechanisms motivating the identification design. Section IV develops the IPO-reform design and presents quasi-experimental evidence, including DiD and IV results. Section V presents the pre-registered experiment and evidence on loss aversion. Section VI develops the model and its implications. Section VII concludes.

II. Conceptual Framework and Data

Cash temperature is a state variable that summarizes an investor's attitude toward cash along a particular dimension. The framework is designed for environments in which money is repeatedly reallocated and relabeled as it cycles through different uses. In this section, we formalize cash temperature through three maintained assumptions about how labels evolve and then describe the dataset used to construct and test the measure.

A. The Temperature Framework

The origin of cash often matters for economic decisions (Raghubir and Srivastava (2008) and Meyer and Pagel (2022)). To sharpen definitions, consider an agent who repeatedly allocates money across a set of *containers*. A container is an objective destination for funds, such as a savings account or a risky asset position. Let $\mathcal{K}$ denote the set of containers. For each container $k \in \mathcal{K}$ and each dimension $d \in \mathcal{D}$, assign a container temperature $\theta_k^d \in [0, 1]$ that summarizes the container's nature along dimension d. Throughout the paper, we study a particular pecuniary dimension: *stability of value*. In this dimension, stable containers (e.g., savings accounts) have low temperature, while unstable containers (e.g., risky assets) have high temperature.

The distinction between containers and mental accounts is important. A *container* is a physical account or asset position characterized by objective features; a *mental account* is a subjective category that may or may not be organized along the same dimensions. By starting with containers, we avoid assuming how investors categorize money mentally. Instead, we test whether stability—an objective feature of containers—predicts behavior in a way consistent with systematic relabeling.

The novelty of the framework comes from repeated recycling. Investors experience frequent inflows of brokerage cash from savings accounts and from risky-asset sales, and a large share of these flows represent recycled funds that re-enter the same decision environment. To model this process, we require a simple discipline governing what is stable and what is refreshed over time. We therefore impose three maintained assumptions.

Assumption T1 (container temperature is fixed). *For each dimension $d \in \mathcal{D}$, the temperature of container $k \in \mathcal{K}$, denoted θ_k^d, is constant over time and does not depend on inflows or outflows.*

This assumption rules out arbitrary shifts in container "type" and treats container stability as exogenous.

Assumption T2 (temperature assimilation at purposeful allocation). *If cash is purposefully allocated to container k, then when that cash later leaves container k it inherits the temperature θ_k^d for each dimension d, regardless of its prior history.*

Two features are central. First, relabeling is tied to purposeful allocation: for cash temperature to change, funds must be intentionally directed to a container with a specific use, such as investing in stocks for potential appreciation or transferring funds to a savings account for safekeeping. Absent such a salient purpose, cash that sits idle—for example, pooled as brokerage cash—does not automatically reset labels. This feature underpins our empirical focus on brokerage-cash composition. Second, the assignment is Markovian: the temperature of cash is determined solely by its most recent purposeful container, which keeps the relabeling process tractable.

Assumption T3 (temperature decay). *Once assigned, cash temperature decays at a rate $\beta \in [0, 1]$, converging toward a benchmark level of 0 over time.*

Decay captures noisy recall and recency (Azeredo da Silveira and Woodford (2019) and Nagel and Xu (2022)). It also makes the state variable empirically realistic: after long periods without salient relabeling, investors are unlikely to sharply distinguish cash by origin.

These assumptions discipline the construction of a temperature state variable from observed cash flows. Importantly, they are not required for our causal evidence: in Section IV, we develop an identification strategy that does not rely on a constructed temperature measure and therefore does not inherit any bookkeeping assumption embedded in $\theta_{i,t}$.

Our framework does not, in its most general form, specify which dimension d matters. Broadly, dimensions can be pecuniary (related to preservation or change of value) or non-pecuniary (related to the container's purpose orthogonal to value), such as moral cleansing in mental money laundering (Imas, Loewenstein, and Morewedge (2021)). In the remainder of the paper, we focus on a pecuniary dimension: container stability.

B. Data

Our main dataset contains daily holdings for 46,016 individual investors in the Chinese stock market from January 1, 2006, to December 31, 2016. A key advantage is the ability to match daily holdings to detailed daily bank–brokerage cash transfers, which allows us to infer the composition of brokerage cash at the investor-day level. Table 1a assesses representativeness by comparing the distribution of investors (by average portfolio value) in our sample to that in the population.

Brokerage cash is quantitatively important in our sample. Table 1b shows that investors hold 52,820 CNY (approximately 8,000 USD) in brokerage cash on an average day, about 18% of their stock portfolio value. These balances are also large relative to immediate daily flows (stock buys and sells), which makes the composition of available cash a meaningful state variable for trading decisions.

In addition to the proprietary holdings and transfer data, we use firm-level information on 3,083 A-share listed firms from the WIND database.

The Chinese stock market is well suited to test the temperature framework for three reasons. First, tax-based incentives are limited: there is no capital-gains tax on stock investment in China. Second, the efficient clearing system ensures cash balances are accurately recorded in our data. Third, the IPO reform within our sample period provides quasi-experimental variation in the origin of investable brokerage cash.

III. Algorithm-Based Empirical Evidence

This section introduces two algorithms for computing brokerage-cash temperature, presents algorithm-based evidence for the cash-temperature effect, and motivates the quasi-experimental design in Section IV.

A. Two Algorithms for Temperature Measurement

We operationalize temperature along a specific dimension: container stability. A stable container, assigned temperature 0, preserves value and is relatively predictable; an unstable container, assigned temperature 1, is exposed to value fluctuations and greater uncertainty. This binary container classification is sufficient to discipline the empirical construction while remaining robust to heterogeneity in how investors subjectively rank intermediate assets.

Table 1: Sample Composition and Summary Statistics

This table describes the sample of 46,016 individual brokerage accounts in the Chinese stock market from January 1, 2006, to December 31, 2016. Panel A compares the sample against the population of 53 million accounts registered at the Shanghai Stock Exchange between 2016 and 2019 (Jones, Shi, Zhang, and Zhang, 2021). Accounts are grouped by average holding value in CNY: Smallest (< 100K), Small ([100K, 500K)), Medium ([500K, 3M)), Large ([3M, 10M)), and Largest (≥ 10M). Panel B reports account-level summary statistics. "Cash Bal." is the end-of-day brokerage cash balance averaged across trading days; "Stock Bal." is the end-of-day market value of stock holdings. "Buy Value" and "Sell Value" are the daily CNY values of holdings-implied stock buys and sells, averaged across trading days. "Stock Num." is the end-of-day count of distinct stocks held. "Holding Horizon" is the average number of days a stock is held across all positions ever held. Columns 1–4 are in thousands of CNY.

Panel A: Representativeness

	Sample		Population	
	Number	Share	Number	Share
Smallest [0, 100K)	25,083	54.51%	31,410,000	58.72%
Small [100K, 500K)	15,017	32.63%	15,282,000	28.57%
Medium [500K, 3M)	5,226	11.36%	5,827,000	10.89%
Large [3M, 10M)	551	1.20%	735,000	1.37%
Largest [10M, ∞)	139	0.30%	235,000	0.44%
Total	46,016	100%	53,489,000	100%

Panel B: Summary Statistics

	Cash Bal.	Stock Bal.	Buy Value	Sell Value	Stock Num.	Holding Horizon
Mean	52.82	294.38	15.85	18.81	3.45	57.06
S.D.	857.82	1,646.67	125.09	630.51	4.33	89.97
Min	0.03	0.00	0.00	0.00	0.00	1.00
25%	3.89	23.55	0.84	0.82	1.68	12.49
Median	11.10	66.72	2.86	2.82	2.50	28.08
75%	32.40	198.29	9.34	9.23	3.95	64.57
Max	132,154.22	192,921.97	13,103.28	132,328.63	392.89	2023.00
Obs.	46,016	46,016	46,016	46,016	46,016	45,905

1. Cash-Flow Accounting

To define temperature, we first summarize the cash that is available to investor i on day t using observed balances and net cash flows. Let $B_{i,t}^{\text{start}}$ and $B_{i,t}^{\text{end}}$ denote the start-of-day and end-of-day brokerage cash balances. Let $T_{i,t}^{\text{inter}}$ denote the net bank–brokerage transfer that occurs between the last transaction on day $t-1$ and the first transaction on day t (an inter-day transfer), and let $T_{i,t}^{\text{intra}}$ denote the net within-day bank–brokerage transfer on day t. Let $\text{Trade}_{i,t}$ denote the net change in brokerage cash due to trading activity during day t. These objects satisfy the following accounting identities:

$$B_{i,t}^{\text{start}} = B_{i,t-1}^{\text{end}} + T_{i,t}^{\text{inter}}, \tag{1}$$

$$B_{i,t}^{\text{end}} = B_{i,t}^{\text{start}} + \text{Trade}_{i,t} + T_{i,t}^{\text{intra}}.$$

We now combine and decompose the terms in equation (1) to construct an investor's total cash available on each day. Because $T_{i,t}^{\text{inter}}$ occurs between trading days, its effect is reflected beginning on day t. We therefore define total transfer-in on day t as the sum of positive inter-day and within-day transfers:

$$\text{TransferIn}_{i,t} \equiv \max\{T_{i,t}^{\text{inter}}, 0\} + \max\{T_{i,t}^{\text{intra}}, 0\}.$$

For our purposes, only inflows enter the "resources available" decomposition; negative transfers are outflows and are treated as cash usage rather than resources.

It is useful to further decompose $\text{Trade}_{i,t}$ because different components have distinct economic interpretations in our setting. In particular, the temperature construction treats stable inflows differently from cash generated by risky-asset trading. We therefore separate $\text{Trade}_{i,t}$ into IPO-related cash flows (deposits and refunds), net cash changes from trading other non-stock assets, and net cash changes from stock trades.[2] For stock trades, define

$$\text{StockTrd}_{i,t} \equiv \text{StockSell}_{i,t} - \text{StockBuy}_{i,t},$$

where $\text{StockSell}_{i,t}$ and $\text{StockBuy}_{i,t}$ are the holdings-implied CNY values of stocks sold and purchased by investor i on day t.

2. Resources Available on Day t

Let $\text{TotalCash}_{i,t}$ denote total cash available on day t:

$$\text{TotalCash}_{i,t} = \text{Refund}_{i,t} + \text{TransferIn}_{i,t} + \text{StockSell}_{i,t} + \text{Div}_{i,t} + \text{OtherSell}_{i,t} + B^{\text{end}}_{i,t-1}, \tag{2}$$

which is the sum of all observable funding sources on day t, abstracting from within-day ordering. Each term on the right-hand side is non-negative by construction.[3] Although we do not observe the exact intra-day sequence of transactions, it is natural to think that investors evaluate their available resources before executing purchases. Accordingly, $\text{TotalCash}_{i,t}$ serves as an empirical proxy for the investor's effective budget set when making stock-purchase decisions on day t.

[2] In China, investors can trade exchange-traded funds (ETF), treasury repurchase agreements (repo), listed open-ended funds (LOF), and other assets within the brokerage account.

[3] For example, a positive bank transfer increases resources and enters $\text{TotalCash}_{i,t}$. A negative transfer is treated as a cash outflow (usage) and therefore does not enter equation (2).

3. Cold and Hot Inflows Under the Binary Container System

We next assign a container temperature to each component in equation (2). We adopt a binary container system for two reasons. First, finer distinctions would require reliable within-day sequencing of cash components, which is infeasible without full intra-day flow timing for all sources. Second, investors may differ in how they rank intermediate assets by stability; a coarser classification is therefore less sensitive to heterogeneity. Importantly, even though container temperature is binary, brokerage-cash temperature is continuous on $[0, 1]$ because it aggregates across sources and evolves over time.

In this binary system, IPO cash pools and bank savings accounts are cold containers.[4] Common stocks and other tradable risky assets are hot containers. Under Assumption T2 (assimilation), the temperature of cash leaving a container reflects the container rather than the cash's earlier history. Accordingly, $\text{Refund}_{i,t}$ and $\text{TransferIn}_{i,t}$ are cold inflows, while $\text{StockSell}_{i,t}$, $\text{Div}_{i,t}$, and $\text{OtherSell}_{i,t}$ are hot inflows:[5]

$$\text{ColdCash}_{i,t} \equiv \text{Refund}_{i,t} + \text{TransferIn}_{i,t},$$

$$\text{HotCash}_{i,t} \equiv \text{StockSell}_{i,t} + \text{Div}_{i,t} + \text{OtherSell}_{i,t}.$$

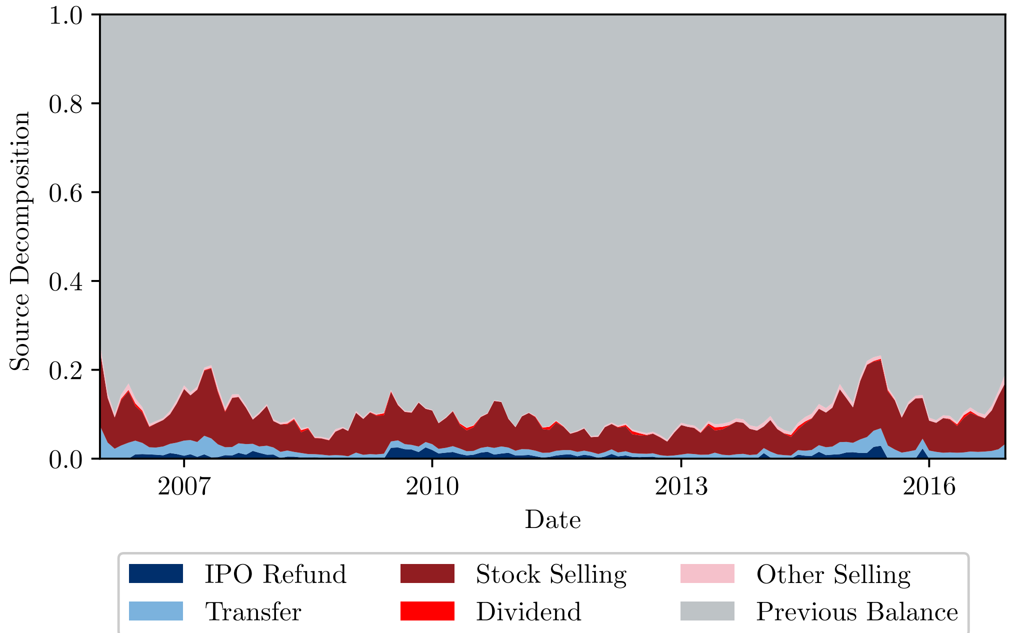
The temperature of the carried-over balance $B^{end}_{i,t-1}$ is not directly defined. Under Assumption T2, leaving cash idle in the brokerage account does not reset its label absent a salient, purposeful allocation. Under Assumption T3, the temperature of the carried-over

[4] Institutional details of IPO cash pools are provided in Section IV.

[5] Dividends are treated as hot inflows because they are returns generated within the brokerage account from risky-asset holdings, analogous to sale proceeds. Our results are robust to alternative classifications of dividends, and in practice their quantitative importance is limited given the relatively small magnitude of dividend payments in the Chinese stock market.

Figure 1: Source Decomposition of Brokerage Cash

The figure plots the monthly composition of total available cash $\text{TotalCash}_{i,t}$ defined in equation (2) for the sample of 46,016 investors from January 2006 to December 2016. The six sources are IPO refunds ($\text{Refund}_{i,t}$), bank–brokerage transfer-ins ($\text{TransferIn}_{i,t}$), stock sales ($\text{StockSell}_{i,t}$), dividends ($\text{Div}_{i,t}$), other-asset sales ($\text{OtherSell}_{i,t}$), and the previous-day cash balance ($B^{\text{end}}_{i,t-1}$). Each source's weight is the monthly average share across all investors.



balance decays overnight. Figure 1 shows that $B^{end}_{i,t-1}$ is quantitatively important throughout the sample, so any algorithmic temperature construction must specify how outflows are allocated across cold and hot components to update end-of-day temperature.

We therefore propose two outflow-allocation algorithms that can be interpreted as two extreme bookkeeping rules.

Algorithm A1 (proportional mixing). Investors fully pool cold and hot cash. Whenever an outflow occurs (e.g., a stock purchase or a transfer-out), the outflow is funded proportionally from each component.

Algorithm A2 (pecking order). Investors track cold and hot balances separately and "match" funding sources to outflow purposes, drawing first on the balance whose temperature is closer to the intended use and using the other type only after the first is depleted. For instance, under A2 a stock purchase is deducted from hot balances first (then cold), whereas an outward cash transfer is deducted from cold balances first (then hot).

We do not take a stance on which rule best describes each investor. Instead, A1 and A2 bracket a broad set of plausible mental-bookkeeping processes; actual behavior may lie between them. When our main empirical patterns hold under both A1 and A2, they are naturally interpreted as robust to the unobserved investor-specific allocation rule.

Under both A1 and A2, decay occurs overnight: the temperature of the carried-over balance on day t equals its end-of-day temperature on day $t-1$ multiplied by $\beta \in [0,1]$.

Although A1 and A2 differ in how outflows are allocated, cash temperature $\theta_{i,t}$ is, in either case, the weighted-average temperature of all cash available to investor i on day t. Equivalently, $\theta_{i,t}$ is the (decay-adjusted) share of *hot* cash in total available cash. Formally,

$$\theta_{i,t} = \frac{\text{HotCash}_{i,t} + \beta\,\theta_{i,t-1}\,B^{\text{end}}_{i,t-1}}{\text{TotalCash}_{i,t}}. \tag{3}$$

Table 2 illustrates the construction over three days. On day t, the investor receives only a cold transfer-in and then buys stock; the purchase is funded entirely with cold cash, so both algorithms coincide. On day $t+1$, the investor sells stock (a hot inflow) and then buys stock (an outflow). Under Algorithm A1, the purchase is funded proportionally from hot and cold balances, so the end-of-day cash remains relatively hot and θ stays high. Under Algorithm A2, the purchase draws down hot cash first, leaving the end-of-day cash relatively cold and therefore implying a lower θ. From $t+1$ to $t+2$, there are no new flows; the only

Table 2: Example: Cash Temperature under Two Algorithms

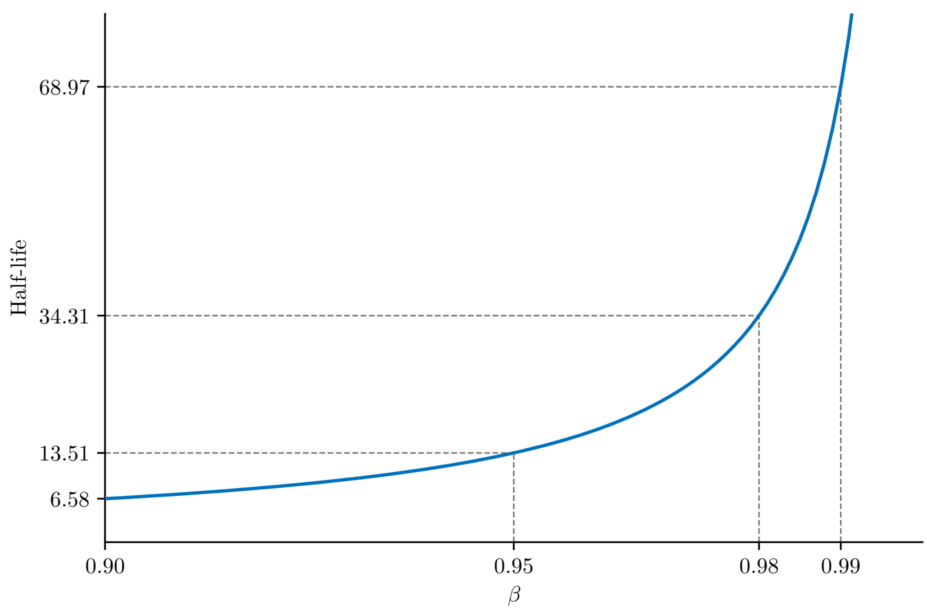
This table illustrates the construction of cash temperature under Algorithm A1 (proportional spending) and Algorithm A2 (pecking order) using a simple numerical example. The example starts with a cold transfer of 100 on day t. Within each day, the investor sells first and then buys. Cash temperature θ is a weighted-average property of all cash available on that day, as defined in equation (3). Temperature decays overnight at rate $\beta = 0.90$, so absent new cash flows, $\theta_{t+1} = \beta\,\theta_t$. Algorithms A1 and A2 differ only in how outflows are booked.

	Within Day					End-of-Day θ	
Day	Start Balance	Transfer-In	Stock Sell	Stock Buy	End Balance	Under A1	Under A2
t	0	100	0	40	60	0.00	0.00
$t+1$	60	0	60	30	90	0.50	0.33
$t+2$	90	0	0	0	90	0.45	0.30

change comes from overnight decay applied to the carried-over balance. As a result, θ declines under both algorithms.

Figure 2: Temperature Decay and Implied Half-Life

The figure plots the half-life implied by a daily decay rate $\beta \in [0, 1]$. Half-life is the number of days required for temperature to decay to one-half of its current level, i.e., T satisfying $\beta^T = 1/2$.



To build intuition for the magnitude of β, Figure 2 plots the implied half-life.[6]

[6]Half-life is the number of days required to reduce the current temperature to one-half, i.e., T satisfying $\beta^T = 1/2$.

Because half-life is convex in β, it becomes very sensitive when β is close to one: for example, $\beta = 0.90$ implies a half-life of about 7 trading days, whereas $\beta = 0.98$ implies a half-life of about 34 trading days.

Figure 3 summarizes aggregate dynamics. Panel (a) reports the monthly mean of $\theta_{i,t}$, while Panel (b) reports the median and interquartile range. The market index (SSE Composite Index) is included for comparison. On aggregate, A1 and A2 track similar variation, with A1 assigning a slightly higher level of temperature.[7]

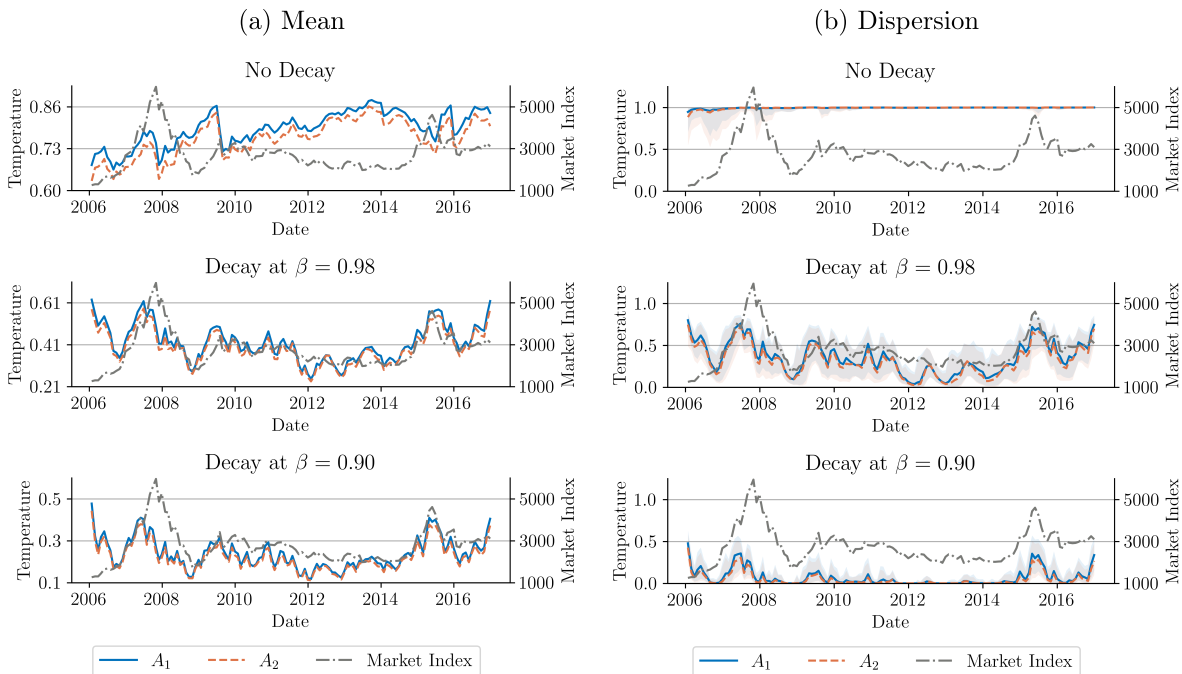
When $\beta < 1$, aggregate temperature is pro-cyclical and co-moves positively with the market index. This comovement can arise mechanically (higher markets induce more trading and therefore more hot inflows) and potentially through behavior (hotter cash may support greater willingness to buy at higher prices). The empirical and theoretical analyses that follow are consistent with the latter channel playing a meaningful role.

The decay parameter governs how quickly the influence of past cash flows dissipates in the construction of $\theta_{i,t}$. In the baseline specification, we set $\beta = 0.90$, which implies an economically interpretable half-life of approximately one trading week. This baseline choice reflects an ex post refinement of the economic interpretation of decay: β is intended to capture the persistence of cash-source labels within brokerage cash. A one-week half-life is consistent with the high-frequency nature of brokerage cash dynamics. Within a short horizon, accounts may experience multiple transfers, purchases, and sales; a relatively faster decay therefore places greater weight on recent cash-source events and concentrates variation in $\theta_{i,t}$ in the days immediately following the arrival of "hot" cash, rather than allowing earlier

[7]By construction, A1 mechanically preserves the hot share after stock purchases, whereas A2 tends to draw down hot cash first. Because buying stocks is more frequent than cashing out, A1 is expected to deliver a slightly higher average temperature.

Figure 3: Aggregate Cash Temperature

The figure plots monthly time series of aggregate temperature for the sample of 46,016 investors from January 2006 to December 2016. Panel (a) shows the monthly mean of temperature under Algorithms A1 (solid) and A2 (dashed) for three decay rates: $\beta = 1$, $\beta = 0.98$, and $\beta = 0.90$. Panel (b) shows the monthly median (solid and dashed) and the interquartile range (25%–75% band) under the same specifications. The monthly Shanghai Stock Exchange (SSE) Composite Index is overlaid for comparison.



flows to exert persistent influence over a long horizon.

Importantly, this parameter choice does not drive the results. Our coefficient estimates and economic conclusions remain quantitatively and qualitatively similar under alternative decay parameters. The corresponding robustness results are reported in Table 10 and Table 13 in Internet Appendix A.

B. Suggestive Evidence

We begin by documenting how cash temperature relates to the characteristics of purchased stocks. We focus on the first purchase for each investor–stock pair. This initial trade is economically important: it accounts, on average, for more than 80% of the maximum position size over the life of the investor–stock pair (He and Hu (2022)). Importantly, focusing on the first purchase also limits the role of investor–stock–specific experiences—such as prior gains or losses, learning, or feedback effects—allowing us to more cleanly isolate how cash temperature shapes initial stock selection.

Figure 4 visualizes the relation between cash temperature and stock selection. We compute $\theta_{i,t}$ for each initial purchase (under A1 or A2) and sort purchases into ten equally sized bins on $[0, 1]$ based on $\theta_{i,t}$. Within each bin, we compute the mean and 95% confidence interval of nine market-adjusted characteristics of the purchased stocks, described in the notes to Figure 4.

We use realized daily return volatility over the past month as our main risk measure (rather than market beta) because investors hold under-diversified portfolios with a median of 2.50 stocks (Table 1b). We measure momentum as the realized return over the past month and short-term subsequent performance as the return over the next month; the one-month horizon aligns with the median holding horizon.[8] Long-term subsequent performance is measured as the return over the next year. To mitigate the influence of outliers, we winsorize all raw characteristics at the 1% and 99% percentiles.[9]

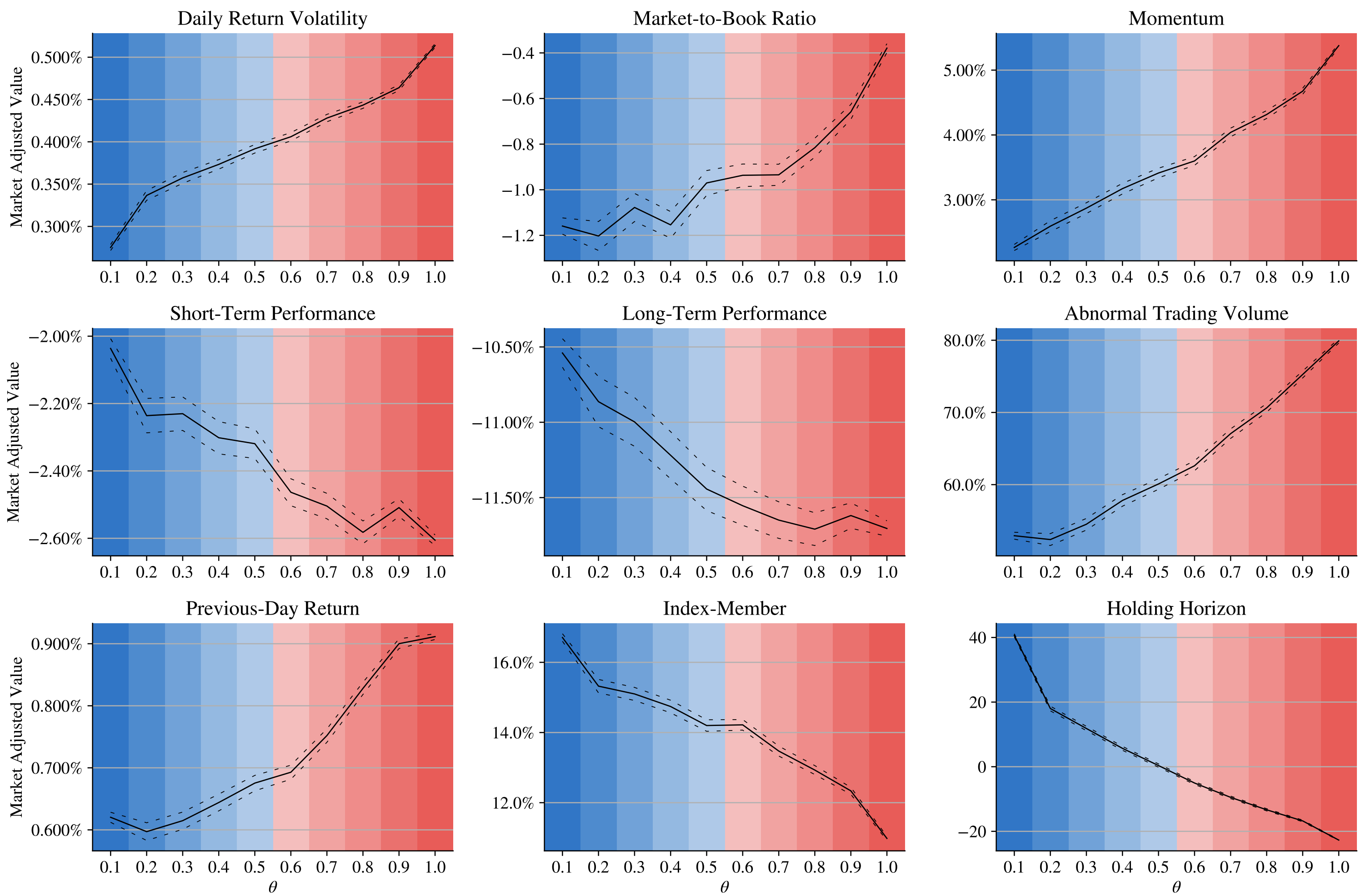
The pattern is monotonic and economically interpretable. Stocks purchased with colder cash tend to exhibit lower risk (lower realized volatility), lower valuation and weaker recent run-ups (lower market-to-book and momentum), higher subsequent returns (higher short- and long-horizon), and weaker attention proxies (lower abnormal volume and lower

[8]The results are robust to alternative horizons. See Table 11 in Internet Appendix A.

[9]The results are robust to percentile transformations of stock characteristics. See Table 12 in Internet Appendix A.

Figure 4: Cash Temperature and Stock Characteristics

For each initial purchase of stock j by investor i on day t, we construct cash temperature $\theta_{i,t}$ using Algorithm A1 with decay $\beta = 0.90$. We sort purchases into ten equal-sized bins on $[0, 1]$ based on $\theta_{i,t}$. Each panel plots the mean (solid line) and 95% confidence interval (band) of the market-adjusted value of a stock characteristic, where market adjustment subtracts the cross-sectional average across all listed stocks on the same day. All characteristics are winsorized at the 1% and 99% percentiles. The nine characteristics are: realized daily return volatility over the past month; market-to-book ratio; momentum (past-month return); subsequent one-month return; subsequent one-year return; abnormal trading volume following Barber and Odean (2008); previous-day return; an indicator for index membership (Shanghai Stock Exchange (SSE) Composite Index, Shenzhen Component Index, or China Securities 300 Index; and the number of days the stock remains in the investor's portfolio.



previous-day return). These stocks are also more likely to be index-members and are held for longer.[10]

Taken together, the nine panels point to a coherent interpretation: when using colder cash, investors behave more cautiously. Here, "cautiousness" is not a single primitive; it is reflected in a constellation of choices—greater aversion to risk, less willingness to chase recent winners or expensive stocks, better ex-post realized performance, lower reliance on attention-driven heuristics, stronger tilting toward mainstream (index) stocks, and longer holding horizons.

The binned evidence in Figure 4 removes common time variation through market adjustment, but it does not control for investor fixed effects or other covariates. We therefore estimate:

$$y_{i,j,t} = \alpha\, \theta_{i,t} + X'_{i,t}\gamma + \lambda_i + \lambda_t + \varepsilon_{i,j,t}, \tag{4}$$

where $y_{i,j,t}$ is one of the nine characteristics of stock j; $\theta_{i,t}$ is cash temperature under A1 or A2; λ_i and λ_t are account and day fixed effects. The control vector $X_{i,t}$ includes $\text{RealizedLoss}_{i,t}$, an indicator for whether investor i realizes losses on day t (to capture mental account rollover effect; Frydman et al. (2018)), and $\text{CmlPaperLoss}_{i,t-1}$, an indicator based on cumulative gains and losses through day $t-1$ (to capture house money and prospect-theory channels; Thaler and Johnson (1990) and Kahneman and Tversky (1979)). We also control for investor size using total cash available ($\text{TotalCash}_{i,t}$) and the lagged total value of stock holdings ($\text{TotalHolding}_{i,t-1}$).

[10] These patterns are robust under both A1 and A2. See Figure 16 in Internet Appendix A.

Table 3: Algorithm-Based Regression: Risk

This table reports ordinary least squares (OLS) estimates relating stock risk to cash temperature at the time of purchase. For investor i on day t, cash temperature $\theta_{i,t}$ is constructed using Algorithm A1 or Algorithm A2 with decay $\beta = 0.90$. RealizedLoss$_{i,t}$ equals one if investor i realizes a loss on day t, and CmlPaperLoss$_{i,t-1}$ equals one if investor i has accumulated net paper losses through day $t-1$. TotalCash$_{i,t}$ is total cash on day t, and TotalHolding$_{i,t-1}$ is the market value of stock holdings on day $t-1$. The dependent variable in columns 1–4 is realized daily return volatility over the past month (raw units), winsorized at the 1% and 99% percentiles; columns 5–8 use the within-day cross-sectional percentile of the same volatility measure. Columns 1–2 and 5–6 use $\theta_{i,t}$ from Algorithm A1, and columns 3–4 and 7–8 use Algorithm A2. All specifications include account and day fixed effects. The sample consists of 46,016 investors from January 1, 2006 to December 31, 2016. Standard errors are clustered at the account and day levels. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	Risk: Raw				Risk: Percentile			
	Algorithm A1		Algorithm A2		Algorithm A1		Algorithm A2	
$\theta_{i,t}$	0.123***	0.108***	0.115***	0.100***	3.591***	3.209***	3.356***	2.966***
	(45.81)	(40.27)	(54.18)	(38.51)	(59.43)	(42.71)	(46.47)	(40.96)
RealizedLoss$_{i,t}$		0.031***		0.032***		0.799***		0.833***
		(22.47)		(23.29)		(21.03)		(21.96)
CmlPaperLoss$_{i,t-1}$		−0.004**		−0.004**		−0.096*		−0.098*
		(−2.32)		(−2.36)		(−1.91)		(−1.95)
TotalCash$_{i,t}$		0.000		0.000		0.000		0.000
		(0.56)		(0.55)		(0.69)		(0.68)
TotalHolding$_{i,t-1}$		−0.000		−0.000		0.000		0.000
		(−0.40)		(−0.24)		(0.04)		(0.18)
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.5511	0.5516	0.5510	0.5516	0.1392	0.1397	0.1391	0.1396
Obs.	6,339,852	6,298,503	6,340,338	6,298,595	6,339,852	6,298,503	6,340,338	6,298,595

Table 4: Algorithm-Based Regression: More Dimensions

This table reports estimates from ordinary least squares (OLS) regressions of eight stock characteristics on cash temperature $\theta_{i,t}$ and control variables at the time of purchase. For investor i on day t, $\theta_{i,t}$ is constructed using Algorithm A1 with a decay parameter $\beta = 0.90$. The set of control variables is identical to that in Table 3, except that industry fixed effects are additionally included in the market-to-book regression reported in column 1. The dependent variables in columns 1–8 are the market-to-book ratio; momentum, measured as the realized return over the past month; short-term performance, defined as the return over the subsequent month; long-term performance, defined as the return over the subsequent year; abnormal trading volume following Barber and Odean (2008); previous-day return; an indicator for whether the stock is a constituent of the SSE Composite Index, the Shenzhen Component Index, or the CSI 300 Index; and the number of days the stock remains in the investor's portfolio, respectively. All dependent variables are measured in raw units and winsorized at the 1% and 99% percentiles. All specifications include account and day fixed effects. The sample consists of 46,016 investors from January 1, 2006, to December 31, 2016. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	Price		Performance		Attention		Others	
	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
$\theta_{i,t}$	18.788***	1.851***	−0.423***	−0.829***	16.636***	0.213***	−2.279***	−20.318***
	(20.43)	(42.32)	(−15.22)	(−10.02)	(36.20)	(23.12)	(−21.29)	(−41.61)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2457	0.3838	0.4961	0.5674	0.2883	0.3082	0.1127	0.2072
Obs.	6,297,871	6,298,503	6,397,196	6,378,832	5,871,906	6,371,243	6,398,907	6,399,768

We begin with the risk measure. Table 3 reports estimates under both algorithms. The left four columns use raw volatility, while the right four columns use its percentile transformation. Across specifications, the estimate of α is positive and statistically significant: hotter cash predicts selection of riskier stocks. In magnitude, moving from $\theta_{i,t} = 0$ (fully cold) to $\theta_{i,t} = 1$ (fully hot) shifts the selected stock by roughly 3 percentiles in the cross-section of listed stocks.

For the remaining eight characteristics, Table 4 reports estimates that mirror the graphical patterns: α is positive (negative) for characteristics that are negatively (positively) associated with cautiousness. The effect remains economically sizable across these additional characteristics. For example, moving from fully cold to fully hot cash raises purchased-stock momentum by about 3.4 cross-sectional percentiles and increases the abnormal trading volume by 3.4 percentiles (Table 12). Together, these results show that the cash-temperature effect persists after absorbing time-invariant investor heterogeneity and controlling for observable covariates.

C. Alternative Explanations and Robustness: A Horse-Race Analysis

A natural concern is that $\theta_{i,t}$ may be correlated with other forces that also shape stock choice, so the patterns documented above need not reflect an independent cash-composition effect. Table 5 addresses the most plausible confounds by introducing targeted controls, interactions, and sample restrictions.

Recent gains (house money). Temperature mechanically covaries with recent gains: hot cash often arrives after selling appreciated positions, and classic "house money" mechanisms predict higher risk taking after gains. If temperature were merely proxying for gain-driven risk seeking, conditioning flexibly on realized and paper gains and losses—and allowing the slope on temperature to differ on realized-gain days—should largely absorb the temperature coefficient. We therefore add a rich set of gain/loss proxies over multiple past horizons (day, week, and month) and include the interaction $\theta_{i,t} \times \text{RealizedGain}_{i,t}$.[11] Empirically, the baseline temperature coefficient in column 1 remains economically meaningful, while the incremental gain-day interaction is modest. This suggests that temperature is not simply standing in for the classic "playing with gains" channel.

A further distinction is dynamic: a pure gain-based label is inherently static and does not naturally incorporate *decay*, whereas temperature is allowed to fade absent refreshing. To examine this dynamic implication, the next specification in column 2 allows the cash-temperature effect to vary with elapsed inactive time by interacting $\theta_{i,t}$ with the number of *no-activity days* since the most recent hot inflow. Here, no-activity days are defined as the days following the last hot cash injection during which the account experiences neither trades nor transfers. This interaction captures whether the effect of hot cash attenuates with the passage of calendar time even in the absence of intervening account activity that could otherwise refresh or weaken the influence of cash composition. The estimates show that it does: the impact of hot cash declines as inactive time since inflow increases, consistent with decay in cash-source composition rather than attenuation driven by ongoing account activity.

Rebalancing and rollover. Temperature is mechanically linked to selling and

[11] We do not separately include $\text{RealizedGain}_{i,t}$ in these specifications because gain and loss indicators generate near-redundant partitions of the same states; the interaction term isolates whether the temperature slope changes on realized-gain days.

Table 5: Horse-Race: Realized Volatility

This table reports coefficient estimates from regressions of the realized volatility of the purchased stock on cash temperature $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.90$. Column 1, *Realized Gains*, augments the baseline controls with investors' paper and realized gains and losses over the past week and month and includes the interaction term $\theta_{i,t} \times \text{RealizedGain}_{i,t}$, where $\text{RealizedGain}_{i,t}$ equals one if the investor realizes a gain (i.e., has house money) on day t. Column 2, *Decay*, adds the interaction term $\theta_{i,t} \times \text{NoActivityDays}_{i,t}$, where $\text{NoActivityDays}_{i,t}$ denotes the number of days without any trading or cash-transfer activity since the most recent arrival of hot cash. Column 3, *No Reinvest*, adds the realized volatility of the most recently sold stock to the baseline controls and restricts the sample to purchases not financed by same-day stock sales. Column 4, *No Similar*, further restricts the *No Reinvest* sample by excluding purchases of stocks that are similar to the most recently sold stock, defined as belonging to the same industry or having realized volatility within ten percentiles of each other in the market-wide cross-section. Column 5, *Recent Trade*, adds investors' trading activity in the past week (number of trades, total buy amount, and total sell amount) to the baseline controls. Column 6, *Interacted FE*, uses the same controls as column 5 but replaces account fixed effects with account-by-month fixed effects to account for time-varying investor trading habits. Column 7, *Pre-Open*, redefines the cash temperature measure $\theta_{i,t}$ by using only cash available immediately before the market opens each day. Column 8, *Pure Cold/Hot*, restricts the sample to observations in which either newly injected cold cash on a given day is at least 90% of total cash or newly received hot cash is at least 90%. Unless otherwise noted, all specifications include the baseline controls (cumulative paper loss, realized loss indicator, total available cash, and the previous day's portfolio value) as well as account and day fixed effects. Standard errors are clustered at the account and day levels, except for column 6, which clusters at the account-by-month and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	House Money		Rebalancing		Investor Style		Cash Source	
	Realized Gains	Decay	No Reinvest	No Similar	Recent Trade	Interacted FE	Pre-Open	Pure Cold/Hot
$\theta_{i,t}$	0.105***	0.105***	0.108***	0.053***	0.106***	0.017***	0.109***	0.078***
	(34.09)	(38.64)	(33.35)	(17.47)	(40.46)	(7.49)	(36.27)	(23.22)
$\theta_{i,t} \times \text{RealizedGain}_{i,t}$	0.002							
	(0.81)							
$\theta_{i,t} \times \text{NoActivityDays}_{i,t}$		−0.002***						
		(−5.21)						
Controls	Past G&Ls	Baseline	Prev. Char.	Baseline	Intensity	Intensity	Baseline	Baseline
Account FE	Y	Y	Y	Y	Y		Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Account×Month FE						Y		
Adj. R^2	0.5517	0.5520	0.5834	0.5698	0.5517	0.5927	0.5519	0.5237
Obs.	6,298,535	6,270,125	2,386,886	1,587,947	6,298,535	5,897,961	6,273,491	2,140,944

re-buying if investors routinely finance purchases with contemporaneous sales proceeds. We address this possibility in two steps. The *No Reinvest* specification in column 3 restricts the sample to purchases not financed by a same-day stock sale and controls for the realized volatility of the most recently sold stock as a proxy for the risk exposure being unwound. The *No Similar* specification in column 4 further excludes purchases that closely resemble the most recently sold stock, where similarity is defined as the same industry and realized volatility within ten market-wide percentiles. These restrictions are designed to rule out common rebalancing practices and mental account rollovers. The temperature coefficient remains positive and statistically significant, indicating that the relation between $\theta_{i,t}$ and risk taking is not an artifact of short-horizon rebalancing.

Time-varying investor "style." Even with account fixed effects, one might worry that an investor could enter a temporary risk-on regime—trading more aggressively and thereby both heating up cash (through more frequent buy–sell cycles) and buying riskier stocks. We address this by controlling directly for recent trading activity (number of trades and total buy/sell amounts over the past week) in column 5 and, more stringently, adding account-by-month fixed effects in column 6. This specification absorbs any slow-moving investor-level shifts in "style." The temperature effect remains robust.

Measurement and intra-day ordering. Because we do not observe the precise intra-day sequence of inflows and outflows, temperature may be measured with error at the moment a purchase is made. We therefore implement two conservative strategies. First, we construct a pre-open temperature measure using only cash composition as of the market open, deliberately ignoring within-day inflows that arrive after trading begins. Second, we restrict to the "pure cold/hot" subsample where the account's cash is overwhelmingly cold or overwhelmingly hot, so that classification is least sensitive to within-day sequencing and bookkeeping conventions. The corresponding temperature coefficient in columns 7–8 remains robust under both strategies, suggesting that unobserved intra-day ordering is not driving the results.

Analogous horse-race analyses for $\theta_{i,t}$ under alternative decay specifications and across additional outcome dimensions are reported in Internet Appendix Tables 13, 14, 16, 17, and 18. Taken together, these results show that the temperature effect is not subsumed by gain/loss states, is not driven by rebalancing activity or time-varying investor types, and is robust to conservative alternative cash temperature definitions.

D. Discussion

The graphical patterns in Figure 4 and the baseline estimates in Tables 3 and 4 support the cash-temperature effect. Nonetheless, three identification concerns motivate a design that relies less on constructed temperature and on behavioral bookkeeping assumptions.

First, reverse causality is possible: when an investor plans to buy an "exciting" stock (riskier, with stronger recent performance, or more attention-grabbing), she may raise funds by selling existing holdings rather than waiting for a cold inflow. In that case, cash sources would be endogenously shaped by the target asset.

Second, time-varying unobserved investor states—such as attention, liquidity needs, or short-run constraints—could affect both funding flows and stock selection.

Third, temperature construction relies on a bookkeeping rule. While A1 and A2 are economically sensible ways to track cash composition, some transfers that appear “cold” in transaction records may not be perceived as cold by investors (e.g., pass-through transfers across multiple accounts).

The horse-race analysis in Table 5 mitigates some of these concerns, but a clean identification strategy should (i) break the link between cash flows and target assets, (ii) mitigate unobserved investor-day states, and (iii) minimize reliance on bookkeeping assumptions. We next exploit an institutional reform that delivers such variation.

IV. Algorithm-Free Identification

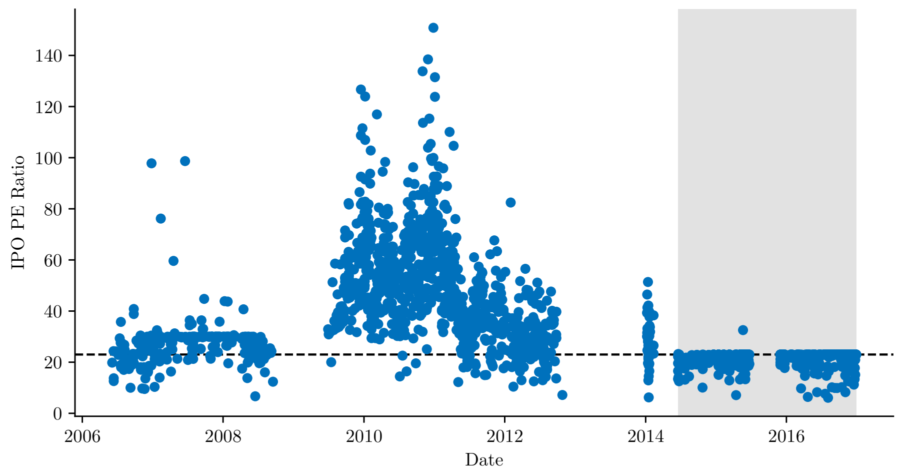
This section exploits a quasi-natural experiment in China’s IPO lottery system. We first describe the institutional background and the 2016 reform that generates exogenous variation in the origin of investable brokerage cash on IPO-result announcement days. We then articulate identifying assumptions and a testable prediction implied by the temperature framework. Finally, we present reduced-form Difference-in-Differences estimates and complementary instrumental-variable evidence that links the reform-induced variation to the algorithm-based temperature measure.

A. Institutional Details

Chinese financial markets have undergone several reforms over the past three decades, providing rich institutional variation. We focus on reforms to the Chinese IPO system. Qian, Ritter, and Shao (2022) reviews Chinese IPO reforms and facts, and He and Wei (2022) reviews recent papers on the broader Chinese financial system and economy. On the firm

Figure 5: IPO Underpricing with the Price-to-Earnings (PE) Cap

The figure plots the IPO Price-to-Earnings (PE) ratio of 1,732 firms between January 1, 2006, and December 31, 2016, in the Chinese stock market. The horizontal dashed line marks the regulatory cap of 23 announced on January 12, 2014. The shaded band marks the identification period (June 17, 2014 to December 31, 2016) in which the cap was strictly enforced.



side, there are three major phases. In phase one (1992–2000), a quota allocation system assigned the total face value allowed for going public to a limited number of firms. In phase two (2001–2018), an approval system was adopted: underwriters submitted IPO applications and the Chinese Securities Regulatory Commission (CSRC) approved a subset, often after long delays (Piotroski and Zhang (2014), Cong and Howell (2021), and Lee, Qu, and Shen (2021)). Within phase two, a key reform occurred on January 12, 2014, when the CSRC imposed an upper bound of 23 on the PE ratio for IPO pricing (Figure 5).[12] In phase three (2019–present), a registration system resembling those in developed markets has been progressively adopted to reduce regulatory intervention in IPO pricing and timing.

On the investor side, the most relevant reform took place on January 1, 2016. Under the pre-reform regime, eligible investors were required to submit a cash deposit to an IPO

[12]The only exception in the shaded period in Figure 5 was 603026.SH, which was approved to have an IPO PE ratio of 32.25 to ensure that its IPO price was not lower than book value per share.

cash pool on the application day to participate in an IPO lottery.[13] Deposits were frozen for two trading days. After the result announcement, the deposit net of any payment for allocated shares was refunded (Li, Pearson, and Zhang (2021)). Under the post-reform regime, no deposit is required prior to the result announcement, so there is no corresponding refund. Figure 6 summarizes the two regimes.

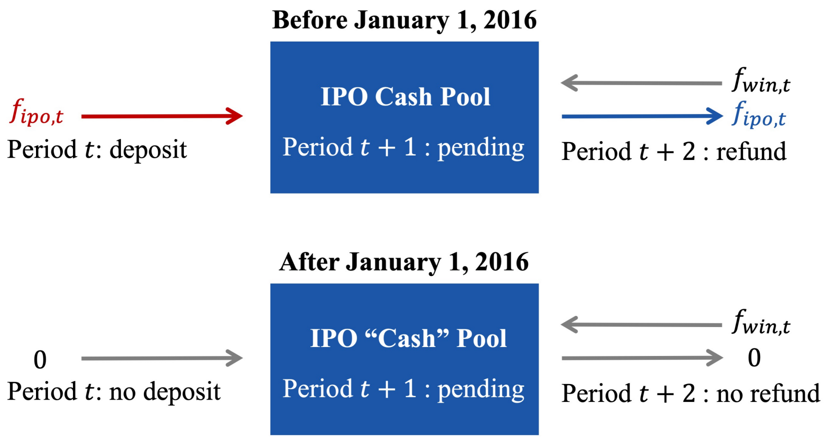
Under both regimes, eligibility is determined mechanically from pre-existing holdings. If investor i wants to participate on day t, the system computes the average value of her end-of-day stock holdings across Shanghai (SH) and Shenzhen (SZ) exchanges between $t-22$ and $t-2$: $\overline{v}_{i,t} = \overline{v}^{\text{SH}}_{i,t} + \overline{v}^{\text{SZ}}_{i,t}$. Participation requires $\overline{v}_{i,t} \geq 10{,}000$ CNY. The number of lottery tickets is proportional to holdings and differs across exchanges: for SH IPOs, each ticket corresponds to 1,000 shares and each 10,000 CNY of $\overline{v}^{\text{SH}}_{i,t}$ grants one ticket; for SZ IPOs, each ticket corresponds to 500 shares and each 5,000 CNY of $\overline{v}^{\text{SZ}}_{i,t}$ grants one ticket. Eligibility is additive across multiple IPOs on the same day. Lottery outcomes are recorded at the ticket level.

As a numerical example, suppose an investor holds $\overline{v}^{\text{SH}}_{i,t} = 29{,}000$ CNY and $\overline{v}^{\text{SZ}}_{i,t} = 8{,}500$ CNY on average between $t-22$ and $t-2$. On day t, two SH IPOs (firms A and B) and one SZ IPO (firm C) are open for application with IPO prices $p^{\text{SH}}_{t,A} = 2$, $p^{\text{SH}}_{t,B} = 1$, and $p^{\text{SZ}}_{t,C} = 3$. The investor can apply for 2,000 shares of each SH IPO and 500 shares of the SZ IPO. The maximum application value is therefore
$p^{\text{SH}}_{t,A} \times 2{,}000 + p^{\text{SH}}_{t,B} \times 2{,}000 + p^{\text{SZ}}_{t,C} \times 500 = 7{,}500$ CNY. Suppose she applies for the maximum and wins one SH ticket of firm B only. Under the old regime, she submits 7,500 CNY on day

[13] As indicated by Table 6, IPO events were extremely popular, and submitted deposits far exceeded what issuing firms ultimately needed. A lottery therefore determined allocations.

Figure 6: IPO Lottery Procedures Before and After the 2016 Reform

The upper panel depicts the pre-reform regime. A participant submits a deposit $f_{ipo,t}$ on the application day t; the deposit is frozen during a two-day pending period; and the deposit net of any payment for allocated shares ($f_{win,t}$) is refunded on the result announcement day. The lower panel depicts the post-reform regime: deposits and refunds are both zero. The participant submits only an application on day t and pays $f_{win,t}$ if shares are won.



t and receives a refund of 6,500 CNY on day $t+2$. Under the new regime, she submits no cash on day t; on day $t+2$, she pays 1,000 CNY for the shares won.

We focus on the period between June 17, 2014, and December 31, 2016, for two reasons. First, the investor-side reform occurred during this window, generating policy-driven variation. Second, the IPO PE ratio cap was strictly enforced (Figure 5), generating systematic underpricing. As a result, participating in IPO lotteries was highly attractive, supporting the identifying assumptions in Section IV.B.

Figure 7 illustrates the degree of underpricing. It is noteworthy that 100% of IPO stocks in this period hit the daily upper return limits of 44% and 10% on the first and second trading days, respectively, and almost all continued hitting the 10% limit for the next several days.[14] Winning an IPO lottery was therefore widely perceived as a near-sure gain realized within days.

[14]The fractions of stocks hitting the upper limit on days 3 to 5 are 99.8%, 98.9%, and 96.7%, respectively.

Table 6: IPO Summary Statistics in China

This table presents summary statistics for 539 IPO stocks between June 17, 2014, and December 31, 2016, in the Chinese stock market. In both panels, column 1 reports the total number of accounts (in thousands) participating in the IPO lottery; column 2 reports the ratio of the total application amount submitted by all market participants divided by the actual amount issued by the IPO firm; column 3 reports the winning odds (in percent), defined as one over the overbuy multiple in column 2; column 4 reports the number of consecutive days the IPO stock hits the upper limit starting from the first trading day; and column 5 reports the number of IPO stocks in each month. Panel A reports the summary statistics under the old regime (June 17, 2014, to December 31, 2015). Panel B reports the summary statistics under the new regime (January 1, 2016, to December 31, 2016).

Panel A: Old Regime

	App. Account	Overbuy	Winning Odds	Up Limit Days	IPOs Per Month
Mean	1,204.39	248.12	0.53	10.65	15.63
S.D.	729.87	134.78	0.30	5.43	14.82
Min	381.62	55.64	0.12	1.00	0.00
25%	717.62	151.45	0.32	6.00	1.50
Median	984.18	216.00	0.46	10.00	11.00
75%	1,488.11	317.00	0.66	14.00	24.00
Max	7,301.31	808.78	1.80	29.00	48.00
Obs.	297	297	297	297	19.00

Panel B: New Regime

	App. Account	Overbuy	Winning Odds	Up Limit Days	IPOs Per Month
Mean	11,234.08	3,318.66	0.05	12.69	20.17
S.D.	2,122.57	1,772.70	0.05	4.84	13.10
Min	6,698.16	213.99	0.01	2.00	4.00
25%	9,612.50	2,168.65	0.02	9.00	13.75
Median	11,365.64	2,963.95	0.03	12.50	15.00
75%	12,876.49	4,173.97	0.05	16.00	26.50
Max	15,262.79	8,568.76	0.47	29.00	49.00
Obs.	242	242	242	242	12

Figure 7: Returns of IPO Stocks After Listing

The figure plots the distribution of daily returns of IPO stocks in their first nine trading days. The sample includes 539 IPO stocks between June 17, 2014, and December 31, 2016. Daily returns are capped at 44% (-44%) on the first trading day and 10% (-10%) thereafter. The limiting values at -10%, 10%, and 44% are labeled on the x-axis.

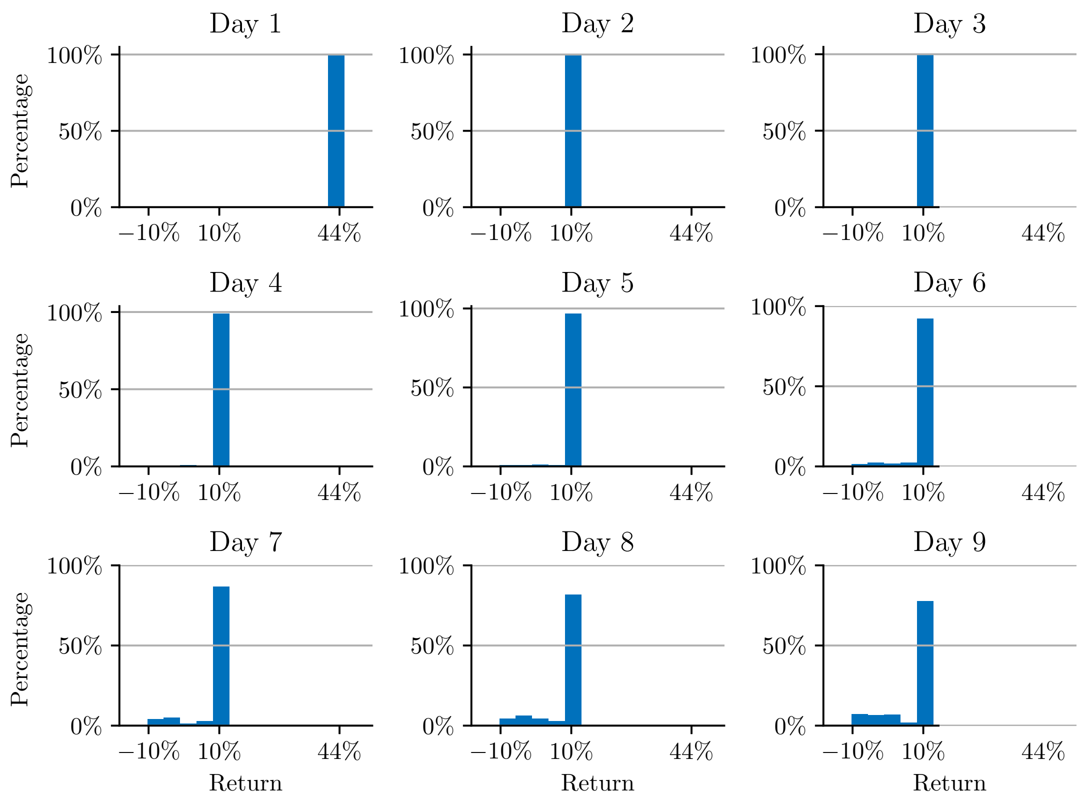


Table 6 provides additional context. Total application value was 248 times the actual needed value on average under the old regime and 3,319 times under the new regime. Under both regimes, IPO stocks hit the upper limit for over ten consecutive trading days on average. There were about 15 to 20 IPO stocks per month in this period, indicating that IPO events were frequent rather than exceptional.

B. Identifying Assumptions and Hypothesis

The institutional setting implies two identifying assumptions. The first delivers a testable prediction under the temperature framework. The second clarifies why the variation we exploit is plausibly orthogonal to contemporaneous stock-choice shocks.

Assumption I1. *Refunded IPO cash under the old regime is cold cash.*

This assumption maps directly into the temperature framework in Section II. Submitting cash for IPO participation under the old regime is a deliberate reallocation of brokerage cash into a segregated IPO cash pool. The pool is administratively frozen for a fixed two-day window and, except for any payment for allocated shares, the deposit is refunded mechanically. In the language of the framework, cash placed into a stable container inherits the container's temperature (Assumption T2). The key institutional feature is the high predictability of both the holding period and the redemption of principal.

A natural question is whether IPO participation resembles purchasing a lottery ticket and therefore "heats up" the cash. Although intuitive, the analogy does not fully apply in this setting. Buying a lottery ticket entails a high probability of permanently losing the ticket price. By contrast, under the old Chinese IPO regime, applicants almost surely received their deposit back because winning odds were low, and principal was not exposed to price risk while frozen. For winners, only a small share of the deposit was converted into IPO shares; during our sample period, underpricing induced by the PE cap and binding daily price limits made short-horizon IPO gains highly predictable (Figure 7). Investors participated routinely and understood the process as temporarily parking cash in an authority-guarded escrow-like account in exchange for a small chance of obtaining a near-sure gain. These features make the IPO cash pool a plausible cold container and the subsequent refund a plausible cold-cash shock. We do not observe investors' perceptions of refunded IPO cash directly, however, so Assumption I1 should be understood as a maintained assumption grounded in the institutional features of the setting.

Assumption I2. *The extent of IPO-lottery participation is not driven by an investor's stock choices on the IPO-result announcement day or by shocks to unobserved investor characteristics that affect those stock choices.*

For identification, it suffices that transitory shocks to unobserved investor characteristics around IPO events are not systematically related to both ex-ante participation and ex-post stock choices, conditional on controls. The exceptional attractiveness and routine nature of IPO events imply that, under the old regime, deposit submission is primarily motivated by participation in the IPO lottery rather than by plans to buy particular secondary market stocks on the announcement day, mitigating reverse-causality concerns. Moreover, participation is governed by eligibility and take-up. In the numerical example above, eligibility is the maximum amount the investor can apply for (7,500 CNY). Under the old regime, take-up is directly observed, which may vary because participation ties up liquidity for two days. Under the new regime, participation is essentially costless, so full take-up by eligible investors is a natural benchmark: no cash is tied up ex ante, participation rises sharply (Table 6), and winners can forgo allocation without penalty. Any occasional non-participation by eligible investors under the new regime would therefore overstate virtual refunds and understate the magnitudes of β_1 and β_2 in equation (5), implying that our estimates are conservative.

These assumptions lead to a testable prediction.

Hypothesis. *Holding fixed the fraction of (actual or virtual) IPO refund in total available cash, investors under the old regime—relative to themselves under the new regime—select stocks more cautiously on IPO-result announcement days.*

The hypothesis compares the two regimes at a common "refund intensity." Consider scenario A under the old regime: an investor has 10,000 CNY available on the result day, of which 7,500 CNY arrives as an actual refund. Consider scenario B under the new regime: a comparable investor has the same 10,000 CNY available and learns that her 7,500 CNY application was unsuccessful, generating a "virtual" refund share of 75%. The difference is that in scenario A the funds passed through the IPO cash pool and therefore underwent a cooling treatment, whereas in scenario B they did not. Systematic differences in stock choices between the two scenarios at each refund-share level therefore trace back to the cooling treatment.

To test the hypothesis, we estimate the following Difference-in-Differences (DiD) regression:

$$y_{i,j,t} = \beta_1 \, \text{Refund}_{i,t} \times \text{Regime}_t + \beta_2 \, \text{Refund}_{i,t} + controls_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,j,t}, \tag{5}$$

where $y_{i,j,t}$ is a characteristic of stock j purchased by investor i on an IPO-result announcement day t; $\text{Refund}_{i,t}$ is the IPO refund amount scaled by total available cash; Regime_t equals one under the old regime; and $controls_{i,t}$ includes an IPO-winning indicator and the fractions of other cash sources ($\text{TransferIn}_{i,t}$, $\text{OtherSell}_{i,t}$, $\text{Div}_{i,t}$, and $B^{\text{end}}_{i,t-1}$), as well as the same set of controls used in regression in equation (4). Account fixed effects (λ_i) and day fixed effects (λ_t) are included; Regime_t is omitted due to collinearity with day fixed effects.

IPO shares obtained in a lottery are not tradable until one to two weeks after the result announcement. Accordingly, stock j in equation (5) is a stock purchased in the secondary market, not the IPO stock.

The key parameter is β_1, which captures the incremental effect of an actual (cooled) refund under the old regime relative to a virtual (uncooled) refund under the new regime at the same refund-share level. The hypothesis implies $\beta_1 < 0$ ($\beta_1 > 0$) for characteristics that are negatively (positively) related to cautiousness.

C. Results and Discussion

In our dataset, we observe IPO deposits and refunds directly under the old regime. Under the new regime, by design, there is no corresponding cash flow. To construct $\text{Refund}_{i,t}$ on post-reform days, we assume that eligible investors participate to the full extent under the new regime. Specifically, we use the holdings-implied maximum eligible amount as the (unobserved) application amount for each investor–IPO pair and combine it with lottery winning records, inferred from subsequent holdings, to compute a "virtual" IPO refund.

We restrict attention to secondary market stock purchases on IPO-result announcement days so that the refund shock is not confounded by delays. To mitigate concerns about multiple accounts, we drop accounts with any over-application record—cases in which observed IPO deposits under the old regime, or win amounts under either regime, exceed the holdings-implied maximum application amount. Under the new regime, we truncate the virtual refund share to lie in $[0, 1]$ to ensure comparability.[15] The final sample consists of 227,018 purchase observations from 9,241 investors across 238 IPO-result announcement days.

Table 7 reports DiD estimates for the same nine stock characteristics examined in the algorithm-based analysis. Receiving an actual (cooled) IPO refund under the old regime leads investors to buy stocks that are safer (column 1), exhibit lower valuation and weaker recent run-ups (columns 2–3), have better long-run subsequent performance (column 5), are less attention-grabbing (columns 6–7), are more likely to be index-members (column 8), and are held longer (column 9).

Overall, the DiD results indicate that investors deploy colder cash more cautiously than hotter cash, consistent with a causal cash-temperature effect. In economic terms, consider an investor for whom the refund accounts for all available cash on the purchase day (i.e., a refund share of 100%). Relative to a virtual refund of the same share under the new regime, an actual cooled refund under the old regime shifts the characteristics of purchased stocks by roughly 2.3 cross-sectional percentiles in realized volatility and 2.8 percentiles in momentum (Table 20), with similarly meaningful effects on future performance and

[15]About 80% of observations have the virtual refund share within $[0, 1]$ under the new regime without adjustment; these observations form the main analysis sample. For robustness, we also use all observations, winsorize the measure at 1, and require total available cash to be at least 5,000 CNY; the results remain robust.

Table 7: Difference-in-Differences

This table reports the estimates from a DiD design that relies on the quasi-natural experiment of the IPO lottery reform on January 1, 2016. Variable $\text{Refund}_{i,t}$ is the IPO refund amount standardized by the total cash available for investor i on day t; Regime_t is an indicator that equals 1 if the IPO lottery result announced on day t is under the old regime, and equals 0 if it is under the new regime; the control variables include an indicator for IPO winning and fraction of other four cash sources, i.e., $\text{TransferIn}_{i,t}$, $\text{OtherSell}_{i,t}$, $\text{Div}_{i,t}$, and $B^{\text{end}}_{i,t-1}$, in addition to the same set of control variables used in regression (4). For the market-to-book ratio regression in column 2, the industry dummies are added to controls. The dependent variable in column 1 is the realized daily return volatility in the past month measured in raw units and winsorized at the 1% and 99% percentiles; the dependent variables in columns 2–9 are the same as in columns 1–8 of Table 4, respectively. Account and day fixed effects are added to all specifications. The sample of 9,241 investors on 238 IPO announcement days between June 17, 2014, and December 31, 2016, is used. Standard errors are clustered on account and day. Robust t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8	9
	Risk	Price		Performance		Attention		Others	
	Realized Vlt.	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
$\text{Refund}_{i,t} \times \text{Regime}_t$	−0.076***	−26.798**	−1.544***	0.217	2.405**	−11.226***	−0.264***	3.259***	10.259***
	(−2.64)	(−2.26)	(−3.18)	(0.88)	(2.46)	(−2.69)	(−3.26)	(2.98)	(4.60)
$\text{Refund}_{i,t}$	0.080***	16.439*	0.830***	−0.151	−2.184***	9.299***	0.141***	−1.759**	−3.898***
	(3.99)	(1.86)	(2.95)	(−0.85)	(−2.97)	(3.51)	(2.67)	(−2.42)	(−4.98)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.4491	0.2648	0.2509	0.5340	0.4723	0.3406	0.2899	0.1170	0.2772
Obs.	224,628	224,559	224,628	226,982	226,374	211,969	226,965	227,018	227,018

attention-grabbing characteristics.

The estimates are robust to alternative specifications, including different horizons in characteristic construction and nonlinear transformations of dependent variables.[16]

Instrumental-variable evidence. A remaining concern is that the algorithm-based temperature measure $\theta_{i,t}$ may be endogenous at the investor-day level. The IPO reform provides a clean source of exogenous variation in temperature: holding fixed the refund share $\text{Refund}_{i,t}$, only under the old regime does the refund pass through the frozen IPO cash pool and undergo the cooling treatment. We therefore instrument $\theta_{i,t}$ with $\text{Refund}_{i,t} \times \text{Regime}_t$ and estimate a 2SLS version of the baseline regressions.

Table 8 reports the 2SLS estimates. Panel A shows a strong first stage: the excluded instrument $\text{Refund}_{i,t} \times \text{Regime}_t$ is highly significant, and the Kleibergen–Paap rk Wald F statistic is 28,434, indicating that weak-instrument concerns are immaterial. The negative first-stage coefficient implies that, for a given refund share, cash is materially colder under the old regime than under the new regime, consistent with the cooling channel implied by Assumption I1.

Panel B shows that second-stage estimates line up with the temperature framework. Hotter cash (a higher instrumented $\theta_{i,t}$) leads investors to buy stocks with higher realized volatility (column 1), higher valuation and stronger momentum (columns 2–3), worse long-run subsequent performance (column 5), and more attention-grabbing characteristics (columns 6–7). Hotter cash is also associated with a lower propensity to buy index-member stocks and shorter holding horizons (columns 8–9). Short-term subsequent performance is not statistically distinguishable from zero in this design (column 4). Overall, the IV results

[16]See Table 19 and Table 20 in Internet Appendix A.

Table 8: Instrumental-Variable Evidence (2SLS)

This table reports instrumental-variable (2SLS) estimates that instrument the cash-temperature measure $\theta_{i,t}$ with the interaction between the IPO refund fraction and the old-regime indicator, $\text{Refund}_{i,t} \times \text{Regime}_t$. Panel A reports the first-stage results, where the dependent variable is the cash-temperature measure $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.90$. The specification includes $\text{Refund}_{i,t}$, the full set of controls—cumulative paper loss, realized loss indicator, total available cash, the previous day's portfolio value, the IPO-winning indicator, and the fractions of other cash sources—as well as account and day fixed effects. Industry fixed effects are added for the market-to-book regression. Standard errors are clustered at the account and day levels, and robust t-statistics are reported in parentheses. For compactness, we report a single Kleibergen–Paap rk Wald F statistic computed using the largest available sample; the values are very similar across column-specific samples, with a minimum value of 27,198. Panel B reports the second-stage estimates of outcome variables on the instrumented cash-temperature measure. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: First Stage

	$\theta_{i,t}$
Excluded instrument: $\text{Refund}_{i,t} \times \text{Regime}_t$	-1.029^{***}
	(-168.62)
$\text{Refund}_{i,t}$	0.061^{***}
	(16.35)
Controls	Y
Account FE	Y
Day FE	Y
Observations	227,014
Kleibergen–Paap rk Wald F	28,434

Panel B: Second Stage

	1	2	3	4	5	6	7	8	9
	Risk	Price		Performance		Attention		Others	
	Realized Vlt.	M–B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
$\theta_{i,t}$ (IV)	0.074^{***}	26.055^{**}	1.500^{***}	-0.211	-2.337^{**}	10.893^{***}	0.256^{***}	-3.166^{***}	-9.967^{***}
	(2.64)	(2.26)	(3.16)	(-0.88)	(-2.46)	(2.69)	(3.24)	(-2.97)	(-4.63)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	224,624	224,555	224,624	226,978	226,370	211,965	226,961	227,014	227,014

complement the DiD evidence and provide a direct quasi-experimental link from the reform-induced cooling variation to the algorithm-based temperature measure.

Internet Appendix Table 21 reports two additional sample restrictions. Panel A restricts attention to refund-dominant observations—cases in which the refund share is either very small or very large—so that IPO refunds are either effectively irrelevant or close to the sole driver of available cash on that day. Panel B excludes observations consistent with immediate refund-management strategies, in which the refund is transferred out on the same day under the old regime, making it unlikely to be used for secondary market purchases. Across both panels, second-stage estimates remain qualitatively unchanged and economically comparable, and first-stage F statistics remain large.

V. An Experiment

This section presents a pre-registered online experiment that randomly assigns cash source and elicits risk taking. The objective is to isolate the underlying preference channel in a controlled environment rather than to reproduce all features of the field setting.

A. Experimental Design

The pre-registered online experiment was conducted on October 18, 2023.[17] We recruited 405 participants from Prolific who passed the attention check and submitted complete responses. Prolific is a platform that facilitates the recruitment of diverse survey and experiment participants and is widely used in finance and economics (Bergman, Chinco,

[17] The pre-registration document is available at https://aspredicted.org/G68_B1C.

Hartzmark, and Sussman (2020)). We imposed standard eligibility criteria (U.S. residence, English proficiency, and a 100% previous approval rate). The median duration of the experiment was 9 minutes.

At the beginning of the experiment, each participant was endowed with both a savings account and a brokerage account, each containing 100 Lira (a hypothetical currency convertible to USD at a 200:1 ratio). For the first nine periods, participants observed the evolution of these accounts without making decisions. The savings account accrued a risk-free return, while the brokerage account was invested in a volatile stock whose price fluctuated each period. A mandatory 5-second pause between periods encouraged attention to account changes.

The key decision occurred in period 10. Participants were informed that the money in both accounts was now available for use. The savings-account balance (109.37 Lira) and the brokerage-account balance (108.66 Lira) were fixed across subjects and intentionally close to rule out wealth effects. Participants were then randomly assigned to one of two treatments: a savings-account treatment, in which they used the savings-account balance to purchase a risky stock, and a brokerage-account treatment, in which they used the brokerage-account balance.

Two stocks, M and N, were available in period 10. Both had a price of 100 Lira per share and a binary next-period price outcome with equal probabilities. Specifically, the next-period price of stock M was $p_{M,L}$ or $p_{M,H}$ with probability 0.5 each; similarly, stock N's next-period price was $p_{N,L}$ or $p_{N,H}$ with probability 0.5 each. To probe mechanisms, we considered two payoff scenarios: a loss-likely scenario with $(90, 110, 50, 150)$ for $(p_{M,L}, p_{M,H}, p_{N,L}, p_{N,H})$, and a loss-unlikely scenario with $(140, 160, 100, 200)$. In both scenarios, stocks M and N have the same expected return but different risk. The experiment therefore has four groups—each combining one treatment with one scenario—and targeted a sample size of about 100 per group.

After participants made an unalterable stock selection in period 10 but before observing the realized outcome, we elicited three post-investment evaluations in randomized order. Participants rated, separately for each account, (i) risk tolerance, (ii) disutility from a hypothetical loss of 50 Lira, and (iii) utility from a hypothetical gain of 50 Lira, each on a 0–10 slider scale. See Internet Appendix C for detailed instructions and question wording.

This design has three advantages. First, it requires no active choice until the final period, which limits confounding influences from earlier decisions and isolates the temperature manipulation. Second, because both accounts start from and end with comparable endowments, wealth and house money effects are also mitigated. Third, contrasting loss-likely and loss-unlikely environments directly isolates whether the effect hinges on sensitivity to losses, which is central to our proposed mechanism. At the same time, the design is intentionally parsimonious. Participants make a single terminal choice, so the experiment is designed to isolate the preference channel rather than to directly test the refreshing and decay of cash labels over repeated account activity.

The naming of the two accounts is intentional. The instructions emphasized that the accounts are economically equivalent in payoff convertibility and that all funds belong to the participant. Any differential perceptions induced by account labels and observed dynamics are therefore central to the mechanism. In the language of our framework, these perceptions correspond to temperature assimilation (Assumption T2 in Section II). Differential behavior across treatments, despite clarifications of economic equivalence, therefore provides direct evidence of perceived non-fungibility.

Finally, while the field evidence spans multiple stock-characteristic dimensions, the experiment focuses primarily on risk. With a two-stock choice and a modest sample size, risk is the most direct and best-powered outcome.

B. Main Result

Figure 8 reports the fraction of participants choosing the riskier stock N across the four groups. Under the loss-likely scenario, the cash-temperature effect is economically sizable: participants assigned to use higher-temperature brokerage cash are more likely to select the riskier stock than those assigned to use savings cash, with the share choosing N rising from 39% to 53%—a 14-percentage-point increase (about 36% relative to the savings-cash baseline). By contrast, under the loss-unlikely scenario, this between-treatment difference is absent.

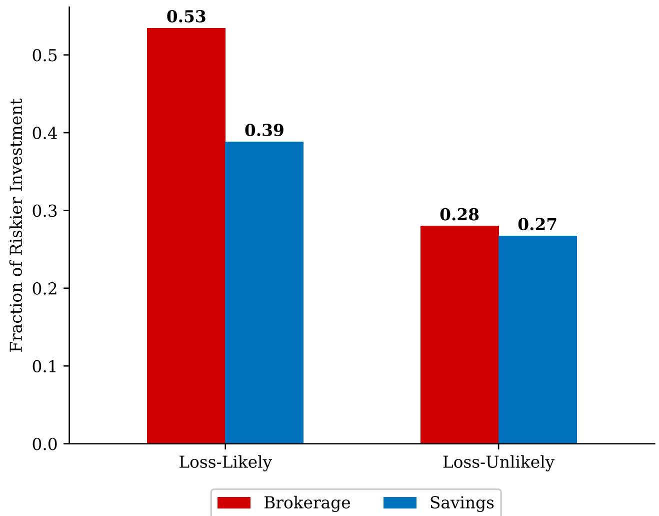
This pattern points naturally to loss aversion. A key implication of prospect theory (Kahneman and Tversky (1979)) is that losses generate disproportionately large disutility relative to gains of the same magnitude. The fact that the treatment effect appears only when losses are possible suggests that cash source operates primarily through sensitivity to losses rather than through a general shift in risk appetite. This mechanism guides the modeling approach in Section VI.

We also note that the overall share choosing the riskier stock is lower in the loss-unlikely scenario.[18] One plausible interpretation is that, in this scenario, stock M offers

[18] The fact that 53% of subjects choose the riskier stock with brokerage cash does not imply loss-loving preferences. A loss-averse subject may still choose N when stakes are small or when other forces (e.g., probability misperception) are present.

Figure 8: Selection of the Riskier Stock in the Experiment

The figure plots the proportion of subjects who choose the riskier stock in period 10. The left pair of bars corresponds to the loss-likely scenario and the right pair corresponds to the loss-unlikely scenario. Bars compare the brokerage-account treatment and the savings-account treatment (as indicated in the figure legend).



a salient sure gain of 40 Lira in its worst case, which may serve as a reference point. Relative to that benchmark, choosing N exposes the participant to the possibility of forgoing the sure gain, which may itself be perceived as a reference-point loss.

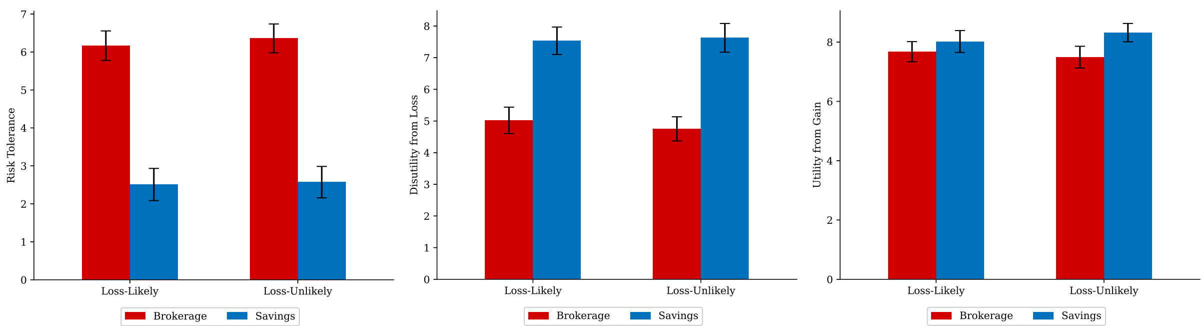
To probe perceptions directly, we elicit post-investment evaluations for each account after the stock selection but before outcome realization. For each question, subjects rate the brokerage and savings accounts separately on a 0–10 scale. Figure 9 reports average scores and 95% confidence intervals.

Three observations emerge. First, perceived risk tolerance is substantially higher for brokerage cash than for savings cash. Second, the difference is driven primarily by the loss dimension: participants report significantly lower disutility from losses in the brokerage account than in the savings account, whereas the differential response to gains is comparatively modest. Third, because the loss-likely and loss-unlikely scenarios differ only in

Figure 9: Post-investment Evaluations

The figure reports average responses to three post-investment questions, pooled across treatment groups. Panel (a) reports perceived risk tolerance (0: strongly prefer saving at a risk-free rate; 10: strongly prefer investing in risky assets even when large gains and losses are possible). Panel (b) reports disutility from a hypothetical loss of 50 Lira (0: not painful; 10: very painful). Panel (c) reports utility from a hypothetical gain of 50 Lira (0: not exciting; 10: very exciting). Within each panel, the left pair corresponds to the loss-likely scenario and the right pair corresponds to the loss-unlikely scenario. Bars compare evaluations of the brokerage and savings accounts (as indicated in the figure legend). Confidence intervals are 95%.

(a) Risk Tolerance (b) Disutility from Loss (c) Utility from Gain



the final-period stock-selection task, the similarity of the three post-investment responses across the two scenarios suggests that participants attended to the instructions and formed account-specific perceptions that are stable across payoff environments.

Taken together, the experimental evidence indicates that participants are more reluctant to take risk when funds are framed as coming from the savings account, and that this difference operates primarily through heightened sensitivity to losses. The experiment therefore helps isolate a plausible preference channel underlying the field patterns. Table 22 in Internet Appendix D reports additional results on investor heterogeneity in the experiment.

C. Discussion and External Validity

The experiment is intentionally parsimonious: it holds the budget set fixed and varies only the account frame, so that differences in choices and evaluations can be interpreted through the lens of loss sensitivity.

As a one-shot task, its strength is in isolating a mechanism rather than reproducing the full dynamic structure of the brokerage-account setting. In particular, the experiment does not directly test whether cash labels are refreshed by subsequent account activity or decay with the passage of inactive time. We view those dynamic predictions as coming primarily from the brokerage-account evidence, with the experiment providing complementary causal evidence that cash source affects risk taking and that loss sensitivity is a plausible underlying mechanism.

As in any mechanism-focused design, the experiment abstracts from several features of real-world trading and uses modest stakes. Taken together with the quasi-experimental IPO refund shock and the brokerage-account evidence, however, the three settings strengthen inference through triangulation.

A natural extension is to bring the manipulation closer to brokerage cash flows by varying the framing of investable funds within a single account (e.g., "sell proceeds" versus "fresh deposit") while holding payoffs and probabilities fixed.

VI. Model

The experimental results in Section V suggest that cash temperature operates through an attenuation in the marginal evaluation of gains and losses, with the disutility from losses particularly sensitive to the cold- versus hot-cash frame. We develop a model to formalize this mechanism and derive equilibrium implications.

The model embeds a temperature-dependent *sensitivity* to future gains and losses: hotter cash reduces how strongly investors react to realized gains and losses, holding beliefs fixed. This mapping is disciplined by the experimental evidence, which holds payoff magnitudes and probabilities fixed while shifting perceived cash type across accounts. Other mappings are possible—for example, temperature could affect probability weighting or perceived risk/ambiguity—but we focus on sensitivity because it aligns most directly with the observed pattern that the same hypothetical loss is perceived as more painful under cold cash.

The model delivers three central implications that mirror our empirical findings: higher temperature increases risk taking, raises prices, and lowers expected returns. It also generates broader predictions, including the coexistence of limited market participation and overbuying, overreaction to shocks, and price fluctuations not driven by fundamentals.

Sections VI.A–VI.C present a myopic version of the model to highlight the key mechanism and its predictions. Section VI.D extends the framework to a dynamic setting and shows how temperature smoothing emerges once cash temperature is endogenized. Section VI.E briefly discusses potential extensions to multi-asset environments.

A. Setup

Consider an infinite-horizon economy in discrete time with a continuum of investors of unit mass. In each period t, there is a one-period risky asset in unit supply with next-period payoff d_{t+1}, where $d_{t+1} \sim \mathcal{N}(\mu, \sigma^2)$. Assume that $\{d_{t+1}\}_{t\geq 0}$ are i.i.d. over time, so the risky asset has the same fundamental distribution in every period. Investors can also hold idle cash with zero net return.

Each incumbent investor exits the economy with probability $\eta \in (0,1)$ in every period t and consumes accumulated wealth upon exit. A new cohort of investors with mass η enters each period to keep the total mass equal to one. Each entering cohort is endowed with homogeneous initial wealth w_0. In period t, a cohort-τ investor who remains in the economy has wealth $w_{\tau,t}$ and cash temperature $\theta_{\tau,t}$, observes the risky-asset price p_t, and chooses the dollar amount $a_{\tau,t}$ invested in the risky asset (so idle cash is $w_{\tau,t} - a_{\tau,t}$). Formally, the cohort-τ value function $U_{\tau,t}(w_{\tau,t}; \theta_{\tau,t})$ is defined by

$$\max_{\{a_{\tau,t'}\}_{t'=t}^{\infty}} \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \eta \left(\mathbb{E}_t [w_{\tau,t'+1}] - \frac{1}{2}\gamma \mathrm{Var}_t [w_{\tau,t'+1}] + f(\theta_{\tau,t}) \sum_{j=t}^{t'} \mathbb{E}_t [v(\Delta w_{\tau,j+1})] \right) \tag{6}$$

$$\text{s.t. } w_{\tau,t'+1} = w_{\tau,t} + \sum_{j=t}^{t'} \Delta w_{\tau,j+1}, \tag{7}$$

where

$$v(\Delta w_{\tau,j+1}) = \begin{cases} \Delta w_{\tau,j+1} & \text{if } \Delta w_{\tau,j+1} \geq 0, \\ \lambda \Delta w_{\tau,j+1} & \text{if } \Delta w_{\tau,j+1} < 0, \end{cases} \tag{8}$$

$$\text{with } \lambda > 1, \quad \Delta w_{\tau,j+1} = \frac{d_{j+1} - p_j}{p_j} a_{\tau,j}.$$

and

$$
(9) \qquad f\left(\theta_{\tau,t}\right) = \begin{cases} \exp\left\{\frac{\theta_{\tau,t}}{\theta_{\tau,t}-1}\right\} & \text{if } 0 \leq \theta_{\tau,t} < 1, \\ 0 & \text{if } \theta_{\tau,t} = 1, \end{cases}
$$

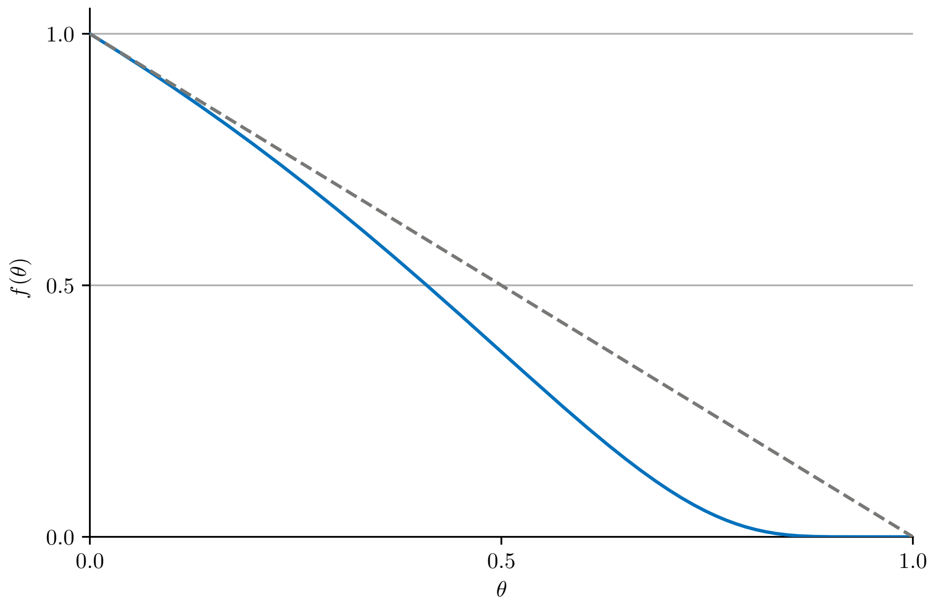
$$
\text{with} \quad \theta_{\tau,t+1} = \begin{cases} \frac{\theta_{\tau,t}(w_{\tau,t}-a_{\tau,t})\beta+\frac{a_{\tau,t}}{p_t}d_{t+1}}{(w_{\tau,t}-a_{\tau,t})+\frac{a_{\tau,t}}{p_t}d_{t+1}} & \text{if } t+1 > \tau, \\ 0 & \text{if } t+1 = \tau. \end{cases}
$$

In equation (6), the weight $(1-\eta)^{t'-t}\eta$ is the probability that the investor exits in period $t'+1$ conditional on being present in period t. The first two terms capture mean–variance preferences over exit wealth, where γ measures risk aversion. The third term adds narrow-framed, period-by-period evaluation of gains and losses as in prospect theory. We adopt a linear (kinked) prospect-theory value function in equation (8), which preserves narrow framing and loss aversion while keeping the analysis tractable. Linear formulations have been used in related settings, including Barberis, Huang, and Santos (2001) and Barberis and Huang (2001). Prospect-theory preferences have been successful in capturing investor behavior under uncertainty (Barberis and Huang (2001), Barberis et al. (2001), Barberis and Xiong (2009), and Barberis, Jin, and Wang (2021)). The reference point embedded in equation (8) is the status quo (the purchase price). We adopt this baseline to highlight the temperature–sensitivity channel.

The novelty lies in the mapping $f\left(\theta_{\tau,t}\right)$ from cash temperature to the sensitivity with which the cohort evaluates future gains and losses. The negative derivative of $f(\cdot)$ implies that higher temperature reduces sensitivity. Intuitively, the same one-dollar loss is less

Figure 10: Temperature and Sensitivity

The figure plots $f(\theta)$ from equation (9) (solid) and the linear benchmark $1-\theta$ (dashed). The function $f(\theta)$ is concave for $\theta \in (0, 0.5)$ and convex for $\theta \in (0.5, 1)$.



painful (and the same one-dollar gain is less exciting) when an investor uses hotter cash.

This assumption is consistent with several related theories. First, it can be motivated by prospective accounting and decoupling (Prelec and Loewenstein (1998)): investors may "pay" a mental cost when converting cold cash into gambling cash and subsequently react less to ongoing fluctuations. Second, it is consistent with expectation-based reference dependence (Kőszegi and Rabin (2006)): when cash originates from an unstable container, expectations of stability are lower, so realized gains and losses are less surprising and elicit weaker marginal reactions.

As defined in equation (9), each entering cohort starts with $\theta_{\tau,\tau} = 0$, implying $f(0) = 1$. New investors have not yet generated transaction-return cash, so their funds are purely cold. From period $t = \tau + 1$ onward, the cohort receives risky-asset payoffs, which mechanically raise temperature and lower sensitivity. This temperature disparity between new and seasoned cohorts is central for the model's predictions.

The mapping $f(\cdot)$ in equation (9) is nonlinear. A linear alternative such as $1-\theta$ is feasible, but the chosen functional form has two useful properties: it transitions from concave to convex around $\theta = 0.5$ and becomes relatively flat near $\theta = 1$. Sensitivity therefore drops quickly at low temperature and changes little once temperature is high. Figure 10 illustrates these properties.

The model is not the first to introduce history dependence into prospect-theory preferences. In Barberis et al. (2001), the loss-aversion parameter λ depends on prior losses. Our approach differs in two ways. First, the state variable is cash composition (temperature) rather than the history of gains and losses. Second, the sensitivity adjustment is symmetric for gains and losses: hotter cash attenuates both, whereas many history-dependent formulations focus primarily on losses. For example, Barberis et al. (2001) allows history dependence primarily through losses; in our model, the sensitivity adjustment is symmetric for gains and losses. Empirically, history dependence through funding origins remains robust even after controlling flexibly for gain/loss states, motivating the temperature-based channel.

Before solving the model, we show that the maximization problem in equations (6)–(7) can be equivalently rewritten as a myopic problem when investors treat cash temperature as an exogenous state variable. We derive the main implications under this benchmark and then relax this assumption in Section VI.D, where investors internalize the effect of current portfolio choices on future temperature.

Proposition 1. *For cohort τ in period t, $\forall \tau \leq t$, the portfolio choice problem in equations*

(6)-(7) is equivalent to

$$(10) \qquad \max_{a_{\tau,t}} \mathbb{E}_t \left[w_{\tau,t+1}\right] - \frac{1}{2}\gamma\, Var_t \left[w_{\tau,t+1}\right] + f\left(\theta_{\tau,t}\right) \mathbb{E}_t \left[v\left(\Delta w_{\tau,t+1}\right)\right]$$

$$(11) \qquad s.t.\ \ w_{\tau,t+1} = w_{\tau,t} + \Delta w_{\tau,t+1}.$$

Proof. See Internet Appendix B1. ■

The intuition behind Proposition 1 is straightforward. In equation (6), $\theta_{\tau,t}$ is the only state variable, but under the myopic assumption investors do not anticipate how current choices affect future temperature. Consequently, cohort τ in period t evaluates future gains and losses using $f(\theta_{\tau,t})$ and treats subsequent temperature changes as unexpected shocks. Without a commitment device, investors re-optimize each period, yielding myopic portfolio choices.

B. Equilibrium

We begin by simplifying the objective function in equation (10). The linearity of the prospect-theory value function in equation (8) allows us to rewrite $\mathbb{E}_t\left[v\left(\Delta w_{\tau,t+1}\right)\right]$ as a linear function of $a_{\tau,t}$.

Lemma 1. *The prospect theory term in equation (10) is a linear function of $a_{\tau,t}$, i.e.,*

$$(12) \qquad \mathbb{E}_t\left[v\left(\Delta w_{\tau,t+1}\right)\right] = \frac{g\left(p_t\right)}{p_t} a_{\tau,t}.$$

For $a_{\tau,t} > 0$, $g(p_t)$ is given by

$$g(p_t) = (\mu - p_t)\left[1 + (\lambda - 1)\,\Phi\left(-\frac{\mu - p_t}{\sigma}\right)\right] + \phi\left(-\frac{\mu - p_t}{\sigma}\right)\sigma(1-\lambda), \tag{13}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the cumulative distribution function (c.d.f.) and probability density function (p.d.f.) of the standard normal distribution, respectively.

Proof. See Internet Appendix B2. ∎

Lemma 1 implies that the objective function in equation (10) is quadratic in $a_{\tau,t}$, yielding a closed-form optimal portfolio choice.

Proposition 2. *With no short selling and no borrowing, given the risky-asset price p_t and cash temperature $\theta_{\tau,t}$, cohort τ's demand for the risky asset in period t (in dollars), $\forall \tau \leq t$, is*

$$a_{\tau,t} = \begin{cases} 0 & \text{if } a^{\star}_{\tau,t} < 0, \\ a^{\star}_{\tau,t} & \text{if } 0 \leq a^{\star}_{\tau,t} \leq w_{\tau,t}, \\ w_{\tau,t} & \text{if } a^{\star}_{\tau,t} > w_{\tau,t}. \end{cases} \tag{14}$$

with the unconstrained demand given by

$$a^{\star}_{\tau,t} = \frac{p_t(\mu - p_t)}{\gamma\sigma^2} + \frac{p_t g(p_t)}{\gamma\sigma^2} f(\theta_{\tau,t}), \tag{15}$$

where $f(\theta_{\tau,t})$ and $g(p_t)$ are defined in equations (9) and (13), respectively.

Proof. See Internet Appendix B3. ∎

Given Proposition 2, equilibrium price is obtained by aggregating cohort demands and imposing market clearing. Since cohort τ purchases $a_{\tau,t}/p_t$ shares and supply is one share, market clearing is equivalent to $\sum_{\tau\leq t}\eta(1-\eta)^{t-\tau}a_{\tau,t}=p_t$.

Definition 1. *p_t is an equilibrium of the economy $\{U_{\tau,t},w_{\tau,t},\theta_{\tau,t}\}_{\tau\leq t}$ in period t if and only if there exist $\{a_{\tau,t}\}_{\tau\leq t}$ such that:*

(1) Utility maximization: $\{a_{\tau,t}\}_{\tau\leq t}$ are given by Proposition 2;

(2) Market clearing: $\{a_{\tau,t}\}_{\tau\leq t}$ satisfy

$$\sum_{\tau\leq t}\eta\left(1-\eta\right)^{t-\tau}a_{\tau,t}=p_t. \tag{16}$$

In the initial period, there is a single cohort with mass 1 and temperature $\theta_{0,0}=0$. The equilibrium price at $t=0$ is characterized by the following corollary.

Corollary 1. *In period $t=0$, the equilibrium price p_0 is*

$$p_0=\begin{cases}0 & \text{if } p_0^\star<0,\\ p_0^\star & \text{if } 0\leq p_0^\star\leq w_{0,0},\\ w_{0,0} & \text{if } p_0^\star>w_{0,0}.\end{cases} \tag{17}$$

where

$$p_0^\star=\mu-\gamma\sigma^2+g\left(p_0^\star\right). \tag{18}$$

Proof. See Internet Appendix B4. ■

C. Numerical Results

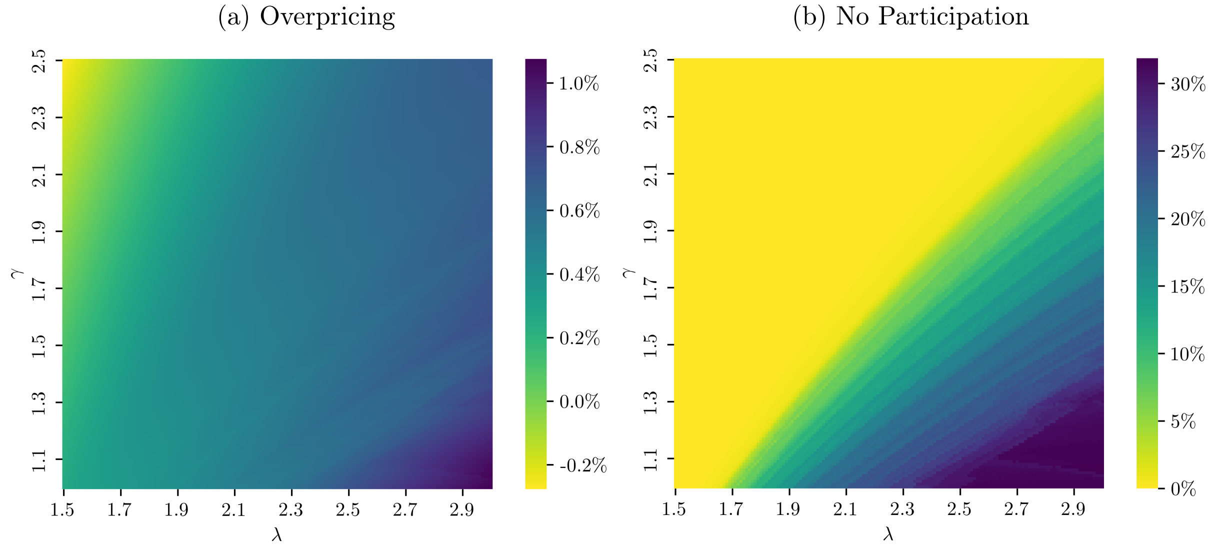
The initial price p_0 in equation (17) is the benchmark of a traditional model without a cash-temperature channel. Starting in period 1, cohort $\tau = 0$ receives hot cash from its $t = 0$ investment, so $\theta_{0,1}$ rises and the cohort becomes less sensitive to gains and losses. To illustrate implications for price and participation, we simulate the economy for 50 periods, compute the average price over these periods, and report the difference between that average and p_0 (scaled by p_0) as a heat map in Figure 11a. We also compute, in each period, the mass of investors who optimally choose zero risky holding and report the average mass over the 50 periods in Figure 11b.

The key finding is that lower γ and higher λ generate both larger price increases (overpricing) and a greater fraction of non-participating investors. A lower γ raises $p_0^\star$ via equation (18), which increases the probability of losses and therefore makes $g\left(p_0^\star\right)$ more likely to be negative. A higher λ amplifies the penalty on losses, further reducing $g\left(p_0^\star\right)$. When $g\left(p_0^\star\right) < 0$, the prospect-theory term discourages risky holdings. Temperature dynamics relax this penalty: when the penalty is larger to begin with, the reduction in sensitivity induced by rising temperature produces a larger increase in risky demand and prices, consistent with Figure 11a. Meanwhile, entering cohorts start with $\theta = 0$ and are therefore most sensitive; when prices are high, some entrants optimally choose not to participate, explaining Figure 11b.

Simulations starting from $t = 0$ highlight the mechanism but rely on the special role of cohort $\tau = 0$. For the main simulations below, we first characterize a deterministic steady state and initialize simulations at that steady state.

Figure 11: Preference Parameters: Sensitivity Analysis

The figure reports sensitivity tests for loss aversion $\lambda \in [1.5, 3.0]$ and risk aversion $\gamma \in [1.0, 2.5]$. The economy is simulated for 50 periods starting from the initial period with price p_0 given by Corollary 1. Other parameters are: initial wealth $w_0 = 2$; risky-asset mean and standard deviation $\mu = 1.012$ and $\sigma = 0.09$ (monthly Shanghai Stock Exchange (SSE) Composite Index returns, January–December 2016). Panel (a) reports overpricing (average price over 50 periods minus p_0, scaled by p_0). Panel (b) reports the average mass of investors who choose zero risky holding over the same horizon.



Definition 2. *A deterministic steady state* $\left\{\widehat{U}_{\tau,t}, \widehat{w}_{\tau,t}, \widehat{\theta}_{\tau,t}\right\}_{\tau \leq t}$ *is attained in period t if and only if:*

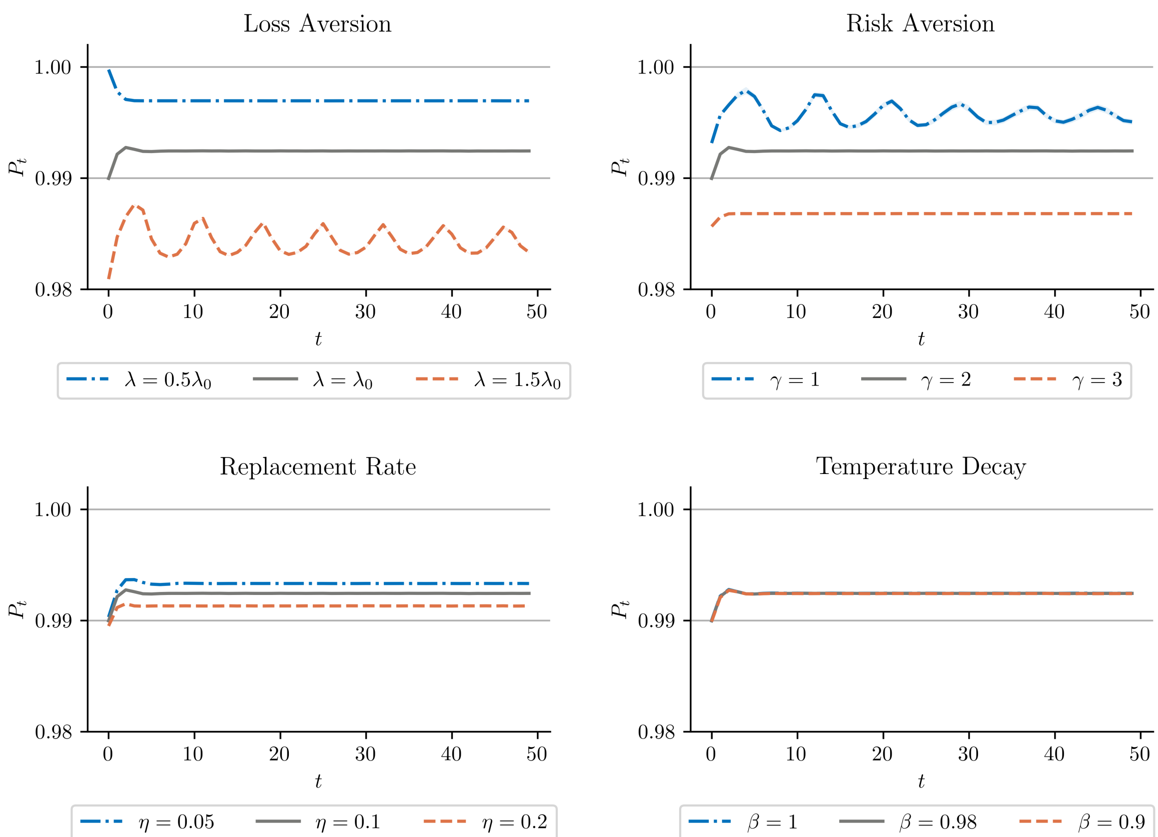
(1) Cohort τ's size is $\eta(1-\eta)^{t-\tau}$, $\forall \tau \leq t$;

(2) Price, wealth distribution, and holdings distribution remain constant when the risky payoff equals its mean, i.e., $p_{t+1} = p_t$, $w_{\tau+1,t+1} = w_{\tau,t}$, and $a_{\tau+1,t+1} = a_{\tau,t}$ for all $\tau \leq t$ if $d_{t+1} = \mu$.

Because the economy is subject to aggregate risk in every period, the steady state is defined conditional on $d_{t+1} = \mu$. In simulations with stochastic payoffs, the price path is relatively flat after the economy reaches this steady state. This reflects the stabilizing property of $f(\cdot)$ near $\theta = 1$, which dampens the impact of small temperature fluctuations. Accordingly, the simulations below emphasize temperature shocks.

Figure 12: Equilibrium Price Following a Negative Temperature Shock

The figure plots equilibrium prices from simulations that start from the deterministic steady state and impose a shock that reduces cash temperature by 50% for all agents. Baseline values are $\lambda = \lambda_0$ (2.25), $\gamma = 2$, $\eta = 0.1$, and $\beta = 0.98$. The upper-left panel varies λ ($0.5\lambda_0$ and $1.5\lambda_0$); the upper-right varies γ (1 and 3); the lower-left varies η (0.05 and 0.2); and the lower-right varies β (1 and 0.9). Other parameters are $w_0 = 2$, $\mu = 1.012$, and $\sigma = 0.09$ (monthly Shanghai Stock Exchange (SSE) Composite Index returns, January–December 2016). Each setting is simulated 100 times; the mean and 95% confidence interval are shown.



We compute the deterministic steady state and then simulate the economy under different parameter values. We vary loss aversion λ ($0.5\lambda_0$, λ_0, $1.5\lambda_0$), risk aversion γ (1, 2, 3), replacement rate η (0.05, 0.1, 0.2), and temperature decay β (1, 0.98, 0.9), taking the middle value as baseline.[19] We set $\lambda_0 = 2.25$, the value estimated for the median participant in Tversky and Kahneman (1992). For each configuration, we impose a negative temperature shock that reduces temperature by 50% for all agents (motivated by large cold inflows such as transfers or IPO refunds) and simulate forward for 50 periods, repeating the exercise 100 times across payoff paths.[20]

Figure 12 shows that prices typically rise as aggregate temperature recovers from a negative shock (except under the lowest λ). For sufficiently large λ and small γ, prices can overshoot and become volatile. The mechanism operates through temperature disparities across cohorts. When a negative temperature shock hits in period t, existing cohorts reduce risky holdings and the price falls. The entering cohort ($\tau = t$), however, starts with $\theta_{t,t} = 0$ and is unaffected by the shock; at the lower price, entrants are willing to absorb more risk. In period $t+1$, this cohort receives payoffs from its larger position, which raises its temperature relative to the counterfactual without the shock. Before the economy transitions back to steady state, early post-shock entrant cohorts therefore accumulate unusually hot cash and sustain elevated demand, generating overreaction.

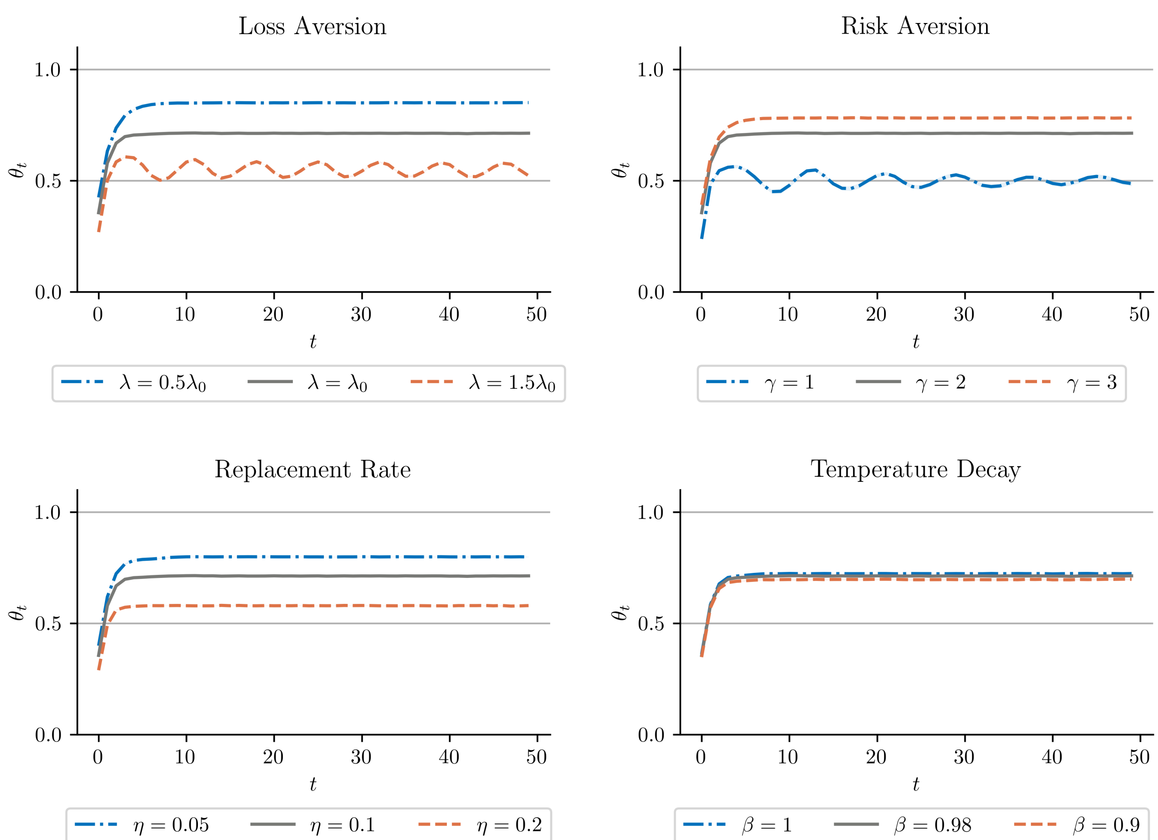
The same logic also generates reversals. When the price overshoots above its steady-state level, some late post-shock entrant cohorts optimally remain on the sidelines. Nonparticipation upon entry implies no participation in the next period as well, because

[19] The empirical baseline uses $\beta = 0.9$ to capture high-frequency account-level cash-composition dynamics, whereas the simulation section adopts $\beta = 0.98$ as a benchmark for slower-moving aggregate temperature dynamics; all qualitative implications are robust to $\beta \in \{0.9, 0.98, 1\}$.

[20] In the reported results, we vary one parameter at a time and hold the other three at baseline values.

Figure 13: Aggregate Temperature in Simulations

The figure plots the mass-weighted average cash temperature from the simulations in Figure 12. The mean and 95% confidence interval are shown.



cash temperature remains at zero without realized payoffs from risky holdings. As existing cohorts gradually unwind positions as they exit, the price declines until it becomes sufficiently low that multiple sidelined cohorts re-enter simultaneously, pushing the price up again. Consistent with Figure 12, such back-and-forth adjustment is more likely when temperature disparities are stronger—that is, when $\mathbb{E}_t[v(\Delta w_{\tau,t+1})]$ is larger, as implied by higher λ or lower γ.

Figure 14: Temperature Disparity: Time Series and Cross-Section

The figure illustrates temperature disparity in simulations that start from the deterministic steady state and impose a 50% reduction in temperature for all agents. Parameters take baseline values: $\lambda = \lambda_0$ (2.25), $\gamma = 2$, $\eta = 0.1$, and $\beta = 0.98$. Panel (a) plots holdings (top) and cash temperature (bottom) over 50 periods for the cohort entering at the shock date. Panel (b) plots the cross-section in period 50 of holdings (top) and temperature (bottom) across cohorts. Other parameters are $w_0 = 2$, $\mu = 1.012$, and $\sigma = 0.09$ (monthly Shanghai Stock Exchange (SSE) Composite Index returns, January–December 2016). Each setting is simulated 100 times; the mean and 95% confidence interval are shown.

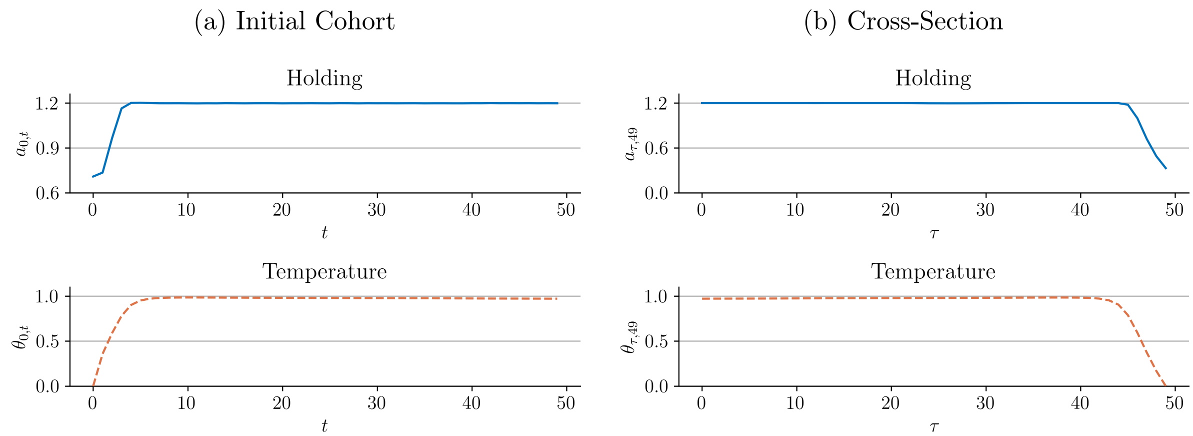


Figure 13 shows that aggregate temperature rises as the economy recovers from the negative shock. Parameter values that generate larger price movements also generate more pronounced temperature fluctuations, yielding positive comovement between temperature and price—consistent with the pro-cyclical patterns in Figure 3. For the non-preference parameters, the replacement rate η is mechanically negatively related to aggregate temperature: higher turnover replaces more hot incumbents with cold entrants. The effect of the decay parameter β is limited because cohorts receive relatively large hot inflows through payoffs each period.

Figure 14 highlights the role of disparity. Panel (a) shows that the entering cohort's temperature rises from 0 toward 1 over roughly five periods and remains near 1 thereafter, while holdings increase as temperature rises. Panel (b) shows that older cohorts have similarly high temperatures and holdings, while younger cohorts have lower levels of both. The economically relevant force is therefore the disparity between new entrants and seasoned cohorts, rather than small differences among seasoned cohorts.

In summary, the myopic model featuring temperature disparity delivers three implications aligned with our empirical evidence: (i) higher cash temperature increases risk taking, (ii) higher cash temperature raises prices, and (iii) higher cash temperature lowers expected returns holding fundamentals fixed. It also generates three classic patterns: the coexistence of no participation and overbuying, overreaction to shocks, and price fluctuations not driven by fundamentals.

D. Extension to a Dynamic Setting

Proposition 1 relies on the assumption that $f(\theta_{\tau,t})$ in equation (6) is treated as fixed across future periods when the investor solves the period-t problem. We now lift this restriction and consider a dynamic model in which investors internalize how current investment affects future cash temperature. We then compare the dynamic and myopic settings to highlight temperature smoothing.

Consider the following dynamic variant of equations (6)–(7) for cohort τ in period t:

(19)

$$\max_{\{a_{\tau,t'}\}_{t'=t}^{\infty}} \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \eta \left(\mathbb{E}_t \left[w_{\tau,t'+1} \right] - \frac{1}{2} \gamma \text{Var}_t \left[w_{\tau,t'+1} \right] + \mathbb{E}_t \left[\sum_{j=t}^{t'} f\left(\theta_{\tau,j}\right) v\left(\Delta w_{\tau,j+1}\right) \right] \right)$$

(20)
$$\text{s.t. } w_{\tau,t'+1} = w_{\tau,t} + \sum_{j=t}^{t'} \Delta w_{\tau,j+1}$$

where $v\left(\Delta w_{\tau,j+1}\right)$ and $f\left(\theta_{\tau,t}\right)$ are defined in equations (8) and (9), respectively. Relative to equation (6), the key difference is that sensitivity $f\left(\theta_{\tau,j}\right)$ now evolves endogenously with the portfolio path. As a result, the first-order condition for $a_{\tau,t}$ involves $\partial f\left(\theta_{\tau,j}\right) / \partial a_{\tau,t}$ for $j \geq t+1$, making the problem genuinely dynamic.[21]

The dynamic problem is challenging. We therefore apply a simplifying approximation that preserves the key economics. In Figure 15a, we plot $f\left(\theta_{\tau,\tau+j}\right)$ for $j = 1, 2, 3, 4$ against initial risky holding $a_{\tau,\tau}$.[22] An important observation is that

(21)
$$\frac{\partial f\left(\theta_{\tau,\tau+j}\right)}{\partial a_{\tau,\tau}} = 0, \ \forall j \geq 2,$$

approximately holds over the relevant range of $a_{\tau,\tau}$ (marked in gray), which implies that initial portfolio choice mainly affects next-period sensitivity.

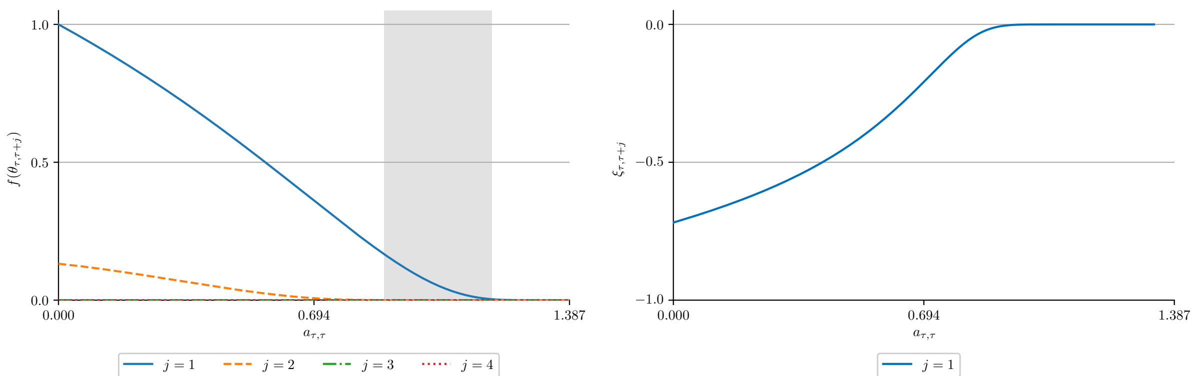
[21] The objective in equation (19) is no longer quadratic and need not be single-peaked. The discussion below focuses on interior solutions, which obtain under regularity conditions in Internet Appendix B7. When corner solutions are relevant, the solution can be obtained by comparing utility at all-in risky investment, no participation, and the interior candidate.

[22] Figure 15 is approximate for computational convenience. First, the steady-state price is computed under the myopic setting. Second, when computing $\xi_{\tau,t}(\cdot)$ in equation (24), we set $\hat{a}^{\star}_{\tau,\tau+1} = \hat{a}^{\star}_{\tau,\tau}$. This understates the magnitude of $\xi_{\tau,t}$ and therefore understates the speed at which $f(\theta)$ converges to 0. The approximation nonetheless supports equation (21).

Figure 15: Sensitivity Dynamics in the Dynamic Model

Panel (a) plots sensitivity $f(\theta_{\tau,\tau+j})$ for $j = 1, 2, 3, 4$ against initial risky holding $a_{\tau,\tau}$, where $f(\cdot)$ is defined in equation (9). Results are based on the deterministic steady state with $\beta = 1$ and baseline parameter values $\lambda = \lambda_0$ (2.25), $\gamma = 2$, and $\eta = 0.1$. Initial wealth is set to $w_{\tau,\tau} = 1.387$ so that the model's optimal idle-cash share matches the brokerage-cash share in the data. The gray band marks the interval $[\underline{a}_{\tau,\tau}, \overline{a}_{\tau,\tau}]$, where $\underline{a}_{\tau,\tau} = 0.884$ and $\overline{a}_{\tau,\tau} = 1.176$ are the minimum and maximum optimal risky holdings corresponding to temperature 0 and 1. Panel (b) plots the temperature-smoothing term $\xi_{\tau,\tau+1}$ defined in equation (24) against $a_{\tau,\tau}$ under the same settings.

(a) Future Sensitivities (b) Temperature Smoothing



Motivated by this approximation, we adopt the simplifying condition

(22) $$\frac{\partial f\left(\theta_{\tau,t+j}\right)}{\partial a_{\tau,t}} = 0, \ \forall j \geq 2 \text{ and } \forall t \geq \tau,$$

which yields results that are quantitatively close to those from the full dynamic problem.

Proposition 3 solves equations (19)–(20) under equation (22), and Proposition 4 compares optimal holding paths with and without internalizing the temperature channel. The qualitative takeaway is robust to relaxing equation (22).[23]

Proposition 3. *For cohort τ in period t, $\forall t \geq \tau$, given the deterministic steady state price $\hat{p}$ of the risky asset and cash temperature $\theta_{\tau,t}$, the interior solution to problem in equations*

[23]Relaxing equation (22) adds additional negative terms to the coefficient on the penalty term $g(\hat{p})$ in equation (23) because $\partial f(\theta_{\tau,\tau+j})/\partial a_{\tau,\tau} < 0$ for all $j \geq 1$. Under regularity conditions analogous to those in Proposition 4, this strengthens the result that optimal initial risky holding in the dynamic setting exceeds that in the myopic setting.

(19)-(20) with $\beta = 1$ and condition in equation (22) is characterized by

$$\hat{a}^{\star}_{\tau,t} = \frac{\hat{p}\left(\mu - \hat{p}\right)}{\gamma\sigma^2} + \left(1 + \xi_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \hat{a}^{\star}_{\tau,t+1}; \theta_{\tau,t}, w_{\tau,t}\right)\right)\frac{\hat{p}g\left(\hat{p}\right)}{\gamma\sigma^2} f\left(\theta_{\tau,t}\right), \tag{23}$$

where the temperature smoothing term $\xi_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \hat{a}^{\star}_{\tau,t+1}; \theta_{\tau,t}, w_{\tau,t}\right)$ is given by

$$\begin{aligned} &\xi_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \hat{a}^{\star}_{\tau,t+1}; \theta_{\tau,t}, w_{\tau,t}\right) \\ &= \left(1 - \eta\right)\hat{a}^{\star}_{\tau,t+1}\exp\left\{\frac{\mu\hat{a}^{\star}_{\tau,t}}{\hat{p}\left(\theta_{\tau,t} - 1\right)\left(w_{\tau,t} - \hat{a}^{\star}_{\tau,t}\right)} + \frac{\sigma^2\left(\hat{a}^{\star}_{\tau,t}\right)^2}{2\hat{p}^2\left(\theta_{\tau,t} - 1\right)^2\left(w_{\tau,t} - \hat{a}^{\star}_{\tau,t}\right)^2}\right\} \\ &\quad \times \left[\frac{\mu}{\hat{p}\left(\theta_{\tau,t} - 1\right)} + \frac{\sigma^2\hat{a}^{\star}_{\tau,t}}{\hat{p}^2\left(\theta_{\tau,t} - 1\right)^2\left(w_{\tau,t} - \hat{a}^{\star}_{\tau,t}\right)}\right]\frac{w_{\tau,t}}{\left(w_{\tau,t} - \hat{a}^{\star}_{\tau,t}\right)^2}. \end{aligned} \tag{24}$$

Proof. See Internet Appendix B6. ■

Relative to the myopic solution $a^{\star}_{\tau,t}$ in equation (15), the dynamic solution in equation (23) differs only through the additional term $\xi_{\tau,t}(\cdot)$ that modifies the coefficient on the penalty term $g(\hat{p})$. The comparison between $\hat{a}^{\star}_{\tau,t}$ and $a^{\star}_{\tau,t}$ is therefore governed by the sign of $\xi_{\tau,t}(\cdot)$.

Proposition 4. *Under regularity conditions, let $\left\{\hat{a}^{\star}_{\tau,t}\right\}_{t=\tau}^{\infty}$ denote the sequence implied by equation (23) and $\left\{a^{\star}_{\tau,t}\right\}_{t=\tau}^{\infty}$ the sequence given by equation (15) at the deterministic steady state. Then temperature smoothing obtains:*

1. *upon entry, $\hat{a}^{\star}_{\tau,\tau} > a^{\star}_{\tau,\tau}$;*
2. *there exists $t_0 > \tau$ such that $\hat{a}^{\star}_{\tau,t_0} < a^{\star}_{\tau,t_0}$.*

Proof. See Internet Appendix B7. ■

Figure 15b sheds light on the mechanism. The temperature-smoothing term $\xi_{\tau,\tau+1}$ in equation (24) is strongly negative when the entrant's initial risky position is too small to generate enough hot cash to raise temperature in period $\tau+1$. Entrants who internalize the cash-temperature channel therefore have a strong incentive to invest sufficiently today to avoid remaining in a high-sensitivity (cold) state tomorrow. This force implies $\hat{a}^{\star}_{\tau,\tau} > a^{\star}_{\tau,\tau}$ when sensitivity is highest upon entry. As temperature rises and sensitivity falls, the sign reverses: in a later period t_0, $\xi_{\tau,t_0}(\cdot) > 0$ implies $\hat{a}^{\star}_{\tau,t_0} < a^{\star}_{\tau,t_0}$, so the dynamic investor tilts toward a smaller risky position than the myopic benchmark. Anticipating how today's choice affects tomorrow's temperature thus smooths the time path of risky holdings, and for any initial $a_{\tau,\tau}$ within the relevant range, temperature approaches 1 and sensitivity approaches 0 relatively quickly. The same pattern holds across parameter values (Internet Appendix B5).

Three insights follow. First, the myopic model predicts sharp differences between entering and existing cohorts due to temperature disparity; the dynamic model attenuates these differences because investors internalize and partially offset the cash-temperature effect. Empirically, strong responses to cold-cash injections, as we find, suggest that the effect is not fully internalized.

Second, internalizing the effect improves time consistency but does not eliminate the channel.[24] Even in the dynamic model, relative to a counterfactual economy in which temperature is always 0, investors hold more risk, prices are higher, and expected returns are lower.

Finally, the fact that understanding the mechanism does not eliminate it points to

[24]This is natural because the cash-temperature effect operates through preferences rather than beliefs or information; awareness does not remove it as long as preferences remain unchanged.

potential policy interventions. Although a one-time cold-cash injection may have little effect once the mechanism is well understood, regular cold-cash arrivals can still shape behavior. For example, if stock-sale proceeds are routinely routed first into a savings account (a cold container) rather than credited directly to brokerage cash, investors may trade more cautiously.[25]

E. Discussion: A Multi-Asset Environment

Section VI.D shows that cash temperature is a state variable that investors may rationally internalize because today's trades affect the composition—and hence the temperature—of tomorrow's investable cash. The mechanism does not rely on there being only one risky asset. What matters is that, holding beliefs fixed, colder cash makes losses feel more salient and increases the marginal disutility of downside outcomes.

To see this in a standard N-asset environment, let $x_t \in \mathbb{R}^N$ denote the vector of new purchases (or risky positions) chosen at date t, with excess return vector $\tilde{R}_{t+1}$. A parsimonious way to embed temperature is to augment a benchmark expected-utility objective with a temperature-indexed penalty for downside outcomes:

$$\max_{x_t} \ \mathbb{E}\left[u(W_{t+1})\right] \ - \ \Lambda(\theta_t)\,\mathbb{E}\left[\phi\Big(-x_t'\tilde{R}_{t+1}\Big)\right], \tag{25}$$

where $\phi(\cdot)$ is increasing and convex on $\mathbb{R}_+$ (e.g., a prospect-theory-style loss term) and $\Lambda(\theta_t)$ is decreasing in temperature (colder cash $\Rightarrow$ larger Λ). This formulation captures the preference-based channel documented in the experiment and provides a multi-asset

[25] In Singapore, brokerage systems differ in whether cash distributions are paid directly to a linked bank account or to the brokerage account.

counterpart to the myopic and dynamic single-asset models: when θ_t is low, investors behave as if downside payoffs carry a larger shadow cost, holding beliefs fixed.

Taking first-order conditions in the presence of the temperature term yields systematic *cross-sectional* tilts relative to the benchmark solution. When $\Lambda(\theta_t)$ rises, the investor puts greater weight on avoiding losses, so optimal new purchases shift toward assets whose returns are less sensitive to adverse market states. Importantly, this is not merely a "buy less" prediction: even for a given level of aggregate risky demand, colder cash generates a *composition* effect—conditional on buying, investors rotate away from more speculative positions and toward assets with more defensive return profiles. This logic aligns with our empirical evidence: when cash is colder, investors tilt new purchases toward safer characteristics such as lower volatility and index-member stocks, and away from characteristics associated with more aggressive strategies, including high market-to-book, strong recent momentum, and attention-grabbing stocks.

VII. Conclusion

This paper studies how the origin of brokerage cash shapes investors' subsequent stock choices. We introduce a cash-temperature framework in which funds inherit the "temperature" of their source, with temperature increasing in source instability. In this framework, cash arriving as an IPO refund or via transfers from a savings account is cold, whereas cash generated by selling stocks or other risky assets is hot. Our central insight is that the non-fungibility of brokerage cash is inherently dynamic: cash labels are refreshed by new inflows and recycled trading proceeds, and attenuate over time in the absence of further salient account activity.

We construct an account-day temperature measure using two bookkeeping algorithms that track the evolving composition of brokerage cash. Across nine characteristics, the evidence reveals a unified pattern: investors deploy colder cash more cautiously, selecting safer and less attention-driven stocks, tilting toward more mainstream (index) constituents, and holding positions longer. These patterns remain distinct from close substitutes emphasized in the literature. In horse-race specifications that additionally control for recent realized gains and losses, rebalancing and mental account rollover, and trading intensity, cash temperature continues to predict stock selection in the same direction. Moreover, the cash-temperature effect attenuates with elapsed inactive time since hot inflows, consistent with decay in cash-source composition rather than attenuation driven by ongoing account activity.

We address alternative interpretations in two complementary ways. First, we exploit China's IPO lottery reform on January 1, 2016, which generates quasi-exogenous variation in whether funds pass through a frozen IPO cash pool. Difference-in-differences estimates show that cooled IPO refunds causally shift stock selection toward cautious characteristics, with economically meaningful magnitudes of 1 to 4 percentiles. Second, a pre-registered online experiment that randomly assigns cash source supports a causal interpretation of the cash-temperature effect and points to loss sensitivity as a plausible channel.

Beyond documenting the non-fungibility of brokerage cash, we develop a model motivated by the experiment in which cash temperature attenuates sensitivity to gains and losses. The model aligns with empirical findings on risk taking, prices, and returns and can rationalize several classic patterns emphasized in the literature: the coexistence of non-participation and overbuying, overreaction to shocks, and price fluctuations not driven by fundamentals. The dynamic version further highlights that institutional design—in particular, how transaction revenues and transfers are routed across accounts—can shape incentives for risk taking.

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Internet Appendix A: Additional Empirical Analysis

This appendix presents additional empirical analyses that examine the robustness of the cash-temperature effect.

For the algorithm-based results, we vary both the temperature construction and how characteristics are measured. Figure 16 and Table 9 replicate the baseline bin and regression analyses using Algorithm A2 (with $\beta = 0.90$) instead of A1. Table 10 reports results under alternative decay parameters. Table 11 examines alternative horizons for computing a subset of stock characteristics, and Table 12 reports the corresponding results using within-day percentile transformations of characteristics.

For the "horse-race" analysis in Table 5, we further confirm its robustness to the choice of decay parameter by reporting corresponding results in Table 13 under an alternative decay specification of $\beta = 0.98$. We also extend the analysis from realized volatility to the other characteristics. Table 14 augments the baseline specification with the rich set of gain/loss controls, as well as the interaction terms $\theta_{i,t} \times \text{RealizedGain}_{i,t}$ and $\theta_{i,t} \times \text{NoActivityDays}_{i,t}$, to distinguish the temperature effect from the "house money" and mental account rollover effects. Table 15 reports additional decay tests that use calendar days since the most recent hot inflow as the elapsed-time measure and show that the attenuation pattern is robust to explicitly accounting for intervening account activity. Table 16 implements the no-reinvest and no-similar restrictions to rule out mechanical rebalancing and rollover. Table 17 conditions on investor style and trading intensity (e.g., recent trading activity and tighter fixed effects) to absorb time-varying risk-on regimes. Finally, Table 18 applies conservative alternative temperature constructions (pre-open) and restricts to a pure cold/hot subsample to address measurement concerns.

For the algorithm-free identification based on the IPO lottery reform, we conduct analogous robustness checks that vary characteristic horizons and use percentile transformations. Results are presented in Table 19 and Table 20, respectively.

Finally, Table 21 reports instrumental-variables (2SLS) estimates analogous to Table 8, repeating the specification on two subsamples to assess robustness.

Figure 16: Cash Temperature and Stock Characteristics: Algorithm A2

The figure replicates Figure 4 using cash temperature $\theta_{i,t}$ constructed under Algorithm A2 with decay $\beta = 0.90$. Purchases are sorted into ten equal-sized bins on $[0, 1]$ based on $\theta_{i,t}$. Each panel plots the mean and 95% confidence interval of the market-adjusted characteristic. Market adjustment subtracts the cross-sectional average across all listed stocks on the same day. Characteristics are winsorized at the 1% and 99% percentiles. The nine characteristics correspond to those in Figure 4.

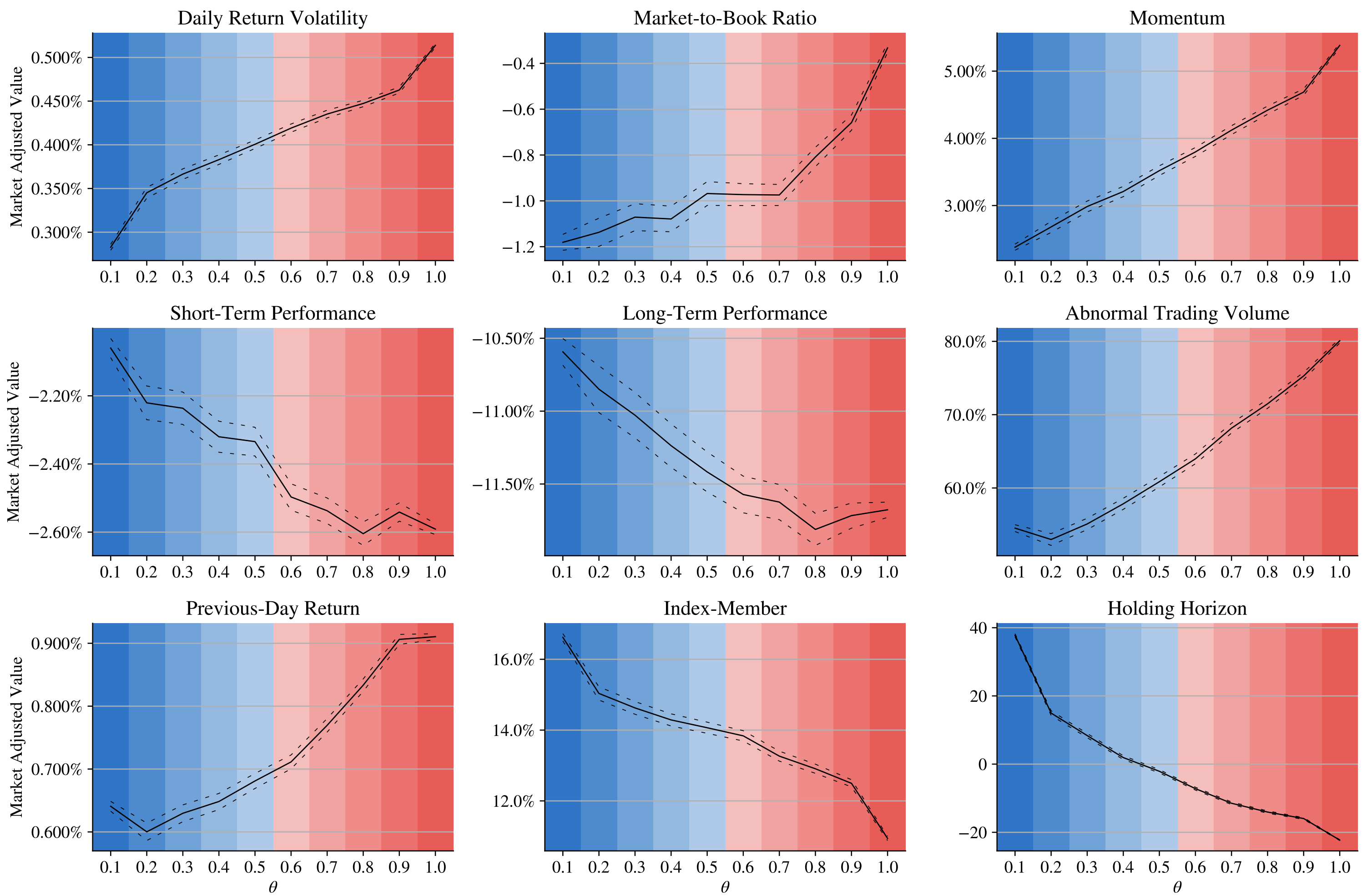


Table 9: Algorithm Robustness: A2

This table reports ordinary least squares (OLS) estimates from regressions of eight stock characteristics on cash temperature $\theta_{i,t}$ and controls at the time of purchase. For investor i on day t, $\theta_{i,t}$ is constructed under Algorithm A2 with a daily decay parameter $\beta = 0.90$. The set of control variables is identical to that in Table 4. The dependent variables in columns 1–8 are the market-to-book ratio; momentum (realized return over the past month); short-term performance (realized return in the subsequent month); long-term performance (realized return over the subsequent year); abnormal trading volume following Barber and Odean (2008); previous-day return; an indicator for membership in the SSE Composite Index, Shenzhen Component Index, or CSI 300 Index; and the number of days the stock remains in the portfolio, respectively. All dependent variables are raw values winsorized at the 1% and 99% percentiles. Account and day fixed effects are included in all specifications. The sample consists of 46,016 investors from January 1, 2006, to December 31, 2016. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
$\theta_{i,t}$	18.577***	1.686***	−0.402***	−0.790***	14.565***	0.181***	−2.138***	−18.177***
	(20.31)	(39.88)	(−14.85)	(−9.79)	(32.57)	(20.47)	(−20.78)	(−39.84)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2457	0.3838	0.4961	0.5674	0.2882	0.3081	0.1127	0.2069
Obs.	6,297,959	6,298,595	6,397,288	6,378,921	5,871,995	6,371,335	6,398,999	6,399,860

Table 10: Algorithm Robustness: Alternative Decay Parameters

This table reports ordinary least squares (OLS) estimates from regressions of nine stock characteristics on cash temperature $\theta_{i,t}$ and controls at the time of purchase. For investor i on day t, $\theta_{i,t}$ is constructed under Algorithm A1 with decay parameter $\beta = 1$ in Panel A and $\beta = 0.98$ in Panel B. The set of control variables is identical to that in Table 4. The dependent variables in columns 1–9 are realized daily return volatility over the past month; the market-to-book ratio; momentum (realized return over the past month); short-term performance (realized return in the subsequent month); long-term performance (realized return over the subsequent year); abnormal trading volume following Barber and Odean (2008); previous-day return; an indicator for membership in the SSE Composite Index, Shenzhen Component Index, or CSI 300 Index; and the number of days the stock remains in the portfolio, respectively. All dependent variables are raw values winsorized at the 1% and 99% percentiles. Account and day fixed effects are included in all specifications. The sample consists of 46,016 investors from January 1, 2006, to December 31, 2016. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: $\beta = 1$

	1	2	3	4	5	6	7	8	9
	Realized Vlt.	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
$\theta_{i,t}$	0.060***	8.437***	0.850***	−0.271***	−0.505***	5.932***	0.046***	−1.152***	−12.145***
	(24.81)	(9.43)	(21.50)	(−10.60)	(−6.63)	(14.52)	(5.43)	(−11.44)	(−26.40)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.5513	0.2456	0.3834	0.4961	0.5674	0.2879	0.3080	0.1126	0.2062
Obs.	6,298,503	6,297,871	6,298,503	6,397,196	6,378,832	5,871,906	6,371,243	6,398,907	6,399,768

Panel B: $\beta = 0.98$

	1	2	3	4	5	6	7	8	9
	Realized Vlt.	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
$\theta_{i,t}$	0.101***	15.189***	1.538***	−0.390***	−0.817***	12.906***	0.135***	−1.955***	−19.778***
	(36.93)	(16.66)	(36.50)	(−14.40)	(−10.08)	(29.07)	(15.12)	(−18.42)	(−38.62)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.5515	0.2457	0.3836	0.4961	0.5674	0.2881	0.3081	0.1127	0.2070
Obs.	6,298,503	6,297,871	6,298,503	6,397,196	6,378,832	5,871,906	6,371,243	6,398,907	6,399,768

Table 11: Algorithm Robustness: Different Horizons

This table reports ordinary least squares (OLS) estimates from regressions of four stock characteristics on cash temperature $\theta_{i,t}$ and controls at the time of purchase. For investor i on day t, $\theta_{i,t}$ is constructed under Algorithm A1 with a daily decay parameter $\beta = 0.90$. The set of control variables is identical to that in Table 4. The dependent variables in columns 1–4 are risk, measured as realized daily return volatility over the past three months; momentum, measured as realized return over the past three months; short-term performance, measured as the return over the subsequent three months; and long-term performance, measured as the return over the subsequent six months, respectively. All dependent variables are raw values winsorized at the 1% and 99% percentiles. Account and day fixed effects are included in all specifications. The sample consists of 46,016 investors from January 1, 2006, to December 31, 2016. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4
	Realized Vlt.	MOM	Short Pfm.	Long Pfm.
$\theta_{i,t}$	0.082***	3.103***	−0.569***	−0.798***
	(37.87)	(41.96)	(−13.03)	(−13.10)
Controls	Y	Y	Y	Y
Account FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Adj. R^2	0.5967	0.4627	0.5379	0.5436
Obs.	6,206,895	6,206,895	6,392,568	6,387,422

Table 12: Algorithm Robustness: Percentile Transformation

This table reports ordinary least squares (OLS) estimates from regressions of six stock characteristics on cash temperature $\theta_{i,t}$ and controls at the time of purchase. For investor i on day t, $\theta_{i,t}$ is constructed under Algorithm A1 with a daily decay parameter $\beta = 0.90$. The set of control variables is identical to that in Table 4. The dependent variables in columns 1–6 are the market-to-book ratio; momentum (realized return over the past month); short-term performance (realized return in the subsequent month); long-term performance (realized return over the subsequent year); abnormal trading volume following Barber and Odean (2008); and previous-day return, respectively. All dependent variables are expressed as daily cross-sectional percentiles. Account and day fixed effects are included in all specifications. The sample consists of 46,016 investors from January 1, 2006, to December 31, 2016. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6
	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.
$\theta_{i,t}$	1.780***	3.390***	−1.197***	−1.007***	3.378***	1.479***
	(31.64)	(43.64)	(−19.40)	(−15.47)	(41.34)	(21.86)
Controls	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.3218	0.1171	0.0472	0.0499	0.1101	0.0672
Obs.	6,297,871	6,298,503	6,397,196	6,378,832	5,871,906	6,371,243

Table 13: Horse-Race Robustness: Alternative Decay Parameter

This table reports coefficient estimates from regressions of the realized volatility of the purchased stock on cash temperature $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.98$. Column 1, *Realized Gains*, augments the baseline controls with investors' paper and realized gains and losses over the past week and month and includes the interaction term $\theta_{i,t} \times \text{RealizedGain}_{i,t}$, where $\text{RealizedGain}_{i,t}$ equals one if the investor realizes a gain (i.e., has house money) on day t. Column 2, *Decay*, adds the interaction term $\theta_{i,t} \times \text{NoActivityDays}_{i,t}$, where $\text{NoActivityDays}_{i,t}$ denotes the number of days without any trading or cash-transfer activity since the most recent arrival of hot cash. Column 3, *No Reinvest*, adds the realized volatility of the most recently sold stock to the baseline controls and restricts the sample to purchases not financed by same-day stock sales. Column 4, *No Similar*, further restricts the *No Reinvest* sample by excluding purchases of stocks that are similar to the most recently sold stock, defined as belonging to the same industry or having realized volatility within ten percentiles of each other in the market-wide cross-section. Column 5, *Recent Trade*, adds investors' trading activity in the past week (number of trades, total buy amount, and total sell amount) to the baseline controls. Column 6, *Interacted FE*, uses the same controls as column 5 but replaces account fixed effects with account-by-month fixed effects to account for time-varying investor trading habits. Column 6, *Pre-Open*, redefines the cash temperature measure $\theta_{i,t}$ by using only cash available immediately before the market opens each day. Column 8, *Pure Cold/Hot*, restricts the sample to observations in which either newly injected cold cash on a given day is at least 90% of total cash or newly received hot cash is at least 90%. Unless otherwise noted, all specifications include the baseline controls (cumulative paper loss, realized loss indicator, total available cash, and the previous day's portfolio value) as well as account and day fixed effects. Standard errors are clustered at the account and day levels, except for column 6, which clusters at the account-by-month and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	House Money		Rebalancing		Investor Style		Cash Source	
	Realized Gains	Decay	No Reinvest	No Similar	Recent Trade	Interacted FE	Pre-Open	Pure Cold/Hot
$\theta_{i,t}$	0.087***	0.094***	0.084***	0.037***	0.099***	0.013***	0.086***	0.075***
	(30.72)	(33.82)	(28.71)	(13.67)	(37.04)	(5.88)	(31.23)	(22.70)
$\theta_{i,t} \times \text{RealizedGain}_{i,t}$	0.020***							
	(11.55)							
$\theta_{i,t} \times \text{NoActivityDays}_{i,t}$		−0.005***						
		(−8.85)						
Controls	Past G&Ls	Baseline	Prev. Char.	Baseline	Intensity	Intensity	Baseline	Baseline
Account FE	Y	Y	Y	Y	Y		Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Account×Month FE						Y		
Adj. R^2	0.5516	0.5520	0.5833	0.5698	0.5516	0.5927	0.5518	0.5237
Obs.	6,298,535	6,270,125	2,386,886	1,587,947	6,298,535	5,897,961	6,273,491	2,140,944

Table 14: Horse-Race Robustness: More Outcomes for House Money Tests

This table reports coefficient estimates from regressions of stock characteristics on cash temperature $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.90$. Panel A augments the baseline controls with paper and realized gains and losses over the past week and month and includes the interaction term $\theta_{i,t} \times \text{RealizedGain}_{i,t}$, where the indicator equals one if the investor realizes a gain on day t. Panel B includes the interaction term $\theta_{i,t} \times \text{NoActivityDays}_{i,t}$, where $\text{NoActivityDays}_{i,t}$ denotes the number of days without any trading or cash-transfer activity since the most recent hot-cash inflow. Baseline controls include cumulative paper loss, realized loss indicator, total available cash, and the previous day's portfolio value. Industry fixed effects are added for the market-to-book regression. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	Price		Performance		Attention		Others	
	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
Panel A: Realized Gains								
$\theta_{i,t}$	14.463***	1.952***	−0.354***	−0.913***	19.068***	0.228***	−1.727***	−19.188***
	(13.78)	(38.54)	(−11.46)	(−9.60)	(35.49)	(22.08)	(−13.91)	(−32.00)
$\theta_{i,t} \times \text{RealizedGain}_{i,t}$	5.562***	−0.098**	−0.091***	0.081	−3.120***	−0.032***	−0.678***	−0.215
	(6.72)	(−2.54)	(−3.75)	(1.17)	(−7.85)	(−4.10)	(−7.51)	(−0.48)
Controls	Past G&Ls	Past G&Ls	Past G&Ls	Past G&Ls	Past G&Ls	Past G&Ls	Past G&Ls	Past G&Ls
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2457	0.3840	0.4961	0.5675	0.2884	0.3082	0.1127	0.2076
Obs.	6,297,903	6,298,535	6,397,228	6,378,863	5,871,937	6,371,275	6,398,939	6,399,800
Panel B: Decay								
$\theta_{i,t}$	17.922***	1.834***	−0.413***	−0.785***	16.534***	0.211***	−2.206***	−20.190***
	(19.19)	(41.58)	(−14.85)	(−9.40)	(35.71)	(22.58)	(−20.20)	(−40.86)
$\theta_{i,t} \times \text{NoActivityDays}_{i,t}$	−0.471**	−0.043***	0.004	0.024	−0.696***	−0.016***	0.088***	0.271***
	(−1.98)	(−4.85)	(1.17)	(1.49)	(−5.28)	(−5.39)	(5.03)	(3.12)
Controls	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2458	0.3838	0.4961	0.5666	0.2880	0.3083	0.1127	0.2058
Obs.	6,269,841	6,270,125	6,368,412	6,350,190	5,845,689	6,342,592	6,370,111	6,370,939

Table 15: Horse-Race Robustness: Alternative Decay Tests

This table reports coefficient estimates from regressions of the realized volatility of the purchased stock on cash temperature $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.90$. Both columns use $\text{Days}_{i,t}$, defined as the number of calendar days since the most recent arrival of hot cash, as the elapsed-time measure, rather than $\text{NoActivityDays}_{i,t}$. Column 1, *Activity Interaction*, includes the interaction term $\theta_{i,t} \times \text{Days}_{i,t}$ and further interacts $\theta_{i,t}$ with $\text{ActivityDays}_{i,t}$, defined as the number of days with any account activity since the most recent hot inflow. Account activity includes cash transfers as well as asset purchases or sales. Column 2, *Sample Restriction*, includes the interaction term $\theta_{i,t} \times \text{Days}_{i,t}$ and restricts the sample to observations with no account activity after the most recent hot inflow. Both specifications include the baseline controls (cumulative paper loss, realized loss indicator, total available cash, and the previous day's portfolio value) as well as account and day fixed effects. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2
	Activity Interaction	Sample Restriction
$\theta_{i,t}$	0.105***	0.090***
	(38.91)	(30.11)
$\theta_{i,t} \times \text{Days}_{i,t}$	-0.002^{***}	-0.005^{***}
	(-4.87)	(-6.25)
$\theta_{i,t} \times \text{ActivityDays}_{i,t}$	0.003	
	(0.72)	
Controls	Baseline	Baseline
Account FE	Y	Y
Day FE	Y	Y
Adj. R^2	0.5520	0.5502
Obs.	6,270,125	5,730,943

Table 16: Horse-Race Robustness: More Outcomes for Rebalancing Tests

This table reports coefficient estimates from regressions of stock characteristics on cash temperature $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.90$. The sample excludes purchases financed by same-day stock sales. Panel A additionally controls for the corresponding characteristic of the most recently sold stock, whereas Panel B further excludes purchases of stocks that are similar to the most recently sold stock, defined as belonging to the same industry or having the corresponding characteristic within ten percentiles of each other in the market-wide cross-section. The baseline controls for both panels are cumulative paper loss, realized loss indicator, total available cash, and the previous day's portfolio value. Industry fixed effects are added for the market-to-book regression. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7
	Price		Performance		Attention		Others
	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index
Panel A: No Reinvest							
$\theta_{i,t}$	16.671***	1.825***	−0.387***	−0.824***	14.180***	0.236***	−2.094***
	(14.40)	(36.35)	(−12.24)	(−8.28)	(26.29)	(15.57)	(−16.60)
Controls	Prev. Char.	Prev. Char.	Prev. Char.	Prev. Char.	Prev. Char.	Prev. Char.	Prev. Char.
Account FE	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2452	0.4236	0.5136	0.5887	0.3290	0.3632	0.1283
Obs.	2,394,024	2,386,886	2,449,663	2,435,986	2,090,640	2,440,718	2,451,094
Panel B: No Similar							
$\theta_{i,t}$	10.328***	1.152***	−0.405***	−0.596***	9.396***	0.154***	−2.174***
	(7.78)	(21.32)	(−10.62)	(−5.10)	(15.87)	(13.26)	(−14.83)
Controls	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Account FE	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2361	0.4121	0.5082	0.5874	0.3084	0.3501	0.1017
Obs.	1,592,171	1,587,928	1,619,520	1,614,465	1,484,044	1,609,876	1,619,971

Table 17: Horse-Race Robustness: More Outcomes for Investor Style Tests

This table reports coefficient estimates from regressions of stock characteristics on cash temperature $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.90$. The specification augments the baseline controls—cumulative paper loss, realized loss indicator, total available cash, and the previous day's portfolio value—with investors' trading activity in the past week (number of trades, total buy amount, and total sell amount). Panel A includes account and day fixed effects. Panel B replaces account fixed effects with account-by-month fixed effects. Industry fixed effects are added for the market-to-book regression in both panels. Standard errors are clustered at the account and day levels in Panel A, and at the account-by-month and day levels in Panel B. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	Price		Performance		Attention		Others	
	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
Panel A: Recent Trade								
$\theta_{i,t}$	18.531***	1.841***	−0.420***	−0.814***	16.612***	0.213***	−2.258***	−20.210***
	(19.71)	(42.50)	(−15.07)	(−9.94)	(36.32)	(22.96)	(−21.00)	(−41.71)
Controls	Intensity	Intensity	Intensity	Intensity	Intensity	Intensity	Intensity	Intensity
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2457	0.3839	0.4961	0.5674	0.2883	0.3082	0.1127	0.2073
Obs.	6,297,871	6,298,503	6,397,196	6,378,832	5,871,906	6,371,243	6,398,907	6,399,768
Panel B: Interacted FE								
$\theta_{i,t}$	6.080***	0.676***	−0.845***	−0.809***	6.222***	0.086***	−0.404***	8.306***
	(6.23)	(15.44)	(−25.96)	(−9.62)	(13.48)	(8.65)	(−3.89)	(29.99)
Controls	Intensity	Intensity	Intensity	Intensity	Intensity	Intensity	Intensity	Intensity
Account×Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2859	0.4316	0.5177	0.5909	0.3378	0.3273	0.1744	0.4270
Obs.	5,896,760	5,897,933	5,997,202	5,978,715	5,468,422	5,971,190	5,998,885	5,999,648

Table 18: Horse-Race Robustness: More Outcomes for Cash Source Tests

This table reports coefficient estimates from regressions of stock characteristics on cash temperature $\theta_{i,t}$, constructed using Algorithm A1 with a daily decay parameter $\beta = 0.90$. Panel A computes $\theta_{i,t}$ using only cash available prior to the market open. Panel B restricts the sample to observations in which either newly injected cold cash or newly received hot cash accounts for at least 90% of total available cash. The baseline controls for both panels are cumulative paper loss, realized loss indicator, total available cash, and the previous day's portfolio value. Industry fixed effects are added for the market-to-book regression. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8
	Price		Performance		Attention		Others	
	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
Panel A: Pre-Open								
$\theta_{i,t}$	16.584***	1.919***	−0.413***	−0.933***	18.295***	0.241***	−1.949***	−21.376***
	(18.07)	(43.18)	(−16.60)	(−11.88)	(38.46)	(27.35)	(−18.86)	(−41.79)
Controls	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2457	0.3841	0.4960	0.5631	0.2884	0.3083	0.1126	0.2075
Obs.	6,273,235	6,273,484	6,371,681	6,353,516	5,848,829	6,345,908	6,373,386	6,374,204
Panel B: Pure Cold/Hot								
$\theta_{i,t}$	16.046***	1.153***	−0.333***	−0.861***	9.717***	0.102***	−1.867***	−12.790***
	(11.89)	(19.48)	(−8.29)	(−7.60)	(15.20)	(8.36)	(−12.73)	(−26.86)
Controls	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2360	0.3575	0.4801	0.5584	0.2779	0.2807	0.1102	0.2245
Obs.	2,146,853	2,140,921	2,178,028	2,171,680	1,991,350	2,169,344	2,178,647	2,178,913

Table 19: DiD Robustness: Different Horizons

This table reports the estimates from a DiD design that relies on the quasi-natural experiment of the IPO lottery reform on January 1, 2016. Variable $\text{Refund}_{i,t}$ is the IPO refund amount standardized by the total cash available for investor i on day t; Regime_t is an indicator that equals 1 if the IPO lottery result announced on day t is under the old regime, and equals 0 if it is under the new regime; the control variables are the same as in Table 7. The dependent variables in columns 1–4 are risk (realized daily return volatility in the past three months), momentum (realized return in the past three months), short-term performance (return in the next three months), and long-term performance (return in the next six months), respectively. All dependent variables are measured in raw units and winsorized at the 1% and 99% percentiles. Account and day fixed effects are added to all specifications. The sample of 9,241 investors on 238 IPO announcement days between June 17, 2014, and December 31, 2016, is used. Standard errors are clustered on account and day. Robust t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4
	Realized Vlt.	MOM	Short Pfm.	Long Pfm.
$\text{Refund}_{i,t} \times \text{Regime}_t$	-0.046^{**}	-1.360^{*}	0.337	1.633^{**}
	(−2.13)	(−1.85)	(0.73)	(2.58)
$\text{Refund}_{i,t}$	0.051^{***}	1.164^{**}	−0.126	-1.106^{***}
	(3.14)	(2.36)	(−0.42)	(−2.73)
Controls	Y	Y	Y	Y
Account FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Adj. R^2	0.4730	0.4235	0.6121	0.5246
Obs.	220,950	220,950	226,787	226,524

Table 20: DiD Robustness: Percentile Transformation

This table reports the estimates from a DiD design that relies on the quasi-natural experiment of the IPO lottery reform on January 1, 2016. Variable $\text{Refund}_{i,t}$ is the IPO refund amount standardized by the total cash available for investor i on day t; Regime_t is an indicator that equals 1 if the IPO lottery result announced on day t is under the old regime, and equals 0 if it is under the new regime; the control variables are the same as in Table 7. The dependent variables in columns 1–7 are risk (realized daily return volatility in the past month), market-to-book ratio, momentum (realized return in the past month), short-term performance (return in the next month), long-term performance (return in the next year), abnormal trading volume used in Barber and Odean (2008), and previous-day return, respectively. All dependent variables are in percentiles sorted daily. Account and day fixed effects are added to all specifications. The sample of 9,241 investors on 238 IPO announcement days between June 17, 2014, and December 31, 2016, is used. Standard errors are clustered on account and day. Robust t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7
	Realized Vlt.	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.
$\text{Refund}_{i,t} \times \text{Regime}_t$	−2.251***	−1.563***	−2.834***	1.026*	2.434***	−3.735***	−2.113***
	(−2.64)	(−2.62)	(−3.83)	(1.82)	(2.70)	(−4.43)	(−3.43)
$\text{Refund}_{i,t}$	2.317***	0.972**	1.800***	−0.600	−2.308***	3.203***	1.000**
	(4.02)	(2.37)	(3.59)	(−1.24)	(−3.18)	(5.30)	(2.19)
Controls	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.1707	0.4367	0.1384	0.0570	0.0804	0.1319	0.0712
Obs.	224,628	224,559	224,628	226,982	226,374	211,969	226,965

Table 21: 2SLS Robustness: Alternative Samples

This table reports two-stage least squares (2SLS) estimates that instrument the cash-temperature measure $\theta_{i,t}$ with the interaction between the IPO refund fraction and the old-regime indicator, $\text{Refund}_{i,t} \times \text{Regime}_t$. The first stage exploits exogenous variation from the IPO lottery reform. Panel A restricts the sample to refund-dominant observations, defined as cases in which the IPO refund fraction is either at most 10% or at least 90%. Panel B restricts the sample to transactions without refund-management strategies by excluding observations in which refunds are transferred out on the same day under the old regime. All specifications include $\text{Refund}_{i,t}$, the full set of controls—cumulative paper loss, realized loss indicator, total available cash, the previous day's portfolio value, the IPO-winning indicator, and the fractions of other cash sources—as well as account and day fixed effects. Industry fixed effects are added for the market-to-book regression. The minimum and maximum first-stage Kleibergen–Paap rk Wald F statistics are reported at the bottom of each panel. Standard errors are clustered at the account and day levels. Robust t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8	9
	Risk	Price		Performance		Attention		Others	
	Realized Vlt.	M-B	MOM	Short	Long	Abn. Trd.	Prev. Ret.	Index	Horizon
Panel A: Refund-Dominant Sample									
$\theta_{i,t}$ (IV)	0.071^{**}	27.331^{*}	1.257^{**}	-0.270	-2.294^{**}	12.383^{**}	0.327^{***}	-2.813^{**}	-12.302^{***}
	(2.51)	(1.93)	(2.00)	(−0.85)	(−2.43)	(2.60)	(3.34)	(−2.09)	(−4.50)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	154,886	154,518	154,886	156,315	155,831	147,355	156,300	156,344	156,344
Kleibergen–Paap rk Wald F	[20,457, 21,128]								
Panel B: No-Strategy Sample									
$\theta_{i,t}$ (IV)	0.132^{**}	53.703^{**}	1.348^{*}	-0.919^{*}	-4.668^{***}	4.954	0.366^{***}	-3.909^{**}	-13.078^{***}
	(2.29)	(2.38)	(1.76)	(−1.91)	(−2.72)	(0.76)	(3.11)	(−2.17)	(−3.76)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	119,496	120,009	119,496	121,027	120,824	110,883	121,024	121,036	121,036
Kleibergen–Paap rk Wald F	[9,127, 9,343]								

Internet Appendix B: Proofs for the Model

B1. Proof of Proposition 1

Proof. Combining equations (7) and (8) yields

$$w_{\tau,t'+1} = w_{\tau,t} + \sum_{j=t}^{t'} \frac{d_{j+1} - p_j}{p_j} a_{\tau,j}. \tag{26}$$

Substituting equation (26) into equation (6), we can write the cohort-τ problem at time t as

$$\begin{aligned} \max_{\{a_{\tau,t'}\}_{t'=t}^{\infty}} & \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \eta \, \mathbb{E}_t \left[w_{\tau,t} + \sum_{j=t}^{t'} \frac{d_{j+1} - p_j}{p_j} a_{\tau,j} \right] \\ & - \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \eta \frac{1}{2} \gamma \operatorname{Var}_t \left[w_{\tau,t} + \sum_{j=t}^{t'} \frac{d_{j+1} - p_j}{p_j} a_{\tau,j} \right] \\ & + f(\theta_{\tau,t}) \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \eta \sum_{j=t}^{t'} \mathbb{E}_t \left[v\left(\frac{d_{j+1} - p_j}{p_j} a_{\tau,j} \right) \right]. \end{aligned} \tag{27}$$

By linearity of $\mathbb{E}_t[\cdot]$, the first term in equation (27) equals

$$\begin{aligned} & \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \eta \, \mathbb{E}_t[w_{\tau,t}] + \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \eta \left(\sum_{j=t}^{t'} \mathbb{E}_t \left[\frac{d_{j+1} - p_j}{p_j} \right] a_{\tau,j} \right) \\ = & \frac{\eta}{1-(1-\eta)} \mathbb{E}_t[w_{\tau,t}] + \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \frac{\eta}{1-(1-\eta)} \mathbb{E}_t \left[\frac{d_{t'+1} - p_{t'}}{p_{t'}} \right] a_{\tau,t'} \\ = & \mathbb{E}_t[w_{\tau,t}] + \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \mathbb{E}_t \left[\frac{d_{t'+1} - p_{t'}}{p_{t'}} \right] a_{\tau,t'}. \end{aligned} \tag{28}$$

Similarly, using the independence of payoffs across dates, the variance term and the prospect-theory term in equation (27) can be written as

$$
-\frac{1}{2}\gamma \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \left(\mathrm{Var}_t \left[\frac{d_{t'+1} - p_{t'}}{p_{t'}} \right] a_{\tau,t'}^2 \right), \tag{29}
$$

and

$$
f(\theta_{\tau,t}) \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \mathbb{E}_t \left[v\left(\frac{d_{t'+1} - p_{t'}}{p_{t'}} a_{\tau,t'} \right) \right], \tag{30}
$$

respectively.

Substituting equation (28)–(30) back into equation (27) yields

$$
\begin{aligned}
\max_{\{a_{\tau,t'}\}_{t'=t}^{\infty}} \; & \mathbb{E}_t[w_{\tau,t}] + \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \mathbb{E}_t \left[\frac{d_{t'+1} - p_{t'}}{p_{t'}} \right] a_{\tau,t'} \\
& - \frac{1}{2}\gamma \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \left(\mathrm{Var}_t \left[\frac{d_{t'+1} - p_{t'}}{p_{t'}} \right] a_{\tau,t'}^2 \right) \\
& + f(\theta_{\tau,t}) \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \mathbb{E}_t \left[v\left(\frac{d_{t'+1} - p_{t'}}{p_{t'}} a_{\tau,t'} \right) \right].
\end{aligned} \tag{31}
$$

Because each choice $a_{\tau,t'}$ (for $t' \geq t$) appears only in the t'-th term of each summation in equation (31), the problem separates across dates into independent maximization problems. Specifically, for each $t' \geq t$,

$$
\max_{a_{\tau,t'}} \mathbb{E}_t \left[\frac{d_{t'+1} - p_{t'}}{p_{t'}} \right] a_{\tau,t'} - \frac{1}{2}\gamma \mathrm{Var}_t \left[\frac{d_{t'+1} - p_{t'}}{p_{t'}} \right] a_{\tau,t'}^2 + f(\theta_{\tau,t}) \mathbb{E}_t \left[v\left(\frac{d_{t'+1} - p_{t'}}{p_{t'}} a_{\tau,t'} \right) \right]. \tag{32}
$$

In particular, at $t' = t$, equation (32) is equivalent to equations (10)–(11), which completes the proof. ∎

B2. Proof of Lemma 1

Proof. By equation (8), we can write

$$\mathbb{E}_t[v(\Delta w_{\tau,t+1})] = \mathbb{E}_t[\Delta w_{\tau,t+1} \mid \Delta w_{\tau,t+1} \geq 0] \times \mathbb{P}\left\{\Delta w_{\tau,t+1} \geq 0\right\}$$
$$+ \mathbb{E}_t[\lambda \Delta w_{\tau,t+1} \mid \Delta w_{\tau,t+1} < 0] \times \mathbb{P}\left\{\Delta w_{\tau,t+1} < 0\right\}. \tag{33}$$

Since $\Delta w_{\tau,t+1} = \frac{d_{t+1}-p_t}{p_t} a_{\tau,t}$ and $d_{t+1} \sim \mathcal{N}(\mu, \sigma^2)$, it follows that

$$\Delta w_{\tau,t+1} \sim \mathcal{N}\left(\frac{\mu - p_t}{p_t} a_{\tau,t}, \left(\frac{a_{\tau,t}}{p_t}\right)^2 \sigma^2\right).$$

For $X \sim \mathcal{N}(m, v^2)$, the truncated mean is

$$\mathbb{E}[X \mid a < X < b] = m + \frac{\phi\left(\frac{a-m}{v}\right) - \phi\left(\frac{b-m}{v}\right)}{\Phi\left(\frac{b-m}{v}\right) - \Phi\left(\frac{a-m}{v}\right)} v, \tag{34}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ denote the c.d.f. and p.d.f. of the standard normal distribution. Taking $(a, b) = (0, \infty)$ and $(a, b) = (-\infty, 0)$ in equation (34) yields

$$\mathbb{E}[X \mid X \geq 0] = m + \frac{\phi\left(\frac{-m}{v}\right)}{1 - \Phi\left(\frac{-m}{v}\right)} v, \tag{35}$$

$$\mathbb{E}[X \mid X < 0] = m - \frac{\phi\left(\frac{-m}{v}\right)}{\Phi\left(\frac{-m}{v}\right)} v. \tag{36}$$

Now take $m = \frac{\mu - p_t}{p_t} a_{\tau,t}$ and $v = \frac{a_{\tau,t}}{p_t}\sigma$. For $a_{\tau,t} > 0$, we have $\frac{-m}{v} = -\frac{\mu - p_t}{\sigma}$, and substituting equations (35)–(36) into equation (33) gives

$$
\begin{aligned}
\mathbb{E}_t[v(\Delta w_{\tau,t+1})] &= \left(m + \frac{\phi\left(\frac{-m}{v}\right)}{1-\Phi\left(\frac{-m}{v}\right)}v\right)\left(1-\Phi\left(\frac{-m}{v}\right)\right) + \lambda\left(m - \frac{\phi\left(\frac{-m}{v}\right)}{\Phi\left(\frac{-m}{v}\right)}v\right)\Phi\left(\frac{-m}{v}\right) \\
&= \left(\frac{\mu-p_t}{p_t}a_{\tau,t} + \frac{\phi\left(-\frac{\mu-p_t}{\sigma}\right)}{1-\Phi\left(-\frac{\mu-p_t}{\sigma}\right)}\frac{a_{\tau,t}}{p_t}\sigma\right)\left(1-\Phi\left(-\frac{\mu-p_t}{\sigma}\right)\right) \\
&\quad + \lambda\left(\frac{\mu-p_t}{p_t}a_{\tau,t} - \frac{\phi\left(-\frac{\mu-p_t}{\sigma}\right)}{\Phi\left(-\frac{\mu-p_t}{\sigma}\right)}\frac{a_{\tau,t}}{p_t}\sigma\right)\Phi\left(-\frac{\mu-p_t}{\sigma}\right) \\
&= a_{\tau,t}\frac{1}{p_t}\left[(\mu-p_t)\left(1+(\lambda-1)\Phi\left(-\frac{\mu-p_t}{\sigma}\right)\right) + \phi\left(-\frac{\mu-p_t}{\sigma}\right)\sigma(1-\lambda)\right],
\end{aligned}
$$

which is equation (12) with equation (13) substituted. ■

B3. Proof of Proposition 2

Proof. We first solve for the unconstrained demand $a^{\star}_{\tau,t}$ of cohort τ in period t.

Using equation (10), the objective can be written as

$$
\max_{a_{\tau,t}} \frac{\mu-p_t}{p_t}a_{\tau,t} - \frac{1}{2}\gamma\frac{\sigma^2}{p_t^2}a_{\tau,t}^2 + f(\theta_{\tau,t})\frac{g(p_t)}{p_t}a_{\tau,t}. \tag{37}
$$

The first-order condition is

$$
0 = \frac{\mu-p_t}{p_t} - \gamma\frac{\sigma^2}{p_t^2}a^{\star}_{\tau,t} + f(\theta_{\tau,t})\frac{g(p_t)}{p_t},
$$

which implies

$$
a^{\star}_{\tau,t} = \frac{p_t(\mu-p_t)}{\gamma\sigma^2} + \frac{p_t g(p_t)}{\gamma\sigma^2}f(\theta_{\tau,t}),
$$

establishing equation (15).

Now impose the short-selling and borrowing constraints. Since equation (37) is strictly concave in $a_{\tau,t}$, the constrained optimum is the feasible point closest to $a^{\star}_{\tau,t}$. Hence, if $a^{\star}_{\tau,t} < 0$, the short-selling constraint binds and $a_{\tau,t} = 0$; if $a^{\star}_{\tau,t} > w_{\tau,t}$, the borrowing constraint binds and $a_{\tau,t} = w_{\tau,t}$. ∎

B4. Proof of Corollary 1

Proof. For the initial cohort $\tau = 0$ at $t = 0$, we have $\theta_{0,0} = 0$. By equation (15),

$$a^{\star}_{0,0} = \frac{p^{\star}_0 \left(\mu - p^{\star}_0\right)}{\gamma\sigma^2} + \frac{p^{\star}_0 g\left(p^{\star}_0\right)}{\gamma\sigma^2}, \tag{38}$$

where $p^{\star}_0$ denotes the equilibrium price under an interior solution.

Because cohort $\tau = 0$ is the only cohort in the economy and has unit mass, market clearing condition in equation (16) reduces to $a^{\star}_{0,0} = p^{\star}_0$. Substituting this identity into equation (38) yields

$$p^{\star}_0 = \frac{p^{\star}_0 \left(\mu - p^{\star}_0\right)}{\gamma\sigma^2} + \frac{p^{\star}_0 g\left(p^{\star}_0\right)}{\gamma\sigma^2} \quad \Rightarrow \quad p^{\star}_0 = \mu - \gamma\sigma^2 + g\left(p^{\star}_0\right),$$

which establishes the interior solution. Corner solutions follow from equation (16). ∎

B5. Other Parameter Values for Figure 15

Figure 17: Future Sensitivities: Other Parameter Values

The figure plots sensitivity $f(\theta_{\tau,\tau+j})$ for $j = 1, 2, 3, 4$ against initial risky holding $a_{\tau,\tau}$, where $f(\cdot)$ is defined in equation (9). Each panel uses the deterministic steady state with $\beta = 1$ and parameter values for λ, γ, and η as specified. Initial wealth is set so that the model's optimal idle cash share matches the brokerage-cash share in the data. The gray band marks $[\underline{a}_{\tau,\tau}, \overline{a}_{\tau,\tau}]$, where $\underline{a}_{\tau,\tau}$ and $\overline{a}_{\tau,\tau}$ are the minimum and maximum optimal risky holdings corresponding to temperatures 0 and 1.

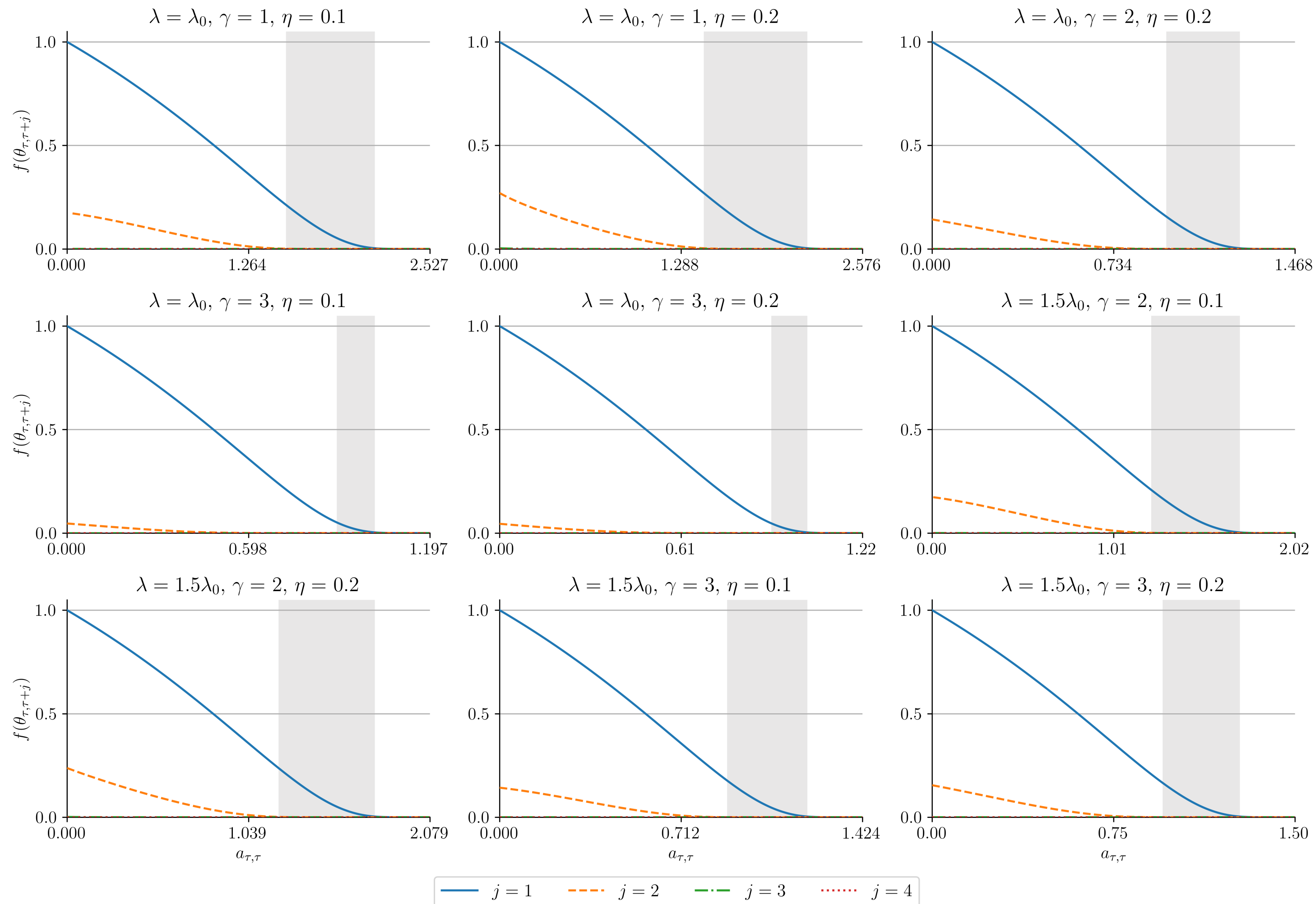
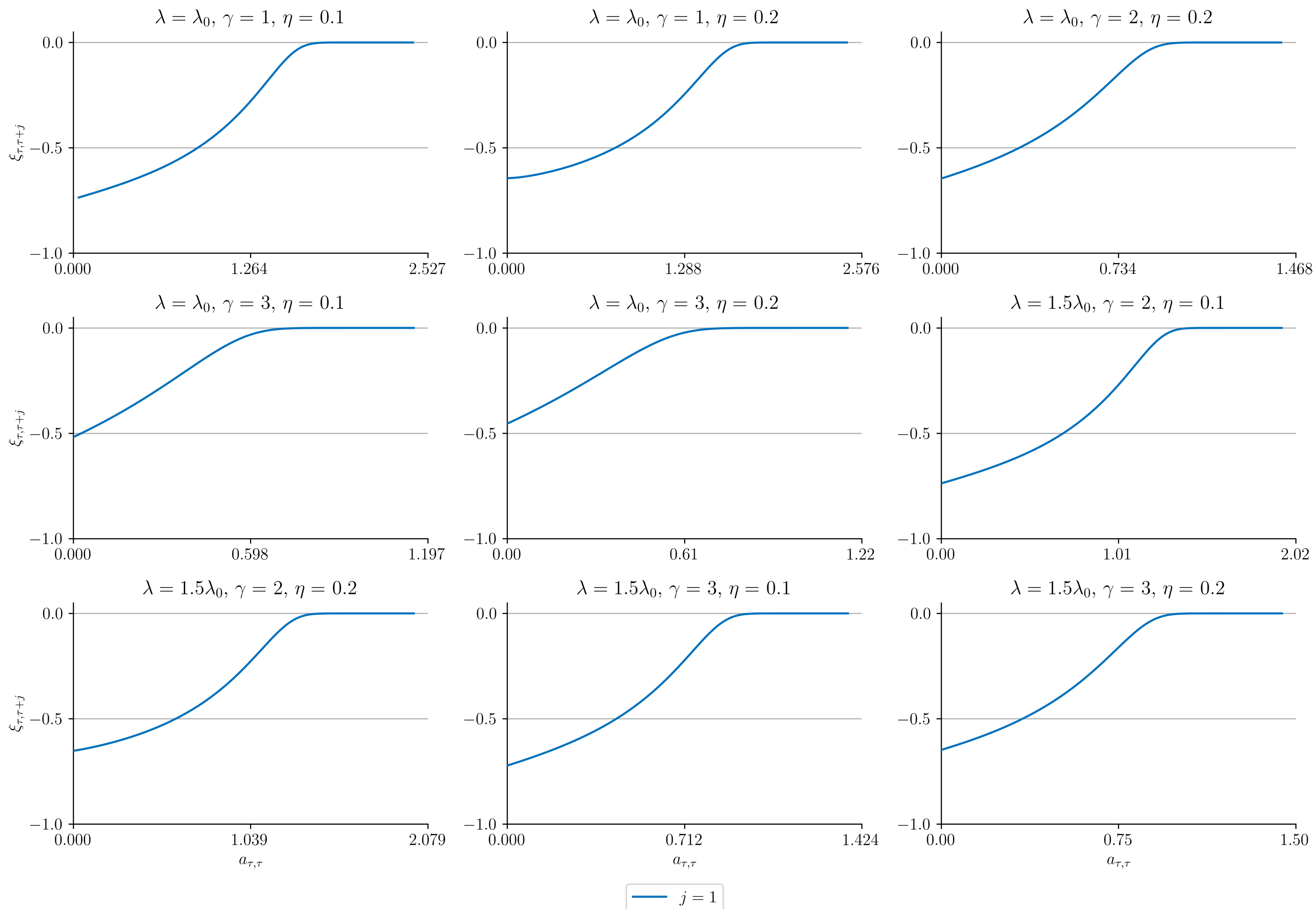


Figure 18: Temperature Smoothing: Other Parameter Values

The figure plots the temperature-smoothing term $\xi_{\tau,\tau+1}$ defined in equation (24) against initial risky holding $a_{\tau,\tau}$. Each panel uses the deterministic steady state with $\beta = 1$ and parameter values for λ, γ, and η as specified. Initial wealth is set so that the model's optimal idle cash share matches the brokerage-cash share in the data.



B6. Proof of Proposition 3

We begin with two lemmas that simplify the proof. Lemma 2 rewrites the objective function in equation (19).

Lemma 2. *With the condition in equation (22), the objective function in equation (19) for cohort τ in period t is equivalent to*

$$\max_{\{a_{\tau,t'}\}_{t'=t}^{\infty}} \mathbb{E}_t[w_{\tau,t}] + \sum_{t'=t}^{\infty} (1-\eta)^{t'-t}\, \mathbb{E}_t\left[\frac{d_{t'+1}-\hat{p}}{\hat{p}}\right] a_{\tau,t'} - \frac{1}{2}\gamma \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \left(Var_t\left[\frac{d_{t'+1}-\hat{p}}{\hat{p}}\right] a_{\tau,t'}^2 \right)$$

(39)

$$+ f\left(\theta_{\tau,t}\right) \mathbb{E}_t\left[v\left(\frac{d_{t+1}-\hat{p}}{\hat{p}} a_{\tau,t}\right)\right] + (1-\eta)\, \mathbb{E}_t[f\left(\theta_{\tau,t+1}\right)]\, \mathbb{E}_t\left[v\left(\frac{d_{t+2}-\hat{p}}{\hat{p}} a_{\tau,t+1}\right)\right],$$

where $\hat{p}$ is the deterministic steady-state price of the risky asset.

Proof. The first three terms in equation (39) correspond to the mean–variance component and follow directly from equation (31) in the proof of Proposition 1 (with $p_{t'} = \hat{p}$ under equation (22)). It remains to derive the last two terms, which come from the prospect-theory component in equation (19):

$$\begin{aligned}
&\sum_{t'=t}^{\infty}(1-\eta)^{t'-t}\eta\,\mathbb{E}_t\left[\sum_{j=t}^{t'}f\left(\theta_{\tau,j}\right)v\left(\Delta w_{\tau,j+1}\right)\right]\\
&=\sum_{t'=t}^{\infty}(1-\eta)^{t'-t}\eta\,f\left(\theta_{\tau,t}\right)\mathbb{E}_t[v\left(\Delta w_{\tau,t+1}\right)]+\sum_{j=1}^{\infty}\sum_{t'=t+j}^{\infty}(1-\eta)^{t'-t}\eta\,\mathbb{E}_t[f\left(\theta_{\tau,t+j}\right)v\left(\Delta w_{\tau,t+j+1}\right)]\\
&=f\left(\theta_{\tau,t}\right)\mathbb{E}_t[v\left(\Delta w_{\tau,t+1}\right)]+\sum_{j=1}^{\infty}(1-\eta)^{j}\ \mathbb{E}_t\left[f\left(\theta_{\tau,t+j}\right)v\left(\frac{d_{t+j+1}-\hat{p}}{\hat{p}}a_{\tau,t+j}\right)\right]
\end{aligned}$$

(40)

$$=f\left(\theta_{\tau,t}\right)\mathbb{E}_t[v\left(\Delta w_{\tau,t+1}\right)]+\sum_{j=1}^{\infty}(1-\eta)^{j}\ \mathbb{E}_t[f\left(\theta_{\tau,t+j}\right)]\ \mathbb{E}_t\left[v\left(\frac{d_{t+j+1}-\hat{p}}{\hat{p}}a_{\tau,t+j}\right)\right],$$

where the last equality uses the assumption that risky-asset returns are i.i.d. across periods.

For any $j\geq 1$, note that

$$\frac{\partial}{\partial a_{\tau,t}}\mathbb{E}_t\left[v\left(\frac{d_{t+j+1}-\hat{p}}{\hat{p}}a_{\tau,t+j}\right)\right]=0.$$

Therefore, under the condition in equation (22),

$$\frac{\partial}{\partial a_{\tau,t}}\left\{\mathbb{E}_t[f\left(\theta_{\tau,t+j}\right)]\ \mathbb{E}_t\left[v\left(\frac{d_{t+j+1}-\hat{p}}{\hat{p}}a_{\tau,t+j}\right)\right]\right\}=\frac{\partial}{\partial a_{\tau,t}}\mathbb{E}_t[f\left(\theta_{\tau,t+j}\right)]\ \mathbb{E}_t\left[v\left(\frac{d_{t+j+1}-\hat{p}}{\hat{p}}a_{\tau,t+j}\right)\right],$$

for $j=1$, and it equals 0 for $j>1$.

Hence, terms in equation (40) with $j\geq 2$ do not enter the first-order condition for $a_{\tau,t}$ and can be omitted when solving for $\hat{a}^{\star}_{\tau,t}$. This yields the objective in equation (39). ■

Lemma 3 provides a closed-form expression for $\mathbb{E}_t[f\left(\theta_{\tau,t+1}\right)]$ in equation (39).

Lemma 3. *The period-t expectation of sensitivity in period $t+1$ is*

$$\mathbb{E}_t[f(\theta_{\tau,t+1})] = f(\theta_{\tau,t}) \exp\left\{ \frac{1}{\theta_{\tau,t}-1} \frac{\frac{\mu}{p_t} a_{\tau,t}}{w_{\tau,t}-a_{\tau,t}} + \frac{1}{2}\left(\frac{1}{\theta_{\tau,t}-1}\right)^2 \frac{a_{\tau,t}^2}{\hat{p}^2 (w_{\tau,t}-a_{\tau,t})^2}\sigma^2 \right\},$$

where $\hat{p}$ is the deterministic steady-state price of the risky asset.

Proof. From the law of motion in equation (9),

$$f(\theta_{\tau,t+1}) = \exp\left\{ \frac{\theta_{\tau,t}\beta (w_{\tau,t}-a_{\tau,t}) + \frac{a_{\tau,t}}{\hat{p}} d_{t+1}}{(\theta_{\tau,t}\beta - 1)(w_{\tau,t}-a_{\tau,t})} \right\}. \tag{41}$$

Under the simplifying assumption $\beta = 1$, equation (41) becomes

$$f(\theta_{\tau,t+1}) = \underbrace{\exp\left\{1 + \frac{1}{\theta_{\tau,t}-1}\right\}}_{=f(\theta_{\tau,t})} \exp\left\{ \frac{\frac{d_{t+1}}{\hat{p}} a_{\tau,t}}{(\theta_{\tau,t}-1)(w_{\tau,t}-a_{\tau,t})} \right\}.$$

Taking $\mathbb{E}_t[\cdot]$ and using $d_{t+1} \sim \mathcal{N}(\mu, \sigma^2)$ implies

$$\begin{aligned} \mathbb{E}_t[f(\theta_{\tau,t+1})] &= f(\theta_{\tau,t})\, \mathbb{E}_t\left[\exp\left\{ \frac{\frac{d_{t+1}}{\hat{p}} a_{\tau,t}}{(\theta_{\tau,t}-1)(w_{\tau,t}-a_{\tau,t})} \right\} \right] \\ &= f(\theta_{\tau,t}) \exp\left\{ \frac{\mu a_{\tau,t}}{\hat{p}(\theta_{\tau,t}-1)(w_{\tau,t}-a_{\tau,t})} + \frac{\sigma^2 a_{\tau,t}^2}{2\hat{p}^2 (\theta_{\tau,t}-1)^2 (w_{\tau,t}-a_{\tau,t})^2} \right\}, \end{aligned} \tag{42}$$

since the exponential term is log-normal. ■

We now combine Lemmas 2 and 3 to prove Proposition 3.

Proof. By the payoff distribution, for all $t' \geq t$,

$$\mathbb{E}_t\left[\frac{d_{t'+1} - \hat{p}}{\hat{p}}\right] = \frac{\mu - \hat{p}}{\hat{p}}, \tag{43}$$

$$\mathrm{Var}_t\left[\frac{d_{t'+1} - \hat{p}}{\hat{p}}\right] = \frac{\sigma^2}{\hat{p}^2}. \tag{44}$$

By Lemma 1,

$$\mathbb{E}_t\left[v\left(\frac{d_{t+1} - \hat{p}}{\hat{p}} a_{\tau,t}\right)\right] = \frac{g\left(\hat{p}\right)}{\hat{p}} a_{\tau,t}, \tag{45}$$

$$\mathbb{E}_t\left[v\left(\frac{d_{t+2} - \hat{p}}{\hat{p}} a_{\tau,t+1}\right)\right] = \frac{g\left(\hat{p}\right)}{\hat{p}} a_{\tau,t+1}, \tag{46}$$

where equation (46) holds because $a_{\tau,t+1}$ is chosen at time t.

Substituting equations (43)–(46) and (42) into equation (39), we can equivalently rewrite equation (19) as

$$\begin{aligned}
\max_{\{a_{\tau,t'}\}_{t'=t}^{\infty}} \; & \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \frac{\mu - \hat{p}}{\hat{p}} a_{\tau,t'} - \frac{1}{2}\gamma \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \left(\frac{\sigma^2}{\hat{p}^2} a_{\tau,t'}^2\right) \\
& + f\left(\theta_{\tau,t}\right) \frac{g\left(\hat{p}\right)}{\hat{p}} a_{\tau,t} + (1-\eta)\, \mathbb{E}_t[f\left(\theta_{\tau,t+1}\right)] \frac{g\left(\hat{p}\right)}{\hat{p}} a_{\tau,t+1} \\
\Leftrightarrow \; & \sum_{t'=t}^{\infty} (1-\eta)^{t'-t} \left(\frac{\mu - \hat{p}}{\hat{p}} a_{\tau,t'} - \frac{1}{2}\gamma \frac{\sigma^2}{\hat{p}^2} a_{\tau,t'}^2\right) + f\left(\theta_{\tau,t}\right) \frac{g\left(\hat{p}\right)}{\hat{p}} a_{\tau,t} \\
& + (1-\eta)\, f\left(\theta_{\tau,t}\right) \exp\left\{\frac{\mu a_{\tau,t}}{\hat{p}\left(\theta_{\tau,t} - 1\right)\left(w_{\tau,t} - a_{\tau,t}\right)} + \frac{\sigma^2 a_{\tau,t}^2}{2\hat{p}^2\left(\theta_{\tau,t} - 1\right)^2\left(w_{\tau,t} - a_{\tau,t}\right)^2}\right\} \frac{g\left(\hat{p}\right)}{\hat{p}} a_{\tau,t+1}.
\end{aligned}$$

Taking the partial derivative with respect to $a_{\tau,t}$ yields the first-order condition

$$\begin{aligned}
0 = & \frac{\mu - \hat{p}}{\hat{p}} - \gamma \frac{\sigma^2}{\hat{p}^2} \hat{a}^{\star}_{\tau,t} + \frac{g\left(\hat{p}\right)}{\hat{p}} f\left(\theta_{\tau,t}\right) + (1-\eta) \frac{g\left(\hat{p}\right)}{\hat{p}} \hat{a}^{\star}_{\tau,t+1} f\left(\theta_{\tau,t}\right) \\
& \times \underbrace{\exp\left\{ \frac{\mu \hat{a}^{\star}_{\tau,t}}{\hat{p}\left(\theta_{\tau,t}-1\right)\left(w_{\tau,t}-\hat{a}^{\star}_{\tau,t}\right)} + \frac{\sigma^2 \left(\hat{a}^{\star}_{\tau,t}\right)^2}{2\hat{p}^2 \left(\theta_{\tau,t}-1\right)^2 \left(w_{\tau,t}-\hat{a}^{\star}_{\tau,t}\right)^2} \right\}}_{\equiv A_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right)} \\
& \times \underbrace{\left[\frac{\mu}{\hat{p}\left(\theta_{\tau,t}-1\right)} + \frac{\sigma^2 \hat{a}^{\star}_{\tau,t}}{\hat{p}^2 \left(\theta_{\tau,t}-1\right)^2 \left(w_{\tau,t}-\hat{a}^{\star}_{\tau,t}\right)} \right]}_{\equiv B_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right)} \underbrace{\frac{w_{\tau,t}}{\left(w_{\tau,t}-\hat{a}^{\star}_{\tau,t}\right)^2}}_{\equiv C_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right)} .
\end{aligned} \tag{47}$$

Rearranging equation (47) gives equation (23):

$$\begin{aligned}
\hat{a}^{\star}_{\tau,t} = & \frac{\hat{p}\left(\mu - \hat{p}\right)}{\gamma \sigma^2} + \frac{\hat{p} g\left(\hat{p}\right)}{\gamma \sigma^2} f\left(\theta_{\tau,t}\right) \\
& \times \left[1 + \underbrace{(1-\eta)\, \hat{a}^{\star}_{\tau,t+1} A_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right) B_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right) C_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right)}_{= \xi_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \hat{a}^{\star}_{\tau,t+1}; \theta_{\tau,t}, w_{\tau,t}\right)} \right],
\end{aligned} \tag{48}$$

where $A_{\tau,t}(\cdot)$, $B_{\tau,t}(\cdot)$, and $C_{\tau,t}(\cdot)$ are defined in equation (47). ■

B7. Proof of Proposition 4

Proof. We impose three regularity conditions in Proposition 4. First, $g(\hat{p}) < 0$ for positive risky holdings, which holds when λ is sufficiently large given (μ, σ). Second, $a^{\star}_{\tau,\tau} > 0$, so that the myopic optimal risky holding is positive. Third, wealth must not be too small, as stated in equation (52).

By construction, $A_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right) > 0$ and $C_{\tau,t}\left(\hat{a}^{\star}_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\right) > 0$. Under the condition $g(\hat{p}) < 0$ for positive risky holdings, the definition of $g(\cdot)$ in equation (13) implies

$$(\mu - \hat{p}) \left[1 + (\lambda - 1)\, \Phi\!\left(-\frac{\mu - \hat{p}}{\sigma}\right)\right] + \phi\!\left(-\frac{\mu - \hat{p}}{\sigma}\right) \sigma\, (1 - \lambda) < 0$$

$$\Rightarrow \quad (\mu - \hat{p}) \left[-1 + (1 - \lambda)\, \Phi\!\left(-\frac{\mu - \hat{p}}{\sigma}\right)\right] + \phi\!\left(-\frac{\mu - \hat{p}}{\sigma}\right) \sigma\, (\lambda - 1) > 0. \tag{49}$$

For negative risky holdings, applying the same algebra as in Lemma 1 yields

$$(\mu - \hat{p}) \left[\lambda + (1 - \lambda)\, \Phi\!\left(-\frac{\mu - \hat{p}}{\sigma}\right)\right] + \phi\!\left(-\frac{\mu - \hat{p}}{\sigma}\right) \sigma\, (\lambda - 1) > 0, \tag{50}$$

which holds because the left-hand side of equation (50) exceeds the left-hand side of equation (49) when $\mu - \hat{p} > 0$ (implied by $a^\star_{\tau,\tau} > 0$ and $g(\hat{p}) < 0$). Hence, $\hat{a}^\star_{\tau,t+1} g(\hat{p}) < 0$ holds regardless of the sign of $\hat{a}^\star_{\tau,t+1}$.

It follows from equation (48) that the sign of $\xi_{\tau,t}\big(\hat{a}^\star_{\tau,t}, \hat{a}^\star_{\tau,t+1}; \theta_{\tau,t}, w_{\tau,t}\big)$ is determined by the sign of $B_{\tau,t}\big(\hat{a}^\star_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\big)$. In particular,

$$B_{\tau,t}\big(\hat{a}^\star_{\tau,t}, \theta_{\tau,t}, w_{\tau,t}\big) < 0 \quad \Longleftrightarrow \quad \hat{a}^\star_{\tau,t} < \hat{a}^{\text{cutoff}}_{\tau,t}, \text{ where } \hat{a}^{\text{cutoff}}_{\tau,t} = \frac{\mu \hat{p}\, (1 - \theta_{\tau,t})\, w_{\tau,t}}{\sigma^2 + \mu \hat{p}\, (1 - \theta_{\tau,t})}. \tag{51}$$

Step 1: Temperature smoothing at entry. With $\theta_{\tau,\tau} = 0$, equation (51) reduces to $\hat{a}^\star_{\tau,\tau} < \mu \hat{p}\, w_{\tau,\tau}/(\sigma^2 + \mu \hat{p})$. We impose the third regularity condition in terms of the *myopic* choice,

$$w_{\tau,\tau} > a^\star_{\tau,\tau} \left(1 + \frac{\sigma^2}{\mu \hat{p}}\right), \tag{52}$$

which is equivalent to $a^\star_{\tau,\tau} < \mu \hat{p}\, w_{\tau,\tau}/(\sigma^2 + \mu \hat{p})$. We now show that equation (52) implies

$\hat{a}^{\star}_{\tau,\tau} < \hat{a}^{\text{cutoff}}_{\tau,\tau}$. Suppose instead that $\hat{a}^{\star}_{\tau,\tau} \geq \hat{a}^{\text{cutoff}}_{\tau,\tau}$. Then $B_{\tau,\tau} \geq 0$ and hence $\xi_{\tau,\tau}(\cdot) \geq 0$. Because $g(\hat{p}) < 0$ and $f(\theta_{\tau,\tau}) = 1$, equation (23) implies $\hat{a}^{\star}_{\tau,\tau} \leq a^{\star}_{\tau,\tau}$, which contradicts $a^{\star}_{\tau,\tau} < \hat{a}^{\text{cutoff}}_{\tau,\tau} \leq \hat{a}^{\star}_{\tau,\tau}$. Therefore $\hat{a}^{\star}_{\tau,\tau} < \hat{a}^{\text{cutoff}}_{\tau,\tau}$, so $\xi_{\tau,\tau}(\cdot) < 0$. Since $g(\hat{p}) < 0$, equation (23) then implies $\hat{a}^{\star}_{\tau,\tau} > a^{\star}_{\tau,\tau}$.

Step 2: Existence of t_0 with $\hat{a}^{\star}_{\tau,t_0} < a^{\star}_{\tau,t_0}$. We show by contradiction that there exists $t_0 > \tau$ such that

$$\hat{a}^{\star}_{\tau,t_0} > \hat{a}^{\text{cutoff}}_{\tau,t_0} \quad \Longleftrightarrow \quad \xi_{\tau,t_0}(\cdot) > 0. \tag{53}$$

Suppose instead that $\hat{a}^{\star}_{\tau,t} < \hat{a}^{\text{cutoff}}_{\tau,t}$ for all $t \geq \tau$. Then $B_{\tau,t} < 0$ and hence $\xi_{\tau,t}(\cdot) < 0$ for all $t \geq \tau$. Because $g(\hat{p}) < 0$ and $f(\cdot) > 0$, equation (23) implies $\hat{a}^{\star}_{\tau,t} > a^{\star}_{\tau,t}$ for all $t \geq \tau$. Moreover, the myopic demand $a^{\star}_{\tau,t}$ is increasing in $\theta_{\tau,t}$ since

$$\frac{\partial a^{\star}_{\tau,t}}{\partial \theta_{\tau,t}} = \frac{\hat{p}\, g(\hat{p})}{\gamma \sigma^2} f'(\theta_{\tau,t}) > 0 \quad (\text{as } g(\hat{p}) < 0 \text{ and } f'(\theta) < 0 \text{ for } \theta \in [0,1)).$$

With $\beta = 1$ and $d_{t+1} = \mu > 0$ along the deterministic steady state, $\theta_{\tau,t}$ is nondecreasing and bounded above by one, hence $\theta_{\tau,t} \to 1$. Therefore, by equation (51),

$$\lim_{t \to \infty} \hat{a}^{\text{cutoff}}_{\tau,t} = 0. \tag{54}$$

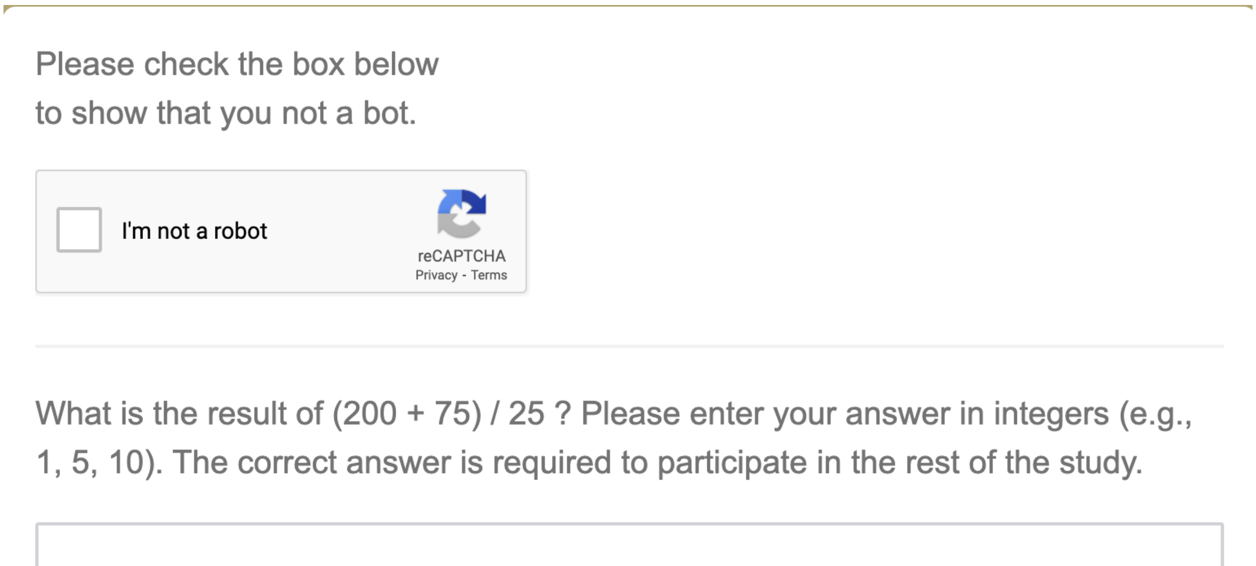
Since $\hat{a}^{\star}_{\tau,t} > a^{\star}_{\tau,t} \geq a^{\star}_{\tau,\tau} > 0$ for all $t \geq \tau$, equation (54) implies that there exists $t_0 > \tau$ such that $\hat{a}^{\star}_{\tau,t_0} > \hat{a}^{\text{cutoff}}_{\tau,t_0}$, contradicting the supposition. This establishes equation (53). Because $g(\hat{p}) < 0$, $\xi_{\tau,t_0}(\cdot) > 0$ implies $\hat{a}^{\star}_{\tau,t_0} < a^{\star}_{\tau,t_0}$, which completes the proof. ■

Internet Appendix C: Experiment Instructions

C1. Attention Checks

Figure 19: Attention Check

Subjects must pass the attention check below to participate in the study.



Please check the box below
to show that you not a bot.

I'm not a robot

reCAPTCHA
Privacy - Terms

What is the result of (200 + 75) / 25 ? Please enter your answer in integers (e.g., 1, 5, 10). The correct answer is required to participate in the rest of the study.

C2. Welcome Screen

Purpose and Procedures

- The purpose of this study is to examine decision-making in financial investment.
- You will be invited to complete a financial investment task.
- The study takes about 6 minutes to complete.
- You will receive financial remuneration for your participation. The exact amount depends on your investment decision. More details will be explained at the beginning of the investment task. To receive the remuneration, you need to complete the entire

study. At the end of the study, you will receive a completion code to be submitted on the Prolific platform.

Instructions

- You have two accounts: a savings account and a brokerage account. Each account has 100 Lira to begin with.
- For both accounts, the ending balance will be converted into USD at the pre-determined conversion rate and will be paid to you after the investment tasks are completed, so **the money in both accounts is yours**.
- There are 10 periods in total.
    - ▷ In the first 9 periods:
        - ◇ Your money in the **savings account** will be saved at a risk-free rate of 1% per period.
        - ◇ Your money in the **brokerage account** will be invested in a risky stock.
        - ◇ You can watch the investment performance of both accounts. No decision needs to be made.
    - ▷ In the last period:
        - ◇ You will need to make an investment decision.

C3. Demographics

Before getting started with the tasks, please answer the following questions.

- How old are you?
- Your gender
- Your highest level of education
- What was your total household income before taxes during the past 12 months?
- Your experience in financial investment

C4. First Nine Periods

- Investment now begins.
- Right now you have **100 Lira available in your savings account** and **100 Lira available in your brokerage account**.
- Click on "Next" to move into period 1.

Period 1

- Now, it comes to Period 1.
- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: all money deposited at the risk-free rate of 1%
    - ◇ Current account value: **100**
  - ▷ **Brokerage account**
    - ◇ Status: all money invested on a risky stock

- ◇ Current account value: **100**

- No action needed. Click on "Next" to continue.

Period 2

- Now, it comes to Period 2.
- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: risk-free deposit **earns** an interest of **1.00**.
    - ◇ Current account value: **101.00**.
  - ▷ **Brokerage account**
    - ◇ Status: risky stock investment **earns** a gain of **5.93**.
    - ◇ Current account value: **105.93**.
- No action needed. Click on "Next" to continue.

Period 3

- Now, it comes to Period 3.
- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: risk-free deposit **earns** an interest of **1.01**.
    - ◇ Current account value: **102.01**.

- ▷ **Brokerage account**
  - ◇ Status: risky stock investment **suffers** a loss of **7.58**.
  - ◇ Current account value: **98.35**.

- No action needed. Click on "Next" to continue.

Period 4

- Now, it comes to Period 4.
- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: risk-free deposit **earns** an interest of **1.02**.
    - ◇ Current account value: **103.03**.
  - ▷ **Brokerage account**
    - ◇ Status: risky stock investment **suffers** a loss of **50.73**.
    - ◇ Current account value: **47.62**.
- No action needed. Click on "Next" to continue.

Period 5

- Now, it comes to Period 5.
- The summary of your accounts:
  - ▷ **Savings account**

- ◇ Status: risk-free deposit **earns** an interest of **1.03**.
- ◇ Current account value: **104.06**.

▷ **Brokerage account**

- ◇ Status: risky stock investment **earns** a gain of **78.40**.
- ◇ Current account value: **126.02**.

- No action needed. Click on "Next" to continue.

Period 6

- Now, it comes to Period 6.
- The summary of your accounts:

▷ **Savings account**

- ◇ Status: risk-free deposit **earns** an interest of **1.04**.
- ◇ Current account value: **105.10**.

▷ **Brokerage account**

- ◇ Status: risky stock investment **suffers** a loss of **52.67**.
- ◇ Current account value: **73.35**.

- No action needed. Click on "Next" to continue.

Period 7

- Now, it comes to Period 7.

- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: risk-free deposit **earns** an interest of **1.05**.
    - ◇ Current account value: **106.15**.
  - ▷ **Brokerage account**
    - ◇ Status: risky stock investment **earns** a gain of **27.96**.
    - ◇ Current account value: **101.31**.
- No action needed. Click on "Next" to continue.

Period 8

- Now, it comes to Period 8.
- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: risk-free deposit **earns** an interest of **1.06**.
    - ◇ Current account value: **107.21**.
  - ▷ **Brokerage account**
    - ◇ Status: risky stock investment **earns** a gain of **49.71**.
    - ◇ Current account value: **151.02**.
- No action needed. Click on "Next" to continue.

Period 9

- Now, it comes to Period 9.
- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: risk-free deposit **earns** an interest of **1.07**.
    - ◇ Current account value: **108.29**.
  - ▷ **Brokerage account**
    - ◇ Status: risky stock investment **suffers** a loss of **74.87**.
    - ◇ Current account value: **76.15**.
- No action needed. Click on "Next" to continue.

C5. Last Period for Decision-Making

Period 10

- Now, it comes to Period 10.
- The summary of your accounts:
  - ▷ **Savings account**
    - ◇ Status: risk-free deposit **earns** an interest of **1.08**.
    - ◇ Current account value: **109.37**.
  - ▷ **Brokerage account**
    - ◇ Status: risky stock investment **earns** a gain of **32.51**.

    - Current account value: **108.66**.

- You need to make an investment decision. See the instructions below.

Brokerage-Account Treatment under Loss-Likely Scenario

- Your **savings account** is now **closed**.
  - The risk-free deposit is withdrawn and the cash balance of **109.37** has been recorded.
  - The balance will be converted into USD and paid to you after the tasks are completed.
- You will be using your **brokerage account cash** to make an **investment**.
  - The risky stock position is liquidated and the current brokerage account cash balance is **108.66**.
  - The final balance of your brokerage account will also be converted into USD and paid to you after the tasks are completed.
- There are two stocks to choose from, M and N. You will use your **brokerage account cash** to buy either 1 share of stock M or 1 share of stock N, then hold it for 1 period, and sell it next period to receive the cash.
  - Stock M:
    - Current price: 100 Lira per share
    - Next period price:

        - with a chance of 1/2 (50%), the price will become 90 (i.e., ***loss of 10*** from the price change)
        - with a chance of 1/2 (50%), the price will become 110 (i.e., ***gain of 10*** from the price change)

  - Stock N:
    - Current price: 100 Lira per share
    - Next period price:
        - with a chance of 1/2 (50%), the price will become 50 (i.e., ***loss of 50*** from the price change)
        - with a chance of 1/2 (50%), the price will become 150 (i.e., ***gain of 50*** from the price change)

  - The next period prices of stock M and stock N are **independent** from each other and **independent** from the risky asset price in the past 9 periods.

Brokerage-Account Treatment under Loss-Unlikely Scenario

- Your **savings account** is now **closed**.
  - The risk-free deposit is withdrawn and the cash balance of **109.37** has been recorded.
  - The balance will be converted into USD and paid to you after the tasks are completed.
- You will be using your **brokerage account cash** to make an **investment**.

- ▷ The risky stock position is liquidated and the current brokerage account cash balance is **108.66**.
- ▷ The final balance of your brokerage account will also be converted into USD and paid to you after the tasks are completed.

- There are two stocks to choose from, M and N. You will use your **brokerage account cash** to buy either 1 share of stock M or 1 share of stock N, then hold it for 1 period, and sell it next period to receive the cash.
  - ▷ Stock M:
    - ◇ Current price: 100 Lira per share
    - ◇ Next period price:
      - · with a chance of 1/2 (50%), the price will become 140 (i.e., ***gain of 40*** from the price change)
      - · with a chance of 1/2 (50%), the price will become 160 (i.e., ***gain of 60*** from the price change)
  - ▷ Stock N:
    - ◇ Current price: 100 Lira per share
    - ◇ Next period price:
      - · with a chance of 1/2 (50%), the price will become 100 (i.e., ***no gain or loss*** from the price change)
      - · with a chance of 1/2 (50%), the price will become 200 (i.e., ***gain of 100*** from the price change)

- ▷ The next period prices of stock M and stock N are **independent** from each other and **independent** from the risky asset price in the past 9 periods.

Savings-Account Treatment under Loss-Likely Scenario

- Your **brokerage account** is now **closed**.
  - ▷ The risky stock position is liquidated and the cash balance of **108.66** has been recorded.
  - ▷ The balance will be converted into USD and paid to you after the tasks are completed.
- You will be using your **savings account cash** to make an **investment**.
  - ▷ The risk-free deposit is withdrawn and the current savings account cash balance is **109.37**.
  - ▷ The final balance of your savings account will also be converted into USD and paid to you after the tasks are completed.
- There are two stocks to choose from, M and N. You will use your **savings account cash** to buy either 1 share of stock M or 1 share of stock N, then hold it for 1 period, and sell it next period to receive the cash.
  - ▷ Stock M:
    - ◇ Current price: 100 Lira per share
    - ◇ Next period price:

    - with a chance of 1/2 (50%), the price will become 90 (i.e., ***loss of 10*** from the price change)
    - with a chance of 1/2 (50%), the price will become 110 (i.e., ***gain of 10*** from the price change)

- ▷ Stock N:
  - ◇ Current price: 100 Lira per share
  - ◇ Next period price:
    - with a chance of 1/2 (50%), the price will become 50 (i.e., ***loss of 50*** from the price change)
    - with a chance of 1/2 (50%), the price will become 150 (i.e., ***gain of 50*** from the price change)
- ▷ The next period prices of stock M and stock N are **independent** from each other and **independent** from the risky asset price in the past 9 periods.

Savings-Account Treatment under Loss-Unlikely Scenario

- Your **brokerage account** is now **closed**.
  - ▷ The risky stock position is liquidated and the cash balance of **108.66** has been recorded.
  - ▷ The balance will be converted into USD and paid to you after the tasks are completed.
- You will be using your **savings account cash** to make an **investment**.

- ▷ The risk-free deposit is withdrawn and the current savings account cash balance is **109.37**.
- ▷ The final balance of your savings account will also be converted into USD and paid to you after the tasks are completed.

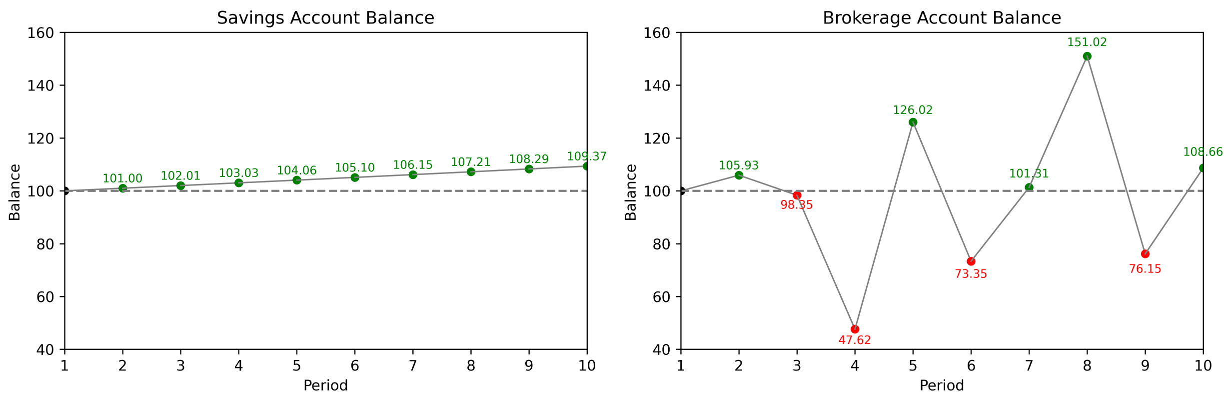
- There are two stocks to choose from, M and N. You will use your **savings account cash** to buy either 1 share of stock M or 1 share of stock N, then hold it for 1 period, and sell it next period to receive the cash.
  - ▷ Stock M:
    - ◇ Current price: 100 Lira per share
    - ◇ Next period price:
      - · with a chance of 1/2 (50%), the price will become 140 (i.e., ***gain of 40*** from the price change)
      - · with a chance of 1/2 (50%), the price will become 160 (i.e., ***gain of 60*** from the price change)
  - ▷ Stock N:
    - ◇ Current price: 100 Lira per share
    - ◇ Next period price:
      - · with a chance of 1/2 (50%), the price will become 100 (i.e., ***no gain or loss*** from the price change)
      - · with a chance of 1/2 (50%), the price will become 200 (i.e., ***gain of 100*** from the price change)

▷ The next period prices of stock M and stock N are **independent** from each other and **independent** from the risky asset price in the past 9 periods.

C6. Performance of Two Accounts

Figure 20: Performance of the Two Accounts

This figure is shown to subjects in every period with data points up to that period. For example, in period 5 the figure displays only the first five data points. The figure below is shown in period 10, the decision period.



C7. Post-Investment Questions

- Before seeing the outcome of your risky investment, please click on "Next" to answer a few questions.

- Now, please evaluate your risk tolerance for your two accounts as of period 10.

  ▷ 0 represents no tolerance for risk at all: you would strongly prefer the cash in that account be saved at the risk-free rate only.

  ▷ 10 represents great tolerance for risk: you very much want to use the cash in that account for risky investment, even if large profit and large loss are both possible.

- If there was an additional **loss of 50** in one of your two accounts, how painful/unacceptable would it be for your two accounts respectively as of period 10?
  - ▹ 0 represents not painful or unacceptable at all.
  - ▹ 10 represents very painful or unacceptable.
- If there was an additional **gain of 50** in one of your two accounts, how happy/exciting would it be for your two accounts respectively as of period 10?
  - ▹ 0 represents not happy/exciting at all.
  - ▹ 10 represents very happy/exciting.

Internet Appendix D: Experimental Evidence on Investor Heterogeneity

We use demographic information to examine heterogeneity in the treatment effect. Specifically, we estimate:

$$\log\left(\frac{\pi}{1-\pi}\right) = \alpha_0 + \alpha_1\,\text{Hot} + \sum_{\text{Demo}_k \in \mathbb{D}} \left(\alpha_k\,\text{Demo}_k \times \text{Hot} + \beta_k\,\text{Demo}_k\right). \tag{55}$$

where π is the probability of selecting the riskier stock and Hot is an indicator that equals one for participants in the brokerage-account treatment. The demographic variables $\mathbb{D} = \{\text{Inc}, \text{Exp}, \text{Gen}, \text{Edu}\}$ capture income, trading experience, gender, and education.

Table 22 reports results for the four demographic variables both individually and jointly. The coefficient α_1 captures the baseline treatment effect: it is positive and statistically significant under the loss-likely scenario (columns 1–6) but is absent under the loss-unlikely scenario (columns 7–12), consistent with Figures 8 and 9.

The interaction coefficient α_k captures heterogeneity relative to the baseline. Heterogeneity is statistically significant only for income, suggesting a diminished cash-temperature effect among higher-income participants. Other demographic factors—trading experience, gender, and education—do not significantly moderate the effect.

Table 22: Heterogeneity

This table reports the estimates from the logit regression (55) of Riskier (i.e., an indicator for buying the riskier stock in the last period) on Hot (i.e., an indicator for brokerage-account treatment), the four demographic variables, and their interactions with Hot. For the demographic variables, Inc is an indicator that equals 1 if the subject's income is above sample median; Exp is an indicator that equals 1 if the subject's trading experience is above sample median; Gen is an indicator that equals 1 if the subject is male; Edu is an indicator that equals 1 if the subject's education level is at least high school. Control variables include the time spent in the decision-making period and time spent for the entire study. Robust t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8	9	10	11	12
	Dependent Variable: Riskier											
	Loss-Likely Sample						Loss-Unlikely Sample					
Hot	0.600**	1.242***	0.847**	1.021**	0.709**	1.872***	0.074	0.318	−0.483	−0.243	0.295	0.015
	(2.10)	(3.01)	(2.03)	(2.41)	(2.25)	(3.19)	(0.23)	(0.70)	(−0.98)	(−0.51)	(0.78)	(0.02)
Inc × Hot		−1.407**				−1.520**		−0.476				−0.975
		(−2.36)				(−2.24)		(−0.75)				(−1.46)
Inc		0.057				0.236		0.076				0.449
		(0.14)				(0.53)		(0.17)				(0.95)
Exp × Hot			−0.594			−0.039			0.992			1.103
			(−1.02)			(−0.06)			(1.52)			(1.64)
Exp			−0.448			−0.597			−0.441			−0.397
			(−1.09)			(−1.33)			(−0.97)			(−0.87)
Gen × Hot				−0.797		−0.759				0.576		0.335
				(−1.37)		(−1.20)				(0.90)		(0.51)
Gen				0.436		0.541				−0.457		−0.365
				(1.04)		(1.17)				(−1.01)		(−0.77)
Edu × Hot					−0.625	−1.004					−0.590	−0.705
					(−0.82)	(−1.11)					(−0.79)	(−0.92)
Edu					0.351	0.205					0.994**	1.033*
					(0.65)	(0.34)					(2.04)	(1.93)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.0188	0.0567	0.0461	0.0256	0.0212	0.0831	0.0022	0.0057	0.0123	0.0069	0.0217	0.0413
Obs.	204	204	204	204	204	204	201	201	201	201	201	201