# Memory and Trading*

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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 5 percentage points. I then document that personal experience affects trading behavior through the different properties of human memory.

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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 related work, they show that experienced inflation affects beliefs about inflation (Malmendier and Nagel, 2016; Malmendier, Nagel, and Yan, 2020). Motivated by this type of evidence, new theories of memory and economic choice – based on decades of experimental memory research – have emerged.

Memory theories can generate the experience effects mentioned above, but they also make additional untested predictions that distinguish them from other explanations for experience effects, such as changing risk preferences. Testing memory models can therefore help to uncover the mechanisms of experience effects, but 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. While similar tests have been run in the controlled laboratory over short timescales (Enke, Schwerter, and Zimmermann, 2021), 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, Gennaioli, and Shleifer (2020) 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 their trading decisions follow the predictions of this theoretical framework. Guided by the theory, I create a measure – called *Memorability* – that captures how strongly two stocks are associated in an investor's memory. Intuitively, *Memorability* is the ratio of similarity (the numerator) and interference (the denominator). An increase in the similarity of two stocks increases the *Memorability* of the stock pair, while an increase in interference from other stocks decreases the *Memorability* of the stock pair. *Memorability* is bounded by 0 and 1.

To estimate *Memorability*, 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 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. This connects stocks that have similar attributes (alphabetically similar tickers) and that were experienced in a similar context (on the same monthly statement), capturing the key characteristics of associative memory theory. To supplement the retail investor data, I also create *Memorability* 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* 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 the 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* on a rolling basis using portfolio statements from the previous twelve months.

With the memory associations captured by *Memorability*, I can test whether memory affects trading behavior. To identify memory-induced trades, I build on the theory and make the additional assumption that recalling a stock increases the probability of trading the stock. Thus, 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 define this second trade as a memory-induced trade.

In my main tests, I regress the probability of a memory-induced trade on *Memorability.* 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* between these two stocks within and across investors. This approach holds fundamentals fixed and only varies *Memorability*. Thus, this regression 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* increases the probability of a memory-induced trade by 4.82 percentage points. Alternatively, an increase in *Memorability* from no memory association to full association leads to an increase in the trade probability by 13.40 percentage points. I find similar effects for mutual funds. In terms of magnitude, these effect sizes are comparable to the rank effect in Hartzmark (2015).

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 I am estimating memory effects rather than attention effects (Peng and Xiong, 2006; Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Chen, An, Yu, 2020). Finally, I show that the memory effect is not a relabeling of the rank effect (Hartzmark, 2015).

To better understand the mechanism behind my results, I zoom in on the different properties of memory and test whether they drive trading decisions individually. 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. However, interference from competing stock pairs reduces this effect. If interference increases by one standard deviation, the trade probability falls by about 3 percentage points. 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 fades away the further two stocks are positioned from each other in an alphabetically ranked portfolio.

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, Tate, and Yan, 2011; Malmendier and Shen, 2019; Malmendier, Nagel, and Yan, 2020). 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 (for an overview, see Barber and Odean, 2013). While much of this literature has focused on retail investors, in a recent study Akepanidtaworn, Di Mascio, Imas, and Schmidt (2021) show that sophisticated investors also use heuristics to make trading decisions. In line with their findings, I show 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, 2021). 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, Gennaioli, and Shleifer, 2020; Wachter and Kahana, 2021; Bordalo, Conlon, Gennaioli, Kwon, and Shleifer, 2021) and forecasting (Azeredo da Silveira, Sung, and Woodford, 2020; Afrouzi, Kwon, Landier, Ma, and Thesmar, 2020). 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, Schwerter, and Zimmermann, 2021; Goedker, Jiao, and Smeets, 2021), while another study uses survey data (Colonnelli, Gormsen, and McQuade, 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. A Theoretical Framework of Memory-Induced Trading

In the following, I provide a stylized theoretical framework that closely follows Bordalo, Gennaioli, and Shleifer (2020) and Kahana (2012). The framework is designed to be as simple as possible to illustrate the main properties of associative memory 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 $e = (q, c)$ consists of hedonic attributes $q$ of the stock and the context $c$ in which the stock was experienced. For simplicity, I focus on a single hedonic attribute: the stock's ticker. A broader version of the theory could include other attributes, such as the stock's price, past performance, industry, and so on. I will also 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. Again, 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, Gennaioli, and Shleifer (2020), I assume that both the hedonic attribute $q$ and the context $c$ are cardinal.

Investors can encounter a cue $\kappa_t = (q_t, c_t)$ at time *t* that stimulates the recall of experiences from the memory database. For instance, if the investor trades a stock with hedonic attributes $q_t$ in context $c_t$, 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, Gennaioli, and Shleifer (2020), I define the similarity between an experience $e_j$ and a cue $\kappa_t$ as the multiplicatively separable distance:

$$S(e_j, \kappa_t) = S_1(|q_t - q|)S_2(|c_t - c|) \tag{1}$$

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 $q$, such as a similar ticker. Second, similarity is higher if the experience and the cue share a similar context $c$. Since context drifts slowly over time, today's context is more similar to yesterday's context than to last year'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 $\kappa_t$, depends on the similarity between $\kappa_t$ and $e_j$, as well as the similarity between $\kappa_t$ and all other experiences stored in the memory database. Formally, the recall probability is given by the following expression:

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

The left-hand side of this expression is the probability of recalling experience $e_j$ conditional on encountering cue $\kappa_t$. The right-hand side of the expression defines this probability as the ratio of two terms. The term in the numerator is the raw similarity of experience $e_j$ and cue $\kappa_t$. All other things equal, if $e_j$ and $\kappa_t$ 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 $\kappa_t$ 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 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 probability of trading stock *j* when encountering cue $\kappa_t$ is a function of the recall probability:

$$P(trade\ stock\ j|\kappa_t) = f\left(P(e_j|\kappa_t)\right) \tag{3}$$

where

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

Equation (3) can be rewritten as:

$$P(trade\ stock\ j|\kappa_t) = f\left(\frac{S(e_j, \kappa_t)}{\sum_{x=1}^{M} S(e_x, \kappa_t)}\right) \tag{5}$$

## 3. Empirical Strategy

To test the predictions of the theoretical framework empirically, I need an empirical measure of $S(e_j, \kappa_t)$. This empirical measure should capture the similarity between the experience $e_j$ and the cue $\kappa_t$. In my setting, experiences and cues each contain one stock.

I construct such a measure by estimating the similarity of stock pairs in an investor's memory. In constructing this measure, I rely on an institutional detail of my data set. Investors in my data set receive monthly statements that display their portfolio holdings in alphabetical order. I define the empirical measure of $S(e_j, \kappa_t)$ as:

$$S_{j,k,i,t} = \sum_{m=1}^{12} d_{j,k,i,m} * w_m \tag{6}$$

Here, $d_{j,k,i,m}$ is a dummy variable that is equal to one if stock *j* immediately follows stock *k* on investor *i*'s portfolio statement in month *m*. This connects stocks that have similar hedonic attributes (alphabetically similar tickers) and that were experienced in a similar context (on the same monthly statement), capturing the key characteristics of associative memory theory. The reason I use the forward-linking is because humans generally read from top to bottom, rather than from the bottom to the top.[1] A second reason for the forward-linking is that the contiguity effect in traditional memory experiments is stronger in the forward direction (Kahana, 2012; Wachter and Kahana, 2021).[2]

The term $w_m$ is a linearly decaying weighting parameter that weights recent occurrences more strongly than distant ones, thereby accounting for recency in recall. I construct this parameter as $w_m = \frac{m}{(12*6.5)}$, where $m$ = 12 for the most recent portfolio statement, $m$ = 11 for the one before that, and so on, until $m$ = 1 for the statement from twelve months ago. These weights sum up to one, bounding $S_{j,k,i,t}$ by zero and one. For each investor, I estimate $S_{j,k,i,t}$ on a rolling basis, using the monthly portfolios holdings from the previous twelve months.

The measure $S_{j,k,i,t}$ 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.

Using this empirical measure of similarity, I can estimate the right-hand side of equation (2):

$$\frac{S_{j,k,i,t}}{\sum_{x=1}^{M} S_{x,k,i,t}} \stackrel{\text{def}}{=} Memorability_{j,k,i,t} \tag{7}$$

[1] I also run robustness tests in which I connect each stock to its predecessor in the ranking and find similar results. These results are displayed in Appendix Table 3.

[2] It is important to note that in traditional memory experiments, the contiguity operates in time, not in alphabetical space.

Analogous to equation (2), the term in the numerator captures the raw similarity between stocks *j* and *k*. The term in the denominator captures interference in recall: if stock *k* is very similar to many stocks in the memory database, the probability of recalling stock *j* is lower. For expositional purposes, I label the combined measure *Memorability*. This is the main measure in my empirical tests.

Plugging *Memorability* into equation (5) shows that conditional on the cue, the probability of trading stock *j* is a function of *Memorability*:

$$P(trade\ stock\ j|\kappa_t)_i = f(Memorability_{j,k,i,t}) \tag{8}$$

Finally, I assume that the cue $\kappa_t$ is a trade in stock *k* and that the function *f* is linear. This yields:

$$P(trade\ stock\ j|trade\ stock\ k)_{i,t} = \alpha + \beta\ Memorability_{j,k,i,t} \tag{9}$$

I estimate this equation using a panel dataset of investors, containing their portfolio holdings and trades. In my empirical tests, I run the following regression, in which *j* and *k* index stocks, *i* indexes investors, *d* trading days, and *t* years (defined as a rolling window of the previous twelve months).

$$P(trade\ stock\ j|trade\ stock\ k)_{i,d,t} = \alpha_{j,k} + \beta\ Memorability_{j,k,i,t} + \varepsilon_{j,k,i,d,t} \tag{10}$$

In this regression, the independent variable *Memorability* is estimated using an investor's portfolio holdings from the previous twelve months. *Memorability* is designed to be orthogonal to stock fundamentals since it is estimated using the alphabetical rankings of tickers on the investor's monthly statements. However, the ideal approach also holds fundamentals fixed and *only* varies *Memorability*. This approach addresses any concerns that the fundamentals of stocks could be correlated in ways that are related to their alphabetical similarity. To implement this, I fix two stocks, $j$ and $k$, and leverage variation in pairwise *Memorability* between those two stocks within and across investors. In the regression, this corresponds to including a stock-pair fixed effect $\alpha_{j,k}$. This is the main specification that I estimate in my empirical analysis.

## 4. Data and Summary Statistics

### *4.1 Retail investors*

I use data on the holdings and trades of retail investors, for the years 1991 to 1996, to calculate *Memorability* and the probability of a memory-induced trade. These data are the same as in Barber and Odean (2000). The investors in this data set received monthly statements containing their portfolio holdings. On the statements, the holdings were displayed in alphabetical order. I use this alphabetical ranking to construct *Memorability*.

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 test for memory-induced trades.[3] 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* 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. On average, investors hold 15 stocks in their portfolio (median: 9). The average probability of a memory-induced trade is 11.98%. *Memorability* ranges from zero to one with an average of 0.6.[4] The tests in this paper are performed at the investor-date-stock-pair level, the level at which *Memorability* and the probability of a memory-induced trade are defined. The high number of observations for these variables –175,081– is because at any point in time, a given stock can be associated with multiple stocks in an investor's memory. Another reason is that some investors trade many stocks on the same day.

[3] In Appendix Table 4, I show that my results also hold when I include trading days on which investors 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, Maggiori, Stroebel, and Utkus (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 focus on whether memory affects which stocks investor choose to trade, conditional on trading.

[4] There are several observations with *Memorability* equal to one. This happens when the cueing stock was only associated with one stock over the past twelve months. For these stock pairs, the numerator and denominator of *Memorability* are identical, resulting in *Memorability* equal to one. In Appendix Table 5, I show that these observations are not driving my results. In these tests, I drop all observations with *Memorability* equal to one and find similar results.

### *4.2 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* and the probability of a memory-induced trade 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* 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*. 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.[5] This restriction 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 19.22% and average *Memorability* is 0.68. These figures are similar to those of the retail investor data.

## 5. Results

### *5.1 Baseline result*

To visualize the relationship between memory and trading in the raw data, Figure 1 presents a binscatter plot in which *Memorability* is on the horizontal axis, and the probability of a memory-

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

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 (10). In this regression, the probability of a memory-induced trade is the dependent variable and *Memorability* 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, increasing *Memorability* by one standard deviation increases the probability of a memory-induced trade by 4.82 percentage points. Further, an increase in *Memorability* 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 trade day fixed effect to address the concern that the trading decision might be driven by the day (e.g., a January effect). In the third column, I include investor*day fixed effects. These fixed effects control for unobservable (potentially time-varying) characteristics of investors, such as sophistication and wealth, which might affect the propensity to engage in memory-induced trading. 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 investor and trading date.

In Panel B of Table 2, I display similar results for mutual funds. The effect size is very similar to that of retail investors. For instance, in the first column, a one standard deviation increase in *Memorability* corresponds to an increase in the probability of a memory-induced trade of 6.16 percentage points. The standard errors in all mutual fund regressions are clustered by fund and quarter.

### *5.2 Ruling out portfolio size effects*

One concern is that my results pick up mechanical effects that are driven by differences in portfolio size. This might be the case if investors are more likely to trade a stock if they hold a smaller number of stocks in their portfolio. Further, two stocks are more likely to be alphabetically adjacent in a smaller portfolio. Therefore, there might mechanically be a positive relationship between *Memorability* and the conditional probability of a stock being traded.

To address this concern, I analyze trading behavior only within fixed portfolio sizes. To implement this test, I augment the regressions from Table 2 with portfolio size fixed effects. These fixed effects ensure that the coefficient on *Memorability* is only estimated within a given portfolio size. Table 3 presents the results. Both in Panel A (retail investors) and Panel B (mutual funds), neither the size nor significance of the coefficient changes compared to Table 2.

I further address the concern of mechanical effects by conducting the following placebo test: for a stock-pair that is associated in an investor's memory, I randomly change the length of the investor's historical experience with these two stocks. Take the example of two stocks that were alphabetically adjacent on an investor's portfolio in 6 of the past 12 monthly statements. In the placebo test, I randomly assign a historical experience between 0 and 12 months to this stock-pair. Using these placebo experiences, I estimate a placebo version of *Memorability* for each stock-pair. By doing so, I randomly vary the strength of the association in the investor's memory, but not the existence of the association itself.

Using *Placebo Memorability*, I rerun my baseline regressions. In these regressions, *Placebo Memorability* should not predict trading. Table 4 presents the results. Indeed, the coefficient is zero in all columns, both for retail investors (Panel A) and mutual funds (Panel B). These findings should further alleviate concerns of mechanical effects.

### *5.3 A simulation of memory-induced trading*

Another way to gauge the plausibility of the empirical results is to simulate an investor's trading behavior, and to compare the simulated results to the empirical results. To implement this test, I run a simulation with a single investor. In the simulation, there exist $N$ stocks in the economy and the investor begins with $n<N$ stocks in year $t$. Over the course of year $t$, the investor trades each stock $j$ on day $d$ with exogenous probability $p$. The tickers of the stocks are randomly assigned, resulting in a random alphabetical order of stocks in the portfolio on each day. I use this alphabetical ranking to estimate *Memorability* for each stock pair on a rolling basis, using the portfolios holdings from the previous year.

Starting in year $t+1$, the investor continues to trade the same way, but now his exogenous trades are accompanied by memory-induced trading. Specifically, conditional on trading stock $k$, the probability that he also trades stock $j$ is given by the probability $q = beta*Memorability$. Here, *beta* dictates the strength of memory-induced trading and *Memorability* measures the strength of the memory association between the two stocks.

I run the simulation with *beta* = 15, which is approximately the coefficient that I empirically estimate in the data (see Table 2). I also set the remaining parameters as follows: there are $N$ = 1,000 stocks in the economy of which the investor holds $n$ = 200 on the first day of year 1. Every day, he trades each stock with probability $p$ = 0.02, and in years 2-6, this exogenous trading is accompanied by memory-induced trading. Panel A of Figure 2 replicates Figure 1 using the simulated data and shows a pattern that is very similar to that displayed in Figure 1.

I also simulate the two extreme cases of no memory trading and full memory trading. In the case of no memory trading, I set *beta* = 0. This simulation is useful in addressing concerns of mechanical effects. In Panel B of Figure 2, I show that without memory trading, there is no relationship between *Memorability* and the trade probability. Since I find no relationship, these results help alleviate the concern that my empirical findings are driven by mechanical effects.

In the case of full memory trading, I set *beta* = 100. This simulation is instructive as it estimates the memory effect for the case that *Memorability* perfectly captures conditional trade probabilities (see equation (9)). In Panel C of Figure 2, I present the results from this simulation.

### *5.4 Addressing attention spillover*

An important concern is that my results might capture attention effects (Peng and Xiong, 2006; Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Jiang, Liu, Peng, and Wang, 2020; Chen, An, and Yu, 2020). 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 address this concern, 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. This test is helpful, as it addresses the concern of attention spillover. Further, it can rule out any theory positing that investors simply trade adjacent stocks. In Table 5, I re-run the regressions for these types of stock pairs.

Panel A of Table 5 presents results using the sample of retail investors. I continue to find strong memory effects, but the coefficients are slightly smaller compared to the baseline results in Table 2. This suggests that attention may aid in the recall of previously experienced stocks. Panel B presents the results for mutual funds, showing memory effects that are very similar to the baseline results.

A drawback of the approach in Table 5 – estimating memory effects in the subsample of stocks that are "memorable" based on their history, but not listed next to each other on the day of the trade – is that it reduces the sample size by more than half. Therefore, as an alternative, I run the regressions using all the data and interact *Memorability* with a dummy equal to one for stocks that are still adjacent on the day of the trade. Table 6 presents the results.

Clearly, including the interaction does not wipe out the baseline effect of *Memorability*. Further, the coefficient on the still-adjacent dummy captures the effect of attention spillover on trading. This attention effect is positive and significant, but smaller in magnitude than the memory effect. Finally, the positive interaction term suggests that attention increases the memory effect by assisting the recall of previously experienced stocks.

### *5.5 Identifying cueing stocks*

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 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 7. Despite the small sample size, I estimate strong memory effects.

In Panel B of Table 7, 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. I find memory effects that are very similar, if not stronger, to the effects estimated using all trades.

### *5.6 Heterogeneity in the memory effect*

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 probability of a memory-induced trade on *Memorability* for each investor and fund manager separately and plot a histogram of the *Memorability* coefficient in Figure 3. 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.

### *5.7 Ruling out the rank effect*

An important 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* is correlated with the probability of a memory-induced trade. To address this concern, in Appendix Table 1, 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* decreases in magnitude but remains statistically significant.

### *5.8 Extremely tight fixed effects*

In Appendix Table 2, 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 column 1, I augment the baseline regression with stock-day fixed effects, which control for stock-specific information on the trading day that might drive the trading decision. In column 2, I interact the stock-pair fixed effects with investor fixed effects. In this specification, the coefficient on *Memorability* 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 column 3, I interact the stock-pair fixed effects with day fixed effects, estimating the coefficient using only variation across investors for the same stock-pair on the same day. This specification addresses the concern that information specific to the *stock-pair* might drive trading behavior. In all specifications, the results are similar to the baseline estimates from Table 2.

## 6. Mechanism

In the previous section, I have presented evidence for memory effects in trading. In the following tests, I probe the different properties of memory separately, to understand how they shape trading decisions. I find that the different properties affect trading decisions as predicted by associative memory theory.

### *6.1 Similarity and interference*

First, I test for the effects of similarity and interference separately. The importance of both similarity and interference for recall is a robust finding (Kahana, 2012; Enke, Schwerter, and Zimmermann, 2021; Bordalo, Conlon, Gennaioli, Kwon, and Shleifer, 2021). As outlined in Section 3, *Memorability* is comprised of both components: the numerator estimates the similarity of a stock pair, while the denominator estimates interference from other stock pairs. The two components have opposing effects on the recall probability: higher similarity increases recall, while higher interference reduces recall.

In Table 8, I include the numerator (similarity) and the denominator (interference) of *Memorability* separately as independent variables into my baseline regressions. As expected, the coefficient on similarity is positive, while the coefficient on interference is negative. These findings show that the memory effect is the result of two competing forces: while similarity increases the effect, interference from competing stock pairs 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 by 4.94

percentage points for retail investors. In contrast, increasing interference by one standard deviation (one std. dev. = 0.32) reduces the trade probability by 3.19 percentage points for retail investors. These effect sizes are very similar for mutual funds: a one standard deviation increase in similarity leads to a 6.01 percentage point increase in the trade probability, while a one standard deviation increase in interference leads to a 4.05 percentage point reduction.

These results provide strong evidence for the driving forces of associative memory models, which help to distinguish my findings from alternative explanations. Especially the negative effect of interference is a signature pattern of associative memory theory.

### *6.2 Memory associations from a different hedonic attribute*

In all my tests so far, I have focused on one hedonic attribute: a stock's ticker. However, stocks differ along various dimensions, all of which can potentially create meaningful memory associations. Therefore, in further tests in Appendix Table 6, I estimate memory associations using a different hedonic attribute: I connect stock pairs based on how similar their company names sound, using the Soundex phonetic algorithm of the National Archives and Records Administration. The estimated memory effects are very similar to the baseline effects in Table 2, emphasizing that various hedonic attributes of stocks – their tickers, or the sound of their company names – can be the source of memory associations that affect trading.

### *6.3 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, 2021).

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. 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. Further, by adding the twelve dummies to the baseline regression, I can test whether the recency effect (from the dummies) coexists with the other memory properties, such as similarity and interference, that are captured by *Memorability*.

I present the results in Table 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 recency effect disappears at about three months into the past. The results are similar for mutual 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 are slightly positive and significant.

The sharp drop off in the coefficients is reminiscent of findings in classic memory experiments (e.g., Murdock, 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, with a sharp drop off in the recall probability for the middle words. Some studies also find somewhat enhanced recall of the first few words (often called the *primacy effect*), a result which I also observe for mutual funds. In my tests, the coefficient on *Memorability* remains positive and significant when the dummies are included, emphasizing that recency coexists with other memory properties.

### *6.4 Contiguity*

In this last section, I focus on another property of memory: the contiguity effect. This effect describes a characteristic pattern that participants display in the word list experiments described in the previous section. Specifically, 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. Further, the recall probability decreases monotonically as a word's serial position increases relative to the word with serial position $n$.

To test for such a contiguity effect in my data, I construct several flavors of *Memorability*. The baseline *Memorability* connects a stock with ranking position $n$ to the stock at position $n+1$. I also create two alternative flavors of *Memorability*: one in which a stock at position $n$ is linked to the stock at position $n+2$; and another in which a stock at position $n$ is linked to the stock at position $n+3$. The intuition behind these alternative flavors is that as two stocks are further from each other in the alphabetical ranking, the memory association between them should become weaker, mirroring the findings from the word list experiments.

In Table 10, I regress the probability of a memory-induced trade on *Memorability*, interacted with two dummy variables: the first dummy variable equals one if *Memorability* is constructed by connecting stock *n* with stock *n+2*; the second dummy equals one if *Memorability* is constructed by connecting stock *n* with stock *n+3.* Thus, the omitted category is if *Memorability* is constructed by connecting stock *n* with stock *n+1*, which is the baseline *Memorability*. As expected, both interaction terms show that the memory effect becomes significantly weaker as the distance between two stocks in the ranking increases.

In Appendix Table 7, I study the contiguity effect in more detail using the holdings of mutual funds. Mutual funds are particularly useful for studying the contiguity effect, since their portfolio holdings are much larger than the holdings of retail investors. These large holdings allow me to connect a stock at ranking position *n* with stocks much further down in the ranking. In Appendix Table 7, I estimate the contiguity effect for additional connections, ranging from connections between stocks with ranking positions *n* and *n+1* all the way to connections between stocks with ranking positions *n* and *n+10*. As predicted by the theory, the memory effect fades away monotonically with distance between the two stocks.

## 7. Conclusion

In this paper, I provide evidence of memory effects in trading. I estimate memory associations of retail investors and mutual fund managers using data from their alphabetically ranked portfolio statements and find that these associations affect their trading decisions. When two stocks are associated in memory, trading one stock increases the probability of trading the other stock. A one standard deviation increase in the strength of this association increases the trade probability by about 5 percentage points.

When I test for the different properties of memory individually, I find that they affect trading behavior as predicted by the theory. The memory effect increases with the similarity between two stocks but decreases if the interference from other stocks is larger. 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 memory associations.

I add to the emerging literature on memory and finance by providing theory-driven, micro-level evidence of memory effects in a financial setting outside of the experimental laboratory. My findings support current memory theories and can guide the development of new models of memory and financial decision-making.

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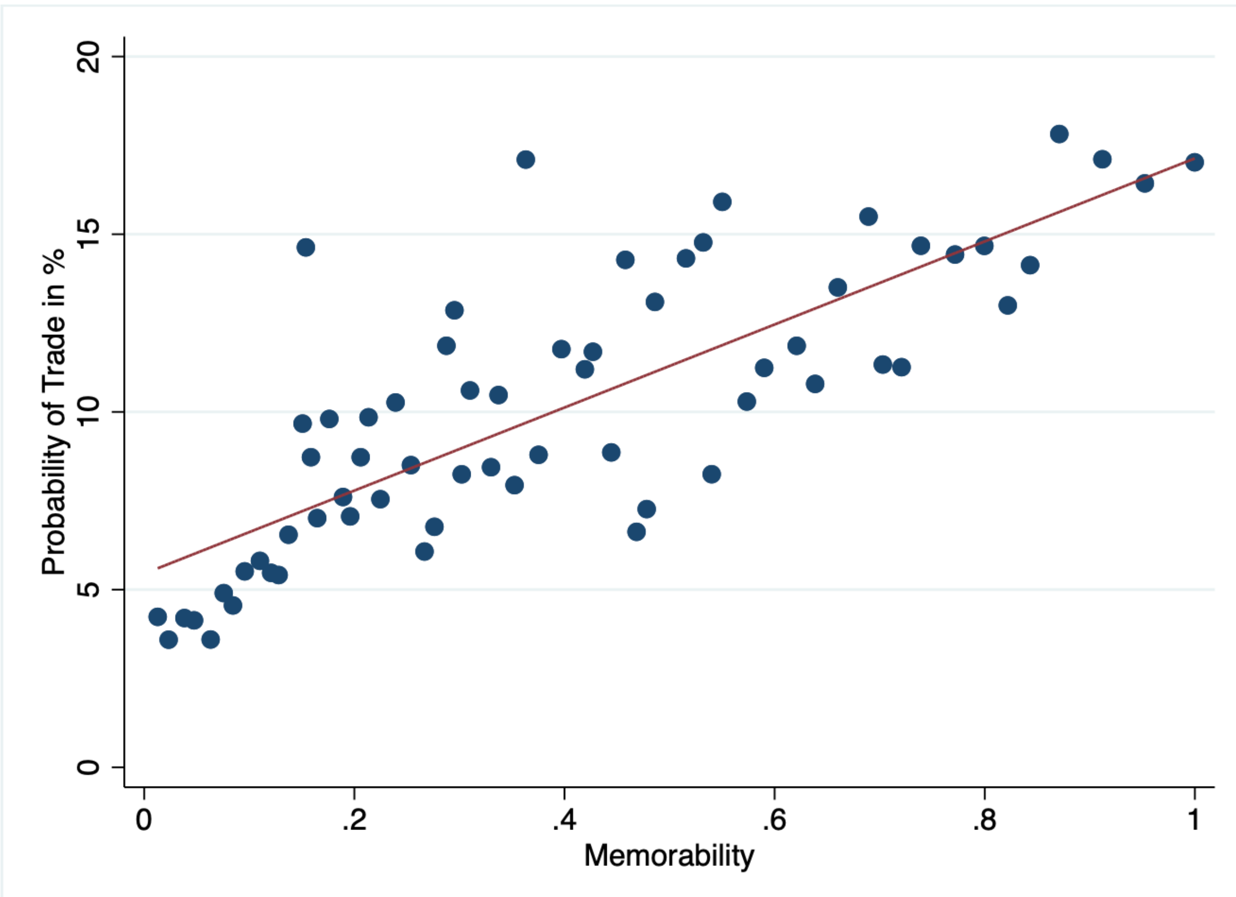
**Figure 1: Baseline result in the raw data**

**Panel A: Retail investors**

This figure shows a binscatter plot 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. 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. The graph includes a linear fit.



**Panel B: Mutual funds**

This figure shows a binscatter plot of the probability of a memory-induced trade against *Memorability*. *Memorability* captures memory associations between stock pairs that are built up over the past four quarters. 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 in the same quarter. The graph includes a linear fit.

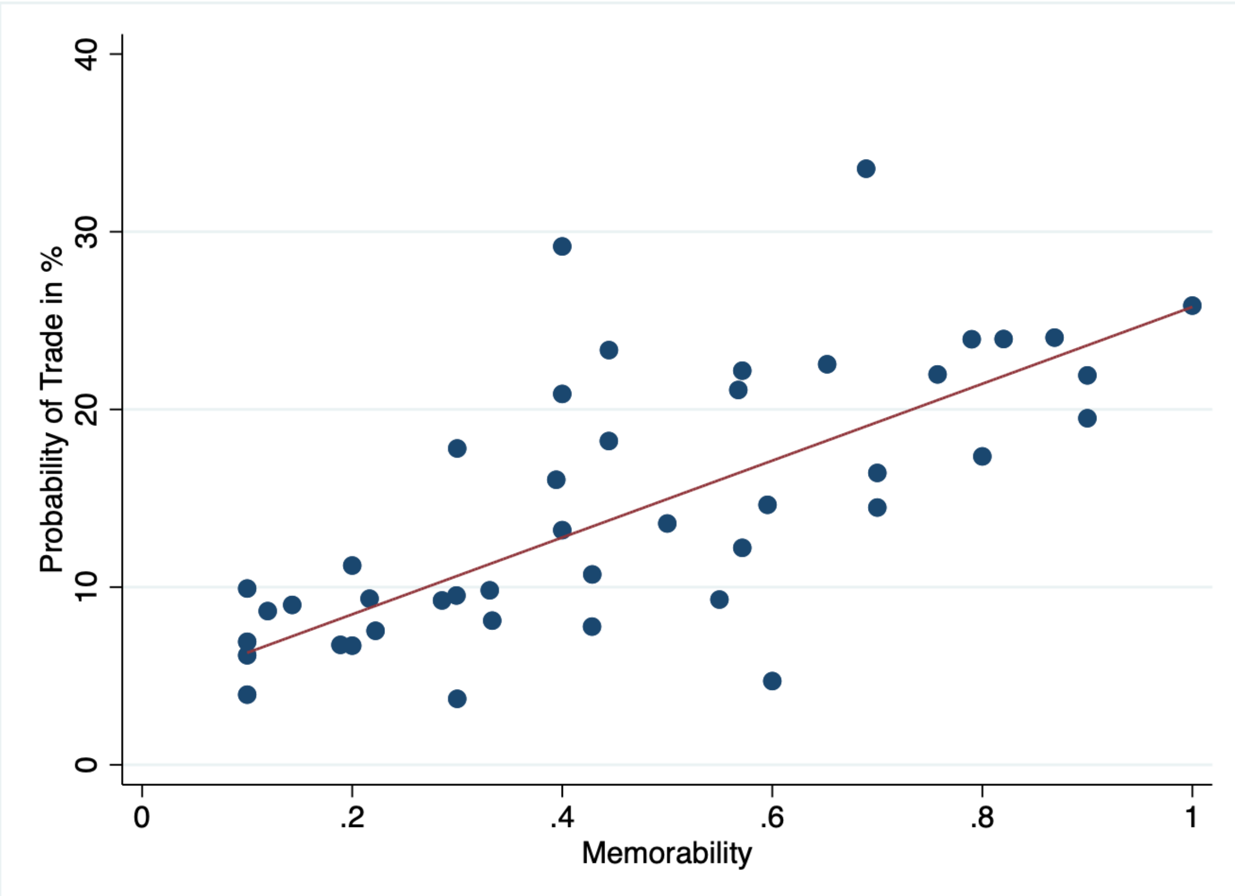
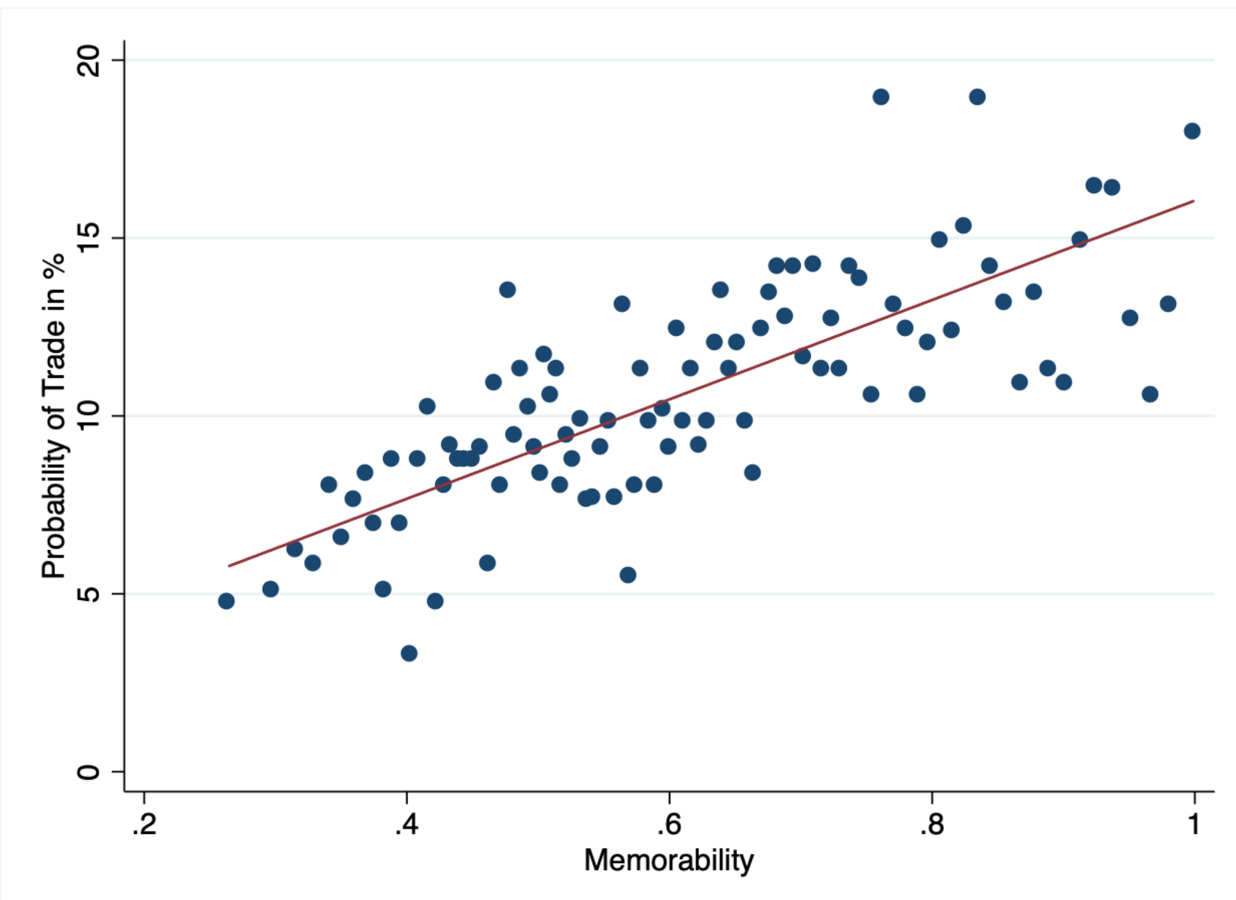


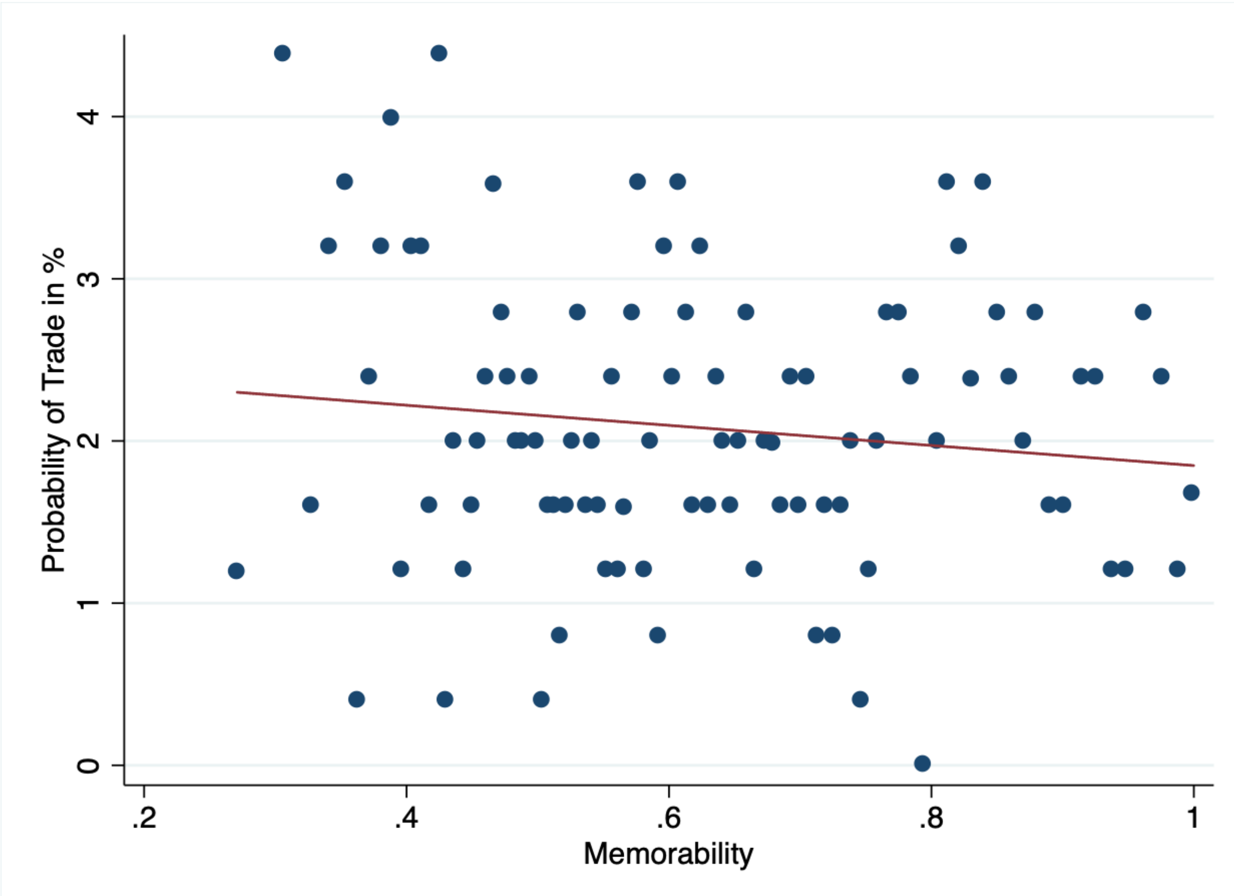
**Figure 2: Simulation**

The following figures replicate Figure 1 using data from a simulation with a single investor. In the simulation, there exist $N$ = 1,000 stocks in the economy and the investor holds each stock with probability 0.2 on day one of year 1. All years have 250 trading days. Over the course of year 1, the investor trades each stock $j$ on day $d$ with exogenous probability $p$ = 0.02. The tickers of the stocks are randomly assigned, resulting in a random alphabetical order of stocks in his portfolio. Starting in year 2 until year 6, the investor continues to trade the same way, but now his exogenous stock trades are accompanied by memory-induced trading: conditional on trading stock $j$, the probability that he also trades stock $k$ is equal to $q = beta*Memorability$, where *beta* dictates the strength of memory-induced trading and *Memorability* measures the strength of the memory association between the two stocks.

**Panel A: *Beta* = 15**



**Panel B: *Beta* = 0 (case of no memory trading)**



**Panel C: *Beta* = 100 (case of full memory trading)**

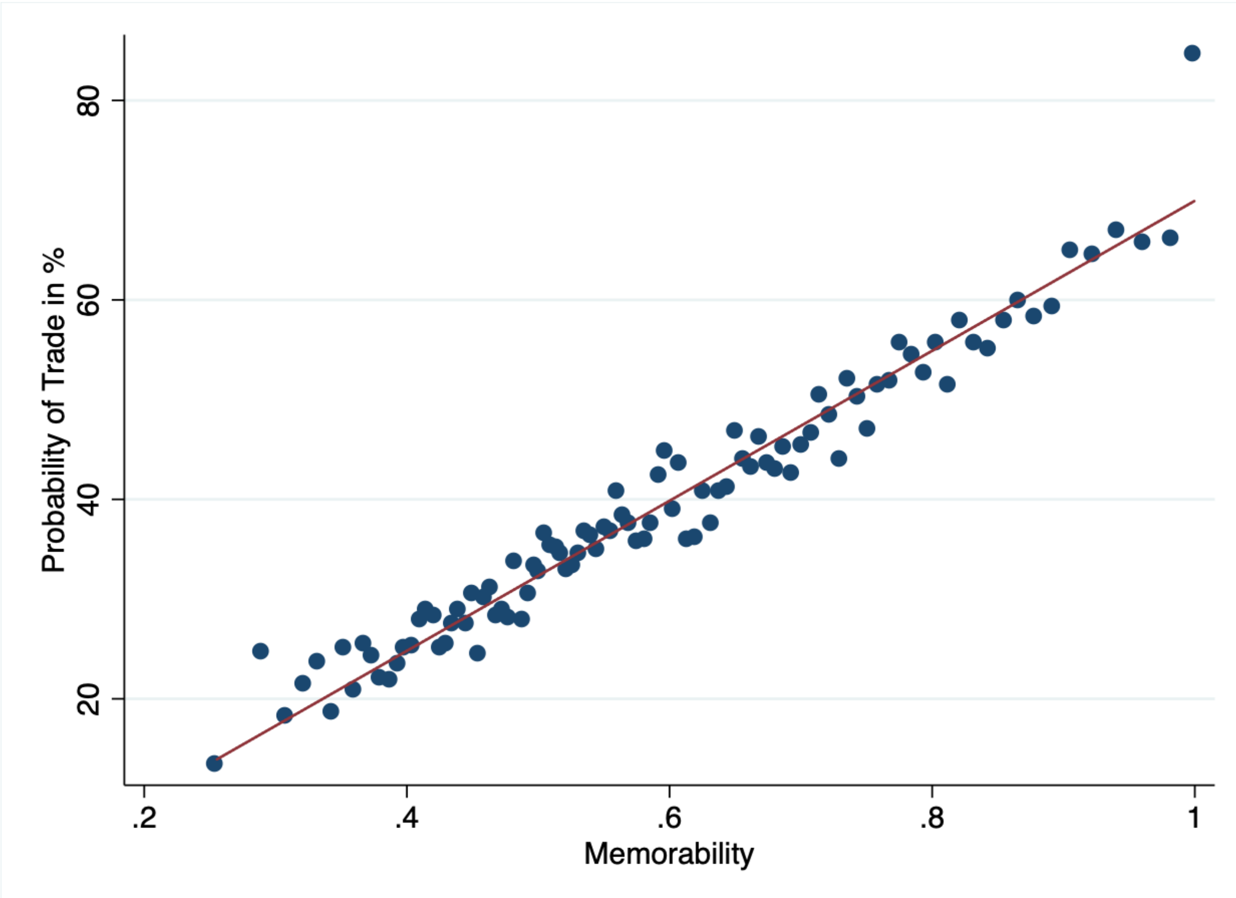
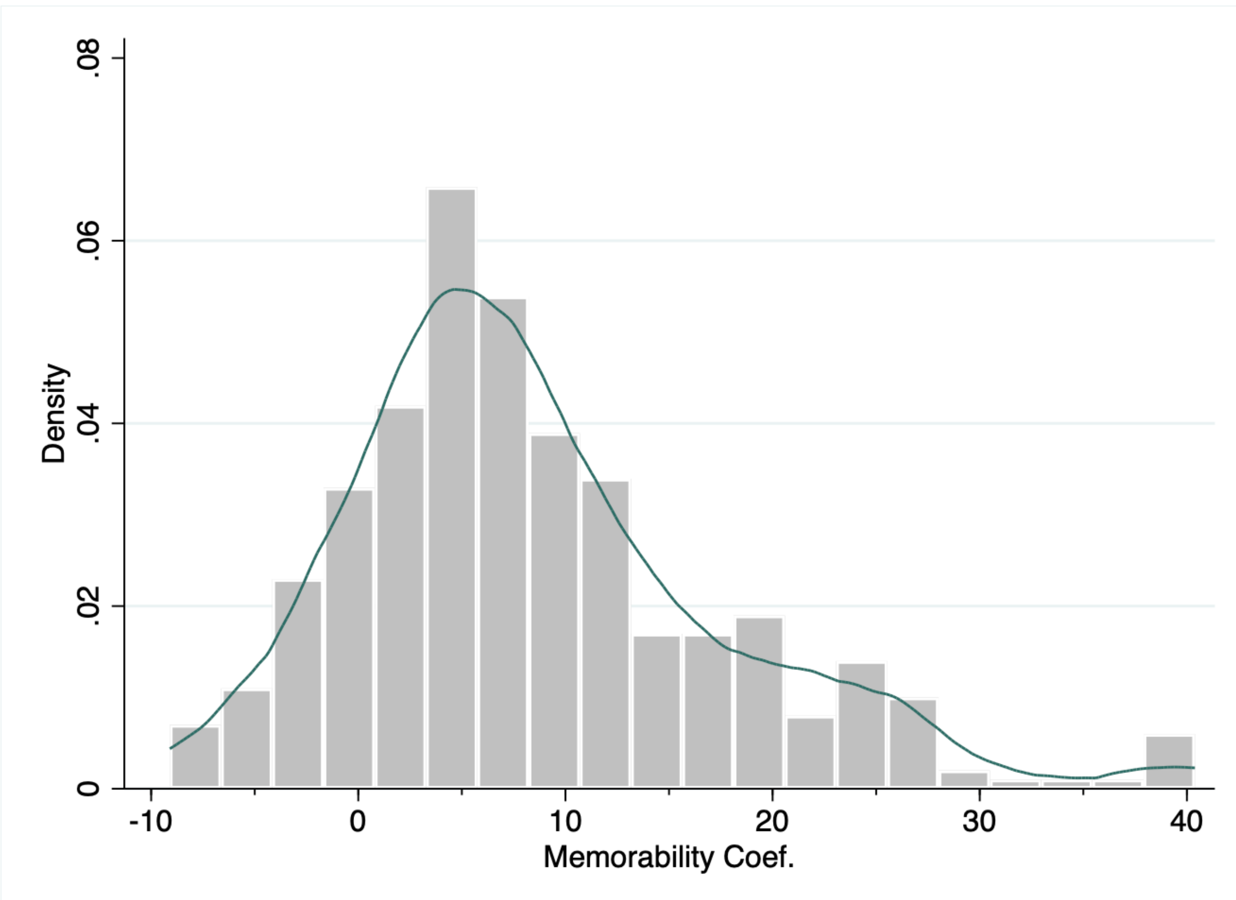


**Figure 3: Heterogeneity in individual coefficients**

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.

**Panel A: Retail investors**



**Panel B: Mutual funds**

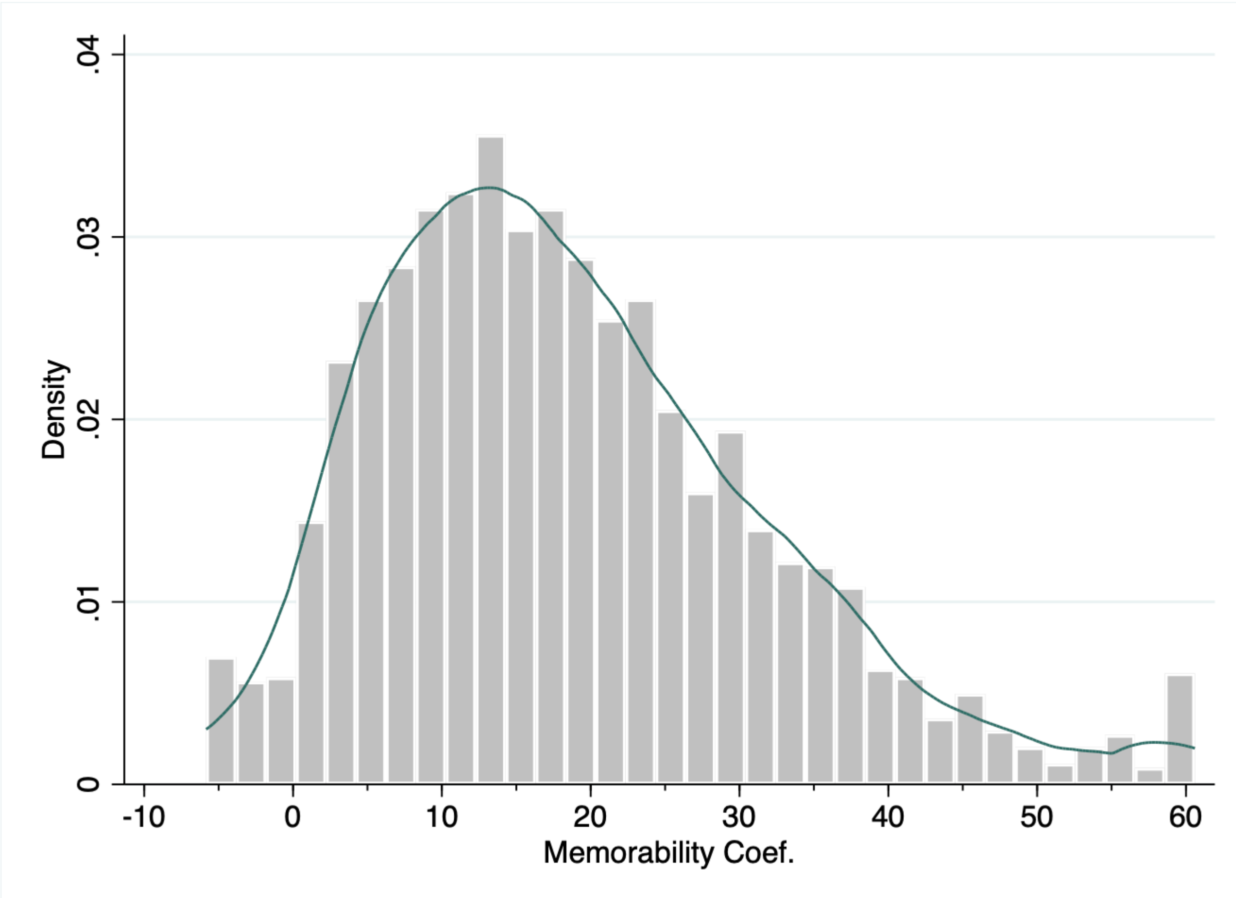


**Table 1: Summary statistics**

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. The probability of a memory-induced trade is defined at the investor-day-stock-pair level and the fund-quarter-stock-pair level, respectively. It measures the probability that conditional on a trade in one stock of the stock pair (the cueing stock), the investor or fund manager also trades the other stock of the stock pair on the same day or 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).

**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 |
| Prob. of memory-induced trade (%) | 11.98 | 0.00 | 0.00 | 0.00 | 32.47 | 0.00 | 100.00 | 175,081 |
| Memorability | 0.60 | 0.27 | 0.59 | 1.00 | 0.36 | 0.01 | 1.00 | 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 |
| Prob. of memory-induced trade (%) | 19.22 | 0.00 | 0.00 | 0.00 | 39.41 | 0.00 | 100.00 | 727,507 |
| Memorability | 0.68 | 0.40 | 0.71 | 1.00 | 0.32 | 0.10 | 1.00 | 727,507 |

**Table 2: Baseline result**

This table presents results from regressions of the probability of 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 13.40*** | 13.20*** | 12.39*** |
| | (0.39) | (0.38) | (0.56) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 175,081 | 175,081 | 138,522 |
| R-squared | 0.30 | 0.31 | 0.60 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 19.24*** | 19.22*** | 17.91*** |
| | (0.40) | (0.40) | (0.34) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 727,507 | 727,507 | 726,518 |
| R-squared | 0.23 | 0.23 | 0.38 |

**Table 3: Including portfolio size fixed effects**

This table presents results from regressions of the probability of a memory-induced trade on memorability. All columns include portfolio size fixed effects. Further, across columns, various other fixed effects are added to the regression. The fixed effects can result in singleton observations, which are dropped during the estimation. Standard errors are clustered by investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 13.45*** | 13.28*** | 12.73*** |
| | (0.41) | (0.41) | (0.58) |
| Portfolio Size FE | yes | yes | yes |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 160,995 | 160,995 | 128,631 |
| R-squared | 0.31 | 0.32 | 0.60 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 18.27*** | 18.28*** | 17.91*** |
| | (0.41) | (0.41) | (0.34) |
| Portfolio Size FE | yes | yes | yes |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 727,490 | 727,490 | 726,518 |
| R-squared | 0.24 | 0.24 | 0.38 |

**Table 4: Placebo tests**

This table presents results from regressions of the probability of a memory-induced trade on a placebo measure of *Memorability*. The placebo measure is constructed by randomizing the length of investors' historical experience with each stock-pair. 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Placebo Memorability | 0.03 | 0.05 | 0.08 |
| | (0.42) | (0.42) | (0.52) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 175,081 | 175,081 | 138,522 |
| R-squared | 0.29 | 0.30 | 0.59 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Placebo Memorability | -0.07 | -0.07 | -0.04 |
| | (0.20) | (0.20) | (0.20) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 727,507 | 727,507 | 726,518 |
| R-squared | 0.21 | 0.21 | 0.37 |

**Table 5: Addressing attention spillover – only non-adjacent stock-pairs**

This table presents results from regressions of the probability of a memory-induced trade on *Memorability*. Only stock pairs that are not adjacent in the ranking on the trading day are retained. 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 9.81*** | 9.72*** | 10.47*** |
| | (0.49) | (0.48) | (0.93) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 79,433 | 79,433 | 50,806 |
| R-squared | 0.32 | 0.34 | 0.64 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 18.43*** | 18.42*** | 17.65*** |
| | (0.37) | (0.38) | (0.35) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 554,441 | 554,441 | 550,926 |
| R-squared | 0.24 | 0.24 | 0.40 |

**Table 6: Addressing attention spillover – interaction with still-adjacent dummy**

This table presents results from regressions of the probability of a memory-induced trade on *Memorability*. *Memorability* is interacted with a dummy that is equal to one of the stock pair is still adjacent on the day of the trade. 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 10.33*** | 10.32*** | 10.93*** |
| | (0.45) | (0.44) | (0.65) |
| Still adjacent (dummy) | 3.46*** | 3.34*** | 3.26*** |
| | (0.40) | (0.40) | (0.55) |
| Memorability x Still adjacent | 3.84*** | 3.68*** | 2.13** |
| | (0.61) | (0.61) | (0.91) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 175,081 | 175,081 | 138,522 |
| R-squared | 0.31 | 0.32 | 0.60 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 18.32*** | 18.31*** | 17.63*** |
| | (0.37) | (0.37) | (0.35) |
| Still adjacent (dummy) | 0.02 | 0.03 | -0.51* |
| | (0.31) | (0.31) | (0.30) |
| Memorability x Still adjacent | 3.26*** | 3.27*** | 1.33*** |
| | (0.55) | (0.55) | (0.39) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 727,507 | 727,507 | 726,518 |
| R-squared | 0.23 | 0.23 | 0.38 |

**Table 7: Identifying cueing stocks**

This table replicates the regressions of Table 2 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 used to estimate the probability of a memory-induced trade 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 used to estimate the probability of a memory-induced trade 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 10.51*** | 11.12*** | 12.17* |
| | (1.44) | (1.66) | (6.23) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 3,194 | 3,018 | 533 |
| R-squared | 0.01 | 0.18 | 0.52 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 21.15*** | 20.97*** | 19.48*** |
| | (0.63) | (0.63) | (0.71) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 74,121 | 74,121 | 54,717 |
| R-squared | 0.03 | 0.04 | 0.28 |

**Table 8: Similarity and Interference**

This table presents results from regressions of the probability of a memory-induced trade on *Similarity* and *Interference*. 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Similarity | 17.66*** | 17.52*** | 14.75*** |
| | (0.56) | (0.55) | (0.72) |
| Interference | -9.96*** | -9.68*** | -10.89*** |
| | (0.50) | (0.47) | (1.02) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 175,081 | 175,081 | 138,522 |
| R-squared | 0.30 | 0.31 | 0.60 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| | | | |
| Similarity | 21.48*** | 21.52*** | 19.94*** |
| | (0.57) | (0.58) | (0.42) |
| Interference | -18.41*** | -18.20*** | -14.61*** |
| | (0.79) | (0.78) | (0.36) |
| | | | |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| | | | |
| Observations | 727,507 | 727,507 | 726,518 |
| R-squared | 0.23 | 0.23 | 0.38 |

**Table 9: Recency**

This table presents results from regressions of the probability of a memory-induced trade on *Memorability*. In Panel A, the regression also includes twelve dummies, one for each of the past twelve months, that are equal to one if the stock pair was associated in that month. In Panel B, the regression also includes four dummies, one for each of the past twelve quarters, that are equal to one if the stock pair was associated 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 5.20*** | 5.25*** | 5.46*** |
| | (0.47) | (0.44) | (0.83) |
| Lag 1 (dummy) | 10.74*** | 10.58*** | 10.50*** |
| | (0.36) | (0.35) | (0.47) |
| Lag 2 (dummy) | 0.98*** | 0.96*** | 1.17*** |
| | (0.30) | (0.30) | (0.38) |
| Lag 3 (dummy) | -0.24 | -0.26 | -0.38 |
| | (0.28) | (0.28) | (0.33) |
| Lag 4 (dummy) | 0.13 | 0.13 | -0.19 |
| | (0.33) | (0.33) | (0.39) |
| Lag 5 (dummy) | -0.38 | -0.34 | -0.50 |
| | (0.31) | (0.31) | (0.37) |
| Lag 6 (dummy) | -0.14 | -0.09 | -0.38 |
| | (0.31) | (0.31) | (0.35) |
| Lag 7 (dummy) | -0.32 | -0.35 | -0.23 |
| | (0.33) | (0.33) | (0.39) |
| Lag 8 (dummy) | -0.27 | -0.26 | -0.13 |
| | (0.33) | (0.32) | (0.38) |
| Lag 9 (dummy) | -0.20 | -0.10 | -0.58 |
| | (0.34) | (0.33) | (0.38) |
| Lag 10 (dummy) | 0.33 | 0.30 | 0.38 |

| | (1) | (2) | (3) |
|---|---|---|---|
| | (0.34) | (0.33) | (0.38) |
| Lag 11 (dummy) | -0.32 | -0.24 | -0.09 |
| | (0.35) | (0.35) | (0.45) |
| Lag 12 (dummy) | -0.05 | 0.07 | 0.07 |
| | (0.34) | (0.34) | (0.43) |
| | | | |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| | | | |
| Observations | 175,081 | 175,081 | 138,522 |
| R-squared | 0.31 | 0.33 | 0.60 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| | | | |
| Memorability | 6.40*** | 6.27*** | 3.94*** |
| | (0.81) | (0.80) | (0.45) |
| Lag 1 (dummy) | 11.96*** | 12.03*** | 12.06*** |
| | (0.50) | (0.50) | (0.30) |
| Lag 2 (dummy) | -1.86*** | -1.77*** | -0.37** |
| | (0.44) | (0.43) | (0.18) |
| Lag 3 (dummy) | 1.08*** | 1.08*** | 0.05 |
| | (0.31) | (0.30) | (0.14) |
| Lag 4 (dummy) | 1.35*** | 1.38*** | 0.92*** |
| | (0.25) | (0.25) | (0.14) |
| | | | |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| | | | |
| Observations | 727,507 | 727,507 | 726,518 |
| R-squared | 0.24 | 0.24 | 0.39 |

**Table 10: Contiguity**

This table presents results from regressions of the probability of a memory-induced trade on *Memorability*. The regression also includes the interaction of *Memorability* with two dummy variables. The first dummy variable is equal to one if *Memorability* is calculated by connecting a stock at position *n* in the alphabetical ranking with a stock at position *n+2* in the ranking. The second dummy variable is equal to one if *Memorability* is calculated by connecting a stock at position *n* in the alphabetical ranking with a stock at position *n+3* in the ranking. If both dummy variables are equal to zero, *Memorability* is calculated as in the baseline, i.e., 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 12.06*** | 11.90*** | 8.54*** |
| | (0.33) | (0.32) | (0.33) |
| Connect n --> n+2 (dummy) | 0.76*** | 0.76*** | 1.22*** |
| | (0.17) | (0.16) | (0.16) |
| Connect n --> n+3 (dummy) | 0.15 | 0.19 | 1.10*** |
| | (0.20) | (0.19) | (0.18) |
| Memorability x Connect n--> n+2 | -4.29*** | -4.25*** | -2.79*** |
| | (0.36) | (0.36) | (0.36) |
| Memorability x Connect n--> n+3 | -5.23*** | -5.26*** | -2.99*** |
| | (0.38) | (0.38) | (0.38) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 630,709 | 630,709 | 619,355 |
| R-squared | 0.38 | 0.39 | 0.57 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 19.22*** | 19.22*** | 17.00*** |
| | (0.42) | (0.41) | (0.32) |
| Connect n --> n+2 (dummy) | 1.96*** | 1.95*** | 3.17*** |
| | (0.15) | (0.15) | (0.11) |
| Connect n --> n+3 (dummy) | 1.56*** | 1.56*** | 3.78*** |
| | (0.23) | (0.23) | (0.15) |
| Memorability x Connect n--> n+2 | -4.89*** | -4.89*** | -4.29*** |
| | (0.20) | (0.20) | (0.17) |
| Memorability x Connect n--> n+3 | -6.19*** | -6.21*** | -5.23*** |
| | (0.28) | (0.28) | (0.23) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 2,514,327 | 2,514,327 | 2,514,285 |
| R-squared | 0.23 | 0.23 | 0.36 |

# Online Appendix

**Appendix Table 1: Ruling out the rank effect (Hartzmark, 2015)**

This table presents results from regressions of the probability of 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 9.60*** | 9.61*** | 10.20*** |
| | (0.56) | (0.54) | (0.78) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 76,967 | 76,967 | 62,931 |
| R-squared | 0.30 | 0.33 | 0.58 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 13.41*** | 13.40*** | 13.63*** |
| | (0.47) | (0.48) | (0.50) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 281,911 | 281,911 | 280,333 |
| R-squared | 0.23 | 0.24 | 0.40 |

**Appendix Table 2: Extremely tight fixed effects**

This table presents results from regressions of the probability of 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 investor and trading day and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 10.94*** | 12.30*** | 10.85*** |
| | (2.20) | (0.59) | (1.97) |
| 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 | 0.79 | 0.43 | 0.74 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 18.55*** | 15.42*** | 18.78*** |
| | (0.40) | (0.42) | (0.45) |
| 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 | 0.40 | 0.50 | 0.41 |

**Appendix Table 3: Linking backwards**

This table presents results from regressions of the probability of a memory-induced trade on an alternative measure of *Memorability*, which 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 14.11*** | 13.89*** | 13.60*** |
| | (0.41) | (0.40) | (0.61) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 175,495 | 175,495 | 138,781 |
| R-squared | 0.30 | 0.31 | 0.60 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 19.61*** | 19.59*** | 18.47*** |
| | (0.41) | (0.41) | (0.36) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 726,993 | 726,993 | 725,988 |
| R-squared | 0.23 | 0.23 | 0.38 |

**Appendix Table 4: Conditioning on only one trade**

This table presents results from regressions of the probability of 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 investor and trading day and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 5.44*** | 5.34*** | 7.97*** |
| | (0.18) | (0.18) | (0.34) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 427,510 | 427,510 | 276,270 |
| R-squared | 0.23 | 0.23 | 0.59 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 19.00*** | 18.99*** | 17.88*** |
| | (0.40) | (0.40) | (0.34) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 734,171 | 734,171 | 729,127 |
| R-squared | 0.23 | 0.23 | 0.38 |

**Appendix Table 5: Only if *Memorability* < 1**

This table presents results from regressions of the probability of 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 investor and trading day and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 13.01*** | 12.77*** | 10.37*** |
| | (0.58) | (0.58) | (0.75) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 106,568 | 106,568 | 96,284 |
| R-squared | 0.31 | 0.33 | 0.59 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 19.60*** | 19.58*** | 18.84*** |
| | (0.45) | (0.45) | (0.45) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 400,642 | 400,642 | 398,235 |
| R-squared | 0.25 | 0.25 | 0.38 |

**Appendix Table 6: Estimating memory associations based on the phonetic similarity of company names**

This table presents results from regressions of the probability of a memory-induced trade on *Phonetic Memorability*. *Phonetic Memorability* is calculated by connecting two stocks based on the phonetic similarity of their company names, regardless of their position in the alphabetical 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 investor and trading day (Panel A) or fund and quarter (Panel B) and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Retail investors**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Phonetic Memorability | 15.19*** | 14.98*** | 15.43*** |
| | (0.43) | (0.42) | (0.56) |
| Stock-pair FE | yes | yes | yes |
| Day FE | | yes | |
| Investor x Day FE | | | yes |
| Observations | 204,687 | 204,687 | 169,569 |
| R-squared | 0.31 | 0.33 | 0.67 |

**Panel B: Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Phonetic Memorability | 19.65*** | 19.64*** | 18.33*** |
| | (0.40) | (0.41) | (0.34) |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| Observations | 741,430 | 741,430 | 740,539 |
| R-squared | 0.23 | 0.23 | 0.40 |

**Appendix Table 7: Contiguity – extended**

This table presents results from regressions of the probability of a memory-induced trade on *Memorability* using data on the holdings of mutual funds. The regression also includes the interaction of *Memorability* with nine dummy variables. The first dummy variable is equal to one if *Memorability* is calculated by connecting a stock at position *n* in the alphabetical ranking with a stock at position *n+2* in the ranking. The second dummy variable is equal to one if *Memorability* is calculated by connecting a stock at position *n* in the alphabetical ranking with a stock at position *n+3* in the ranking. The other dummy variables are defined analogously. If all dummy variables are equal to zero, *Memorability* is calculated as in the baseline, i.e., 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 fund and quarter and displayed in parentheses below the coefficients. *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Mutual funds**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable: | Prob. of memory-induced trade (%) | | |
| Memorability | 19.39*** | 19.39*** | 16.54*** |
| | (0.43) | (0.43) | (0.30) |
| Connect n --> n+2 (dummy) | 1.81*** | 1.79*** | 3.05*** |
| | (0.14) | (0.14) | (0.11) |
| Connect n --> n+3 (dummy) | 1.30*** | 1.28*** | 3.65*** |
| | (0.22) | (0.22) | (0.15) |
| Connect n --> n+4 (dummy) | 0.66** | 0.63** | 3.98*** |
| | (0.28) | (0.28) | (0.15) |
| Connect n --> n+5 (dummy) | -0.10 | -0.12 | 4.11*** |
| | (0.33) | (0.32) | (0.15) |
| Connect n --> n+6 (dummy) | -0.67* | -0.70* | 4.31*** |
| | (0.38) | (0.38) | (0.17) |
| Connect n --> n+7 (dummy) | -1.41*** | -1.44*** | 4.31*** |
| | (0.43) | (0.42) | (0.18) |
| Connect n --> n+8 (dummy) | -2.07*** | -2.11*** | 4.31*** |
| | (0.46) | (0.45) | (0.17) |
| Connect n --> n+9 (dummy) | -2.66*** | -2.70*** | 4.32*** |
| | (0.51) | (0.49) | (0.18) |

| | | | |
|---|---|---|---|
| Connect n --> n+10 (dummy) | -3.09*** | -3.13*** | 4.43*** |
| | (0.54) | (0.53) | (0.18) |
| Memorability x Connect n--> n+2 | -4.65*** | -4.65*** | -4.01*** |
| | (0.18) | (0.18) | (0.16) |
| Memorability x Connect n--> n+3 | -5.97*** | -5.98*** | -4.94*** |
| | (0.25) | (0.26) | (0.21) |
| Memorability x Connect n--> n+4 | -6.92*** | -6.93*** | -5.62*** |
| | (0.28) | (0.29) | (0.23) |
| Memorability x Connect n--> n+5 | -7.51*** | -7.52*** | -6.02*** |
| | (0.31) | (0.31) | (0.22) |
| Memorability x Connect n--> n+6 | -8.14*** | -8.15*** | -6.45*** |
| | (0.33) | (0.33) | (0.23) |
| Memorability x Connect n--> n+7 | -8.53*** | -8.55*** | -6.74*** |
| | (0.34) | (0.35) | (0.24) |
| Memorability x Connect n--> n+8 | -8.72*** | -8.75*** | -6.83*** |
| | (0.35) | (0.36) | (0.23) |
| Memorability x Connect n--> n+9 | -8.88*** | -8.90*** | -6.89*** |
| | (0.36) | (0.37) | (0.23) |
| Memorability x Connect n--> n+10 | -9.21*** | -9.24*** | -7.16*** |
| | (0.36) | (0.36) | (0.23) |
| | | | |
| Stock-pair FE | yes | yes | yes |
| Quarter FE | | yes | |
| Fund x Quarter FE | | | yes |
| | | | |
| Observations | 9,418,474 | 9,418,474 | 9,418,466 |
| R-squared | 0.22 | 0.22 | 0.35 |