Mired in Losses:
How the Disposition Effect Depresses Purchase Behavior

Brad M. Barber[x], Rongtai Chu[*], Yu-Jane Liu[†], Terrance Odean[‡], and Yushui Shi[§]

March 29, 2026

JEL Classification: G11 G41 G14

Keywords: Disposition effect, Stock recommendations, Purchase behavior

[x] Graduate School of Management, University of California, Davis, USA, email: bmbarber@ucdavis.edu
[*] Guanghua School of Management, Peking University, Beijing, China, email: churongtai@stu.pku.edu.cn
[†] Guanghua School of Management, Peking University, Beijing, China, email: yjliu@gsm.pku.edu.cn
[‡] Haas School of Business, University of California, Berkeley, USA, email: odean@berkeley.edu
[§] Monash Business School, Monash University, Australia, email: yushui.shi@monash.edu

Mired in Losses:
How the Disposition Effect Depresses Purchase Behavior

Abstract

Retail investors are less likely to purchase recommended stocks when their portfolios are dominated by unrealized losses. We propose two mechanisms: liquidity and engagement. Investors often finance new purchases by selling existing positions, and reluctance to realize losses can constrain financing. Consistent with a liquidity channel, the negative relation between loss exposure and buying weakens when investors hold more cash and strengthens when trading halts restrict the sale of gain positions. Investors who subscribe to stock recommendations are less likely to view recommendations when they have greater loss exposure, accounting for as much as one-third of their decline in buying.

Consider an investor faced with a new buying opportunity. To take advantage of it, the investor must first engage with the opportunity—review the information and decide whether it is worth pursuing—and then find a way to finance the purchase. If the investor's portfolio is dominated by unrealized losses, confronting the opportunity may draw attention to those losses, and financing the purchase may require realizing one of them. Faced with this prospect, the investor may ignore the opportunity or decline to act on it. In contrast, when unrealized gains are available, funding a new position may be easier and less psychologically costly. Thus, the distribution of unrealized gains and losses in a portfolio may shape not only selling decisions but also investors' willingness to initiate new positions.

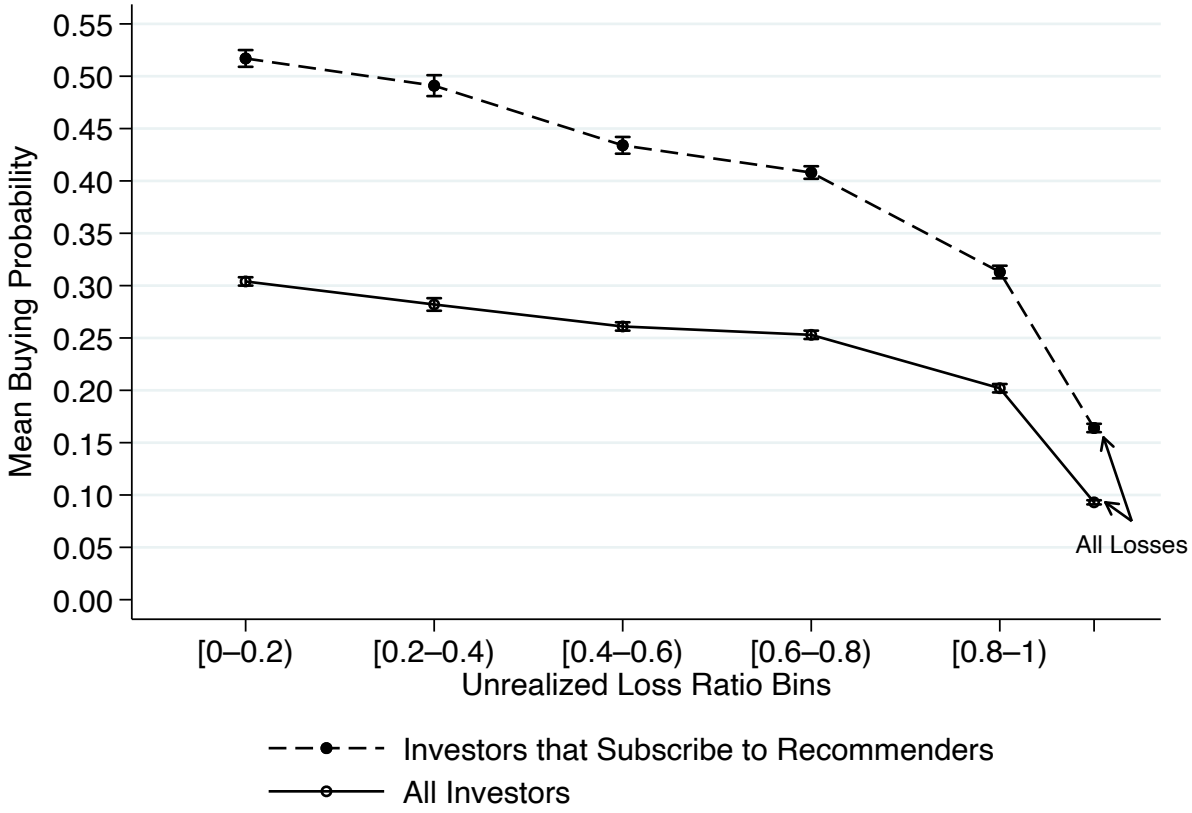
A large literature documents that investors are reluctant to realize losses and more willing to realize gains, a phenomenon known as the disposition effect (Shefrin and Statman 1985; Odean 1998; Kaustia 2004; Frazzini 2006). Prior studies examine how this reluctance distorts selling behavior across asset classes, countries, and investor types. This literature naturally focuses on the selling decisions of investors but does not consider their implications for buying decisions. If selling and buying decisions are linked, either because new purchases are financed through sales of existing holdings or because confronting losses discourages engagement, then the aversion to realizing losses may affect investors' buying decisions. This paper provides novel evidence that unrealized loss exposure significantly reduces the likelihood that investors initiate new stock purchases.

To study how unrealized gains and losses influence buying behavior, we use detailed account-level data from a large Chinese brokerage platform from 2021 to 2023. The data record daily portfolio holdings and transactions, allowing us to measure the distribution of unrealized gains and losses in each investor's portfolio and track when they initiate new stock purchases.

We begin by documenting a simple empirical pattern in investors' trading activity. Figure 1 plots the probability that an investor purchases any stock on a given day as a function of the investor's unrealized loss ratio (ULR), defined as the fraction of portfolio positions held at a loss. Buying declines steadily as ULR increases and drops sharply when investors hold only loss positions. This pattern suggests that unrealized loss exposure discourages investors from initiating new positions.

Figure 1. Mean Daily Buying Probability by Unrealized Loss Ratio (*ULR*) Bins

This figure plots the probability that an investor purchases any stock on a given day as a function of the investor's unrealized loss ratio (*ULR*), defined as the fraction of portfolio positions held at a loss. The sample is 445,188 investors at a Chinese broker from 2021 to 2023. *ULR* bins are constructed in 20 percentage point intervals, along with a separate bin for investors whose entire portfolio consists of loss positions ("All Losses"). The plotted points represent estimated mean buying probabilities within each bin. Whiskers represent 95% confidence intervals based on standard errors clustered by investor and day.



While this evidence suggests that unrealized loss exposure discourages investors from initiating new positions, interpreting the relation between portfolio losses and buying activity is difficult because investors face different investment opportunities at different times. In typical account-level datasets, researchers observe purchases and holdings but cannot precisely measure the investment opportunities available to each investor at a given moment. A lack of buying may reflect the absence of compelling opportunities or limited awareness rather than reluctance to act, as emphasized in prior work on attention-driven trading (Barber and Odean 2008; Da, Engelberg, and Gao 2011). For example, investors with better investment opportunities may both trade more

actively and experience fewer losses, potentially generating a spurious negative relation between loss exposure and buying. To address this challenge, we exploit a setting in which retail investors trading through a large Chinese brokerage platform subscribe to licensed stock recommenders and receive buy recommendations through the platform.[1] Because recommendations are distributed exclusively to subscribed investors and are time-stamped, we observe which investors face the same investment opportunity at the same moment and whether they act on it.

A distinctive feature of our data is that we observe whether investors click through to view detailed information about each recommendation after receiving a notification in the brokerage application. These click-through data allow us to distinguish between engagement and execution decisions and to assess whether reduced buying among investors with unrealized losses reflects a lack of engagement with new investment opportunities or a reluctance to purchase following engagement.

Our sample includes 108 independent stock recommenders who notify 19,988 subscribed investors of more than 12,000 recommendations issued through the platform between 2021 and 2023. Investors who subscribe to recommenders trade more frequently than other investors at the brokerage firm but exhibit the same pattern: buying declines when their portfolios are dominated by unrealized losses (see Figure 1).

Our empirical design compares investors' decisions to purchase the same recommended stock on the same day, while controlling for investor–recommender and recommendation-date fixed effects. By holding constant the specific recommendation and its timing, we ensure that differences in buying behavior are not driven by variation in recommendation quality, stock characteristics, or common market conditions. Identification therefore comes from within-investor variation in portfolio loss exposure across recommendation dates. This setting provides a particularly clean environment to isolate how unrealized portfolio gains and losses affect investors' purchase behavior.

We find that unrealized loss exposure significantly reduces investors' willingness to purchase recommended stocks. The unconditional probability that an investor buys a recommended stock on the recommendation date is 6.3%, whereas investors whose portfolios

[1] The recommendations in our setting predict short-term returns consistent with prior evidence on analyst recommendations (Womack 1996; Barber, Lehavy, McNichols and Trueman 2001). However, positive abnormal returns are not necessary for our analysis. Our design requires only that investors perceive the recommendations as potential investment opportunities and act on them.

consist entirely of unrealized losses are approximately 4 percentage points (ppts) less likely to buy, a decline exceeding 60% relative to the baseline purchase rate. The relation between buying and the unrealized loss ratio is monotonic, with a particularly sharp drop when investors hold no unrealized gains. These findings demonstrate that the disposition effect affects not only selling but also buying decisions. We examine two mechanisms underlying this effect: a liquidity mechanism, in which reluctance to realize losses constrains financing, and an engagement mechanism, in which confronting losses discourages participation.

We first test the liquidity mechanism by examining whether the negative relation between loss exposure and buying weakens when investors have greater available cash. Consistent with the liquidity mechanism, the adverse effect of unrealized losses on purchasing is significantly attenuated among investors with higher cash balances. When investors hold sufficient cash to fund an additional average-sized position, the decline in buying associated with loss exposure is substantially reduced. These findings support a liquidity-based explanation for the decline in purchase activity.

We further test the liquidity mechanism using trading halts, which provide an exogenous shock to the tradability of positions in investors' portfolios. Halts restrict the ability to liquidate specific holdings but do not directly alter investors' beliefs about the attractiveness of new recommendations, thereby isolating the role of realizable gains in financing purchases. Consistent with the liquidity mechanism, halts affecting positions held at gains significantly reduce the likelihood that investors purchase recommended stocks, whereas halts affecting loss positions have no meaningful effect. The decline in buying is largest when the halted position represents the investor's only unrealized gain. This asymmetric response suggests that the availability of realizable gains causally shapes investors' willingness to initiate new positions.

We also examine an engagement mechanism, whereby an unwillingness to confront unrealized losses discourages investors from even considering new opportunities, an "ostrich effect" documented in prior research (Karlsson, Loewenstein, and Seppi 2009; Sicherman et al. 2016). Investors whose portfolios consist entirely of unrealized losses are approximately 28% less likely to view detailed information about buy recommendations in the brokerage application. However, the negative relation between loss exposure and purchasing remains strong even conditional on viewing the recommendation. Back-of-the-envelope calculations suggest that reduced engagement accounts for at most about one-third of the overall decline in buying,

indicating that the liquidity mechanism we propose plays a larger role in the behavior we document.

The effect of loss exposure extends beyond the recommender setting. Investors whose portfolios are dominated by unrealized losses are less likely to initiate new stock positions more generally, not just to follow specific recommendations (see Figure 1). This pattern suggests that loss exposure may distort capital reallocation decisions broadly rather than reflecting features unique to the recommendation environment.

We consider alternative explanations for our findings, including changing beliefs about recommendation quality, time-varying overconfidence following investor gains, and shifts in risk preferences. Several features of the evidence are difficult to reconcile with these accounts. Because we compare investors responding to the same recommendation at the same time, cross-investor differences in buying are not driven by variation in opportunity quality. Moreover, the negative relation between loss exposure and buying is significantly attenuated when investors hold greater cash balances, a pattern that is hard to explain through belief updating, confidence, or risk-preference channels but consistent with a liquidity-based mechanism. The asymmetric response to trading halts further reinforces this interpretation: halts restrict the ability to liquidate gain positions but do not directly alter beliefs about new opportunities, yet halts affecting gains reduce buying while halts affecting losses do not. Finally, the absence of systematic interactions between loss exposure and recommended stock risk characteristics provides little support for a risk-preference explanation. Taken together, the evidence is most consistent with a behavioral mechanism rooted in loss realization aversion.

This paper contributes to a large literature documenting the disposition effect, the tendency of investors to sell investments held at a gain more readily than those held at a loss. Evidence spans equities (Odean 1998; Grinblatt and Keloharju 2001; Frazzini 2006), employee stock options (Heath, Huddart, and Lang 1999), real estate (Genesove and Mayer 2001), derivatives (Locke and Mann 2005; Bergsma, Fodor, and Tedford 2020), cryptocurrencies (Schatzmann and Haslhofer 2023), and contracts for differences (Breitmayer, Hasso, and Pelster 2019). The disposition effect has been documented across countries and investor types.[2]

[2] Evidence of the disposition effect using retail trading data includes the United States (Odean 1998; Dhar and Zhu 2006), Finland (Grinblatt and Keloharju 2001), Israel (Shapira and Venezia 2001), Taiwan (Barber, Lee, Liu, and Odean 2007), the United Kingdom (Richards et al. 2017), China (Cai, Wang, and Bai 2018), and Australia (Jackson

Experimental and neuroeconomic evidence further supports realization utility and anticipated regret as mechanisms underlying this behavior (Weber and Camerer 1998; Frydman et al. 2014; Summers and Duxbury 2012; Frydman and Camerer 2016), and related experimental work highlights behavioral differences between realized and paper losses (Imas 2016). Several theoretical models formalize realization utility as a foundation for the disposition effect (Barberis and Xiong 2012; Ingersoll and Jin 2013). While this literature focuses on selling decisions, we show that the reluctance to sell losers also influences purchase behavior.

Our findings also relate to research examining how past trading outcomes influence subsequent purchase decisions. Investors are more likely to repurchase previously sold stocks after price declines (Strahilevitz, Odean, and Barber 2011) and to buy additional shares of stocks they already own following losses (Odean 1998). In contrast, we examine the initiation of entirely new positions. Because the securities in our setting are not currently held in the investor's portfolio, we show that unrealized losses in unrelated portfolio holdings reduce investors' willingness to pursue new investment opportunities, indicating that the effects of loss realization aversion can spill over across securities and influence broader capital reallocation decisions.

Our findings also relate to recent work that shows investors' portfolio composition can shape selling behavior. An et al. (2024) show that the disposition effect operates at the portfolio level, affecting investors' decisions to realize gains and losses among existing holdings. In contrast, we examine how unrealized loss exposure influences investors' willingness to initiate entirely new positions. Our results show that unrealized losses not only distort selling decisions but can also suppress the initiation of new positions, slowing the reallocation of capital toward new investment opportunities.

More broadly, our findings suggest that loss exposure may contribute to fluctuations in trading activity. Prior research links market returns to subsequent trading volume, often attributed to overconfidence reinforced by self-attribution following gains (Statman, Thorley, and Vorkink 2006). Our results highlight a complementary mechanism: when portfolios are dominated by unrealized gains, investors may be more willing to initiate new positions, whereas widespread losses may discourage participation and slow capital reallocation. While we do not directly test

2003). The effect has also been documented among institutional and professional investors, including mutual fund managers (Cici 2012) and derivatives traders (Bergsma, Fodor, and Tedford 2020).

aggregate trading dynamics, our evidence suggests that loss realization aversion may contribute to procyclical trading activity.

1. Stock Recommenders

This section describes the institutional setting in which licensed stock recommenders distribute recommendations to subscribed investors and explains how we observe investor responses to common investment opportunities.

1.1. Institutional Setting and Regulatory Structure

Professional stock recommenders, employed by brokerage firms, provide recommendations to subscribed retail investors. Recommenders hold the legally required certification for securities investment advisory services issued by the China Securities Regulatory Commission (CSRC), which regulates their professional conduct and advisory activities. During our sample period from 2021 to 2023, our data include 108 independent stock recommenders.

Under CSRC regulations, a licensed recommender may be employed by only one institution at a time and is prohibited from issuing investment recommendations through public media such as television, radio, newspapers, or open online platforms. As a result, recommendations are disseminated exclusively through the brokerage's proprietary platform to subscribed investors. This institutional structure allows us to precisely identify which investors receive a given recommendation and when they receive it.

The brokerage platform displays performance metrics for each recommender, including the average holding-period return of recommended stocks and the fraction of recommendations classified as winners. These statistics are observable to potential subscribers and form part of the information environment in which investors choose whether to follow a recommender.

In Internet Appendix Table IA.1, we document that purchase recommendations positively predict short-term returns, suggesting that investors receive non-trivial investment opportunities from recommenders, which is consistent with a large body of work that documents that analyst recommendations provide investment value (Womack 1996, Barber et al. 2001).

Importantly, our empirical design does not rely on recommendations generating positive abnormal returns. Identification comes from cross-investor variation in purchase decisions conditional on receiving the same recommendation at the same time. As long as investors perceive

recommendations as meaningful opportunities worth considering, heterogeneity in take-up allows us to test how portfolio composition influences purchase behavior.

1.2. Subscription and Investor Information Environment

Investors gain access to recommendations by subscribing to a specific stock recommender through the brokerage platform. Each recommender maintains a dedicated homepage displaying historical performance statistics and related information. (Internet Appendix Figure IA.1 provides a screenshot of the recommender homepage.) Prior to subscription, investors can review summary performance metrics to evaluate the recommender. Access to detailed recommendation histories and ongoing recommendation pools is granted only after subscription.

At the time of subscription, investors choose between a fixed-fee scheme and a transaction-based pricing scheme, with fees and commission rates set by the recommender and disclosed contractually. In our sample, the vast majority of subscriptions are transaction-based. Investors may terminate their subscription at any time and may subscribe to up to three recommenders simultaneously. Because recommendations are accessible only to subscribed investors, and subscription decisions are observable in our data, we are able to precisely determine the set of investment opportunities available to each investor at any point in time.

1.3. Recommendation Issuance, Delivery, and Observability

Recommenders issue buy and sell recommendations for A-share stocks and exchange-traded funds during trading hours. Each recommendation is timestamped by the platform at the moment it is released. Buy recommendations add a stock to the recommender's active pool, while sell recommendations remove it. For each recommendation, the recommender provides a textual rationale that is available on the platform.

Whenever a recommendation is issued, subscribed investors receive immediate notifications via multiple channels, including SMS, WeChat, and smartphone push notifications. These notifications contain the recommender's name, the recommended stock, and the prevailing price at the time of issuance. (Internet Appendix Figure IA.2 provides screenshots of sample notifications.) Investors may then access the brokerage's mobile application to review detailed information about the recommendation and its rationale.

Importantly, we observe high-frequency browsing data from the brokerage's mobile application, allowing us to identify whether an investor views the detailed recommendation information on the day it is issued. (See Internet Appendix Figure IA.3 and discussion for details.) This feature enables us to distinguish between investors who actively consider a recommendation and those who do not engage with it.

2. Data and Summary Statistics

This section describes the data sources, sample construction, variable definitions, and summary statistics used in the analysis.

2.1. Data Sources

The data were provided by a listed brokerage company in China on an anonymous, secure, and restricted-access basis. All analyses were conducted on an internal secured server.

We combine five primary data sources. First, we use detailed data on stock recommenders and investors' subscriptions from 2021 to 2023. These data include recommender identifiers, subscription periods, subscription pricing schemes, and the universe of buy and sell recommendations issued by each recommender. For each recommendation, we observe the recommended stock, the issuance date and time, and the accompanying textual rationale.

Second, we use investors' trade-level data from their general brokerage accounts over the period 2018–2023. These data include stock (or ETF) codes, order and trade timestamps (to the millisecond), trade volume, transaction value (excluding commission), and commission paid.

Third, we use daily holdings data from investors' general accounts over the same period. These data include the number of shares held, market value, and holding cost for each position, as well as cash balances. The holding cost and market value are calculated and recorded directly by the brokerage and correspond to the values displayed to investors in the mobile application.

Fourth, we observe investors' demographic characteristics and high-frequency in-app browsing behavior from the brokerage's mobile application. The browsing data record individual page views and on-page interactions with timestamps accurate to the second.

Finally, we merge these proprietary data with stock-level characteristics obtained from the China Stock Market & Accounting Research (CSMAR) database.

2.2. Sample Construction

Our main unit of observation is the investor–recommender–stock–date level. An observation is created when investor *i* receives a buy recommendation for stock *s* from recommender *r* on date *t*.

Our sample includes 19,988 investors who subscribed to at least one stock recommender and purchased at least one recommended stock during the sample period. We observe 108 independent stock recommenders who issued 12,367 buy recommendations between 2021 and 2023. Combining investors, recommenders, and recommendations yields 1,796,840 investor–recommender–stock–date observations.

We apply two filters. First, we require that the recommended stock *s* is not already held in investor *i*'s portfolio on the day prior to the buy recommendation. Second, because investors may subscribe to up to three recommenders simultaneously, we exclude observations where the same stock *s* is recommended by multiple subscribed recommenders within ten trading days following date *t*. Because identification relies on within investor–recommender and within recommendation-date variation, observations corresponding to singleton fixed-effect groups do not contribute to estimation and are excluded. After applying these filters, the final sample consists of 1,732,402 observations.

2.3. Variable Construction

2.3.1. Dependent Variable: *Buy*

Our primary dependent variable, Buy_{irst}, is an indicator equal to one if investor *i* purchases stock *s* on date *t* with a trade timestamp strictly after the timestamp of recommender *r*'s buy recommendation, and zero otherwise. As an alternative specification, *Buy* equals one if investor *i* purchases stock *s* within ten days of the recommendation.

Purchases refer exclusively to transactions executed through the investor's general brokerage account. Although some investors maintain margin accounts, only 0.7% of recommendations are followed through margin purchases within ten trading days, indicating that nearly all purchase activity occurs in general accounts.

2.3.2. Key Independent Variables: *ULR* and *All_Loss*

Our key explanatory variable is the Unrealized Loss Ratio (*ULR*). *ULR* measures the fraction of investor *i*'s portfolio positions whose market value is below their holding cost as of the day prior to date *t*. A position is classified as an unrealized loss position if its current market value is lower than its holding cost; otherwise, it is classified as an unrealized gain position.

Holding cost, market value, and paper profits are calculated at both the portfolio and individual security level and recorded directly by the brokerage and correspond to the information displayed to investors in the mobile application (see Internet Appendix Figure IA.4). We therefore rely on the same loss classifications that investors observe when making trading decisions. Note that positive paper profits are displayed in red font and losses in blue font making the distinction visually salient.

As an alternative specification, we define *All_Loss*, an indicator equal to one if *ULR* equals one for investor *i* on the day prior to date *t*, and zero otherwise. This specification captures the fully constrained state in which all positions in the investor's portfolio are held at unrealized losses.

2.3.3. Other Variables

In the baseline specification, we include recent portfolio returns measured prior to date *t* as time-varying investor-level controls. Recommendation-date fixed effects absorb all stock-level characteristics and common shocks associated with a given recommendation, rendering separate stock-level controls redundant. In additional analyses, we sort investors by trading frequency, portfolio size, and disposition-effect measures to examine heterogeneity in responses. Detailed definitions of all variables are provided in Internet Appendix Table IA.2.

2.4. Summary Statistics

2.4.1. Regression-Level Variables

Table 1 reports summary statistics for the main variables used in the regression analysis at the investor–recommender–stock–date level. The unconditional probability that investor *i* purchases recommended stock *s* is 6.3% on the day of the recommendation and 8.4% within ten trading days of the recommendation date.

The average *ULR* equals 0.717, indicating that investors hold a substantial fraction of their portfolios at unrealized losses prior to recommendation dates. The indicator *All_Loss* equals one

in 22.9% of observations, suggesting that investors frequently face situations in which all existing positions are in a paper-loss state.

Table 1. Descriptive Statistics

This table reports descriptive statistics of investor-recommender-stock-date observations used to estimate the main results. Buy is an indicator variable equal to one if the recommended stock is bought (either on the same day or within 10 days of the recommendation). *ULR* is the number of unrealized losses divided by the total number of positions. *All_Loss* is an indicator equal to one if all positions are held at a loss. *Portfolio_ret* (x,y) is the portfolio return from day x to y. Halt is an indicator variable equal to one if a stock in the investor's portfolio has a trading halt on the day of the recommendation. *PortfolioCashRatio* is defined as the portfolio share of cash holdings. *PositionCashRatio* is the ratio of cash holdings to the investor's average position size over the past 250 trading days. *SufficientCash* is an indicator variable equal to one if *PositionCashRatio* > 1. View is an indicator variable that equals one if the investor viewed detailed information about the recommender's stock recommendation.

	N	Mean	SD	p25	p50	p75
Buy (Same day)	1,732,428	0.063	0.243	-	-	-
Buy (10 days)	1,732,428	0.084	0.277	-	-	-
ULR (Unrealized loss ratio)	1,732,428	0.717	0.256	0.556	0.750	0.938
All_Loss	1,732,428	0.229	0.420	-	-	-
Portfolio_ret (-5, -1) (%)	1,732,428	-0.069	0.157	-0.122	-0.021	0.027
Portfolio_ret (-20, -6) (%)	1,732,428	-0.209	0.330	-0.322	-0.072	0.016
Portfolio_ret (-250, -21) (%)	1,732,428	-5.241	6.342	-7.583	-2.246	-0.581
Halt	1,732,428	0.006	0.077	-	-	-
PortfolioCashRatio	1,732,428	0.167	0.217	0.005	0.066	0.259
PositionCashRatio	1,732,428	1.571	2.046	0.031	0.576	2.371
SufficientCash	1,732,428	0.412	0.492	-	-	-
View	1,732,428	0.322	0.467	-	-	-
Buy (*Same day*) | *View* = 1	557,518	0.162	0.369	-	-	-

The table also reports descriptive statistics for recent portfolio returns, the frequency of trading halts, cash ratios, and browsing behavior. Approximately 32.2% of recommendations are viewed in detail through the brokerage's mobile application on date *t*, and the same-day purchase rate conditional on viewing is 16.2%.

2.4.2. Investor Characteristics

Table 2 summarizes portfolio holdings, trading activity, and demographic characteristics of the 19,988 subscribed investors in our sample. Subscribed investors are active traders. On

average, investors hold approximately 9.8 stocks and execute 30.4 trades per month. The average total asset value in the general account is 588,391 CNY (about 84,000 USD), with a median of 227,796 CNY (about 32,000 USD), indicating a right-skewed wealth distribution. Annualized portfolio turnover is extremely high.

Table 2. Investor Descriptive Statistics, 2021–2023

This table reports portfolio holdings, trading activity, and performance characteristics of 19,988 investors who subscribed to recommendation services and made at least one purchase following the recommendation during the sample period 2021–2023. Variables are first measured at the investor level and averaged across investors. Internet Appendix Table IA.2 provides detailed definitions of the variables.

	Mean	SD	p25	p50	p75
Panel A: Stock trading					
Total asset value (*CNY*)	588,391.07	1,849,018.63	100,494.46	227,796.43	526,058.32
# Stocks held	9.80	9.98	4.39	7.17	11.81
# ETFs held	0.76	2.61	0.00	0.03	0.64
Holding period (*days*)	38.66	39.29	8.69	21.68	55.95
# Trades (*per month*)	30.39	55.86	6.444	14.509	33.472
Trade size (*CNY*)	32,122.87	76,743.88	9,129.47	17,035.84	33,578.02
Annualized turnover (%)	1730.06	1736.06	379.29	970.10	2562.10
Disposition effect (*PGR/PLR*)	12.71	40.00	2.39	4.81	10.64
Disposition effect (*PGR-PLR*)	0.15	0.13	0.05	0.12	0.23
Panel B: Demographic information					
Female	0.40	0.49	-	-	-
College education	0.72	0.45	-	-	-
Age (*years*)	49.11	11.39	41.00	49.00	57.00
Account experience (*years*)	10.26	7.57	4.00	8.00	15.00

Investors exhibit a pronounced disposition effect. The average ratio of proportion gains realized (PGR) to proportion of losses realized (PLR) equals 12.71, and the average difference between PGR and PLR equals 0.15.

Demographically, 40% of investors are female, 72% have a college-level education, and the average age is 49.1 years.

2.4.3. Recommender Characteristics

Table 3 presents descriptive statistics for the 108 stock recommenders. On average, recommenders have 254 subscribers and issue approximately 5 buy recommendations per month.

The average recommendation period is 22.7 trading days. Recommended stocks tend to be medium- to large-cap firms with moderate book-to-market ratios and positive recent momentum. Recommender performance is strong (see the Internet Appendix Table IA.1 for additional details).

Table 3. Recommender Descriptive Statistics

This table reports descriptive statistics of trading activity and performance characteristics of 108 stock recommenders during the sample period 2021–2023. Variables are first measured at the recommender level and averaged across recommenders. "Weighted mean" is the mean of the variable weighted by number of followers. Table A1, Panel B provides detailed definitions of the variables.

	Mean	Weighted mean	SD	p25	p50	p75
Panel A: Subscribers						
# Subscribers	254	-	1050.79	41	87	209
Panel B: Recommendations						
Recommendation period (*days*)	22.71	16.00	11.03	14.63	16.43	26.11
# Recommended stocks (*per month*)	4.96	9.15	1.84	3.57	3.93	6.02
Panel C: Stock Characteristics of Recommended Stocks						
Ln (*Size*)	16.41	16.38	0.84	15.81	16.36	17.00
Book-to-market ratio	0.70	0.61	0.36	0.53	0.63	0.78
Momentum 1y (%)	21.59	30.95	19.07	8.36	18.78	32.46
Panel D: Recommender Performance						
Winner ratio (%)	70.25	73.27	6.14	64.71	67.79	74.57
Holding-period return (%)	1.14	1.34	1.00	0.28	0.75	1.84

Out of an average 545.04 stocks under recommendation on a given day, 15.66% are being recommended by multiple recommenders. The average number of recommenders behind a recommended stock is 1.28. This evidence suggests that, while some overlap exists, the majority of recommendations are not concentrated on a small set of stocks (see Internet Appendix Table IA.3).

3. Results

3.1. Main Results

The descriptive evidence in Figure 1 suggests a strong negative relation between unrealized loss exposure and buying activity. We next examine this relation more formally using regressions that compare investors responding to the same recommendation at the same time. We begin by estimating the baseline specification, examining the functional form of the effect, exploring

heterogeneity across investor characteristics, and documenting similar patterns outside the recommender setting.

3.1.1. Baseline Regression

We estimate the following specification:

$$Buy_{irst} = \mu_{ir} + \mu_{rst} + \beta ULR_{it} + X_{it}'\Gamma + \varepsilon_{irst}, \quad (1)$$

where Buy_{irst} is an indicator equal to one if investor *i* places an order to purchase the stock associated with recommendation *r* on date *t*, where the order timestamp occurs strictly after the timestamp of recommendation *r*. The unrealized loss ratio (ULR_{it}) denotes the fraction of investor *i*'s portfolio held at unrealized losses immediately prior to the recommendation, and $X_{it}$is a vector of time-varying investor characteristics. Because observations may be correlated within investor and across investors exposed to the same recommendation, we cluster standard errors two-way by investor and by recommendation-date. As a complementary specification, we replace ULR_{it} with an indicator variable, All_Loss_{it}, equal to one if the investor's unrealized loss ratio equals one (i.e., all positions in the investor's portfolio are held at unrealized losses). This specification isolates the fully constrained state in which any sale would require realizing a loss.

The investor-recommender fixed effects (μ_{ir}) absorb all time-invariant characteristics of the relationship between investor *i* and recommender *r*, including persistent differences in trust, attention, or tendency to follow that recommender's advice. The recommendation-date fixed effects (μ_{rst}) absorb all factors specific to a given recommendation, including the identity of the recommended stock, market conditions on that date, and any time-varying beliefs about the recommender that are common across subscribers.

Identification therefore comes from within investor-recommender variation in portfolio composition across recommendation dates. The coefficient on ULR_{it} is identified from differences in purchase behavior when the same investor receives recommendations from the same recommender at different points in time, holding constant the specific recommendation opportunity. In other words, we ask whether an investor is less likely to follow a given recommender when a larger fraction of their portfolio is locked in unrealized losses.

Table 4. Unrealized Losses and Purchase Behavior Following Recommendations

This table reports regression results examining the relationship between holding unrealized losses and investors' likelihood of buying a stock after recommendation. The dependent variable (*Buy*) is an indicator variable that equals one if the investor purchases the recommended stock on the date of the recommendation by placing an order after the recommendation. *ULR* (unrealized loss ratio) is the number of paper-loss positions divided by the total number of positions in an investor's portfolio on the day before the recommendation. *All_Loss* is an indicator variable that equals one if all of an investor's positions are held at a loss, and zero otherwise. *Portfolio_ret* (x,y) is the return on the investor's portfolio from day *x* to day *y* relative to the date of the recommendation on day *t*=0. Standard errors are presented in parentheses and are double clustered by investor and recommendation date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Buy			
	(1)	(2)	(3)	(4)
ULR (Unrealized loss ratio)	-0.055***	-0.060***		
	(0.004)	(0.003)		
All_Loss (*ULR*=1)			-0.053***	-0.041***
			(0.002)	(0.001)
Portfolio_ret (-5, -1)		0.005***		0.005***
		(0.001)		(0.001)
Portfolio_ret (-20, -6)		0.000		0.001**
		(0.000)		(0.000)
Portfolio_ret (-250, -21)		0.000		0.000
		(0.000)		(0.000)
Investor-recommender FE	N	Y	N	Y
Recommendation-date FE	N	Y	N	Y
Observations	1,732,402	1,732,402	1,732,402	1,732,402
R-squared	0.003	0.222	0.009	0.241

Table 4 reports the baseline estimates. Across specifications, the coefficient on ULR_{it} is negative and statistically significant at the 1% level. In the specification with investor-recommender and recommendation-date fixed effects (column 2), the estimated coefficient of -0.060 implies that moving from the 25th percentile of the ULR distribution (0.556) to the 75th percentile (0.938), a change in *ULR* of 0.382, reduces the probability of purchasing a recommended stock by approximately 2.3 ppts (0.060 × 0.382). Given that the unconditional mean of Buy is 6.3%, this represents a decline of roughly 36% relative to the baseline purchase rate.

Columns (3) and (4) report specifications that replace ULR_{it} with All_Loss_{it}, an indicator equal to one when the investor's portfolio consists entirely of unrealized losses. The univariate specification (column 3) indicates a large 5.5 ppts drop in the probability of buying for investors who hold only losses. In the specification with fixed effects (column 4), investors in this fully constrained state are 4.1 ppts less likely to purchase a recommended stock. Given that 22.9% of observations correspond to $All\_Loss = 1$, this effect is both statistically precise and economically meaningful. We obtain similar results using an investor–day dataset constructed from a random sample of all investors at the brokerage (Internet Appendix Table IA.5). Overall, the results indicate that investors whose portfolios are more heavily concentrated in unrealized losses are substantially less likely to follow new recommendations.[3]

The results are robust to alternative constructions of the unit of observation. In particular, when we aggregate the data to the investor-day level and examine whether investors initiate any purchase on a given day, we obtain similar estimates (Internet Appendix Tables IA.5–IA.7). This evidence indicates that the negative relation between loss exposure and buying is not specific to the recommendation-following decision but extends to investors' general purchase behavior.

3.1.2. Functional Form of Loss Exposure

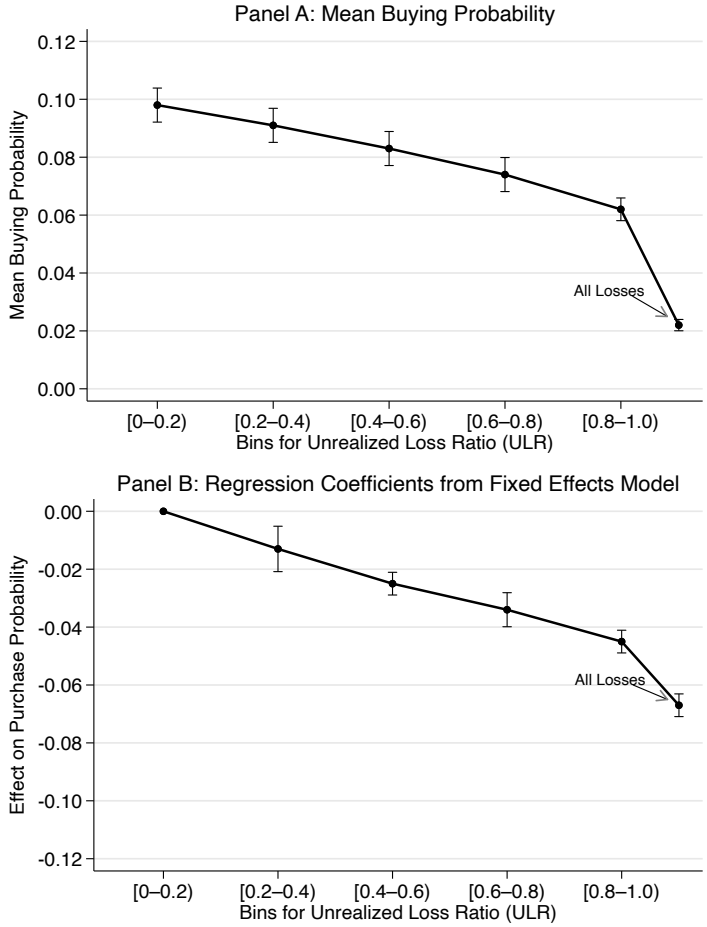
To further examine the relation between loss exposure and recommendation-following behavior, Figure 2 presents purchase probabilities across bins of the unrealized loss ratio (ULR). Panel A plots the unconditional probability that an investor purchases a recommended stock on the recommendation date across ULR bins constructed in 20-percentage-point intervals, along with a separate bin for investors whose entire portfolio consists of unrealized loss positions ("All Losses"). Among investors with less than 20% of their portfolio held at a loss (ULR < 0.2), the probability of following a recommendation is 9.8%. This probability declines steadily across ULR bins, reaching 6.2% for investors with ULR between 0.8 and 1.0. There is then a sharp drop to 2.2% for investors whose portfolios consist entirely of losses.

Panel B reports coefficient estimates from regressions that replace *ULR* with indicators for the same bins while maintaining the baseline specification in column (4) of Table 4.

[3] We replicate these results using a 10-day post-recommendation window to define the dependent variable (Buy) and find similar results (see Internet Appendix Table IA.4). This is not surprising since most of the buying following a recommendation occurs on the day of the recommendation (see Table 1).

Figure 2. Purchase Response by Unrealized Loss Ratio (ULR) Bins

This figure examines how purchase behavior varies with the unrealized loss ratio (*ULR*) among subscribed investors at the time of a recommendation (19,988 investors; 2021–2023; N = 1,732,428 investor–recommendation observations). Panel A plots mean buying probabilities across bins of ULR, constructed in 20-percentage-point intervals, along with a separate category for investors whose entire portfolio consists of loss positions ("All Losses"). Panel B plots coefficient estimates from a regression of the likelihood of purchasing a recommended stock on indicators for these ULR bins, based on a modified version of the baseline specification in Table 4. Whiskers denote 95% confidence intervals using standard errors double-clustered by investor-recommender and recommendation-date.



The relation is strongly monotonic. The likelihood of buying declines steadily as *ULR* increases and falls further when investors hold only loss positions. The pattern indicates that the effect is not driven by a small set of extreme observations but instead reflects a smooth and economically meaningful decline across the distribution of embedded losses.

The sharp drop for the "All Losses" group suggests that purchase behavior is particularly constrained when investors lack any positions that can be liquidated at a gain. This pattern is consistent with reluctance to realize losses limiting the ability to fund new purchases.

3.1.1. Investor Heterogeneity

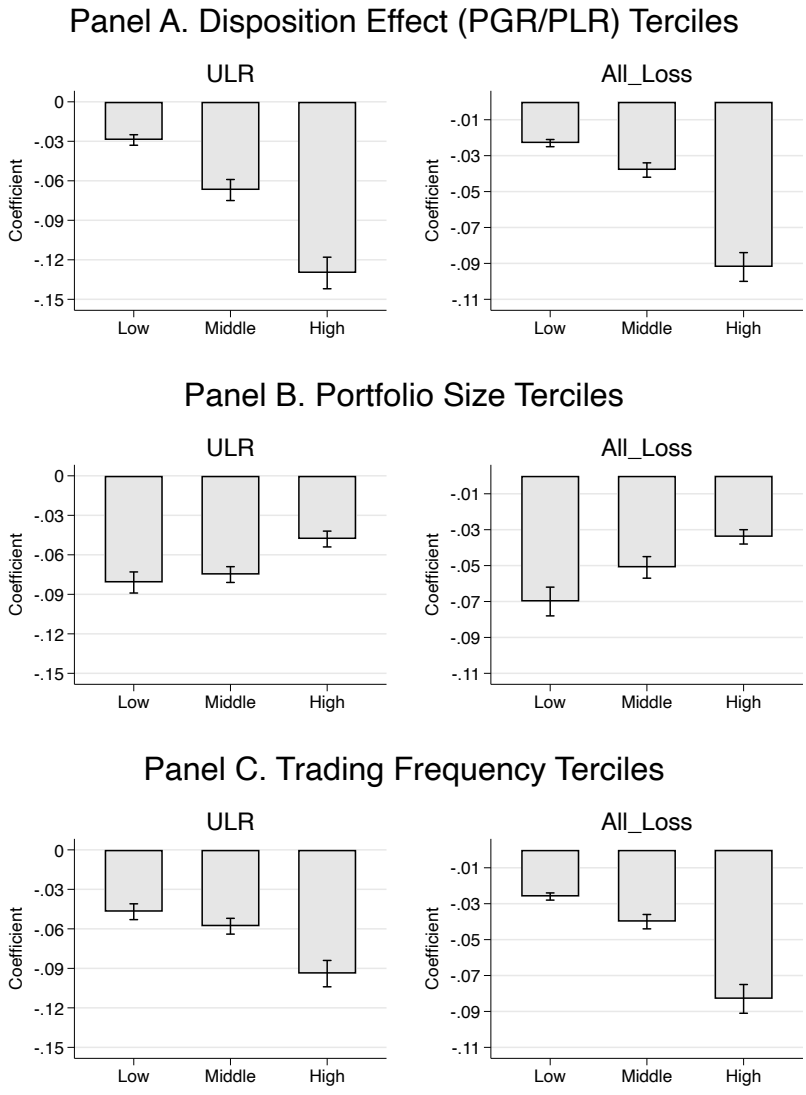
To examine heterogeneity in the effect of loss exposure, we classify investors based on characteristics measured during the 12 months prior to their first subscription to avoid post-subscription confounds. Specifically, we sort investors into terciles based on (i) their disposition effect (PGR/PLR), (ii) portfolio size, and (iii) trading frequency. We then estimate subsample regressions separately for each group using the specifications in Columns (2) and (4) of Table 4.

Figure 3 summarizes the results, with estimates for *ULR* shown on the left of each panel and estimates for *All_Loss* shown on the right. Panel A exhibits a pronounced monotonic pattern across disposition-effect terciles: the negative relation between holding losses and following recommendations strengthens substantially among investors who are more prone to the disposition effect. Panel B shows that the effect attenuates with portfolio size, particularly in the *ULR* specification, consistent with larger portfolios providing greater flexibility to fund purchases without realizing losses. Panel C indicates that the effect is stronger among more frequent traders, although the gradient is more modest than in Panel A.

While these cross-sectional patterns are consistent with a financing-constraint interpretation, they remain correlational. We next examine whether the effect weakens when investors have greater ex-ante cash holdings.

Figure 3. Investor Heterogeneity in the Effect of Loss Exposure

This figure plots coefficient estimates from subsample regressions of same-day recommendation purchases on loss exposure. Investors are sorted into terciles based on pre-subscription disposition effect (Panel A), portfolio size (Panel B), and trading frequency (Panel C). The left column reports coefficient estimates for the Unrealized Loss Ratio (ULR), and the right column reports coefficient estimates for the All_Loss indicator. All regressions follow the specifications in Columns (2) and (4) of Table 4. Whiskers represent 95% confidence intervals.



3.2. Cash Holdings and Financing Constraints

The baseline results indicate that purchase decisions are sensitive to the fraction of the portfolio held at unrealized losses. We next examine whether this spillover effect depends on

investors' available liquidity. When cash is readily available, investors can act on recommendations without first confronting their existing paper losses, reducing the linkage between selling and buying decisions. If the baseline effect operates through financing constraints, the negative impact of paper losses on following recommendations should be weaker when investors have sufficient cash to fund new positions.

To test this hypothesis, we extend the baseline specification by interacting portfolio loss measures with a time-varying indicator for liquidity, while maintaining the same fixed effects structure and clustering procedure:

$$Buy_{irst} = \mu_{ir} + \mu_{rst} + \beta_1 ULR_{it} + \beta_2 SufficientCash_{it} + \beta_3 (ULR_{it} \times SufficientCash_{it}) + X'_{it}\Gamma + \varepsilon_{irst}. \quad (2)$$

The coefficient of interest, β_3, captures whether the ability to finance a new position without selling attenuates the sensitivity of purchase decisions to unrealized losses. *SufficientCash* is an indicator equal to one if the investor's cash holdings exceed their average position size over the past 250 trading days.

Under the financing-constraint hypothesis, we expect $\beta_3 > 0$: sufficient liquidity should weaken the negative effect of holding paper losses on the likelihood of following a recommendation. Table 5 reports the results.

Column (1) shows that the interaction between *SufficientCash* and *ULR* is positive and statistically significant. The estimated coefficient of 0.016 offsets roughly one-fifth of the baseline −0.072 effect of *ULR*, indicating that the negative relation between loss exposure and purchasing is meaningfully weaker when investors can fund new positions without selling existing holdings. Consistent with this interpretation, the coefficient on *SufficientCash* is positive, implying that investors with sufficient liquidity are unconditionally more likely to follow recommendations.

Column (2) repeats the analysis using the indicator *All_Loss*. The interaction between *SufficientCash* and *All_Loss* is again positive and statistically significant. The coefficient of 0.018 offsets roughly 36% of the baseline −0.050 effect of *All_Loss*, indicating that the decline in buying when investors are fully locked into losses is substantially attenuated when they have sufficient cash to finance new purchases.

Table 5. Cash Holdings and the Loss Exposure Effect

This table examines whether cash holdings moderate the relationship between loss exposure and investors' likelihood of purchasing a recommended stock on the recommendation date. Column (1) uses the Unrealized Loss Ratio (*ULR*), defined as the fraction of portfolio positions held at unrealized losses. Column (2) replaces *ULR* with an indicator equal to one if all portfolio positions are held at unrealized losses (All_Loss). *SufficientCash* is an indicator equal to one if the investor's cash holdings exceed their average position size over the past 250 trading days, capturing whether the investor can fund a new position without selling existing holdings. Standard errors are reported in parentheses and are double clustered by investor and recommendation date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
ULR	-0.072***	
	(0.004)	
All_Loss		-0.050***
		(0.002)
SufficientCash	0.046***	0.037***
	(0.002)	(0.001)
SufficientCash × *ULR*	0.016***	
	(0.003)	
SufficientCash × *All_Loss*		0.018***
		(0.003)
Controls	Y	Y
Investor-recommender FE	Y	Y
Recommendation-date FE	Y	Y
Observations	1,732,402	1,732,402
R-squared	0.243	0.244

Overall, these findings support the financing-constraint mechanism. When investors lack liquidity, buying and selling decisions are tightly linked, amplifying the behavioral impact of unrealized losses. When investors hold sufficient cash to fund new positions without selling, this linkage weakens and the distortion in purchase behavior is significantly reduced. Results using alternative liquidity measures based on the portfolio share of cash and cash scaled by average position size are reported in Internet Appendix Table IA.8 and are similar. Results using the investor–day dataset are similar (Internet Appendix Table IA.6).

3.3. Exogenous Liquidity Shocks: Evidence from Trading Halts

Trading halts restrict the ability of investors to liquidate specific positions and therefore impose an exogenous constraint on portfolio liquidity. In the A-share market, formal trading halts fully suspend trading in the affected stock and often extend across trading days; they are distinct from daily price limits, which restrict intraday price movements but do not suspend trading.[4] Because halts are determined by exchange and regulatory rules rather than individual investor decisions, they provide an exogenous shock to the realizability of gains and losses within the portfolio. If investors preferentially fund new purchases by realizing gains rather than losses, then a halt that freezes gain positions should reduce purchase activity more than a halt that freezes loss positions. Importantly, because halts affect tradability rather than beliefs about new recommendations, this design helps distinguish a funding-based mechanism from alternative explanations based on changes in investor beliefs, preferences, or general market conditions, which would not predict differential effects for halted gains and losses.

We begin by classifying halt events according to whether the halted stock is held at a gain or a loss. *HaltGain* equals one if investor *i* holds at least one halted stock on day *t* that is at a paper gain. *HaltLoss* equals one if a halted stock is held at a paper loss. Observations with no halted positions serve as the omitted category. During our sample period, 1,003 distinct halt events affect 685 stocks held by investors in our data, generating over 10,000 investor–recommender–stock–day observations with halted positions. We estimate the following specification:

$$Buy_{irst} = \mu_{ir} + \mu_{rst} + \beta_1 ULR_{it} + \beta_2 HaltGain_{it} + \beta_3 HaltLoss_{it} + \varepsilon_{irst}. \quad (3)$$

Under the funding-based hypothesis, we expect β_2 to be more negative than β_3, reflecting that freezing gain positions constrains the investor's primary source of funding.

To sharpen this test, we distinguish between halts that eliminate all realizable gains and those that restrict only part of the investor's gain positions. *HaltGainOnly* equals one if the halted gain represents the investor's only unrealized gain, while *HaltGainOther* equals one if a halted gain occurs but other tradable gains remain in the portfolio. We then estimate:

[4] In the A-share market, most stocks are subject to ±10% daily price limits (±5% for Special Treatment (ST) stocks). When a stock reaches its limit, trading may continue at the limit price but cannot occur beyond it; trading is not formally suspended. Our analysis uses only formal trading halts, which suspend trading entirely. In our sample, most halts are triggered by corporate events such as restructurings or changes in control, with a smaller fraction related to Special Treatment (ST) designation changes or abnormal price movements.

$$Buy_{irst} = \mu_{ir} + \mu_{rst} + \beta_1 ULR_{it} + \beta_2 HaltGainOnly_{it} + \beta_3 HaltGainOther_{it} + \beta_4 HaltLoss_{it} + \varepsilon_{irst}. \quad (4)$$

This specification allows us to compare halts that remove the investor's only realizable gain to halts that restrict only one of several gains or only losses. It also exploits the sharp increase in the effect of loss exposure when an investor's portfolio contains only losses (see Figures 1 and 2). The funding mechanism predicts the largest decline in purchase activity when a halt eliminates the investor's only unrealized gain, implying $\beta_2 < \beta_3 < 0$, with little effect for halts affecting losses (i.e., β_4 close to zero).

Table 6. Trading Halts as Constraints on Gain-Based Liquidity

This table reports regressions of investors' decisions to buy a recommended stock on indicators capturing trading halts affecting positions in their portfolios. *HaltGain* equals one if the investor holds at least one halted position at a paper gain on the recommendation date, and *HaltLoss* equals one if the investor holds at least one halted position at a paper loss. Column (2) further decomposes *HaltGain* into *HaltGainOnly*, which equals one if the halted gain represents the investor's only unrealized gain, and *HaltGainOther*, which equals one if other unrealized gains remain tradable. The omitted category consists of observations with no halted positions. Standard errors are clustered at the investor and recommendation-date levels. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
ULR	-0.060***	-0.060***
	(0.003)	(0.003)
HaltGain	-0.051***	
	(0.007)	
HaltGainOnly		-0.073***
		(0.009)
HaltGainOther		-0.041***
		(0.005)
HaltLoss	-0.002	-0.002
	(0.008)	(0.013)
Controls	Y	Y
Investor-recommender FE	Y	Y
Recommendation-date FE	Y	Y
Observations	1,732,402	1,732,402
R-squared	0.239	0.239

In the main analysis, we use either *ULR* or *All_Loss* as alternative measures of loss exposure. In the halt specifications, we control for *ULR* because *All_Loss* represents a corner state with no unrealized gains by construction, whereas the halt mechanism operates on the margin where gains are present.

Table 6 reports the results. In Column (1), halts affecting gain positions are associated with a 5.1 ppts reduction in the probability of following a recommendation, while halts affecting loss positions have no statistically significant effect. Column (2) further decomposes halted gains into cases where the halted position represents the investor's only unrealized gain and cases where other gains remain tradable. The estimated reduction in purchase activity is largest when the halted position is the investor's only gain (−7.3 ppts), smaller when other gains remain (−4.1 ppts), and statistically indistinguishable from zero for halted losses. Results using the investor–day dataset are similar (Internet Appendix Table IA.7). Taken together, these results support a causal link between the availability of realizable gains and investors' willingness to initiate new purchases.[5]

3.4. Loss Exposure and Ostrich Effects

The evidence from cash availability and trading halts highlights the role of liquidity constraints in shaping investors' purchase decisions. However, loss exposure may also discourage investors from engaging with new investment opportunities. An attention-driven "ostrich effect" suggests that investors may avoid information that draws attention to prior losses (Karlsson, Loewenstein, and Seppi 2009; Sicherman et al. 2016). Considering new opportunities when portfolios are dominated by losses can generate psychological discomfort, discouraging investors from acquiring information about recommendations and reducing purchase activity.

To examine this channel, we test whether investors with greater loss exposure are less likely to view detailed recommendation information in the brokerage's mobile application. Note, however, that while some investors may refrain from viewing recommendation information in the app to avoid the psychological discomfort of thinking about their losses, others may simply not view the recommendations because they know that their portfolio consists mostly of losses and

[5] The estimated magnitudes should be interpreted relative to the conditional buy rate within investor–recommender and recommendation-date cells, rather than the unconditional mean of 6.3%. *HaltGainOnly* captures a rare portfolio state in which the investor's only unrealized gain is frozen, and the coefficient reflects the within-pair change in purchase probability when this constraint binds.

that they will not act on the recommendation. Thus for some investors not viewing the recommendation information may simply be a manifestation of the liquidity channel.

Using browsing data, we observe whether investors make specific clicks in the brokerage's mobile application that exclusively lead to detailed recommendation information. We construct an indicator variable, *View*, which equals one if the investor views the detailed recommendation message in the mobile application on the recommendation day. As reported in Table 1, the unconditional probability of viewing detailed recommendation information is 32.2%. Moreover, the probability of following a recommendation conditional on viewing is 16.20%, compared to 1.60% conditional on not viewing, indicating that viewing reflects meaningful engagement with the recommendation.

Panel A of Table 7 examines whether loss exposure affects investors' likelihood of viewing recommendation information. The dependent variable is *View*. Columns (1) and (2) use *ULR* and *All_Loss*, respectively, as the independent variable measuring loss exposure. The coefficients on *ULR* and *All_Loss* are −0.140 and −0.091, both statistically significant at the 1% level. Holding all positions at a loss reduces the probability of viewing by 9.1 ppts, representing 28.3% of the average viewing probability (9.1/32.2).

A simple decomposition suggests that reduced attention accounts for a meaningful fraction of the overall decline in following behavior. Holding all positions at a loss reduces the probability of following a recommendation by 4.1 ppts (Table 4, column (4)). Because purchasing without first viewing the message is rare, the 9.1 ppts reduction in viewing mechanically lowers buying by approximately 1.3 ppts, or roughly one-third of the total 4.1 ppts decline.[6] If the viewing effect were entirely attributable to an ostrich effect then this channel would account for about one-third of the overall reduction in buying attributable to holding losses.

[6] Define B as buying a recommended stock, L as holding all losses, and Vas viewing the message. Using $P(B \mid L) = P(V \mid L)P(B \mid V) + P(\neg V \mid L)P(B \mid \neg V) = P(V \mid L)P(B \mid V) + \big(1 - P(V \mid L)\big)P(B \mid \neg V) = P(B|\neg V) + P(V|L)(P(B|V) - P(P|V)P(B|\neg V) = P(B|\neg V) + P(V|L)[(P(B|V) - P(B|\neg V)]$, the portion of the decline in buying attributable to reduced message viewing is $\Delta P(V \mid L)[P(B \mid V) - P(B \mid \neg V)]$. With $\Delta P(V \mid L) = -0.091$(Table 7), $P(B \mid V) = 0.162$(Table 1), and $P(B \mid \neg V) = 0.016$, this implies a reduction of −0.013, or 1.3 percentage points. Relative to the total 4.1 percentage point decline in $P(B \mid L)$, this accounts for about 32% of the decline in buying activity.

Table 7. Loss Exposure and Investor Attention

This table examines how holding paper-loss positions affects investors' attention to recommendation messages and their subsequent purchase decisions conditional on attention. Panel A reports results where the dependent variable, *View*, equals one if the investor views the recommendation message on the recommendation day. Panel B reports results where the dependent variable, *Buy* (Conditional on Viewing), equals one if the investor purchases the recommended stock on the same day, conditional on viewing the message. In each panel, Column (1) uses unrealized loss ratio (*ULR*) as the key independent variable, and Column (2) replaces *ULR* with *All_Loss*, an indicator equal to one if all portfolio positions are held at paper losses. Standard errors are presented in parentheses and are double clustered by investor and recommendation date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Panel A: Dependent Variable: *View*		
ULR	-0.140***	
	(0.004)	
All_Loss		-0.091***
		(0.002)
Controls	Y	Y
Investor-recommender FE	Y	Y
Recommendation-date FE	Y	Y
Observations	1,732,402	1,732,402
R-squared	0.453	0.455
Panel B: Dependent Variable: *Buy* (Conditional on Viewing)		
ULR	-0.080***	
	(0.005)	
All_Loss		-0.055***
		(0.002)
Controls	Y	Y
Investor-recommender FE	Y	Y
Recommendation-date FE	Y	Y
Observations	557,025	557,025
R-squared	0.409	0.409

Note: All specifications include investor-recommender fixed effects, recommendation-date fixed effects, and controls.

Panel B of Table 7 examines the buying conditional on viewing. The coefficients on *ULR* and *All_Loss* are −0.076 and −0.055, respectively, both statistically significant at the 1% level.

Thus, even among investors who actively view recommendation information, holding unrealized losses remains negatively associated with following decisions. These results indicate that the negative relation between loss exposure and following behavior is not driven solely by reduced attention.

Taken together, the evidence suggests that both liquidity constraints and attention-based avoidance contribute to the decline in purchase activity among investors holding unrealized losses. Reduced attention accounts for a meaningful share of the effect, but even conditional on engagement, loss exposure continues to depress buying behavior, consistent with a framework in which multiple mechanisms jointly operate.

4. Alternative Explanations

In this section, we consider alternative explanations for our main results, including time-varying beliefs about recommender ability, investor overconfidence, and changes in risk preferences. While these mechanisms may influence investors' willingness to trade when portfolios are concentrated in unrealized losses, the evidence suggests that they cannot account for the patterns documented above.

4.1. Time-Varying Beliefs about Recommender Ability

Investors who experience favorable outcomes from a recommender may revise upward their beliefs about that recommender's ability and become more likely to follow subsequent recommendations. Because successful recommendations generate unrealized gains, investors with stronger past experiences may both hold more winning positions and exhibit higher take-up of new recommendations. This channel could induce a negative correlation between loss exposure and buying intensity even if unrealized losses do not directly affect behavior.

Our empirical design substantially limits the scope for this mechanism. All baseline specifications include recommender–date fixed effects, which absorb all variation in recommendation quality common across investors. Identification therefore comes from cross-investor differences in responses to the same recommendation at the same time.

A related concern is experience-based updating: investors may overweight their own past outcomes with a recommender, allowing prior realized gains or losses to disproportionately affect future take-up. To address this possibility, we restrict the sample to investor–recommender–date

observations in which none of the investor's current positions can be traced to stocks previously recommended by the focal recommender. Internet Appendix Table IA.9 shows that the main results remain similar in this restricted sample.

Further evidence challenges a belief-updating explanation. Trading halts do not convey information about recommender ability; instead, they temporarily restrict the tradability of specific positions. Consistent with a funding-based mechanism, halts affecting gain positions reduce buying, whereas halts affecting loss positions have little effect. Likewise, the negative relation between loss exposure and buying weakens when investors hold more available cash. These patterns align naturally with financing constraints but are difficult to reconcile with updating about recommender skill.

Taken together, the evidence suggests that time-varying beliefs about recommender ability are unlikely to account for the observed relation between portfolio loss exposure and recommendation-following behavior.

4.2. Investor Overconfidence

We next consider a distinct belief-based explanation rooted in investor overconfidence and self-attribution bias. Investors who attribute past success to their own skill may become overconfident and trade more aggressively (Daniel, Hirshleifer, and Subramanyam 1998, Odean 1998b, and Gervais and Odean 2001). Consistent with this mechanism, Statman, Thorley, and Vorkink (2006) document that trading volume increases following favorable market performance, suggesting that confidence rises after gains. In our setting, investors with lower unrealized loss ratios (*ULR*) may interpret recent performance as evidence of ability and therefore become more willing to initiate new purchases. This channel could generate the observed negative relation between *ULR* and buying intensity even if unrealized losses do not directly affect behavior.

Several features of our evidence are difficult to reconcile with this interpretation. Our empirical design compares investors responding to the same recommendation at the same time, so the variation we exploit reflects differences in portfolio state rather than differences in private information or perceptions of recommendation value. More importantly, as documented above, the effect of *ULR* is sensitive to the availability of realizable gains and cash balances. The attenuation of the effect among investors with greater liquidity, and the asymmetric impact of trading halts on gain versus loss positions, are not natural implications of a performance-driven overconfidence

channel. Confidence about one's ability does not depend on whether gains are halted or on the investor's current cash position, whereas a mechanism tied to the realizability of gains and losses predicts precisely such patterns.

Taken together, the evidence is more consistent with a funding-based mechanism linked to unrealized loss exposure than with overconfidence arising from past investment success.

4.3. Changing Risk Preferences

Another potential explanation is that unrealized losses alter investors' risk preferences. If holding losses increases risk aversion, investors may become less willing to initiate new risky positions, generating a negative relation between ULR and purchase decisions.

This interpretation is less compelling in our setting. Purchases are frequently funded by sales of existing stock positions, implying substitution within equities rather than an increase in overall portfolio risk. Moreover, average annual turnover exceeds 1,700% (Table 2), indicating that these accounts are highly active stock-picking accounts. Because these portfolios consist almost entirely of equities, changes in risk preferences would more naturally affect overall equity exposure rather than the decision to replace one stock with another.

We nevertheless test the risk-preference channel directly. If the effect reflects changes in effective wealth, purchase behavior should respond to the level of unrealized paper profits rather than to the share of positions held at losses. When both variables are included, *ULR* remains economically large and statistically significant, while the effect of unrealized paper profits is substantially smaller (Internet Appendix Table IA.10). Furthermore, interacting *ULR* with stock beta, volatility, and lottery-like characteristics yields no significant effects (Internet Appendix Table IA.11). Together, these results provide little support for a risk-preference explanation and instead point to a mechanism linked to the realizability of gains and losses within the portfolio.

5. Conclusion

Investors frequently face new investment opportunities that require both attention and funding. In this paper, we show that the distribution of unrealized gains and losses in investors' portfolios plays an important role in shaping their willingness to act on such opportunities. Using a setting in which retail investors receive the same stock recommendations at the same time, we document a strong negative relation between portfolio loss exposure and the likelihood of initiating

new purchases. Investors whose portfolios are dominated by unrealized losses are substantially less likely to follow recommendations, even when facing identical investment opportunities.

Our evidence points to two mechanisms underlying this relation. First, unrealized losses create a financing friction. Investors often fund new purchases by selling existing holdings, and reluctance to realize losses constrains this source of funding. Consistent with this mechanism, the negative relation between loss exposure and purchasing weakens when investors hold more cash and strengthens when trading halts restrict the ability to sell gain positions. Second, loss exposure reduces engagement with new opportunities. Investors whose portfolios consist entirely of unrealized losses are significantly less likely to view detailed recommendation information, suggesting that confronting losses discourages attention to potential investments.

Together, these findings show that the disposition effect influences not only selling decisions but also investors' willingness and ability to initiate new positions. Given that the disposition effect has been documented across a wide range of investors, including sophisticated investors such as mutual fund managers, these frictions may extend beyond retail settings. If professional investors are similarly less willing to initiate new positions when mired in losses, this mechanism could affect not only trading behavior but also portfolio performance and the allocation of capital at scale, discouraging reallocation toward new opportunities and potentially contributing to slow-moving capital in financial markets (Duffie 2010).

In summary, our results suggest that behavioral biases embedded in existing portfolios can influence future investment choices and the pace at which investors respond to new information. When investors are mired in losses, they may remain stuck in place, reluctant to realize past losses, and unable to pursue new opportunities.

References

An, Li, Joseph Engelberg, Matthew Henriksson, Baolian Wang, and Jared Williams, 2024, The portfolio-driven disposition effect. *Journal of Finance* 79, 3459–3495.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns. *Journal of Finance* 56, 531–563.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2007, Is the aggregate investor reluctant to realise losses? Evidence from Taiwan. *European Financial Management* 13, 423–447.

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

Barberis, Nicholas, and Wei Xiong, 2012, Realization utility. *Journal of Financial Economics* 104, 251–271.

Bergsma, Kelley, Andy Fodor, and Emily Tedford, 2020, A closer look at the disposition effect in U.S. equity option markets. *Journal of Behavioral Finance* 21, 66–77.

Breitmayer, Bastian, Tim Hasso, and Matthias Pelster, 2019, Culture and the disposition effect. *Economics Letters* 184, 108653.

Cai, Huan, Meining Wang, and Chaonan Bai, 2018, An empirical study of investors' disposition effect in China based on open data from the Chinese stock markets. *International Journal of Economics and Finance* 10, 165–172.

Cici, Gjergji, 2012, The prevalence of the disposition effect in mutual funds' trades. *Journal of Financial and Quantitative Analysis* 47, 795–820.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In Search of Attention. *Journal of Finance* 66, 1461–1499.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance*, 54, 1839-1885.

Dhar, Ravi, and Ning Zhu, 2006, Up close and personal: Investor sophistication and the disposition effect. *Management Science* 52, 726–740.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital. *Journal of Finance* 65, 1237–1267.

Frazzini, Andrea, 2006, The disposition effect and underreaction to news. *Journal of Finance* 61, 2017–2046.

Frydman, Cary, Nicholas Barberis, Colin Camerer, Peter Bossaerts, and Antonio Rangel, 2014, Using neural data to test a theory of investor behavior: An application to realization utility. *Journal of Finance* 69, 907–946.

Frydman, Cary, and Colin F. Camerer, 2016, Neural evidence of regret and its implications for investor behavior. *Review of Financial Studies* 29, 3108–3139.

Genesove, David, and Christopher Mayer, 2001, Loss aversion and seller behavior: Evidence from the housing market. *Quarterly Journal of Economics* 116, 1233–1260.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident. *Review of Financial Studies* 14, 1–27.

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

Heath, Chip, Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise. *Quarterly Journal of Economics* 114, 601–627.

Imas, Alex, 2016, The realization effect: Risk-taking after realized versus paper losses. *American Economic Review* 106, 2086–2109.

Ingersoll, Jonathan E., and Lawrence Jin, 2013, Realization utility with reference-dependent preferences. *Review of Financial Studies* 26, 723–767.

Jackson, Andrew, 2003, The aggregate behaviour of individual investors. Available at SSRN 536942.

Karlsson, Niklas, George Loewenstein, and Duane J. Seppi, 2009, The ostrich effect: Selective attention to information. *Journal of Risk and Uncertainty* 38, 95–115.

Kaustia, Markku, 2004, Market-wide impact of the disposition effect: Evidence from IPO trading volume. *Journal of Financial Markets* 7, 207–235.

Locke, Peter R., and Steven C. Mann, 2005, Professional trader discipline and trade disposition. *Journal of Financial Economics* 76, 401–444.

Odean, Terrance, 1998a, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775–1798.

Odean, Terrance, 1998b, Volume, Volatility, Price, and Profit When All Traders Are Above Average. *Journal of Finance* 53, 1887-1934.

Richards, Daniel W., Janette Rutterford, Devendra Kodwani, and Mark Fenton-O'Creevy, 2017, Stock market investors' use of stop losses and the disposition effect. *European Journal of Finance* 23, 130–152.

Schatzmann, Jürgen E., and Bernhard Haslhofer, 2023, Exploring investor behavior in Bitcoin: A study of the disposition effect. *Digital Finance* 5, 581–612.

Shapira, Zur, and Itzhak Venezia, 2001, Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance* 25, 1573–1587.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance* 40, 777–790.

Sicherman, Nachum, George Loewenstein, Duane J. Seppi, and Stephen P. Utkus, 2016, Financial attention. *Review of Financial Studies* 29, 863–897.

Statman, Meir, Steven Thorley, and Keith Vorkink, 2006, Investor overconfidence and trading volume. *Review of Financial Studies* 19, 1531–1565.

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

Summers, Barbara, and Darren Duxbury, 2012, Decision-dependent emotions and behavioral anomalies. *Organizational Behavior and Human Decision Processes* 118, 226–238.

Weber, Martin, and Colin F. Camerer, 1998, The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behavior & Organization* 33, 167–184.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137–167.

Internet Appendix

Mired in Losses: How the Disposition Effect Depresses Purchase Behavior

Sections

Figures

Tables

I. Further details on recommender services

A. Recommender's homepage

The homepage consists of four main pages: outstanding stock recommendations, history, performance, and strategy notes. The outstanding stock recommendations page lists the stocks currently held in the recommender's stock pool. The history page records all past buy and sell recommendations issued by the recommender. The performance page summarizes key metrics such as trading frequency and the performance of recommended stocks. Finally, the strategy notes

page contains the recommender's periodic reflections and summaries of their overall investment approach over a given period.

The performance page of a stock recommender typically contains three modules (an example displayed in Figure IA1). The top module summarizes the recommender's overall performance and trading frequency. It reports key metrics, including the winner ratio (the fraction of recommended stocks classified as winner stocks), the average holding-period return, and the number of stocks recommended per month. The middle module presents a selection of past recommendation examples chosen by the recommender. Specifically, this module displays representative recommendations, including the stock name, the dates of the buy and sell recommendations, the corresponding buy price and sell price, as well as the holding-period return and the maximum return achieved during the holding period for each completed recommendation. The bottom module provides an overview of the subscription pricing.

After reviewing these three modules, investors can decide whether to subscribe to the recommender. If they choose to subscribe, they can click the "subscribe now" button located at the bottom right of the page. The platform then presents a detailed electronic subscription contract specifying the pricing terms. The subscription becomes effective once the investor reviews and signs the contract.

B. Pricing of Recommender Services

When subscribing to a recommender, investors choose between two broad pricing schemes: a fixed-fee plan or a commission-based plan. Under the fixed-fee scheme, investors pay an upfront fee for a fixed subscription period, typically 3 months (3.57% of investor–recommender observations).

Alternatively, investors may opt for a transaction-based pricing scheme, under which no upfront fee is charged at the time of subscription. Instead, an additional commission is imposed on transactions of the recommended stocks under certain predefined conditions after the subscription. Under the commission-based scheme, each recommender offers one pre-specified commission structure, and investors who choose this option are charged according to that structure. Across recommenders, we observe two types of commission-based pricing arrangements. First, a universal add-on commission of 10–15 basis points is charged on all trades executed during the subscription period, regardless of whether the trades are recommended by the recommender

(12.68%). Second, a performance-based commission of 30 basis points is charged only on recommended stocks and only when the investor sells the stock at a gain (83.75%). The specific criteria are listed below:

Case 1. Sale of the recommended stocks following recommendation

- When the recommender recommends selling the stock,
- The sell realizes a profit greater than 2%, and
- The investor sells the recommended stock within 20 days following the sell recommendation.

Case 2. Sale initiated by investors before recommendation

-When the investor sells a stock that was previously recommended by the recommender before the recommender issues a sell recommendation,

- Regardless of whether the transaction results in a gain or a loss.

Case 3. Sale after subscription termination

- When the investor sells a stock within 30 days after terminating the subscription,
- Regardless of whether the transaction results in a profit or a loss.

C. The T+1 trading rule in the Chinese stock market

The Chinese A-share market operates under a T+1 trading system, under which investors are not allowed to sell shares on the same trading day they purchased. According to the relevant regulations issued by the China Securities Regulatory Commission (CSRC) and the stock exchanges, stocks purchased on day t can only be sold starting from trading day $t+1$.

Importantly, while shares purchased on day t cannot be sold on the same day, the cash proceeds from selling previously held shares on day t can be used immediately to purchase other stocks on the same day, although such cash cannot be withdrawn until the next trading day. This institutional feature implies that investors' ability to finance new stock purchases on a given day depends on whether they can liquidate existing positions. As a result, when investors are reluctant or unable to sell their current holdings—particularly losing positions—their effective liquidity for financing new purchases may be constrained, even though trading itself is permitted.

D. Browsing data

The browsing data record each individual click, including both page views and specific on-page interactions, together with time stamps accurate to the second. Panels A and B of Figure IA4 present two examples of an investor's in-application browsing behavior on November 7, 2023, in which the investor browses detailed recommendation information through the recommender's homepage and the message center following a buy recommendation for *Jiuzhou yaoye* issued at 9:57:06 by the recommender *Short-term Leader*. The data allow us to trace the investor's sequence of actions for each click. Taking Panel A as an example, the investor first visits the recommender's homepage at 9:58:09. After viewing the detailed recommendation message, the investor then opens the stock detail page for *Jiuzhou yaoye* (stock code: 603456) at 9:59:04, subsequently switches the price chart (K-line) to the monthly view at 10:00:20, and finally clicks the "Buy" button at 10:00:59 on the stock detail page to place an order for the recommended stock. Therefore, the variable *View message* for this case is set at one as the investor browses the recommender's homepage after receiving the recommendation notification.

There are several caveats to using this data. First, investors' browsing activity outside the mobile application (e.g., on computers) is not recorded. Second, some browsing activity may not be successfully captured for mechanical reasons. For example, users may restrict the application from collecting data for privacy reasons.

Figure IA.1. Recommender's homepage

This figure presents the recommender's homepage as observed by investors prior to subscription. The left panel shows the original interface of the brokerage mobile application, while the right panel presents a translated version. The page reports several key performance metrics. Holding-period return is defined as (sell price - buy price) / buy price and **highest return** is defined as (the highest price during the holding period - buy price) / buy price. The winner ratio is calculated as the number of winner stocks (including both past winner stocks and currently held winner stocks) divided by the total number of recommendations, including current and past recommendations. The absolute winner ratio is defined as the fraction of past recommendations that yield a holding-period return greater than 2%, where we classify such stocks as absolute winner stocks.

Fengkou No.1
(recommender name)

Recommended stocks	History	Performance (current page)	Strategy notes

Winner ratio (past 3 months)	Winner ratio (up to now)	Absolute winner ratio
62.5%	**86.9%**	**71.4%**
Average holding-period return	# recommended stocks (per month)	# winner stocks /# historical recommendations
4.41%	**6.56 times**	**72/84 times**

Recommendation Samples (78 stocks)

	Sell/Buy date	Sell/Buy price	Holding-period /Highest return
Jinlei gufen (stock code: 300443)	08-29 06-09	27.01 19.78	36.55% 46.81%
Rationale for buy recommendation: available after subscription			
Rationale for sell recommendation: available after subscription			
Jinghua xincai (stock code: 603683)	03-04 02-20	14.22 10.34	37.52% 39.07%
Rationale for buy recommendation: available after subscription			
Rationale for sell recommendation: available after subscription			
Weike keji (stock code: 301196)	02-20 02-13	46.85 35.44	32.20% 32.28%

No subscription fee, an add on commission of 0.3% | **Subscribe Now**

Figure IA.2. Recommendation notifications

This figure illustrates recommendation information delivered to investors at different stages. Panels A and B present recommendation notifications, delivered via SMS and WeChat, respectively. Panels C and D present detailed recommendation information displayed within the broker's mobile application, including the message center and the recommender's homepage, respectively. In each panel, the left and right subpanel shows the original interface as received by investors and an English translation version.

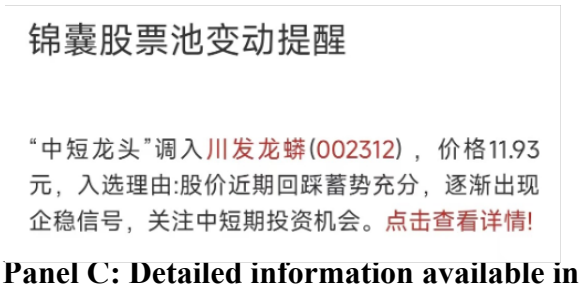
[Broker name]: Dear client, your subscribed recommender "Short-term leader" recommends to buy stock "**Chuanfa longmang**"(stock code:002312). The current price is at 11.93 CNY. You can check the recommendation rationale in [Broker name] APP. Investing involves risk; investors should exercise discretion when making

Panel A: Recommendation notification via SMS

[Broker name] **Recommendation notification**	
Recommender name:	Short-term leader
Recommended stock:	**Chuanfa longmang** (stock code: 002312)
Recommendation type:	Buy
Current stock price:	11.93 CNY
Recommendation rationale:	The recommendation is based on the recommender's analysis. Please refer to the [Broker name] app for the exact information.

Panel B: Recommendation notification via WeChat

Figure IA.2 cont'd



Notification of changes to the recommendation stock pool
[Broker name]
"Short-term leader" recommends to buy stock "Chuanfa longmang"(stock code:002312). The current stock price is at 11.93 CNY. Recommendation rationale: After a recent pullback, the stock is showing early signs of stabilization, presenting short-term opportunities. Click for more information.

Panel C: Detailed information available in the brokerage's mobile application message center

2025-12-02

10:22:08	Buy	**Chuanfa longmang** (stock code:002312)	11.93

Rationale for buy recommendation:After a recent pullback, the stock is showing early signs of stabilization, presenting short-term opportunities.

One-click trade

Panel D: Detailed information on recommender's homepage

Figure IA.3. Stock holdings page in the brokerage's mobile application

This figure presents the stock holdings page viewed by investors in the brokerage's mobile application. The left panel shows the original interface of the brokerage's mobile application, while the right panel presents a translated version. For each position, paper profit (CNY) equals the difference between the current price and the holding cost per share multiplied by the number of shares held, while paper profit (%) is the corresponding return relative to the holding cost. Gains and losses based on the sign of paper profit are displayed in different colors (red for gains and blue for losses). Daily profit change (CNY) is measured as the change in market value from the previous trading day, net of intraday trading expenditures and proceeds, and daily profit change (%) is scaled by the market value at the end of the previous trading day.

Holdings

Name: (holder's name) ID:(account number)

Buy	Sell	Order cancellation	Holdings (current page)	More

CNY (general) account

(Portfolio information)

Total asset value	Paper profit (CNY)	Daily profit change (CNY)
7846.47	-156.63	+176.00
Market value of stocks	Available cash for trade	Available cash for withdrawal
7678.00	168.47	168.47

(Position information)

Juren wangluo (stock code: 002558)

Daily profit change: 145.00 3.40%

Market value: 4414.00	Position percentage: 56.25%
Paper profit (CNY): 445.36	Paper profit (%) : 11.22%
Current price: 44.140	Holding cost per share : 39.686
# shares held: 100	# shares available for sale: 100

Shiji huatong (stock code: 002602)

Daily profit change: 6.00 0.36%

Market value: 1680.00	Position percentage: 21.41%
Paper profit (CNY): -346.05	Paper profit (%) : -17.08%
Current price: 16.800	Holding cost per share : 20.261
# shares held: 100	# shares available for sale: 100

Wanmei shijie (stock code: 002604)

Daily profit change: 25.00 1.60%

Market value: 1584.00	Position percentage: 20.19%
Paper profit (CNY): -255.94	Paper profit (%) : -13.90%
Current price: 15.840	Holding cost per share : 18.399
# shares held: 100	# shares available for sale: 100

Figure IA.4. Two examples of in-application browsing data

This figure illustrates all browsing- and click-level actions of an individual investor within the brokerage's mobile application. Panel A shows an example of the investor's browsing path through the recommender's homepage between 9:58:09 and 10:00:59, and Panel B shows an example through the message center between 10:00:03 and 10:03:07, both for accessing detailed recommendation information on November 7, 2023.

Click time	Click event	Supplementary page description (optional)
November 7, 2023 9:58:09	Recommender's homepage is opened.	Recommender name: Short-term leader
November 7, 2023 9:59:04	The stock detail page is opened.	Jiuzhou yaoye (stock code: 603456)
November 7, 2023 10:00:20	The price chart view is switched to monthly.	Jiuzhou yaoye (stock code: 603456)
November 7, 2023 10:00:59	"Buy" button is clicked.	Jiuzhou yaoye (stock code: 603456)

Panel A: An example of viewing detailed recommendation information through the recommender's homepage

Click time	Click event	Supplementary page description (optional)
November 7, 2023 10:00:03	The message center is opened.	-
November 7, 2023 10:00:09	The message page is opened.	(The detailed recommendation information)
November 7, 2023 10:00:15	The stock detail page is opened.	Jiuzhou yaoye (stock code: 603456)
November 7, 2023 10:03:07	"Buy" button is clicked.	Jiuzhou yaoye (stock code: 603456)

Panel B: An example of viewing detailed recommendation information through the message center

Table IA.1. Variable definitions

Variable	Definition
Panel A Trading, portfolio, and performance characteristics of investors	
Total asset value (*CNY*)	Average aggregate market value of total investor assets, measured as the sum of market value of cash, stock, and ETF holdings.
# *Stocks held*	Average number of stocks held in the portfolio.
# *ETFs held*	Average number of ETFs held in the portfolio.
Holding period (days)	Average number of days from first purchase to the first sale across newly opened positions.
# *Trades* (*per month*)	Average number of trades per month.
Trade size (*CNY*)	Average trade size (in CNY).
Annualized turnover	(250 / number of trading days in the period) × (aggregate buy dollar volume + aggregate sell dollar volume during the period) / (2 × average total asset value) ×100.
Disposition effect (*PGR*/*PLR*)	Ratio of the proportion of gains realized (number of stocks sold at a gain divided by the total number of realized and paper gains) to the proportion of losses realized (number of stocks sold at a loss divided by the total number of realized and paper losses).
Female	Equals one if the investor is female, and zero otherwise.
College education	Equals one if the investor has received higher education (college, undergraduate, or graduate), and zero otherwise.
Age	Investor age as of 2023.
Account experience	Account age as of 2023.
Panel B Trading and performance characteristics of stock recommenders	
# *Subscribers*	Number of investors who subscribed to the stock recommender during the sample period.
Recommendation period (*days*)	Average number of days between the recommendation date and the end date.
# *Recommended stocks* (*per month*)	Average monthly number of recommendations made by the stock recommender.
Ln (*Size*)	Average of logged firm size across all stocks recommended during the period.
Book-to-market ratio	Average of book-to-market ratio across all stocks recommended during the period.
Momentum_1y	Average of past 12-month return across all stocks recommended during the period.
Winner ratio (%)	Percentage of recommendations with sell prices greater than buy prices.
Holding-period return (%)	Average holding returns of recommendations, calculated from the recommendation date to the end date. Holding return for a recommendation is calculated as 100 × (sell price – buy price) / Buy price.

Table IA.2. Performance of recommenders' stock recommendations

This table evaluates the performance of stock recommendations issued by stock recommenders. Panel A presents the portfolio-based analysis. Stocks are included in the portfolio on the trading day following a recommendation and held until the corresponding sell signal is issued. The weight of a stock in the aggregate portfolio is determined by the number of times it appears across the 108 recommenders' portfolios (i.e., its total count across recommenders) divided by the total number of stock holdings across all recommenders on that day, counting duplicates. The portfolio is formed and rebalanced daily. The table reports annualized raw returns and alphas (in percentages) based on various factor models. Panel B reports the overall performance of recommenders' recommendation signals by computing the average returns following recommendations over various forward-looking windows. Returns are measured using four metrics: raw return, DGTW-adjusted abnormal return, net-market return, and return relative to investors' equal-weighted portfolios. All measures are computed at the investor-recommender-recommendation level, and standard errors are clustered at the investor level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolio-based analysis

	Raw return	FF3	FFC4	FF5
Aggregate portfolio	10.846***	8.338***	8.221***	8.640***
	(4.47)	(5.11)	(4.96)	(5.39)

Panel B: Signal-based analysis

Holding period	[1, 5]	[1, 10]	[1, 20]	[1, 60]	[1, 250]
Raw return	0.882***	1.072***	1.375***	0.643	-3.859***
	(6.68)	(10.46)	(13.52)	(1.37)	(-7.57)
Abnormal DGTW return	0.692***	0.877***	1.043***	0.424	-3.071***
	(10.62)	(4.76)	(7.83)	(1.51)	(-4.84)
Net market return	0.963***	1.205***	1.863***	2.141***	-0.896*
	(6.75)	(10.87)	(13.79)	(4.13)	(-1.67)
Return relative to investor portfolio	1.653***	2.656***	3.758***	4.895***	7.041***
	(12.46)	(17.73)	(14.57)	(12.62)	(16.53)

Table IA.3: Overlap of recommendations across recommenders.

This table reports the frequency with which multiple recommenders are recommending the same stocks on a given day. A stock-day is flagged as "being recommended" when the stock is currently being recommended by any recommender. Then, we classify the flagged stock-day observations into groups based on the number of recommenders concurrently recommending the same stocks. The table reports the time-series average of the number of stocks in each category.

Number of recommenders	Average number of stocks being recommended	Frequency
Total	545.04	100.00%
1	459.69	84.34%
2	50.13	9.20%
3	19.93	3.66%
4	8.22	1.51%
5	3.61	0.66%
6	1.78	0.33%
>=7	1.68	0.31%

Table IA.4. Main Results with 10-day Buy Indicator: Unrealized Losses and Purchase Behavior Following Recommendations

This table reports regression results examining the relationship between holding unrealized losses and investors' likelihood of buying a stock after recommendation. The dependent variable (*Buy*) is an indicator variable that equals one if the investor purchases the recommended stock on the date of the recommendation or following 10 days by placing an order after the recommendation. *ULR* (unrealized loss ratio) is the number of paper-loss positions divided by the total number of positions in an investor's portfolio on the day before the recommendation. *All_Loss* is an indicator variable that equals one if all of an investor's positions are held at a loss, and zero otherwise. *Portfolio_ret* (x,y) is the return on the investor's portfolio from day *x* to day *y* relative to the date of the recommendation on day *t*=0. Standard errors are presented in parentheses and are double clustered by investor and recommendation date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Buy			
	(1)	(2)	(3)	(4)
ULR (Unrealized loss ratio)	-0.070***	-0.069***		
	(0.003)	(0.003)		
All_Loss (*ULR*=1)			-0.044***	-0.045***
			(0.001)	(0.001)
Portfolio_ret (-5, -1)		0.005***		0.006***
		(0.001)		(0.001)
Portfolio_ret (-20, -6)		0.001		0.001**
		(0.000)		(0.000)
Portfolio_ret (-250, -21)		0.000		0.000
		(0.000)		(0.000)
Investor-recommender FE	Y	Y	Y	Y
Recommendation-date FE	Y	Y	Y	Y
Observations	1,732,402	1,732,402	1,732,402	1,732,402
R-squared	0.248	0.248	0.248	0.249

Table IA.5. Main Results for Investor-Day Dataset

This table examines the relation between unrealized loss exposure and investors' likelihood of initiating a new stock purchase using an investor–day panel. The dependent variable, *Buy*, is an indicator equal to one if the investor initiates at least one new stock position on that day (i.e., purchases a stock not held at the end of the previous trading day). The sample consists of a random subset of 42,250 investors from the full brokerage dataset. Columns (1) and (2) use the Unrealized Loss Ratio (ULR), defined as the fraction of portfolio positions held at unrealized losses. Columns (3) and (4) replace ULR with an indicator equal to one if all portfolio positions are held at unrealized losses (*All_Loss*). *Portfolio_ret* (x,y) denote cumulative portfolio returns over the indicated past trading-day windows. Columns (2) and (4) include investor and date fixed effects. Standard errors are reported in parentheses and are double clustered by investor and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Buy			
	(1)	(2)	(3)	(4)
ULR	-0.101***	-0.100***		
	(0.003)	(0.002)		
All Loss (ULR=1)			-0.103***	-0.096***
			(0.002)	(0.001)
Portfolio ret (-5,-1)		0.111***		0.104***
		(0.002)		(0.002)
Portfolio ret (-20,-6)		0.037		0.037**
		(0.001)		(0.001)
Portfolio ret (-250,-21)		-0.000		0.000
		(0.000)		(0.000)
Constant	0.162***		0.138***	
	(0.003)		(0.002)	
Investor FE	N	Y	N	Y
Date FE	N	Y	N	Y
Observations	27,884,430	27,884,430	27,884,430	27,884,430
R-squared	0.013	0.194	0.031	0.205

Table IA.6. Cash Holdings and Loss Exposure: Investor-Day Dataset

This table examines whether cash holdings moderate the relationship between loss exposure and investors' likelihood of initiating a new stock purchase using an investor–day panel. The dependent variable, *Buy*, is an indicator equal to one if the investor initiates at least one new stock position on that day (i.e., purchases a stock not held at the end of the previous trading day). Column (1) uses the Unrealized Loss Ratio (ULR), defined as the fraction of portfolio positions held at unrealized losses. Column (2) replaces ULR with an indicator equal to one if all portfolio positions are held at unrealized losses (All_Loss). SufficientCash is an indicator equal to one if the investor's cash holdings exceed their average position size over the past 250 trading days, capturing whether the investor can fund a new position without selling existing holdings. The sample consists of a random subset of 42,250 investors from the full brokerage dataset. All specifications include controls for lagged portfolio returns. Standard errors are reported in parentheses and are double clustered by investor and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
ULR	-0.112***	
	(0.002)	
All_Loss		-0.098***
		(0.001)
SufficientCash	0.061***	0.080***
	(0.002)	(0.001)
SufficientCash × *ULR*	0.080***	
	(0.002)	
SufficientCash × *All_Loss*		0.030***
		(0.001)
Controls	Y	Y
Investor FE	Y	Y
Date FE	Y	Y
Observations	27,884,430	27,884,430
R-squared	0.224	0.235

Table IA.7. Trading Halts: Investor-Day Dataset

This table examines the effect of trading halts on investors' likelihood of initiating a new stock purchase using an investor–day panel. The dependent variable, *Buy*, is an indicator equal to one if the investor initiates at least one new stock position on that day (i.e., purchases a stock not held at the end of the previous trading day). HaltGain is an indicator equal to one if the investor holds at least one position that is both suspended from trading (halted) and currently at an unrealized gain. HaltLoss is defined analogously for positions at an unrealized loss. In alternative specifications, HaltGainOnly identifies investor-days on which the investor's only unrealized gain position is halted, while HaltGainOther identifies investor-days on which at least one gain position is halted but other realizable gains remain. The sample consists of a random subset of 42,250 investors from the full brokerage dataset. All specifications include controls for lagged portfolio returns and incorporate investor and date fixed effects. Standard errors are reported in parentheses and are double clustered by investor and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
ULR	-0.100***	-0.100***
	(0.002)	(0.002)
HaltGain	-0.026***	
	(0.003)	
HaltGainOnly		-0.069***
		(0.002)
HaltGainOther		-0.020***
		(0.001)
HatlLoss	-0.011***	-0.011***
	(0.001)	(0.001)
Controls	Y	Y
Investor FE	Y	Y
Date FE	Y	Y
Observations	27,884,430	27,884,430
R-squared	0.194	0.205

Table IA.8. Cash Holdings and the Loss Exposure Effect: full set of liquidity measures

This table examines whether alternative measures of cash holdings moderate the relationship between loss exposure and investors' likelihood of purchasing a recommended stock on the recommendation date. Columns (1)–(2) use the Unrealized Loss Ratio (*ULR*), defined as the fraction of portfolio positions held at unrealized losses. Columns (3)–(4) replace ULR with an indicator equal to one if all portfolio positions are held at unrealized losses (*All_Loss*). *PortfolioCashRatio* is the share of the portfolio held in cash. *PositionCashRatio* is the ratio of cash holdings to the investor's average position size over the past 250 trading days. Standard errors are reported in parentheses and are double clustered by investor and recommendation date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
ULR	-0.062***	-0.073***		
	(0.003)	(0.003)		
All_Loss			-0.049***	-0.049***
			(0.002)	(0.002)
PortfolioCashRatio	0.053***		0.043***	
	(0.004)		(0.003)	
PositionCashRatio		0.013***		0.011***
		(0.001)		(0.001)
PortfolioCashRatio × *ULR*	0.025***			
	(0.005)			
PositionCashRatio × *ULR*		0.024***		
		(0.006)		
PortfolioCashRatio × *All_Loss*			0.031***	
			(0.003)	
PositionCashRatio × *All_Loss*				0.025***
				(0.005)
Controls	Y	Y	Y	Y
Investor-recommender FE	Y	Y	Y	Y
Recommendation-date FE	Y	Y	Y	Y
Observations	1,732,402	1,732,402	1,732,402	1,732,402
R-squared	0.242	0.243	0.244	0.244

Table IA.9. Recommender experience and prior recommendation exposure restriction

This table replicates the four specifications in Table 4 using a restricted sample that excludes observations in which any currently held position can be traced to a stock previously recommended by the focal recommender. This restriction removes cases in which an investor's current portfolio state may directly reflect prior recommendation outcomes from that recommender and thus limits the scope for experience-based updating about recommender ability. All other variables, fixed effects, and clustering follow Table 4. The estimated effects of *ULR* and *All_Loss* remain similar to those reported in Table 4.

	(1)	(2)	(3)	(4)
ULR	-0.048***	-0.051***		
	(0.004)	(0.002)		
All Loss (ULR=1)			-0.039***	-0.038***
			(0.002)	(0.001)
Constant	0.089***		0.065***	
	(0.004)		(0.002)	
Investor-recommender FE	N	Y	N	Y
Recommendation-date FE	N	Y	N	Y
Observations	808,334	808,334	808,334	808,334
R-squared	0.003	0.223	0.006	0.243

Table IA.10. Unrealized profits versus Unrealized loss ratio

This table replicates the four specifications in Table 4, adding a measure of unrealized profits (*UP*) to each specification. *UP* measures total unrealized gains or losses in the investor's portfolio, defined as the difference between market value and holding cost, scaled by holding cost, and computed on the day prior to the recommendation. All other variables, fixed effects, and clustering follow Table 4. *ULR* and *All_Loss* remain economically large and statistically significant across specifications aft while the effect of unrealized profits while the effect of unrealized profits is substantially smaller in economic magnitude. In particular, moving from the 25th to the 75th percentile of *ULR* implies an increase in purchase probability of roughly 2 ppts, whereas the corresponding interquartile change in unrealized profits implies a change of less than 0.5 ppts.

	(1)	(2)	(3)	(4)
ULR	-0.041***	-0.058***		
	(0.004)	(0.003)		
All Loss (ULR=1)			-0.049***	-0.039***
			(0.002)	(0.001)
UP	0.041***	0.014***	0.046***	0.030***
	(0.006)	(0.005)	(0.005)	(0.004)
Constant	0.098***		0.080***	
	(0.004)		(0.002)	
Investor-recommender FE	N	Y	N	Y
Recommendation-date FE	N	Y	N	Y
Observations	1,732,402	1,732,402	1,732,402	1,732,402
R-squared	0.013	0.240	0.009	0.241

Table IA.11. Risk preference tests: *Loss* interactions with stock characteristics

This table examines whether the relation between loss exposure and purchasing varies with the characteristics of the recommended stock. We replicate the specifications in Table 4 and augment them by interacting *ULR* (Panel A) or *All_Loss* (Panel B) with characteristics of the recommended stock, including including *Ln* (*Size*), *Book-to-market ratio*, *Momentum_1y*, *Lottery type stock*, *Stock's social media posts*, and *Beta*. All specifications include investor–recommender fixed effects, recommendation-date fixed effects, and the full set of controls from Table 4. Standard errors are double clustered by investor and recommendation date. The interaction terms are small and statistically insignificant across specifications, indicating that loss exposure does not systematically shift investors' preferences across stocks with different risk or attention-related characteristics. These results provide little support for a risk-preference explanation.

	Stock Characteristic for Interaction Term					
	Ln (Size)	*Book-to-market ratio*	*Momentum_1y*	*Lottery type stock*	*Stock's social media posts*	*Beta*
Panel A: Independent Variable: *ULR*						
ULR	-0.059***	-0.059***	-0.059***	-0.061***	-0.061***	-0.061***
	(0.014)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
ULR × *Stock characteristics*	-0.001	0.002	-0.005	0.001	0.001	0.001
	(0.001)	(0.002)	(0.004)	(0.006)	(0.001)	(0.003)
Controls	Y	Y	Y	Y	Y	Y
Investor-recommender FE	Y	Y	Y	Y	Y	Y
Recommendation-date FE	Y	Y	Y	Y	Y	Y
Observations	1,732,402	1,732,402	1,732,402	1,732,402	1,732,402	1,732,402
R-squared	0.241	0.240	0.240	0.240	0.240	0.240
Panel B: Independent Variable: *All_Loss*						
All_Loss (ULR=1)	-0.042***	-0.042***	-0.040***	-0.040***	-0.041***	-0.037***
	(0.014)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
All_Loss × *Stock characteristics*	-0.001	-0.002	-0.002	-0.001	0.000	-0.002
	(0.001)	(0.001)	(0.002)	(0.004)	(0.000)	(0.001)
Controls	Y	Y	Y	Y	Y	Y
Investor-recommender FE	Y	Y	Y	Y	Y	Y
Recommendation-date FE	Y	Y	Y	Y	Y	Y
Observations	1,732,402	1,732,402	1,732,402	1,732,402	1,732,402	1,732,402
R-squared	0.241	0.241	0.241	0.241	0.241	0.241