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Memory and Trading

By

Constantin Charles

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Abstract

I test the predictions of human memory models in a high-stakes trading environment. Using alphabetical rankings of stocks from portfolio statements, I estimate plausibly random associations of adjacent stocks in an investor's memory. When two stocks are associated in an investor's memory, trading one stock cues the recall of the other, and increases the probability that the investor also trades the other stock. Increasing the memory strength of this association by one standard deviation increases the trade probability by about 5 percentage points. I then document that personal experience affects trading behavior through the different properties of human memory. My results help uncover the sources of experience effects and provide guidance for models of memory and financial decision-making. My results also demonstrate how theory-guided tests can uncover new facts about investor behavior.

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1 Introduction

An increasing body of empirical work documents that past experiences are important for determining financial decisions. Malmendier and Nagel (2011) show that investors who lived through the Great Depression are less likely to invest in the stock market later in life. In a similar context, experienced inflation has a disproportionate effect on expected inflation (Malmendier and Nagel (2016); Malmendier et al. (2021)). Motivated by this type of evidence, new theories of memory and economic choice – based on decades of experimental memory research – have emerged.

Memory theories have broad applications in finance. For instance, they can can generate the experience effects mentioned above (Wachter and Kahana (2021)), they can generate overreaction to news (Da Silveira et al. (2020); Bordalo et al. (2022b)), they can shed light on investor behavior during financial crises (Wachter and Kahana (2021)), and they can explain asset pricing puzzles (Nagel and Xu (2022)). However, despite their promise, empirical tests of these models in finance remain scarce.

In this paper, I develop an empirical proxy for an investor's memory that I use to conduct sharp tests of the growing class of memory models in finance. In doing so, I document a new fact about how individual investors and mutual fund managers behave. While similar tests have been run in the controlled laboratory over short timescales (Enke et al. (2022)), my empirical approach allows me to assess whether these memory models also provide reasonable predictions over timescales of years and in a high-stakes trading environment. I find that many of the properties of memory that have been embraced by the psychology literature for over a century (Kahana (2012)) also emerge in a database of individual investor trading decisions.

I design my empirical tests by applying the theory of Bordalo et al. (2020), which builds on associative memory theory, to a setting of trading. The key idea of this theory is that a cue (e.g., a trade) triggers the recall of past trading experiences, especially those that are similar to the cue. The probability of recalling an experience is determined by two competing forces: similarity and interference. If the similarity between the cue and the experience is higher, the investor is more likely to recall the experience. However, if the cue is similar to many experiences in the investor's memory, these other experiences interfere with recall and reduce the probability that the investor recalls the focal experience.

I use the Barber and Odean (2000) data on the holdings and trades of retail investors to test whether trading decisions follow the predictions of this theoretical framework. Guided by the theory, I develop a measure – called $Memorability_{jkit}$ – that captures how strongly two stocks (j and k) are associated in investor i's memory on day t. An increase in the similarity of two stocks increases $Memorability_{jkit}$ of the stock pair, while an increase in interference from other stocks decreases $Memorability_{jkit}$ of the stock pair. $Memorability_{jkit}$ is the ratio of similarity to interference, and is bounded by 0 and 1.

To construct $Memorability_{jkit}$, I rely on an institutional feature that determines how investors receive information about their portfolio holdings. The investors in the Barber and Odean (2000) data receive monthly paper statements that display their portfolio holdings in alphabetical order. I use this alphabetical ranking to connect stocks that are adjacent on an investor's monthly statement. My approach is inspired by classic experiments from the memory literature, in which participants study lists of random words. A striking finding is that adjacent words on the list are much more strongly associated in memory than any other two words on the list. The key idea behind my approach is that investors' portfolio listings are very similar to the word lists in these experiments, allowing me to apply these insights to my institutional setting. To supplement the retail investor data and test for memory effects among professional investors, I also construct $Memorability_{jkit}$ for mutual fund managers using the alphabetical ranking of the fund's portfolio holdings. I source the quarterly holdings of mutual funds from Thomson Financial.

By relying on alphabetical rankings, $Memorability_{jkit}$ is designed to capture associations that are orthogonal to stock fundamentals. The key assumption is that stock fundamentals are unrelated to the alphabetical ranking in an investor's portfolio. Further, the associations are investor-specific: since alphabetical rankings differ across investors, the same two stocks may be associated for one investor but not for another. Finally, the associations may change over time, even for the same investor. Because the alphabetical ranking can change from one month to the next, two stocks might be associated at one point, but this association can fade away as time progresses. I compute $Memorability_{jkit}$ on a rolling basis using portfolio statements from the previous twelve months.

With the memory associations captured by $Memorability_{jkit}$, I can test whether memory associations affect trading behavior. To classify trades as memory-induced trades, I assume that recalling a stock increases the probability of trading the stock. Specifically, I assume that when an investor trades a stock, this trade (=the cue) brings back the memory of associated stocks. If the investor also trades an associated stock on the same day, I classify this second trade as a memory-induced trade.

In my main tests, I regress a dummy variable indicating a memory-induced trade on $Memorability_{jkit}$. I also include stock-pair fixed effects into this regression. By including stock-pair fixed effects, I fix two stocks, j and k, and leverage variation in $Memorability_{jkit}$ within and across investors. This approach holds stock fundamentals fixed and only varies $Memorability_{jkit}$, which corresponds to a thought experiment in which I exogenously increase the memory association between two stocks to see how this affects the probability of a memory-induced trade.

Using this specification, I find that a one-standard deviation increase in $Memorability_{jkit}$ increases the probability of a memory-induced trade by 4.82 percentage points. Put differently, an increase in $Memorability_{jkit}$ from no memory association to full association leads to an increase in the trade probability of 13.40 percentage points. I find similar effects for the trades of mutual fund managers. In terms of magnitude, these effect sizes are comparable to the rank effect in Hartzmark (2015).

To better understand the mechanism behind my results, I zoom in on the different properties of memory and test whether they drive individual trading decisions. These properties have decades of empirical support in the memory literature (Kahana (2012)). First, I test for the separate effects of similarity and interference. As expected, if the similarity between two stocks increases by one standard deviation, the probability of a memory-induced trade increases by about 5 percentage points. Crucially, interference from competing stock pairs reduces this effect, as predicted by theory. If interference increases by one standard deviation, the trade probability falls by about 3 percentage points. These results validate a key prediction of associative memory theory (Bordalo et al. (2020); Bordalo et al. (2022a)).

Second, I test for the recency effect, i.e., whether recent experiences are easier to recall than experiences from the distant past. Indeed, I find a stronger memory effect for associations estimated from recent monthly statements than for associations estimated from distant monthly statements. Third, I test for a characteristic pattern of memory, called the contiguity effect. This well-established effect refers to the finding that two items share a stronger association if they were experienced closer together. In line with this prediction, I find that the memory effect is weaker the further two stocks are positioned from each other in an alphabetically ranked portfolio. In sum, the memory-induced trades that I document are consistent with several sharp predictions of memory theory.

I provide several robustness tests that help rule out alternative theories. First, I show that the memory effect is not mechanically driven by portfolio size. I also show that stock-specific or stock-pair-specific information on the trading day cannot explain my results. Further, I show that my results are not a relabeling the rank effect (Hartzmark (2015)). Finally, I perform tests aimed at addressing concerns that my results might be driven by attention spillover rather than memory (Peng and Xiong (2006); Barber and Odean (2008); Hirshleifer et al. (2009); Da et al. (2011); An et al. (2022)). In these tests, I continue to find memory effects for stock pairs that were historically close to each other on a statement, but that are not close on the most recent portfolio statement.

I contribute to the literature on experience effects, which has shown that life experiences have strong and persistent effects on financial decisions (Malmendier and Nagel (2011, 2016); Malmendier et al. (2011); Malmendier and Shen (2020); Malmendier et al. (2021)). My results help uncover the mechanism behind these experience effects, since I design precise tests of memory theories that can generate such experience effects.

I also contribute to the large literature on investor behavior. While much of this literature has focused on retail investors (for an overview, see Barber and Odean (2013)), several studies also analyze trading behavior at the professional level (Wermers (1999); Griffin et al. (2003); Frazzini (2006); Jin and Scherbina (2011); Hartzmark (2015); Akepanidtaworn et al. (2021)). I add to this literature by showing that memory effects in trading are pervasive amongst both retail and institutional investors. Recent work has also incorporated memory into asset pricing (Bodoh-Creed (2020); Nagel and Xu (2022)). My results lend support to this approach by providing evidence of memory effects in financial markets.

More broadly, my findings relate to work that incorporates aspects of human memory into economic choice (Gilboa and Schmeidler (1995); Mullainathan (2002); Hirshleifer and Welch (2002); Bordalo et al. (2020); Wachter and Kahana (2021); Bordalo et al. (2022a)) and forecasting (Da Silveira et al. (2020); Afrouzi et al. (2022)). While the theoretical literature has pushed ahead in this area, empirical evidence of such memory effects remains scarce. To help fill this gap, two recent studies provide evidence from the experimental laboratory (Enke et al. (2022); Gödker et al. (2022)), while another study uses survey data (Colonnelli et al. (2021)). I test the models using trading decisions from high-stakes financial markets and support this growing body of theoretical work with evidence from the field.

2 Empirical Strategy

In order to test whether the memory associations of stocks in an investor's mind systematically affect trading decisions, I need a measure that captures which stocks are associated in memory for each investor at each point in time. In the ideal experiment, I would randomly associate different stocks for different investors and then test whether these associations drive trading decisions. I approximate this ideal experiment by building on decades worth of theoretical and experimental work from the memory literature (Kahana (2012)), and discuss my approach in this section. In Appendix A, I also present a theoretical framework that illustrates the main forces of associative memory theory in a trading setting.

In associative memory theory, recall is driven by two competing forces: similarity and interference. To illustrate these forces, consider the following classic experiment from the memory literature. Participants study a list with N random words, which are provided sequentially from $n = 1$ to N. After the study phase, participants are asked to freely recall words from the list. A striking finding is that upon recalling any word with serial position n from the list, participants are much more likely to recall the word with serial position $n + 1$ compared to any other word from the list. In associative memory theory, these two words are encoded as similar in memory because they were experienced immediately after one another. As a result, cueing the word with serial position n triggers the recall of the word with serial position $n + 1$.

However, recall is also affected by a second force: interference. If the cueing word is associated with many other words – e.g., because the participant studied several lists containing the cueing word – associations from these other lists can lead to interference in recall. That is, the participant might recall an associated word from one of the other lists instead of the word with serial position $n+1$ from the focal word list.

In my empirical strategy, I apply these insights to my institutional setting to estimate which stocks are associated in an investor's memory. In estimating these associations, I rely on an important feature of my data set. Investors in my data set receive monthly paper statements that display their portfolio holdings in alphabetical order. The key idea behind my approach is that these portfolio listings are very similar to the word lists from the experiments described above. Further, the alphabetical rankings allow me to estimate associations that are orthogonal to stock fundamentals (I discuss this feature in more detail below). I estimate the similarity between two stocks as follows:

$$S_{jkit} = \sum_{m=1}^{12} d_{jkim} \cdot w_m \tag{1}$$

Here, d_{jkim} is a dummy variable that is equal to one if stock j immediately follows stock k on investor i's alphabetically ranked portfolio statement in month m.[1] As in the word list experiments, adjacent stocks on a statement are experienced immediately after one another and should therefore be more strongly associated in memory than stocks that are located further away from each other. Thus, the dummy variable d_{jkim} is a simple measure that is driven by the key forces of associative memory theory.

To account for the role of recency in recall, the term w_m is a weighting parameter that decays linearly from the most recent portfolio statement down to zero for portfolio statements that are older than twelve months.[2] This weighting scheme is inspired by Malmendier and Nagel (2011), which shows that such a linear weighting scheme is a good approximation for

[1] I use forward-linking because humans generally read from top to bottom. In robustness tests, I link each stock to its predecessor in the ranking and find similar results. These results are displayed in Appendix Table A.1.

[2] The importance of recency in recall is well-documented in the memory literature. In the word list experiments described above, participants are generally most likely to recall words from the end of the list, since these are the words that they experienced most recently (Murdock Jr (1962)).

the recency effect in the domain of experience effects in finance.[3] The weights sum up to one, bounding S_{jkit} by zero and one. For each investor, I estimate S_{jkit} on a rolling basis, using the monthly portfolios holdings from the previous twelve months.

The measure S_{jkit} is designed to capture associations that are orthogonal to stock fundamentals by relying on the alphabetical rankings of tickers in investors' monthly statements. The key assumption is that the alphabetical ranking in an investor's portfolio is unrelated to stock fundamentals. It is worth noting that I do not need to assume that an individual stock's ticker is unrelated to its fundamentals, since my measure is defined by the association of two stocks. Further, the associations are investor-specific: since alphabetical rankings differ across investors, the same two stocks may be associated for one investor but not for another. Finally, the associations may change over time, even for the same investor. Because the alphabetical ranking can change from one month to the next, two stocks might be associated at one point, but this association can fade away as time progresses. Using this measure of similarity, I can construct the following composite measure:

$$Memorability_{jkit} \equiv \frac{S_{jkit}}{\sum_{x=1}^{M} S_{xkit}} \tag{2}$$

This measure captures the two key forces of associative memory theory. The term in the numerator is the pairwise similarity between stocks j and k. All else equal, if the similarity between j and k is higher, the strength of the memory association between j and k increases. As a result, when cued with stock k, the investor is more likely to recall stock j.

In contrast, the term in the denominator captures interference. Interference refers to the idea that the cue (here, stock k) might be similar to many stocks in the investor's memory. These other stocks interfere with the recall of stock j. The denominator measures interference by summing the similarities between stock k and all M stocks in the memory database. If this sum is larger, interference is larger, and the probability of recalling stock j is lower. For expositional purposes, I label the combined measure $Memorability_{jkit}$. This is the main measure in my empirical tests.

To connect this measure to trading behavior, I make the following additional assumption:

[3] My results are robust to alternative weighting schemes. In Table 10, I show that I find similar results for (1) a weighting scheme that is calibrated to the data, and (2) if I omit the weighting scheme altogether.

when an investor recalls a stock, he is more likely to trade the stock. Suppose that, as in the theoretical framework in Appendix A, there is a cue κ that contains stock k. Then, conditional on the cue κ, the probability of trading the associated stock j is an increasing function of $Memorability_{jkit}$. I assume that the cue κ is a trade in stock k and that the function f is linear. This yields:

$$P(\text{Trade Stock } j|\text{Trade Stock } k)_{it} = \alpha + \beta \cdot Memorability_{jkit} \tag{3}$$

I estimate this equation using the trades of a panel dataset of investors. In my empirical tests, I run the following regression, in which j and k index stocks, i investors, and t trading days.

$$I(\text{Trade Stock } j|\text{Trade Stock } k)_{it} = \alpha_{jk} + \beta \cdot Memorability_{jkit} + \epsilon_{jkit} \tag{4}$$

In this regression, the dependent variable is a dummy variable that is equal to one if, conditional on trading stock k, the investor also trades the associated stock j on the same day. The independent variable $Memorability_{jkit}$ captures the strength of the memory association and is estimated using the investor's portfolio holdings from the previous twelve months.

While $Memorability_{jkit}$ is designed to be orthogonal to stock fundamentals, the ideal approach also holds stock fundamentals fixed and only varies $Memorability_{jkit}$. This approach addresses any concerns that the fundamentals of stocks could be correlated in ways that are related to their alphabetical similarity (Jacobs and Hillert (2016)). To implement this approach, I fix two stocks, j and k, and leverage variation in $Memorability_{jkit}$ between those two stocks within and across investors. In the regression, this corresponds to including a stock-pair fixed effect α_{jk}. This is the main specification that I estimate in my empirical analysis.

3 Data and Summary Statistics

3.1 Retail Investors

I use data on the holdings and trades of retail investors, for the years 1991 to 1996, to calculate $Memorability_{jkit}$ and to identify memory-induced trades. These data are the same as in Barber and Odean (2000). The investors in this data set receive monthly paper statements containing their portfolio holdings. On the statements, the holdings are displayed in alphabetical order. I use this alphabetical ranking to construct $Memorability_{jkit}$.

I retain only common stocks, drop all trades with negative commissions, and match the data to CRSP for information on stock prices and tickers. The data specify the day on which an investor executed a trade, and I retain only days on which an investor traded at least two different stocks. I focus on these days since I require at least one trade to act as a cue, which brings back the memory of associated stocks. The other trade(s) allow me to identify memory-induced trades.[4] Finally, I retain only investors who trade on more than five distinct days in a year, to rule out the concern that my results are driven by investors who hold the same portfolio for an entire year and rebalance their portfolio once a year. This behavior could look like memory-induced trading since it would result in high $Memorability_{jkit}$ between adjacent stock pairs and in high joint trade probabilities.

In Panel A of Table 1, I provide summary statistics for the sample of retail investors, which includes 11,164 distinct investors. For these investors, there are a total of 63,245 investor-days on which an investor sold at least two stocks. In my tests, however, the number of observations is generally larger than 63,245. This is because an observation in my setting is identified by a stock pair that is associated in an investor's memory on a trading day, i.e., a stock pair that was adjacent at least once over the past twelve months. Thus, the number of observations on an investor-day is given by all pairs of associated stocks in the

[4]In Appendix Table A.3, I show that my results also hold when I include trading days on which an investor only traded one stock. These tests implicitly include a prediction task, namely predicting whether an investor will execute a second (potentially memory-induced) trade on the same day. Giglio et al. (2021) show that it is difficult to predict when investors trade. Conditional on trading, however, investors trade according to their beliefs. Therefore, in my main tests, I abstract from predicting whether investors execute a second trade and instead focus on whether memory affects which stocks investor choose to trade, conditional on trading.

investor's memory.[5]

On average, investors in my sample hold 15 stocks in their portfolio (median: 9). The average probability of a memory-induced trade is 12%. When I break out memory-induced trades by buys and sells, I find that memory-induced sells are more likely than memory-induced buys. I explore this asymmetry in more detail in Table 11. $Memorability_{jkit}$ is bounded by zero and one, and has an average of 0.604.[6]

Table 1: Summary Statistics

Panel A: Retail Investors	**Mean**	**p25**	**p50**	**p75**	**Std. Dev.**	**Min**	**Max**	**N**
#Stocks in portfolio	15	5	9	16	29	1	632	63,245
Memory-induced trade (dummy)	0.120	0.000	0.000	0.000	0.325	0.000	1.000	175,081
Memory-induced buy (dummy)	0.031	0.000	0.000	0.000	0.172	0.000	1.000	175,081
Memory-induced sell (dummy)	0.089	0.000	0.000	0.000	0.285	0.000	1.000	175,081
Memorability	0.604	0.267	0.588	1.000	0.356	0.013	1.000	175,081

Panel B: Mutual Funds	**Mean**	**p25**	**p50**	**p75**	**Std. Dev.**	**Min**	**Max**	**N**
#Stocks in portfolio	99	45	68	104	130	2	3,670	54,715
Memory-induced trade (dummy)	0.192	0.000	0.000	0.000	0.394	0.000	1.000	727,507
Memory-induced buy (dummy)	0.084	0.000	0.000	0.000	0.277	0.000	1.000	727,507
Memory-induced sell (dummy)	0.109	0.000	0.000	0.000	0.311	0.000	1.000	727,507
Memorability	0.683	0.400	0.714	1.000	0.325	0.100	1.000	727,507

Notes: This table contains summary statistics of the two samples used in the empirical analysis. Panel A describes the sample of retail investors and Panel B describes the sample of mutual funds. A given stock may be associated with multiple stocks in the investor's or fund manager's memory, resulting in the large number of observations for memory variables. A memory-induced trade is defined at the investor-day-stock-pair level (Panel A) or the fund-quarter-stock-pair level (Panel B) and is a dummy variable that is equal to one if conditional on a trade in one stock of the stock pair (=the cueing stock), the investor (fund manager) also trades the other stock of the stock pair on the same day (in the same quarter). Memorability measures how strongly two stocks of a stock pair are associated in memory. It is bounded by zero (no association) and one (full association).

[5] Notice that I am not double counting stock pairs in my sample. This is because I associate stocks only in the forward direction, resulting in a clear one-directional relationship from cueing to cued stock. In Table A.1, I show similar results when I associate stock pairs in the backward direction.

[6] There are several observations with $Memorability_{jkit}$ equal to one. This happens when the cueing stock was associated with only one stock over the past twelve months. For these stock pairs, the numerator and denominator of $Memorability_{jkit}$ are identical, resulting in $Memorability_{jkit}$ equal to one. In Appendix Table A.2, I show that these observations are not driving my results. In these tests, I drop all observations with $Memorability_{jkit}$ equal to one and find similar results.

3.2 Mutual Fund Managers

I also construct these variables for mutual fund managers using data on funds' quarterly holdings for years 2000 to 2014. I create this sample by merging data on open-end US equity funds contained in the mutual fund database of the Center for Research in Security Prices (CRSP) with data on their quarterly holdings from Thomson Financial. As in Lou (2012), I impose several restrictions to ensure satisfactory data quality. First, I exclude all funds that report an investment objective code indicating "international," "municipal bonds," "bond & preferred," or "metals" in Thomson Financial. Second, I require the aggregate value of equity holdings of a fund-quarter in Thomson Financial to be within the range of 75% and 120% of the fund's total net assets reported in Thomson Financial. Third, total net assets reported in Thomson Financial for a fund-quarter may not differ by more than a factor of two from those reported in the CRSP mutual fund database. Fourth, I exclude all fund-quarters with total net assets of less than $1 million in either the Thomson Financial or the CRSP mutual fund database. For the remaining observations, I cross-check each individual stock holding with data from the CRSP daily stock file as of the holding's reporting date. Specifically, I require that the split-adjusted share price and the number of shares outstanding reported in Thomson Financial do not differ by more than 30% from those reported in the CRSP daily stock file. Finally, shares held by a single fund may not exceed the total number of shares outstanding in the CRSP daily stock file.

Using the resulting sample, I calculate $Memorability_{jkit}$ and identify memory-induced trades in analogy to the sample of retail investors. Due to differences between the two data sets, I make several minor adjustments. In contrast to the retail investor data, I cannot observe how fund managers display their holdings internally. Thus, I construct $Memorability_{jkit}$ for fund managers assuming that managers display their holdings alphabetically. Second, to match the reporting frequency, I weight observations using linearly decaying quarterly weights when constructing $Memorability_{jkit}$. Third, I define a trade as a change in the number of (split-adjusted) shares from the previous report. To reduce measurement error in identifying trades (e.g., due to small differences in the number of shares across reports), I retain only trades that are at least 0.5% of total net assets.[7] This restric-

[7] My results are robust to using higher or lower cutoffs.

tion also allows me to focus on meaningful trades. Finally, I pool all trades that occurred in a quarter, since I cannot observe the exact day on which a mutual fund manager executed a trade.

In Panel B of Table 1, I provide summary statistics for this sample, which includes 3,443 distinct funds. On average, funds hold 99 stocks (median: 68). An appealing aspect of these large portfolios is that I can estimate many memory associations for each fund. The average probability of a memory-induced trade is 19.2% and $Memorability_{jkit}$ is 0.683 on average. These figures are similar to those of the retail investor data.

4 Results

4.1 Baseline Results

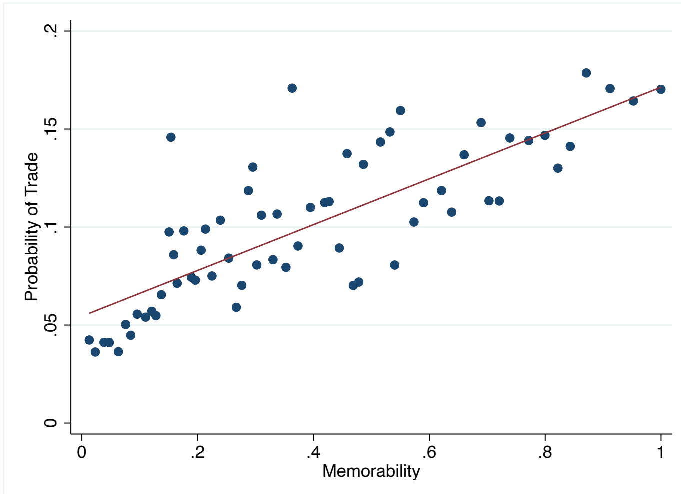
To visualize the relationship between memory and trading in the raw data, Figure 1 presents a binned scatterplot in which $Memorability_{jkit}$ is on the horizontal axis, and the probability of a memory-induced trade is on the vertical axis. Panel A displays this result for retail investors and Panel B for mutual funds. Both figures show that as the strength of the association between two stocks increases, the probability of a memory-induced trade increases as well. In Table 2, I test for this relationship more rigorously by estimating regression 4. In this regression, a dummy indicating a memory-induced trade is the dependent variable and $Memorability_{jkit}$ is the explanatory variable. All specifications include stock-pair fixed effects $\alpha_{j,k}$. By holding fixed two stocks, these fixed effects address concerns that the fundamentals of stocks could be correlated in ways that are related to their alphabetical similarity.

In the first column of Panel A, the coefficient on $Memorability_{jkit}$ implies that increasing $Memorability_{jkit}$ by one standard deviation increases the probability of a memory-induced trade by 4.77 percentage points. Further, an increase in $Memorability_{jkit}$ from no association to full association increases the trade probability by 13.40 percentage points. In terms of economic magnitude, this effect is comparable to the rank effect in Hartzmark (2015).

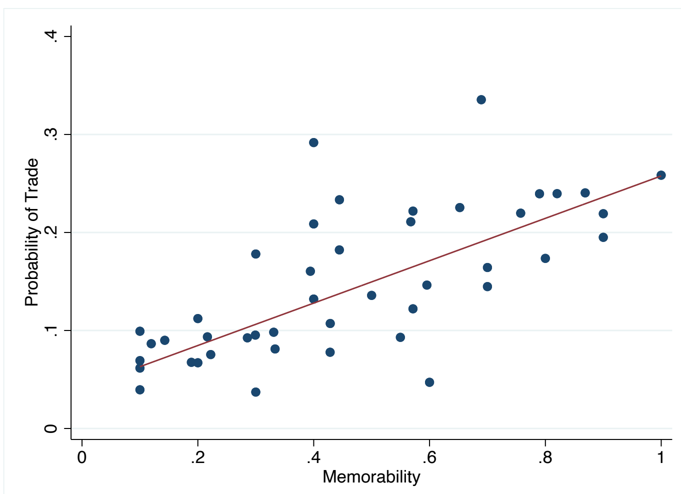
In the second column, I add a trading day fixed effect to address the concern that the trad-

Figure 1. Baseline Results in the Raw Data

(a) Panel A: Retail Investors



(b) Panel B: Mutual Funds



Notes: These figures show binned scatterplots of the probability of a memory-induced trade against Memorability. Memorability captures memory associations between stock pairs that are built up over the past twelve months (Panel A) or past four quarters (Panel B). The probability of a memory-induced trade is the probability that a trade in one stock of the pair (the cueing stock) triggers the recall and trade of the other stock of the pair on the same day (Panel A) or in the same quarter (Panel B). Both graphs include a linear fit.

Table 2: Baseline Results

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.134***	0.132***	0.124***
	(0.004)	(0.004)	(0.005)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	175,081	175,081	138,522
R-squared	0.300	0.313	0.596

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.192***	0.192***	0.179***
	(0.004)	(0.004)	(0.003)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	727,507	727,507	726,518
R-squared	0.232	0.232	0.384

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on Memorability. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

ing decision might be driven by the day (e.g., a January effect). In the third column, I include investor x day fixed effects, which control for unobservable (potentially time-varying) characteristics of investors – such as sophistication and wealth – that might affect the propensity to engage in memory-induced trading. These fixed effects also address the potential concern that my results might be picking up mechanical effects due to differences in portfolio size. Such mechanical effects might occur if investors are more likely to trade a stock when they hold a smaller number of stocks in their portfolio. Further, since two stocks are more likely to be alphabetically adjacent in a smaller portfolio, there might mechanically be a positive relationship between $Memorability_{jkit}$ and the conditional probability of a stock being traded. However, since the size of an investor's portfolio is fixed on a trading day, investor x day fixed effects address this concern by allowing me to estimate the memory effect within fixed portfolio sizes.

The magnitude of the coefficient is very similar even with these additional fixed effects. Across specifications, as the fixed effects become tighter, the number of observations drops since I remove singleton observations. The standard errors in all retail investor regressions are clustered by stock pair, investor, and trading date.

In Panel B of Table 2, I display similar results for mutual funds. The effect size is similar to that of retail investors. For instance, in the first column, a one standard deviation increase in $Memorability_{jkit}$ corresponds to an increase in the probability of a memory-induced trade of 6.24 percentage points. The standard errors in all mutual fund regressions are clustered by stock pair, fund, and quarter.

4.2 Identifying Cueing Trades using Earnings Announcements

One shortcoming of the previous tests is that I cannot distinguish the order in which an investor trades stocks on a given day. In the data, I only observe all the trades that an investor executed on a trading day. In the ideal experiment, I could also observe the order of trades and identify which trades act as cues for the recall of associated stocks. Ideally, I could also identify which of these cueing trades are exogenous.

In this section, I try to identify such cueing trades by looking at trades that were likely triggered by an annual earnings announcement. When an investor trades a stock within

Table 3: Identifying Cueing Trades

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.105***	0.111***	0.122**
	(0.014)	(0.016)	(0.053)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	3,194	3,018	533
R-squared	0.015	0.177	0.521

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.211***	0.210***	0.195***
	(0.007)	(0.007)	(0.007)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	74,121	74,121	54,717
R-squared	0.033	0.035	0.282

Notes: This table replicates the baseline regressions for a specific subset of stock-pairs. In Panel A, only stocks that were traded on the day of their annual earnings announcement or in the two calendar days after the announcement are included as cueing trades. Stocks that are classified as memory-induced trades cannot have had an annual earnings announcement on any of those days. In Panel B, only stocks that were traded in the quarter of their annual earnings announcement are included as cueing trades. Stocks that are classified as memory-induced trades cannot have had an annual earnings announcement in that quarter. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

three days of its annual earnings announcement, I classify it as a cueing trade. I use these cueing trades to estimate whether the investor is more likely to also trade a stock that did *not* have an annual earnings announcement, if the two stocks are associated in memory. I display the results of this test in Panel A of Table 3. Despite the small sample size, I find very similar memory effects.

In Panel B of Table 3, I repeat the analysis for mutual funds. Due to data limitations, I cannot identify the precise day on which a mutual fund traded a stock. Therefore, I classify a trade as a cueing trade if the stock had its annual earnings announcement in a quarter. As before, I use these cueing trades to estimate whether the fund manager is more likely to also trade a stock that did *not* have its annual earnings announcement in that quarter, if the two stocks are associated in memory. Again, I find memory effects that are very similar to the effects estimated using all trades.

4.3 Similarity and Interference

In the following tests, I probe the different properties of memory separately, to understand how they shape trading decisions. First, I test for the effects of similarity and interference separately. The importance of both similarity and interference for recall is a robust finding in laboratory experiments (Kahana (2012); Enke et al. (2022); Bordalo et al. (2022a)). As outlined in Section 2, $Memorability_{jkit}$ is comprised of both components: the numerator captures the similarity of a stock pair, while the denominator captures interference from other stock pairs. These two forces have opposing effects on the recall probability: higher similarity increases recall, while higher interference reduces recall.

In Table 4, I include the numerator (similarity) and the denominator (interference) of $Memorability_{jkit}$ separately as independent variables into my baseline regressions. I expect a positive coefficient on similarity and a negative coefficient on interference. This is precisely what I find. Thus, the memory effect captured by my composite measure $Memorability_{jkit}$ is the result of two competing forces: similarity increases the effect, while interference reduces the effect.

In terms of economic magnitude, using the estimates from the first column, increasing similarity by one standard deviation (one std. dev. = 0.28) increases the trade probability

Table 4: Similarity and Interference

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Similarity	0.177***	0.175***	0.148***
	(0.005)	(0.005)	(0.007)
Interference	-0.100***	-0.097***	-0.109***
	(0.005)	(0.005)	(0.009)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	175,081	175,081	138,522
R-squared	0.299	0.312	0.596

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Similarity	0.215***	0.215***	0.199***
	(0.006)	(0.006)	(0.004)
Interference	-0.184***	-0.182***	-0.146***
	(0.008)	(0.008)	(0.004)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	727,507	727,507	726,518
R-squared	0.231	0.232	0.382

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on Similarity and Interference, which are the numerator and denominator of Memorability, respectively. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

by about 5 percentage points for retail investors. In contrast, increasing interference by one standard deviation (one std. dev. = 0.32) reduces the trade probability by about 3 percentage points for retail investors. These effect sizes are very similar for mutual funds: a one standard deviation increase in similarity leads to a 6 percentage point increase in the trade probability, while a one standard deviation increase in interference leads to a 4 percentage point reduction.

Overall, the results in Table 4 provide strong evidence for the driving forces of associative memory models, which help to distinguish my findings from alternative explanations. The negative effect of interference is a particularly distinctive pattern of associative memory theory.

4.4 Recency

Next, I test for the recency effect, which posits that investors are more likely to recall stocks that they experienced recently. The role of recency is well established in the memory literature (Kahana (2012)) and its importance for financial decisions has been demonstrated in several studies (e.g., Malmendier and Nagel (2011); Nagel and Xu (2022)).

To test for the recency effect, I include dummies for each of the past twelve months, indicating whether two stocks were associated in a given month.[8] The goal of this approach is to unveil the degree of recency by estimating the weighting function over the past twelve months directly. This test is akin to the weighting function in Malmendier and Nagel (2011), except that I do not need to impose the functional form assumptions of Malmendier and Nagel (2011). The prediction is that the magnitude of the coefficients drops off as the dummies move further into the past.

I present the results in the first column of Table 5.[9] As expected, the loading on the most recent dummy is the strongest. Moving further into the past, the magnitude of the coefficients drops off sharply. Indeed, for retail investors (Panel A), the influence of previous statements disappears at about three months into the past. The results are similar for mutual

[8]These dummies are the dummy variables d_{jkim} that I use to construct the similarity measure S_{jkit} described in Section 2.

[9]The results presented in Table 5 control for stock-pair fixed effects. In Appendix Tables A.4 and A.5, I present similar results when I additionally control for day fixed effects and investor x day fixed effects.

Table 5: Recency

Panel A: Retail investors

Dependent variable:	Memory-induced trade (dummy)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lag 1 (dummy)	0.120***										
	(0.003)										
Lag 2 (dummy)	0.014***	0.023***									
	(0.003)	(0.003)									
Lag 3 (dummy)	0.001	0.011***	0.017***								
	(0.003)	(0.003)	(0.004)								
Lag 4 (dummy)	0.004	0.008*	0.011**	0.013**							
	(0.003)	(0.004)	(0.005)	(0.005)							
Lag 5 (dummy)	-0.001	0.005*	0.005	0.007*	0.012***						
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)						
Lag 6 (dummy)	0.001	0.000	0.002	0.003	0.003	0.006					
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)					
Lag 7 (dummy)	-0.001	0.003	0.003	0.003	0.005	0.005	0.002				
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)				
Lag 8 (dummy)	-0.001	-0.002	-0.001	-0.000	0.002	0.003	0.003	0.005			
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)			
Lag 9 (dummy)	-0.001	0.001	0.002	0.004	0.003	0.004	0.003	-0.002	-0.002		
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)		
Lag 10 (dummy)	0.004	0.009***	0.010***	0.011***	0.010***	0.010***	0.010***	0.010**	0.012***	0.015**	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	
Lag 11 (dummy)	-0.003	-0.002	-0.002	-0.002	0.001	0.004	0.005	0.003	0.000	0.003	-0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.009)
Lag 12 (dummy)	-0.001	-0.003	-0.001	-0.001	-0.000	0.002	0.000	0.001	0.003	0.005	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)	(0.012)
Stock-pair FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	175,081	84,718	67,368	53,976	43,364	34,520	26,950	20,243	14,513	9,558	5,287
R-squared	0.314	0.320	0.331	0.338	0.344	0.351	0.353	0.356	0.376	0.392	0.448

Panel B: Mutual funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Lag 1 (dummy)	0.154***		
	(0.003)		
Lag 2 (dummy)	-0.009**	0.004**	
	(0.004)	(0.002)	
Lag 3 (dummy)	0.018***	0.006***	0.008***
	(0.003)	(0.002)	(0.002)
Lag 4 (dummy)	0.015***	0.001	0.001
	(0.002)	(0.002)	(0.002)
Stock-pair FE	yes	yes	yes
Observations	727,507	209,573	124,337
R-squared	0.238	0.309	0.325

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on a set of dummy variables indicating if a stock pair was associated in a given month (Panel A) or quarter (Panel B). Across columns, an increasing number of lags is omitted with the restriction that the dummy variables of all omitted lags are jointly equal to zero. All regressions include stock-pair fixed effects. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

funds (Panel B), with the most recent association being the most important. In contrast to the retail investors, loadings on the dummies that are furthest in the past remain slightly positive and significant.

One shortcoming of including all dummies simultaneously into the regression is that this approach might overstate the effect drop-off, since the portfolio holdings of investors are sticky. This stickiness creates autocorrelation in the dummies and, when all dummies are included simultaneously, the lag-1 dummy dominates. Therefore, as an alternative approach, I run separate regressions – one for each lag – in which I ensure that all previous lags are jointly equal to zero. For instance, to estimate the coefficient on lag-2, I run a regression with observations for which lag-1 is equal to zero. I run these types of regressions for all lags and display the results in the remaining columns of Table 5.[10] In this alternative approach, the drop-off after the first month remains sharp, but the effect fades way more gradually with time. For retail investors, associations going back up to five months continue to have a significant effect.

Overall, the sharp drop off in the coefficients is a characteristic feature of memory and reminiscent of findings from classic memory experiments (e.g., Murdock Jr (1962)). In these experiments, participants study a list of random words. After the study phase, they are asked to freely recall words from the list. The general finding is that participants have excellent recall of the last few words, but the recall probability drops off sharply for earlier words.

4.5 Contiguity

In this section, I test another property of memory: the "law of contiguity". This law states that two items are more strongly associated in memory if they were experienced closer to one another. The intuition of contiguity can be illustrated with the word list experiments described in Section 2. In these experiments, upon recalling any word with serial position n from the list, participants are most likely to recall the word with serial position $n + 1$.

[10] I cannot run such a regression for lag-12. The reason is that I restrict my sample to a rolling window of 12 months to identify associated stocks. Thus, if I jointly set the dummies for lags 1 through 11 equal to zero, the dummy for lag-12 must mechanically be equal to one. As a result, there is no remaining variation to estimate the coefficient on lag-12.

Further, the recall probability of a word decreases monotonically as the word's serial position increases relative to the cueing word with serial position n. According to the law of contiguity, the words with serial position n and $n+1$ share the strongest association because they were experienced immediately after one another. However, the words with serial positions n and $n+2$ also share a memory association, albeit a weaker one. The further the distance in their respective serial positions, the weaker the memory association between two words.

I apply this intuition to my setting by arguing that two stocks with ranking positions n and $n+1$ on an investor's portfolio statement should share a stronger memory association than two stocks with ranking positions n and $n+2$. To test this prediction empirically, I construct additional flavors of $Memorability_{jkit}$ that capture these increasingly weaker memory associations. Specifically, each flavor $Memorability_{jkit}^{\Delta(d)}$ is constructed by connecting a stock with ranking position n to a stock with ranking position $n+d$. Thus, $d=1$ yields baseline $Memorability_{jkit}$. As d increases, the flavors capture increasingly weaker memory associations.

In Table 6, I regress the dummy variable indicating a memory-induced trade on the different flavors of $Memorability_{jkit}^{\Delta(d)}$. Notice that the number of observations in these regressions is much larger than in my baseline tests. This is because an observation in my setting is identified by a stock pair that is associated in an investor's memory on a trading day. In my baseline tests, I only consider associations of stocks with $d=1$. However, in Table 6, I consider many more associations which are captured by the additional flavors, resulting in many more observations.

As expected, the memory effect becomes weaker as the distance d between two stocks in the ranking increases. Indeed, the effect fades away almost monotonically, both for retail investors (Panel A) and mutual funds (Panel B). The specifications in the third column are particularly useful since they estimate this effect within an investor-day (Panel A) or a fund-quarter (Panel B). That is, conditional on trading stock k, the same investor is more likely to trade stock j if that stock was historically closer to stock k on the previous portfolio statements. These results are fully consistent with the law of contiguity.

Table 6: Contiguity

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability$^{\Delta(1)}$	0.172***	0.172***	0.117***
	(0.003)	(0.003)	(0.003)
Memorability$^{\Delta(2)}$	0.133***	0.132***	0.107***
	(0.003)	(0.003)	(0.003)
Memorability$^{\Delta(3)}$	0.111***	0.110***	0.099***
	(0.003)	(0.003)	(0.003)
Memorability$^{\Delta(4)}$	0.092***	0.091***	0.088***
	(0.003)	(0.003)	(0.003)
Memorability$^{\Delta(5)}$	0.082***	0.081***	0.084***
	(0.003)	(0.003)	(0.003)
Memorability$^{\Delta(6)}$	0.071***	0.069***	0.078***
	(0.003)	(0.003)	(0.003)
Memorability$^{\Delta(7)}$	0.066***	0.065***	0.073***
	(0.004)	(0.003)	(0.003)
Memorability$^{\Delta(8)}$	0.060***	0.059***	0.070***
	(0.004)	(0.003)	(0.003)
Memorability$^{\Delta(9)}$	0.062***	0.060***	0.075***
	(0.004)	(0.004)	(0.004)
Memorability$^{\Delta(10)}$	0.061***	0.059***	0.076***
	(0.006)	(0.005)	(0.004)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	890,068	890,068	876,204
R-squared	0.257	0.271	0.424

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability$^{\Delta(1)}$	0.291***	0.291***	0.232***
	(0.005)	(0.005)	(0.004)
Memorability$^{\Delta(2)}$	0.263***	0.264***	0.220***
	(0.005)	(0.005)	(0.004)
Memorability$^{\Delta(3)}$	0.243***	0.243***	0.210***
	(0.004)	(0.004)	(0.003)
Memorability$^{\Delta(4)}$	0.225***	0.225***	0.202***
	(0.004)	(0.004)	(0.003)
Memorability$^{\Delta(5)}$	0.209***	0.209***	0.195***
	(0.004)	(0.004)	(0.003)
Memorability$^{\Delta(6)}$	0.196***	0.196***	0.189***
	(0.004)	(0.004)	(0.003)
Memorability$^{\Delta(7)}$	0.183***	0.183***	0.183***
	(0.004)	(0.004)	(0.003)
Memorability$^{\Delta(8)}$	0.175***	0.175***	0.182***
	(0.004)	(0.004)	(0.003)
Memorability$^{\Delta(9)}$	0.172***	0.172***	0.186***
	(0.004)	(0.004)	(0.003)
Memorability$^{\Delta(10)}$	0.177***	0.177***	0.199***
	(0.005)	(0.005)	(0.004)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	6,422,474	6,422,474	6,422,462
R-squared	0.215	0.215	0.334

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on different flavors of Memorability. Each flavor of Memorability$^{\Delta(d)}$ is constructed by connecting a stock with ranking position n to a stock with ranking position $n + d$. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

5 Robustness

In the previous section, I have presented evidence for memory effects in trading and shown that the different properties of memory affect trading decisions as predicted by associative memory theory. In the tests that follow, I show the robustness of these results and address several alternative explanations.

5.1 Addressing Attention Spillover

An important concern is that my results might capture attention effects (Peng and Xiong (2006); Barber and Odean (2008); Hirshleifer et al. (2009); Da et al. (2011); Jiang et al. (2022); An et al. (2022)). For instance, if two stocks were historically adjacent on an investor's portfolio – and therefore associated in memory – they might still be adjacent on the day of the trade. Thus, when an investor trades a stock, he might also see the adjacent stock, and decide to trade this stock as well. In this case, my findings would pick up attention-induced trades rather than memory-induced trades.

To help address this concern, I perform the following test. I focus only on stocks that were adjacent on an investor's statement at some point in the previous twelve months – and are therefore associated in the investor's memory – but that are not adjacent on the day of the trade.[11] In Table 7, I re-run the regressions for these types of stock pairs. The first three columns restrict the sample to stock pairs with a ranking distance > 1 on the day of the trade, the middle three columns focus on stock pairs with a ranking distance > 3, and the last three columns on stock pairs with a ranking distance > 5. As the restrictions become more binding, the sample sizes drop accordingly.

Panel A of Table 7 presents results using the sample of retail investors. I continue to find strong memory effects, but the coefficients are somewhat smaller compared to the baseline results in Table 2. Panel B presents the results for mutual funds and also shows memory effects that are similar to the baseline results, albeit slightly weaker. These results suggest that attention does play a role in my setting, but they also show that attention is unlikely to explain the entire observed effect.

[11] This test is also helpful in ruling out any theory positing that investors simply trade adjacent stocks.

Table 7: Non-Adjacent Stock Pairs

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)								
Sample:	Ranking difference >1			Ranking difference >3			Ranking difference >5		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Memorability	0.091***	0.091***	0.104***	0.074***	0.075***	0.069***	0.073***	0.076***	0.052***
	(0.005)	(0.005)	(0.010)	(0.007)	(0.007)	(0.014)	(0.008)	(0.009)	(0.017)
Stock-pair FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Day FE		yes			yes			yes	
Investor x Day FE			yes			yes			yes
Observations	62,912	62,912	39,512	36,538	36,538	21,871	29,201	29,201	17,337
R-squared	0.333	0.359	0.654	0.352	0.393	0.676	0.364	0.413	0.685

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)								
Sample:	Ranking difference >1			Ranking difference >3			Ranking difference >5		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Memorability	0.181***	0.181***	0.175***	0.165***	0.165***	0.163***	0.155***	0.155***	0.156***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Stock-pair FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Quarter FE		yes			yes			yes	
Fund x Quarter FE			yes			yes			yes
Observations	479,219	479,219	474,121	284,643	284,643	275,825	184,748	184,748	175,694
R-squared	0.244	0.245	0.405	0.255	0.256	0.423	0.265	0.266	0.437

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on Memorability. Only stock pairs that are not adjacent in the ranking on the trading day are retained. In Columns (1) - (3) the ranking difference must be larger than 1, in Columns (4) - (6) it must be larger than 3, and in Columns (7) - (9) it must be larger than 5. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

5.2 Not a Relabeling of the Rank Effect

Another concern is that my results might be a relabeling of the rank effect (Hartzmark (2015)). The rank effect is the tendency of investors to sell extremely ranked stocks in their portfolio. Hartzmark (2015) shows that this effect extends to stocks that are first or last in alphabetical rankings. Thus, if investors jointly trade stocks that are very high or low in the alphabetical ranking, such behavior could explain why $Memorability_{jkit}$ is correlated with the probability of a memory-induced trade. To address this concern, in Table 8, I test for memory effects by focusing only on stocks in the middle section of an investor's (Panel A) or a fund manager's (Panel B) alphabetical ranking. The coefficient on $Memorability_{jkit}$ decreases in magnitude but remains statistically significant, suggesting that my results are not simply a relabeling of the rank effect.

5.3 Extremely Tight Fixed Effects

In Table 9, I re-estimate the baseline regressions from Table 2 with additional fixed effects and various interactions of stock-pair fixed effects. While these additional fixed effects are useful in addressing several alternative explanations by controlling for potential omitted variables, they reduce the sample size substantially. In the first column, I augment my baseline regression with stock-day fixed effects, which control for stock-specific information on the trading day that might drive the decision to trade.

In the second column, I interact the stock-pair fixed effects with investor fixed effects. In this specification, the coefficient on $Memorability_{jkit}$ is estimated using only variation for the same stock pair and same investor across different days. This effectively estimates the memory effect within-investor as, over time, a given stock pair becomes more or less associated in memory.

Finally, in the third column, I interact the stock-pair fixed effects with day fixed effects. In this specification, I estimate the coefficient using only variation in the memory strength across investors for the same stock pair on the same day. This approach addresses the concern that stock-pair-specific information on the trading day might drive trading behavior.

In all specifications, the results are similar to the baseline estimates from Table 2. The

Table 8: Not a Relabeling of the Rank Effect

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.096***	0.096***	0.102***
	(0.005)	(0.005)	(0.007)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	76,967	76,967	62,931
R-squared	0.303	0.331	0.582

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.134***	0.134***	0.136***
	(0.005)	(0.005)	(0.005)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	281,911	281,911	280,333
R-squared	0.235	0.236	0.404

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on Memorability. In Panel A, only retail investor portfolios with at least seven stocks are retained and the first two and last two stocks in alphabetical ranking are dropped. In Panel B, only mutual fund portfolios with at least fifty stocks are retained and the first twenty and last twenty stocks in alphabetical ranking are dropped. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9: Extremely Tight Fixed Effects

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.109***	0.123***	0.108***
	(0.020)	(0.006)	(0.020)
Stock-pair FE	yes		
Stock x Day FE	yes		
Stock-pair x Investor FE		yes	
Stock-pair x Day FE			yes
Observations	11,731	119,824	10,024
R-squared	0.789	0.432	0.743

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.185***	0.154***	0.188***
	(0.004)	(0.004)	(0.005)
Stock-pair FE	yes		
Stock x Quarter FE	yes		
Stock-pair x Fund FE		yes	
Stock-pair x Quarter FE			yes
Observations	648,206	465,702	405,097
R-squared	0.401	0.502	0.411

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on Memorability. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

specifications in the second and third column are also helpful in determining whether the results are driven by variation within or across investors. By isolating each type of variation, these results show that the effect is driven both by time series and cross-sectional variation.

5.4 Alternative Weighting Functions

In the construction of my main measure $Memorability_{jkit}$, I use a linearly decaying weighting function to allocate a higher weight to more recent than to more distant experiences. While this approach is motivated by the results in Malmendier and Nagel (2011), this weighting function is arguably somewhat ad hoc. In this section, I show that my results are not sensitive to this particular weighting function.

In the first three columns of Table 10, I show that I find similar, albeit somewhat weaker results when I omit the weighting function altogether. This shows that my results are not driven by the weighting. However, by allocating equal weight to distant experiences (which should have a weaker effect on recall according to memory theory), the effect becomes predictably somewhat weaker.

As an alternative approach, I calibrate the weighting function to the data. To do so, I take the coefficients on each lag from the 11 regressions displayed in Table 5 and use them as weights. I make two minor adjustments: first, I set the weight for lag-12 equal to zero. I also set the weights for negative coefficients (lags 9 and 11) equal to zero. In the remaining three columns of Table 10, I present the results when I use these calibrated weights. Overall, the strength of the memory effect is very similar to the baseline effects presented in Table 2. These findings are in line with the observation in Malmendier and Nagel (2011) that a linear weighting function is a good approximation for the effect of recency in financial decisions.

6 Further Exploration of Memory Effects

This section explores two extensions of the baseline results. I show that the propensity to execute memory-induced trades is heterogeneous across investors and discuss the asymmetry in memory-induced buying and selling decisions.

Table 10: Alternative Weighting Functions

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)					
	(1)	(2)	(3)	(4)	(5)	(6)
Memorability (unweighted)	0.117***	0.116***	0.095***			
	(0.004)	(0.004)	(0.006)			
Memorability (calibrated)				0.149***	0.147***	0.152***
				(0.004)	(0.004)	(0.005)
Stock-pair FE	yes	yes	yes	yes	yes	yes
Day FE		yes			yes	
Investor x Day FE			yes			yes
Observations	175,081	175,081	138,522	171,568	171,568	136,301
R-squared	0.296	0.310	0.594	0.309	0.322	0.604

Panel B: Mutual funds

Dependent variable:	Memory-induced trade (dummy)					
	(1)	(2)	(3)	(4)	(5)	(6)
Memorability (unweighted)	0.166***	0.166***	0.143***			
	(0.004)	(0.004)	(0.003)			
Memorability (calibrated)				0.154***	0.154***	0.143***
				(0.002)	(0.002)	(0.002)
Stock-pair FE	yes	yes	yes	yes	yes	yes
Quarter FE		yes			yes	
Fund x Quarter FE			yes			yes
Observations	727,507	727,507	726,518	726,948	726,948	725,951
R-squared	0.225	0.225	0.377	0.237	0.237	0.389

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on flavors of Memorability that are constructed using different weighting functions. In Columns (1) - (3), Memorability is constructed without a weighting function. In Columns (4) - (6), Memorability is constructed using weights that are calibrated to the data based on the coefficients from Table 5. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

6.1 Heterogeneity

In this section, I estimate the memory effect for each investor and fund manager individually, which allows me to back out the distribution of effect sizes in my sample. Specifically, I regress the dummy variable indicating a memory-induced trade on $Memorability_{jkit}$ for each investor and fund manager separately, and plot a histogram of the resulting $Memorability_{jkit}$ coefficients in Figure 2. I retain only investors and fund managers with at least 100 observations to ensure that there is enough variation to estimate the coefficient.

For both retail investor and fund managers, the bulk of the estimates is positive, showing that the results are not driven by a few outliers with extreme memory effects. Further, both distributions are positively skewed, suggesting that both groups include individuals who are particularly prone to memory-induced trading.

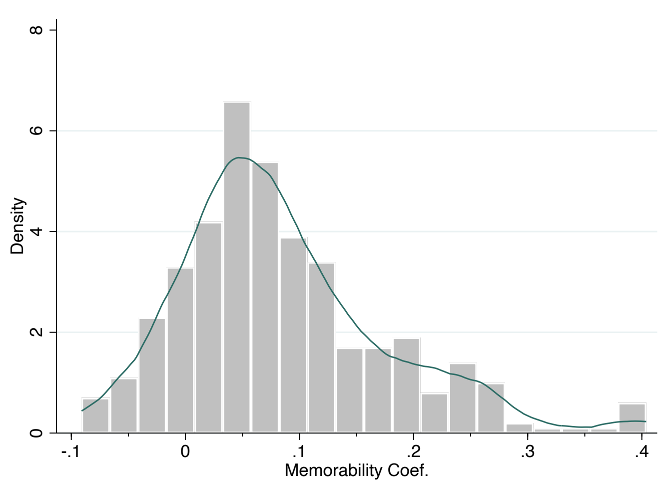
6.2 Buying vs. Selling

In all of my tests so far, I have pooled buys and sells, and focused on trading decisions as a whole. Here, I separate buying from selling decisions to see whether the memory effect operates more strongly in either domain. On the one hand, memory theory is silent on whether the effect should be stronger for buying or selling decisions. On the other hand, recent research has shown that investors – even sophisticated investors – tend to make larger errors on the selling side than the buying side (Akepanidtaworn et al. (2021)). To the extent that memory-induced trades are "errors", the memory effect might be stronger on the selling side.

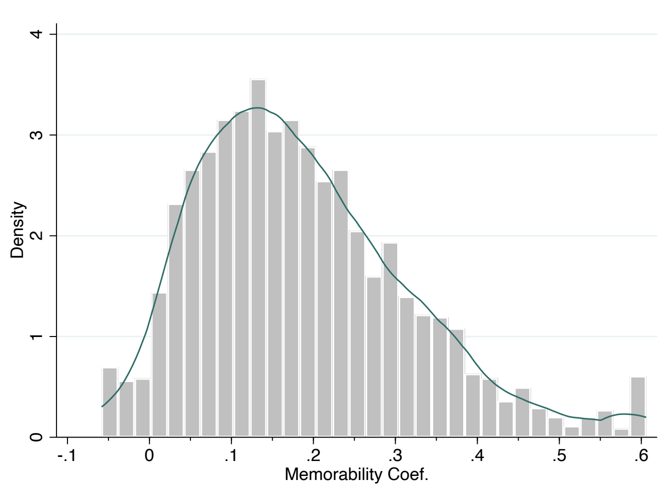
In Table 11, I replicate my baseline regressions using dummies that break out the trading decision as a buy (first three columns) or a sell (last three columns). I find that the memory effect operates in both domains, but that it is stronger for selling decisions. This is consistent with the finding in Akepanidtaworn et al. (2021) that selling decisions are more behavioral than buying decisions.

Figure 2. Heterogeneity in the Memory Effect

(a) Panel A: Retail Investors



(b) Panel B: Mutual Funds



Notes: These figures show densities of the Memorability coefficient, estimated for each investor (Panel A) and each fund manager (Panel B) separately. Only investors and fund managers with at least 100 observations are retained in the sample. The coefficient estimates are winsorized at the 1% and 99% level. The figures include a kernel density estimate.

Table 11: Buying vs. Selling

Panel A: Retail Investors

Dependent variable:	Memory-induced buy (dummy)			Memory-induced sell (dummy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Memorability	0.020***	0.019***	0.006**	0.114***	0.113***	0.118***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
Stock-pair FE	yes	yes	yes	yes	yes	yes
Day FE		yes			yes	
Investor x Day FE			yes			yes
Observations	175,081	175,081	138,522	175,081	175,081	138,522
R-squared	0.249	0.261	0.540	0.280	0.297	0.603

Panel B: Mutual Funds

Dependent variable:	Memory-induced buy (dummy)			Memory-induced sell (dummy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Memorability	0.082***	0.081***	0.061***	0.111***	0.111***	0.118***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Stock-pair FE	yes	yes	yes	yes	yes	yes
Quarter FE		yes			yes	
Fund x Quarter FE			yes			yes
Observations	727,507	727,507	726,518	727,507	727,507	726,518
R-squared	0.175	0.176	0.369	0.168	0.170	0.366

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced buy (first three columns) or a memory-induced sell (last three columns) on Memorability. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

7 Conclusion

Economists are increasingly incorporating aspects of human memory into theoretical models of economic and financial decision-making. These models offer the promise of explaining a variety of empirical facts and puzzles in financial markets. So far, however, tests of these models are confined to the experimental laboratory. My paper contributes to this growing literature by providing theory-driven, micro-level evidence of memory effects in a financial setting outside of the experimental laboratory.

I use the alphabetical rankings of stocks in investors' portfolio statements to estimate which stocks are associated in memory and find that these associations drive trading decisions. When I test for the different properties of memory, I find that they affect trading behavior as predicted by associative memory theory. The memory effect increases with the similarity between two stocks but decreases if interference in recall is higher. Further, associations that were encoded recently have a stronger effect than associations that were encoded further in the past. I also find that the memory effect fades away if two stocks were listed further from each other during the encoding of a memory association.

In my tests, a trade in one stock acts as the cue for the recall of associated stocks. However, investors are surely exposed to many more cues, and the different effects of those cues could be tested empirically. For instance, news events, social interactions, or advertisements could all plausibly act as cues for the recall of associated memories. The type of empirical tests I conduct here could be used as a template for testing these broader predictions of associative memory theory. Another important direction for future research is to test whether the memory effects I document at the individual level are strong enough to impact market outcomes. I explore this possibility in Charles (2022) and find evidence that a similar memory mechanism appears strong enough to distort prices in financial markets, but further tests in different contexts are surely needed.

Appendix

A Theoretical Framework

In the following, I provide a stylized theoretical framework of an investor's memory that closely follows Bordalo et al. (2020), which builds on Kahana (2012). The framework is designed to be as simple as possible to illustrate the main properties of associative memory theory in a setting of trading. An investor's memory is a "database" that contains experiences of past trading opportunities. I define an experience as a stock that was or could have been traded. There are a total of M experiences stored in the database. Each experience $e_j = (q_j, c_j)$ consists of hedonic attributes q of stock j and the context c in which the stock was experienced. The hedonic attributes include a stock's ticker, price, past performance, industry, and so on. For simplicity, I narrowly define context as the monthly portfolio statement on which the investor experienced the stock. This context contains time, and therefore drifts slowly over time. A broader version of context could include the environmental features such as the location and the weather, or emotional features such as the mood of the investor, during the trading opportunity. Finally, as in Bordalo et al. (2020), I assume that both the hedonic attributes q and the context c are cardinal.

Investors can encounter a cue $\kappa = (q_k, c_k)$ that stimulates the recall of experiences from the memory database. For instance, if the investor trades a stock with hedonic attributes q_k in context c_k, that trade acts as a cue for the recall of past experiences. I make two assumptions about recall: first, recall is imperfect, meaning that investors are not always able to recall all their past experiences. Second, recall is tilted towards experiences that are similar to the cue. More similar experiences are more likely to be recalled. Following Bordalo et al. (2020), I define the similarity between an experience e_j and a cue κ as the multiplicatively separable distance:

$$S(e_j, \kappa) = S_1(|q_j - q_k|)S_2(|c_j - c_k|) \tag{A.1}$$

This definition of similarity captures key characteristics of associative memory theory.

First, similarity is higher if the experience and the cue have similar hedonic attributes q.[12] Second, similarity is higher if the experience and the cue share a similar context c. For instance, two stocks that are close to each other on a portfolio statement share a more similar context than two stocks that are far away from each other on the statement. Further, since context drifts slowly over time, today's context is more similar to yesterday's context than to last week's context. Thus, all other things equal, a cue today is more similar to recent experiences than to distant experiences. This captures the role of recency in recall.

The probability that the investor recalls experience e_j when faced with cue κ, depends on the similarity between κ and e_j, as well as the similarity between κ and all other experiences stored in the memory database. Formally, the recall probability is given by the following expression:

$$P(e_j|\kappa) = \frac{S(e_j, \kappa)}{\sum_{x=1}^{M} S(e_x, \kappa)} \tag{A.2}$$

The left-hand side of this expression is the probability of recalling experience e_j conditional on encountering cue κ. The right-hand side of the expression defines this probability as the ratio of two terms. The term in the numerator is the pairwise similarity of experience e_j and cue κ. All other things equal, if e_j and κ are more similar, the investor is more likely to recall e_j. This captures the fact that more similar experiences are easier to recall. In contrast, the term in the denominator captures interference in recall. Interference refers to the idea that the cue might be similar to many experiences in the investor's memory. These other experiences interfere with the recall of e_j. The denominator measures interference by summing the similarities between κ and all M experiences in the memory database. If this sum is larger, interference is larger, and the probability of recalling e_j is lower.

In order to connect this recall probability to trading behavior, I make the following additional assumption: when an investor recalls an experience that contains a stock, he is more likely to trade that stock. Suppose that the experience e_j contains stock j. Then, the

[12] In my empirical analysis, I generally abstract from the role of similar hedonic attributes of stocks on recall by including stock-pair or stock-pair x day fixed effects into all my regressions. This approach holds fixed the hedonic attributes of the cueing and cued stock. I do so to avoid conflating memory effects (potentially due to similar hedonic attributes) with fundamental relationships between stocks that could plausibly be driving trading decisions.

probability of trading stock j when encountering cue κ is a function of the recall probability:

$$P(\text{Trade Stock } j|\kappa) = f(P(e_j|\kappa)) \tag{A.3}$$

where

$$\frac{\partial f}{\partial(P(e_j|\kappa))} > 0 \tag{A.4}$$

Equation A.3 can be rewritten as:

$$P(\text{Trade Stock } j|\kappa) = f(\frac{S(e_j,\kappa)}{\sum_{x=1}^{M} S(e_x,\kappa)}) \tag{A.5}$$

B Additional Tables

Table A.1: Linking Backwards

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.141***	0.139***	0.136***
	(0.004)	(0.004)	(0.006)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	175,495	175,495	138,781
R-squared	0.299	0.313	0.597

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.196***	0.196***	0.185***
	(0.004)	(0.004)	(0.004)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	726,993	726,993	725,988
R-squared	0.232	0.233	0.383

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on a flavor of Memorability that estimates associations between stock pairs by connecting a stock at position n in the alphabetical ranking with a stock at position $n-1$ in the ranking. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Memorability < 1

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.130***	0.128***	0.104***
	(0.006)	(0.006)	(0.007)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	106,568	106,568	96,284
R-squared	0.310	0.327	0.593

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.196***	0.196***	0.188***
	(0.004)	(0.004)	(0.004)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	400,642	400,642	398,235
R-squared	0.253	0.253	0.381

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on Memorability. The sample only includes stock pairs with Memorability < 1. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Conditioning on Only One Trade

Panel A: Retail Investors

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.054***	0.053***	0.080***
	(0.002)	(0.002)	(0.003)
Stock-pair FE	yes	yes	yes
Day FE		yes	
Investor x Day FE			yes
Observations	427,510	427,510	276,270
R-squared	0.227	0.234	0.594

Panel B: Mutual Funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Memorability	0.190***	0.190***	0.179***
	(0.004)	(0.004)	(0.003)
Stock-pair FE	yes	yes	yes
Quarter FE		yes	
Fund x Quarter FE			yes
Observations	734,171	734,171	729,127
R-squared	0.231	0.232	0.384
Observations	648,206	465,702	405,097
R-squared	0.401	0.502	0.411

Notes: This table presents results from regressions of a dummy variable indicating a memory-induced trade on Memorability. The sample includes all days on which an investor traded at least one stock. Across columns, various fixed effects are added to the regression. These fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by stock pair, investor, and trading day (Panel A) or stock pair, fund, and quarter (Panel B) and are displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4: Recency with Additional Fixed Effects (1)

Panel A: Retail investors

Dependent variable:	Memory-induced trade (dummy)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lag 1 (dummy)	0.119***										
	(0.003)										
Lag 2 (dummy)	0.014***	0.024***									
	(0.003)	(0.003)									
Lag 3 (dummy)	0.001	0.010***	0.015***								
	(0.003)	(0.003)	(0.004)								
Lag 4 (dummy)	0.004	0.007*	0.011**	0.012**							
	(0.003)	(0.004)	(0.004)	(0.005)							
Lag 5 (dummy)	-0.001	0.005*	0.005	0.006*	0.013***						
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)						
Lag 6 (dummy)	0.001	0.000	0.002	0.003	0.004	0.006					
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)					
Lag 7 (dummy)	-0.002	0.003	0.003	0.002	0.004	0.004	0.004				
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)				
Lag 8 (dummy)	-0.001	-0.001	-0.001	0.001	0.003	0.003	0.004	0.006			
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)			
Lag 9 (dummy)	0.000	0.002	0.002	0.004	0.004	0.005	0.003	0.000	0.003		
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)		
Lag 10 (dummy)	0.004	0.008***	0.008***	0.010***	0.010***	0.009***	0.010***	0.010**	0.015***	0.021***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	
Lag 11 (dummy)	-0.002	-0.002	-0.002	-0.002	0.000	0.003	0.004	0.002	-0.002	0.002	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.011)
Lag 12 (dummy)	-0.000	-0.002	-0.000	0.001	0.001	0.003	0.002	0.001	0.006	0.008	0.012
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)	(0.008)	(0.014)
Stock-pair FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Day FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	175,081	84,718	67,368	53,976	43,364	34,520	26,949	20,243	14,508	9,516	5,083
R-squared	0.326	0.340	0.356	0.368	0.377	0.391	0.401	0.419	0.459	0.509	0.621

Panel B: Mutual funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Lag 1 (dummy)	0.154***		
	(0.003)		
Lag 2 (dummy)	-0.008**	0.004**	
	(0.004)	(0.002)	
Lag 3 (dummy)	0.018***	0.007***	0.008***
	(0.003)	(0.002)	(0.002)
Lag 4 (dummy)	0.015***	0.002	0.002
	(0.002)	(0.002)	(0.002)
Stock-pair FE	yes	yes	yes
Quarter FE	yes	yes	yes
Observations	727,507	209,573	124,337
R-squared	0.238	0.310	0.326

Notes: This table replicates Table 5 but additionally includes day fixed effects (Panel A) or quarter fixed effects (Panel B).

Table A.5: Recency with Additional Fixed Effects (2)

Panel A: Retail investors

Dependent variable:	Memory-induced trade (dummy)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lag 1 (dummy)	0.117***										
	(0.004)										
Lag 2 (dummy)	0.019***	0.028***									
	(0.003)	(0.006)									
Lag 3 (dummy)	0.002	0.005	0.007								
	(0.003)	(0.005)	(0.007)								
Lag 4 (dummy)	0.003	0.009	0.013*	0.023**							
	(0.003)	(0.006)	(0.007)	(0.010)							
Lag 5 (dummy)	-0.001	0.003	0.001	0.006	0.013						
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)						
Lag 6 (dummy)	0.000	0.002	0.006	0.010**	0.001	0.005					
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)					
Lag 7 (dummy)	0.001	0.001	-0.001	0.001	0.001	-0.000	0.006				
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)	(0.012)				
Lag 8 (dummy)	0.002	-0.001	-0.002	0.002	0.002	0.001	-0.002	-0.020*			
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.009)	(0.012)			
Lag 9 (dummy)	-0.003	-0.004	-0.005	-0.000	-0.004	-0.011*	-0.006	-0.019*	-0.053**		
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)	(0.010)	(0.024)		
Lag 10 (dummy)	0.006*	0.013***	0.016***	0.020***	0.017***	0.018**	0.021**	0.008	-0.012	0.134	
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)	(0.011)	(0.016)	(0.087)	
Lag 11 (dummy)	0.000	-0.003	-0.001	-0.001	-0.003	-0.004	-0.003	-0.008	-0.018	0.059	-0.198
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.008)	(0.010)	(0.014)	(0.046)	(0.241)
Lag 12 (dummy)	-0.002	-0.005	-0.001	0.006	-0.000	-0.003	-0.003	0.001	0.009	0.016	-0.198
	(0.004)	(0.005)	(0.006)	(0.008)	(0.008)	(0.009)	(0.011)	(0.013)	(0.016)	(0.028)	(0.241)
Stock-pair FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Day FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Investor x Day FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	138,522	56,280	42,139	31,404	23,237	16,872	11,846	7,610	4,516	2,250	739
R-squared	0.604	0.632	0.659	0.674	0.697	0.716	0.738	0.759	0.790	0.805	0.791

Panel B: Mutual funds

Dependent variable:	Memory-induced trade (dummy)		
	(1)	(2)	(3)
Lag 1 (dummy)	0.141***		
	(0.002)		
Lag 2 (dummy)	0.004**	0.010***	
	(0.002)	(0.002)	
Lag 3 (dummy)	0.006***	0.003*	0.006***
	(0.001)	(0.002)	(0.002)
Lag 4 (dummy)	0.011***	-0.001	0.002
	(0.001)	(0.002)	(0.003)
Stock-pair FE	yes	yes	yes
Quarter FE	yes	yes	yes
Fund x Quarter FE	yes	yes	yes
Observations	726,518	197,971	110,088
R-squared	0.389	0.473	0.532

Notes: This table replicates Table 5 but additionally includes day and investor x day fixed effects (Panel A) or quarter and fund x quarter fixed effects (Panel B).

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