MANAGEMENT SCIENCE
Vol. 54, No. 6, June 2008, pp. 1052–1064
ISSN 0025-1909 | EISSN 1526-5501 | 08 | 5406 | 1052

DOI 10.1287/mnsc.1070.0845

How Do Decision Frames Influence the Stock Investment Choices of Individual Investors?

Alok Kumar
McCombs School of Business, University of Texas at Austin, Austin, Texas 78712, akumar@mail.utexas.edu

Sonya Seongyeon Lim
Kellstadt Graduate School of Business, DePaul University, Chicago, Illinois 60604, slim1@depaul.edu

This study examines whether the framing mode (narrow versus broad) influences the stock investment decisions of individual investors. Motivated by the experimental evidence, which suggests that separate decisions are more likely to be narrowly framed than simultaneous decisions, we propose trade clustering as a proxy for narrow framing. Using this framing proxy, we show that investors who execute more clustered trades exhibit weaker disposition effects and hold better-diversified portfolios. We also find that the degree of trade clustering is related to investors' stock preferences and portfolio returns. Collectively, the evidence indicates that the choice of decision frames is likely to be an important determinant of investment decisions.

Key words: narrow framing; trade clustering; disposition effect; portfolio diversification; prospect theory
History: Accepted by George Wu, decision analysis; received September 14, 2006. This paper was with the authors 5 months for 2 revisions. Published online in *Articles in Advance* May 7, 2008.

1. Introduction

Traditional portfolio choice models posit that investors formulate their trading decisions by maximizing expected utility defined over their total wealth. In these models, investors evaluate each investment choice according to its impact on the aggregate wealth. However, the extant evidence from psychological research suggests that people tend to consider each decision as unique, often isolating the current choice from their other choices. In other words, people often engage in *narrow framing* (e.g., Kahneman and Lovallo 1993, Kahneman 2003), where the interactions among multiple decisions are often ignored. For example, when offered a monetary gamble, an individual with a narrow decision frame would evaluate the potential payoffs from the gamble in isolation without combining them with her existing wealth. In contrast, an individual with a broad decision frame would integrate the potential payoffs from the gamble with her existing wealth and evaluate the combined outcomes before making a choice.

The notion of framing is applicable to decision making in very general settings, including investment decisions. Tversky and Kahneman (1981, p. 453) define a decision frame as "the decision-maker's conception of the acts, outcomes, and contingencies associated with a particular choice." For any given decision problem, many different decision frames can be potentially induced. The frame that is eventually chosen is influenced by the formulation of the problem and the personal characteristics and habits of the person making the decision.

For instance, when people use simple heuristics and make decisions in an intuitive manner, they are likely to adopt the most readily available frame, which is often narrow and suboptimal (Kahneman 2003). People might also adopt narrow decision frames due to their limited cognitive capacities and because integration requires significant cognitive costs (e.g., Miller 1956; Simon 1957; Tversky and Kahneman 1981, 1986). Some individuals would intentionally choose a decision frame that increases perceived utility and makes the outcome appear more favorable to them (Thaler 1985). In particular, hedonic optimizers would pick a narrow decision frame that segregates gains instead of using a broad decision frame that combines all gains (e.g., Thaler and Johnson 1990, Lim 2006). Additionally, people can engage in narrow framing because nonconsumption utility such as regret influences their decisions (Barberis et al. 2006).

Although the importance of framing in the contexts of portfolio choice and asset pricing has been recognized in the recent theoretical literature (e.g., Barberis and Huang 2001, 2007), empirical tests of narrow framing outside of laboratories have been almost nonexistent. In this study, we use the portfolio holdings and trades of a group of individual investors at a large U.S. discount brokerage house and examine the influence of narrow framing on their stock investment decisions. We focus on narrow framing in a cross-sectional context, where people make each trading decision in isolation and are unable or unwilling to aggregate gains and losses of individual stocks in their portfolios. This type of framing effect is related to, but distinct from, intertemporal framing effects, where people's perceptions of gains and losses are influenced by the evaluation periods (e.g., Benartzi and Thaler 1995, Gneezy et al. 2003).

We examine two important stock investment decisions that are likely to be influenced by the degree of narrow framing. First, we consider the disposition effect, which refers to the empirical observation that investors are reluctant to realize losses but more willing to sell the winners in their portfolios (Shefrin and Statman 1985). We conjecture that some investors exhibit a stronger disposition effect because they narrowly frame stock-level gains and losses instead of adopting a broader frame that considers the overall portfolio performance.

Under the prospect-theoretic explanation of the disposition effect, the tendency to frame decisions narrowly at the individual stock level instead of framing them broadly at the portfolio level influences investors' propensity to sell portfolio winners and losers. The value function in prospect theory is concave in the gain domain and convex in the loss domain. When the value function is defined for each stock, this S-shape implies that investors exhibit risk-averse behavior when contemplating the sale of a winner. They display a greater propensity to sell the winner to obtain a certain payoff. However, when they face the decision to sell a loser, investors exhibit risk-seeking behavior. In this scenario, they prefer to hold on to the loser rather than selling it to experience a certain loss.

Thus, narrow framing investors who are sensitive to the performance of individual stocks instead of the overall portfolio performance exhibit a greater propensity to sell the winners, relative to the losers, in their portfolios. In contrast, investors who adopt a broader decision frame and evaluate the total performance of their respective portfolios are less likely to exhibit this asymmetry, even if they evaluate their portfolio gains and losses using a prospect-theoretic value function.[1]

Second, we examine whether the degree of narrow framing influences investment choices even when they are not induced by prospect-theoretic preferences. Specifically, we focus on investors' portfolio diversification decisions and examine whether some investors underdiversify because they narrowly examine the risks of individual stocks and do not use a broader decision frame to evaluate the aggregate portfolio risk that takes into account the correlation structure of the portfolio. Certain stocks appear unattractive when considered in isolation, but they can bring considerable diversification benefits when added to an existing portfolio. Investors who frame their decisions narrowly are unlikely to perceive such benefits. In contrast, investors who frame their decisions broadly would examine the incremental effect of each stock on the riskiness of their respective portfolios and, therefore, they would hold relatively better-diversified portfolios.

In sum, our main hypothesis posits that investors who frame their decisions narrowly would exhibit stronger disposition effects and weaker diversification skills. Because investors' decision frames cannot be observed, to test this hypothesis we rely on the findings in the experimental psychology literature and identify an appropriate narrow framing proxy. The extant experimental evidence (e.g., Tversky and Kahneman 1981, 1986; Redelmeier and Tversky 1992) indicates that the decision frames that people adopt are influenced by the manner in which different alternatives are presented to them. In particular, the time interval between two consecutive decisions is likely to influence the decision frame, where temporally separated decisions are more likely to be framed narrowly than simultaneous decisions (e.g., Read and Loewenstein 1995, Read et al. 1999).[2]

Motivated by this psychological evidence, we propose the degree of clustering in trades as a proxy for the level of narrow framing in stock investment decisions. Specifically, we posit that, ceteris paribus, investors who execute less-clustered trades are more likely to use narrower decision frames in their investment decisions than are investors who execute more clustered trades.

Using the narrow framing proxy, we find that investors who execute less-clustered trades exhibit a greater propensity to realize gains than losses, and thus, they exhibit greater disposition effects. The negative relation between trade clustering and the disposition effect remains strong even when we control for the effects of demographic and portfolio characteristics that have been identified as important determinants of the disposition effect in previous studies (e.g., Feng and Seasholes 2005, Dhar and Zhu 2006).

Examining the relation between trade clustering and portfolio diversification, we find that investors who execute more clustered trades make relatively better diversification decisions and construct portfolios with relatively lower variances. The diversification–trade clustering relation remains strong when we control for other known determinants of portfolio diversification (e.g., Goetzmann and Kumar 2008). Because we use a narrow framing proxy instead of a direct framing

[1] Barberis and Xiong (2008) point out that prospect theory does not necessarily lead to the disposition effect in a single stock setting. However, framing at the individual stock level is essential to explain why investors exhibit different selling propensities toward "winners" and "losers" within the same portfolio.

[2] Also, see Thaler and Johnson (1990), Linville and Fischer (1991), and Hirst et al. (1994).

measure, we conduct several robustness checks and show that the disposition effect–trade clustering and the diversification–trade clustering relations are robust and are not mechanically induced.

Our empirical evidence also indicates that the degree of trade clustering is related to investors' style preferences and portfolio performance. Investors who execute less-clustered trades exhibit a preference for small-cap and value stocks, and they earn higher raw returns but lower risk-adjusted returns. Collectively, the empirical evidence supports our main hypothesis and indicates that the framing mode is an important determinant of individual investors' stock investment decisions.

The rest of this paper is organized as follows: In §2, we briefly describe the data and define our trade-clustering measures. We present our main empirical results in §§3–5 and summarize the results from our robustness tests in §6. We conclude in §7 with a brief summary of the paper.

2. Clustered Trades and Framing Decisions

2.1. Data Sources

The primary data for our study consist of a six-year (1991–1996) panel of all executed trades and monthly portfolio positions of a group of individual investors at a major U.S. discount brokerage house. For a subset of households, demographic information such as age, income, occupation, marital status, gender, etc. is also available.[3] There are 77,995 households in the database, of which 62,387 have traded in stocks. From this group, we choose 41,039 investors who have executed a minimum of five trades during the six-year sample period. The portfolio and demographic characteristics of investors in our chosen sample are very similar to those of the overall sample.

A typical investor in our sample holds a four-stock portfolio (median is three) with an average size of \$35,629 (median is \$13,869) and executes fewer than 10 trades per year, where the average trade size is \$8,779 (median is \$5,239). Fewer than 10% of the investors hold portfolios over \$100,000 and less than 5% hold more than 10 stocks. These investors execute an average of 41 trades (median is 19) during the six-year sample period, where the average monthly portfolio turnover rate (the average of purchase and sales turnover rates) is 6.59% (median is 2.53%). Further details on the investor database are available in Barber and Odean (2000).

[3] The demographic information is either self-reported at the time the brokerage account is opened or gathered through a survey conducted at the end of the sample period. See Barber and Odean (2001) for details.

In addition to the individual investor database, for each stock in our sample, we obtain monthly prices and returns from the Center for Research on Security Prices. We also obtain the monthly time-series of Fama-French factors and the momentum factor from Professor Ken French's data library available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

2.2. Potential Narrow Framing Proxies

We measure the degree of narrow framing using the degree of clustering in investor's trades. In particular, we identify whether an investor executes trades separately (i.e., one trade at a time) or multiple trades simultaneously. One potential measure that captures the degree of trade clustering (TC) is

$$\mathrm{TC}_i = 1 - \frac{\mathrm{NTDAYS}_i}{\mathrm{NTRADES}_i}, \qquad (1)$$

where NTDAYS_i is the total number of days on which investor i trades stocks, and $\mathrm{NTRADES}_i$ is the total number of stock trades executed by investor i during the sample period. On any given day, multiple investor trades in the same stock are aggregated into a single trade.

A low TC measure for an investor indicates that her trades are temporally separated and, thus, the degree of narrow framing is likely to be higher. In particular, the trade-clustering measure is zero for investors who execute each trade on a separate day. These investors are more likely to adopt narrower decision frames in their investment choices.

For robustness, we consider alternative measures of trade clustering. Specifically, we borrow the "index of cluster size" (ICS) measure from the spatial analysis literature (e.g., Bailey and Gatrell 1995), which measures clustering using the time interval between two consecutive trades. The measure exploits the property that completely random events with no clustering follow a Poisson process. There is evidence of clustering if the variance of the time interval between events is greater than the variance of the time interval under the Poisson process. We also measure TC and ICS based only on stock purchases. These alternative clustering measures are strongly correlated with TC (all correlations are above 0.760) and yield very similar results. For brevity, we only report the results using the TC measure defined in Equation (1).

2.3. Trade Clustering at the Aggregate Level

To begin, we compute the trade-clustering measures for all investors who execute at least five trades during the sample period. The mean TC measure is 0.226 (median is 0.200), which indicates that a typical investor in our sample executes 10 trades over 7.74

trading days.[4] About 16% of all investors execute each trade on a different trading date and, thus, they have a zero TC measure. Although a significant number of investors in our sample have a zero TC score, there is considerable heterogeneity in the extent to which their trades are clustered over time. About 10% of investors have TC greater than 0.50, and these investors execute an average of two trades or more on the days they trade.

2.4. Trade Clustering and Investor Characteristics

How do the personal characteristics of investors who execute more clustered trades differ from those who execute temporally separated trades? Table 1, Panel A reports the average characteristics of investors in the 10 TC deciles. The TC measure is computed for each investor, using all her trades executed during the entire sample period. The sorting results indicate that investors in the highest TC decile hold larger portfolios than those in the bottom decile. The average portfolio size is \$55,770 in TC decile 10 and \$21,690 in TC decile 1. Investors in the highest TC decile also execute more trades per year, but with a smaller size, compared with those in the lowest TC decile. Moreover, high-TC investors have higher turnover rates, although the relation between TC and portfolio turnover is not monotonic. Those investors also have higher incomes, are slightly older, and allocate a larger share of their portfolios to mutual funds.

To examine the relative influences of demographic and portfolio variables on trade clustering, we estimate a cross-sectional regression model, where the trade-clustering variable is the dependent variable and demographic and portfolio variables are employed as independent variables. All variables are standardized so that we can compare the relative influence of each independent variable on the dependent variable. The regression estimates are reported in Table 1, Panel B. The coefficient estimates are broadly consistent with the univariate results reported in Panel A. We find that TC increases with income, age, portfolio size, trades per year, and number of stocks in the portfolio. Moreover, TC is higher for investors who trade foreign securities and mutual funds, which suggests that TC might be associated with a stronger preference for diversification.

3. Trade Clustering and the Disposition Effect

In the first set of formal tests, we examine the first part of our main hypothesis, which posits that investors who adopt narrower decision frames are likely to exhibit a stronger disposition effect.

3.1. The Disposition Effect Measure

We use Odean's (1998) PGR-PLR methodology to measure the disposition effect of each investor. Considering the actual trades and potential trades of investor i during the sample period, we compute the proportions of gains realized (PGR) and proportion of losses realized (PLR) as

$$\mathrm{PGR}_i = \frac{N^i_{\mathrm{gr}}}{N^i_{\mathrm{gr}} + N^i_{\mathrm{gp}}}, \quad \mathrm{PLR}_i = \frac{N^i_{\mathrm{lr}}}{N^i_{\mathrm{lr}} + N^i_{\mathrm{lp}}}, \qquad (2)$$

where N^i_{gr} (N^i_{lr}) is the number of trades by investor i with a realized gain (loss), and N^i_{gp} (N^i_{lp}) is the number of potential or paper trades for investor i with a gain (loss). We compute the disposition effect (DE) of investor i as

$$\mathrm{DE}_i = \mathrm{PGR}_i - \mathrm{PLR}_i. \qquad (3)$$

A positive value of DE indicates that a smaller proportion of losers is sold compared with the proportion of winners sold and, thus, investor i exhibits the disposition effect.

3.2. Peer Group Adjusted Trade Clustering and Disposition Effect Measures

Odean (1998) notes that the PLR and PGR measures are sensitive to portfolio size and trading frequency. Both proportions are likely to be smaller for investors who hold larger portfolios and trade frequently because those portfolios contain a larger number of stocks with capital gains and capital losses. If the DE measure is employed in a cross-sectional analysis in its original form, these dependencies are likely to induce mechanical associations between the DE and the variables that are correlated with portfolio size and trading frequency. Because the trade-clustering measure is correlated with portfolio size, number of stocks, and trading frequency (see Table 1), there might be concerns about a potential mechanically induced relation between TC and the DE.

To guard against the possibility of this mechanical relation, we minimize the potential influences of portfolio size, number of stocks, and trading frequency on TC and DE and define peer group "adjusted" measures of both trade clustering and the disposition effect.[5] We proceed as follows: First, we perform an independent double sort using the portfolio

[4] These statistics do not change in a significant manner if we use different cutoffs for minimum trades. For instance, with 10 minimum trades, the mean TC measure is 0.236 (median is 0.207), which is only marginally different from the mean of 0.226 (median of 0.200).

[5] Following Dhar and Zhu (2006), we also experimented with other related measures of the individual-level disposition effect that are not sensitive to portfolio size and trading frequency. Specifically, we used the following two DE measures: (i) $N^i_{\mathrm{gr}} - N^i_{\mathrm{lr}}/N^i_{\mathrm{gr}} + N^i_{\mathrm{lr}}$ and (ii) $N^i_{\mathrm{gr}}/N^i_{\mathrm{lr}} - N^i_{\mathrm{gp}}/N^i_{\mathrm{lp}}$. The results with these alternative DE measures are very similar to the reported results.

Table 1 Trade Clustering and Investor Characteristics

Panel A: Summary statistics

TC decile	PSize	TSize	Income	Age	PTurn	MFund	TPY
Low TC (TC = 0)	21.69	8.88	86.92	49.15	5.48	0.18	2.95
D2 (0 < TC ≤ 0.063)	25.01	9.69	86.68	49.30	6.35	0.18	3.95
D3 (0.063 < TC ≤ 0.111)	29.99	9.01	86.72	49.58	7.72	0.19	5.83
D4 (0.111 < TC ≤ 0.154)	30.01	8.90	89.69	49.80	8.02	0.20	6.15
D5 (0.154 < TC ≤ 0.200)	37.53	8.76	88.98	50.49	7.68	0.20	7.91
D6 (0.200 < TC ≤ 0.250)	33.67	8.66	88.04	50.60	8.56	0.20	8.16
D7 (0.250 < TC ≤ 0.300)	37.88	9.03	87.91	50.58	8.42	0.20	9.84
D8 (0.300 < TC ≤ 0.375)	38.70	8.67	92.60	50.99	8.28	0.20	11.01
D9 (0.375 < TC ≤ 0.490)	45.18	8.45	92.66	51.68	7.39	0.22	11.98
High TC (TC > 0.490)	55.77	7.72	94.57	51.56	7.90	0.26	50.41
High TC − Low TC	34.07**	−1.16**	7.65**	2.41**	2.42**	0.08**	47.46**

Panel B: Regression estimates

Variable	Estimate	t-statistic
Intercept	0.004	0.661
Income	0.057	4.509
Log(*age*)	0.033	2.490
Professional dummy	−0.005	−0.293
Retired dummy	−0.047	−2.738
Trade size	−0.041	−2.101
Portfolio turnover	0.038	1.920
Mutual fund ownership	0.062	4.711
Short sell dummy	−0.005	−0.545
Option dummy	0.040	0.588
Foreign dummy	0.056	4.712
Number of stocks	0.189	12.227
Log(*trades per year*)	0.235	10.611
Portfolio size	0.072	3.062
Number of investors		10,755
Adjusted R^2		10.88%

Notes. Using the trade-clustering measure for the entire sample period, we rank households and form 10 investor groups. The trade-clustering measure for household i is defined as, $\text{TC}_i = 1 - (\text{NTDAYS}_i)/(\text{NTRADES}_i)$, where NTDAYS_i is the total number of days on which household i traded stocks and NTRADES_i is the total number of stock trades by household i. In Panel A, we report the mean values of several investor and portfolio attributes for the 10 TC deciles. *Portfolio size* (it PSize) is the average size (in thousand dollars) of the household portfolio, *trade size* (TSize) is the average trade size (in thousand dollars), *income* is the total annual household income (in thousand dollars), *Age* is the age of the head of the household, *portfolio turnover* (PTurn) is the average of monthly buy-and-sell turnover rates, *trades per year* (TPY) is the number of trades executed per year by a household, and *mutual fund ownership* (MFund) is the mutual fund holding of a household as a fraction of the total equity portfolio. In Panel B, we report the cross-sectional regression estimates, where TC is the dependent variable and a set of investor characteristics and portfolio variables are employed as independent variables. The *professional* and *retired* dummy variables represent the occupation categories where the professional job category includes investors who hold technical and managerial positions. The remaining investors belong to the nonprofessional category that consists of blue-collar workers, sales and service workers, and clerical workers. *Short sell dummy* is a dummy variable that is set to one if a household makes at least one short sale during the sample period, *option dummy* is set to one if a household makes at least one option trade during the sample period, *foreign dummy* is set to one if a household makes at least one trade in a foreign asset (ADR, foreign stock, or a closed-end country fund), and *number of stocks* is the average number of stocks in the investor portfolio during the sample period. In Panel A, we use the Kolmogorov-Smirnov test to examine the statistical significance of the differences in investor characteristics. In Panel B, all variables are standardized (mean is set to zero and the standard deviation is one) and the standard errors are corrected for heteroskedasticity.

** Denotes significance at the 1% level.

size and the mean monthly trading frequency measures, and define a 10×10 grid. Within each portfolio size-trading frequency category, we further sort portfolios using the average number of stocks measure, and define portfolio quintiles.[6] Altogether, there are 500 bins, where each bin represents a peer group. Each investor is mapped into one of the 500 bins, and a peer group is assigned to her. The peer groups contain an average of 71 investors. The largest peer group consists of 212 investors, and no peer group has fewer than 23 investors.

To facilitate cross-sectional comparisons across peer groups, we standardize the TC measure using the

[6] The results are qualitatively similar when a coarser (5×5) or a finer (20×20) grid is employed to identify the peer groups.

peer group means and standard deviations. Specifically, we obtain a peer group adjusted TC measure for each investor as

$$\mathrm{ATC}_i = \frac{\mathrm{TC}_i - \mathrm{MNTC}_i^{\mathrm{peer}}}{\mathrm{SIGTC}_i^{\mathrm{peer}}}, \tag{4}$$

where $\mathrm{MNTC}_i^{\mathrm{peer}}$ is the mean TC of the peer group of investor i, and $\mathrm{SIGTC}_i^{\mathrm{peer}}$ is the standard deviation of the TC of the peer group of investor i.[7]

A positive (negative) ATC measure for an investor indicates that her trades are more (less) clustered than other investors who exhibit similar trading frequency and hold portfolios with similar number of stocks and of similar size (i.e., her peers). The magnitude of the ATC measure for an investor indicates the number of standard deviations that the investor is away from the mean of her respective peer group. Using the original DE measure, a peer group adjusted disposition effect measure is defined and interpreted in an analogous manner.

3.3. Trade Clustering and the Disposition Effect: Sorting Results

To set the stage, we conduct nonparametric tests and examine the relation between adjusted trade clustering (ATC) and adjusted disposition effect (ADE). First, we compute the ADE and the ATC measures for each investor in the sample, where for greater accuracy we only consider investors who execute at least five sell trades. Both the ATC and the ADE measures are computed using all investor trades executed during the sample period. Next, we rank investors on the basis of their ATC measures and define five investor quintiles that contain the same number of investors.[8] Last, we measure the average ADE for each of the five investor groups.

Table 2 reports the results from our sorting tests. To show the ATC variation across the ATC quintiles, in Panel A, we report the range of the ATC measure for the five ATC quintiles. The ATC measures are negative in the first two quintiles, positive in the last two quintiles, and have mixed signs in the middle quintile.

In Panel B, we report the mean ADE for ATC quintiles. Consistent with our hypothesis, we find that the mean ADE decreases with ATC. The mean ADE is 0.102 in the lowest ATC quintile, and it decreases monotonically along the ATC quintile (see the last row of Panel B). In the highest ATC quintile, the mean ADE is negative (−0.156), which indicates that investors in the group exhibit a lower disposition effect than their respective peer group means. The difference in the mean ADE of the top and the bottom ATC quintiles is large (= −0.258) and statistically significant at the 1% level.

To better understand how the trade clustering and the disposition effect measures are related, we per-

Table 2 Trade Clustering and the Disposition Effect: Sorting Results

Panel A: ATC breakpoints

ATC range	ATC quintiles: Low	Q2	Q3	Q4	High
Low	−0.459	−0.144	−0.073	0.016	0.134
High	−0.144	−0.073	0.016	0.134	0.683

Panel B: Double sort on portfolio size and ATC

Portfolio size	ATC quintiles: Low	Q2	Q3	Q4	High	High − Low
Small	0.163	0.104	0.039	−0.063	−0.169	−0.332**
Q2	0.065	0.039	0.084	−0.101	−0.170	−0.235**
Q3	0.086	0.078	0.045	−0.043	−0.153	−0.239**
Q4	0.068	0.097	0.049	−0.117	−0.073	−0.141**
Large	0.075	0.105	−0.029	−0.006	−0.057	−0.132**
All	0.102	0.064	0.027	−0.099	−0.156	−0.258**

Panel C: Double sort on annual number of trades and ATC

Trades per year	ATC quintiles: Low	Q2	Q3	Q4	High	High − Low
Low	0.124	0.031	−0.065	−0.107	−0.130	−0.254**
Q2	0.161	0.116	0.021	−0.211	−0.222	−0.383**
Q3	0.090	−0.046	−0.010	−0.252	−0.323	−0.413**
Q4	0.106	0.042	0.057	−0.102	−0.235	−0.341**
High	0.084	0.159	0.083	0.014	−0.024	−0.108*

Notes. This table reports the mean adjusted disposition effect (ADE) of investor groups formed on the basis of portfolio size, adjusted trade clustering (ATC), and trades per year measures. In Panel A, we report the lower and the upper limits of the ATC quintiles. In Panel B, ADE is reported for investor groups formed by performing an independent double sort on portfolio size and the trade-clustering measures. In Panel C, investor groups are formed by performing an independent, double sort on number of trades per year and trade-clustering measures. The portfolio size is the average size of an investor's portfolio during the six-year sample period. The adjusted ATC measure is defined as $\mathrm{ATC}_i = (\mathrm{TC}_i - \mathrm{MNTC}_i^{\mathrm{peer}})/\mathrm{SIGTC}_i^{\mathrm{peer}}$, where $\mathrm{MNTC}_i^{\mathrm{peer}}$ is the mean TC of the peer group of investor i and $\mathrm{SIGTC}_i^{\mathrm{peer}}$ is the standard deviation of the TC of the peer group of investor i. TC is defined in Table 1. The peer group of each investor is defined using portfolio size (measured in dollar terms), number of stocks, and trading frequency. The ADE measure for each investor is defined in an analogous manner using the original disposition effect (DE) measure. The DE for an investor is defined as the difference between an investor's propensity to realize gains and the propensity to realize losses. We use the Kolmogorov-Smirnov test to examine the statistical significance of the differences in the adjusted DE measures.

*, ** Denote significance at the 5% and 1% levels, respectively.

[7] For robustness, we also considered a related measure of adjusted trade clustering, where the deflator is $\mathrm{MNTC}_i^{\mathrm{peer}}$ instead of $\mathrm{SIGTC}_i^{\mathrm{peer}}$. Because the scaled ATC measures are sensitive to the small value of the denominator, we considered an unscaled clustering measure, defined as $\mathrm{ATC}_i = \mathrm{TC}_i - \mathrm{MNTC}_i^{\mathrm{peer}}$. Our results are similar when we use these alternative definitions of adjusted trade clustering.

[8] The results are very similar when we form 10 investor groups instead of 5.

form two double sorts and examine the variation in ADE as ATC varies within portfolio size and trading-frequency-based investor groups. In Panel B, we present the average ADE for investor groups that are formed by sorting on the ATC and the portfolio size variables. In Panel C, we report the average ADE for investor groups formed by sorting on ATC and trades per year (i.e., trading frequency) variables.

The results from the double sorts indicate that the ADE measure exhibits some sensitivity to the portfolio size measure within the ATC quintiles, especially in the extreme ATC quintile portfolios. However, the aggregate effect is not very strong because the sensitivity is positive in a few instances and negative in others. Overall, the peer group adjustment methodology appears to be reasonably effective in minimizing the mechanical effects of portfolio size and trading frequency on the DE measure.

More interestingly, we find that the mean ADE decreases with ATC across all portfolio size and trading frequency quintiles. For instance, among large portfolios (highest portfolio size quintile), the mean ADE is largest (=0.075) in the lowest ATC quintile and significantly lower (= −0.057) in the highest ATC quintile. The ADE differential of −0.132 is significant at the 1% level. Similarly, within the subset of investors who trade most often (highest trades per year quintile), the mean ADE is largest (=0.084) in the lowest ATC quintile and significantly lower (= −0.024) in the highest ATC quintile. Again, the mean ADE differential of −0.108 is significant at the 1% level. The other results in the table indicate that the magnitude of the ADE differential is even stronger in the remaining four portfolio size and trading frequency quintiles.

3.4. Disposition Effect Regression Estimates

To better quantify the relation between trade clustering and the disposition effect, we estimate a cross-sectional regression model. In the regression specification, ADE is the dependent variable, and the ATC measure along with a set of demographic and portfolio-related variables are employed as independent variables. The choice of independent variables other than ATC is motivated by the findings in Feng and Seasholes (2005) and Dhar and Zhu (2006), who show that the level of disposition effect is related to a variety of investor characteristics. The variables that are known to influence the trade-clustering measure (see §2.4) are also included in the set of control variables. As before, all regression variables are standardized, and we ensure that our estimates are robust to concerns about multicollinearity.

The disposition effect regression estimates are reported in Table 3. The explanatory variables used in the regression model have been defined earlier (see Table 1), with the exception of the *gender dummy*. It is set to one if the head of the household is male. Although we use peer group adjusted trade clustering and disposition effect measures, to further ensure that the relation between the disposition effect and trade clustering that we identify is not mechanically induced, we employ the three variables that are used to define the peer groups as additional control variables.

Table 3 Trade Clustering and the Disposition Effect: Regression Estimates

Variable	Estimate	t-statistic	Estimate	t-statistic
Intercept	0.005	0.610	0.006	0.328
Adjusted trade clustering	−0.107	−5.464	−0.105	−4.541
Income			−0.021	−1.209
Log(age)			−0.107	−5.198
Professional dummy			0.012	0.557
Retired dummy			0.022	0.941
Gender dummy			0.016	0.842
Portfolio turnover			0.102	3.272
Mutual fund ownership			−0.018	−2.085
Number of stocks			0.008	0.238
Log(trades per year)			0.099	6.487
Portfolio size			−0.014	−1.963
Number of investors		13,683		9,756
Adjusted R^2		6.33%		12.96%

Notes. This table reports the estimates from cross-sectional regressions, where the adjusted disposition effect (ADE) of a household is the dependent variable. The adjusted trade-clustering (ATC) measure and a set of household characteristics are employed as independent variables. *Gender dummy* is set to one (zero) if the head of the household is male (female). Other independent variables are defined in Table 1. Both independent and dependent variables have been standardized (mean is set to zero and standard deviation is one). The standard errors are corrected for heteroskedasticity.

The disposition effect regression estimates indicate that when the ATC measure is the only independent variable, the ATC coefficient estimate is negative and strongly significant (ATC coefficient = −0.107, t-stat = −5.464), and the adjusted R^2 of the cross-sectional regression model is 6.33%. Thus, the ATC measure alone can explain a considerable portion of the cross-sectional variation in the disposition effect.

Even when we introduce the control variables in the regression specification, the ATC coefficient estimate remains highly significant. Specifically, the ATC coefficient estimate is −0.105 with a t-statistic of −4.541. This evidence indicates that trade clustering has an incremental explanatory power over the known determinants of the disposition effect. Furthermore, comparing the ATC coefficient estimate with other coefficient estimates, we find that ATC is one of the strongest determinants of ADE.

For robustness, we consider an alternate trade clustering measure, where we estimate a regression model to remove the effects of portfolio size, trading frequency, and number of stocks on trade clustering. We define a residual trade-clustering (RTC) measure that is the residual from a regression model, where the raw trade-clustering measure is the dependent variable and the three variables used to define the peer groups are the independent variables. We reestimate the disposition effect regression with RTC as the main independent variable instead of ATC.

The RTC coefficient estimates are very similar to the ATC coefficient estimates. When RTC is the only independent variable, the RTC coefficient estimate is −0.090 with a t-statistic of −7.391. When other control variables are included in the regression specification, the RTC coefficient estimate is −0.087 with a t-statistic of −5.467. The RTC estimates are comparable to the ATC coefficient estimates and indicate that the negative disposition effect–trade clustering relation is quite robust.

3.5. Interpretation of the Disposition Effect Results

The sorting results and the DE regression estimates provide strong and robust evidence of a relation between trade clustering and investors' decisions to sell losers. We find that investors who execute more clustered trades exhibit a weaker disposition effect. This evidence is consistent with the first part of our main hypothesis, which posits that investors who adopt narrower decision frames exhibit a stronger disposition effect because they are likely to focus on the gains and losses of individual stock positions instead of examining the overall portfolio performance.

There are two potential interpretations of our findings, both consistent with our first hypothesis. One interpretation is that decision frames influence disposition effect, even though people do not actively choose a narrow decision frame. For example, when investors make intuitive decisions, separate decisions almost subconsciously induce them to adopt a narrow decision frame. As a result, investors exhibit stronger disposition effect when they execute less-clustered trades.

An alternative interpretation of our evidence is that certain investors intentionally choose broader decision frames. The choice of those frames influences the relation between trade clustering and the disposition effect. In particular, hedonic optimizers would choose a decision frame and a level of mental accounting that maximizes their perceived utility (Thaler 1985, Thaler and Johnson 1990). Due to loss aversion and diminishing sensitivity of value function in prospect theory, the impact of a loss is larger than the impact of a gain of the same magnitude, and the sensitivity to gains and losses declines as their magnitudes increase. Therefore, the hedonic editing hypothesis predicts that people would prefer to combine a loss with a larger gain or with another loss because the combined outcome generates higher utility than the total utility generated by segregated outcomes. In fact, Lim (2006) shows empirically that investors choose the timing of their trades to perceive outcomes more favorably.

If investors optimally choose their decision frames by timing their trades, the degree of trade clustering would reflect the level of framing in their trading decisions. Specifically, because a loss is less painful when it is integrated with another loss or with a larger gain, investors might sell a loser when they decide to sell a winner to reduce the pain. As a result, hedonic optimizers would attempt to overcome their reluctance to realize losses by executing clustered trades. If trade clustering and the disposition effect are related through the channel of hedonic optimization, it is consistent with our main hypothesis. The integration of outcomes through simultaneous trades reflects a desire to engage in "portfolio-level thinking." Thus, trade clustering resulting from hedonic optimizing behavior is likely to reflect a broader decision frame, which is exactly the effect we are trying to capture using the trade-clustering measure.

4. Trade Clustering and Portfolio Underdiversification

In the second set of formal tests, we examine the second part of our main hypothesis, which posits that investors who frame their decisions narrowly hold less-diversified portfolios because they pay less attention to stock correlations.

4.1. The Diversification Measure

Following Goetzmann and Kumar (2008), we use a normalized version (NV) of the portfolio variance as the diversification measure. The NV for portfolio p is defined as

$$NV_p = \frac{\sigma_p^2}{\bar{\sigma}^2}, \tag{5}$$

where σ_p^2 is the portfolio variance and $\bar{\sigma}^2$ is the average variance of all stocks in the portfolio. We compute the diversification measure for each investor in the sample, where the average variance of each investor portfolio is estimated using the monthly returns data from the previous five years, and the portfolio variance measure is estimated using the realized portfolio returns. A peer group adjusted diversification (ADIV) measure is defined using the negative of the normalized variance measure and the peer group adjustment methodology described in §3.2, so that ADIV increases as the level of diversification increases.

4.2. Trade Clustering and Diversification: Sorting Results

Table 4 reports the ADIV measures of five investor groups (quintiles) formed by sorting on the ATC mea-

Table 4 Trade Clustering and Portfolio Diversification: Sorting Results

Panel A: Double sort on portfolio size and ATC

Portfolio size	ATC quintiles: Low	Q2	Q3	Q4	High	High − Low
Small	−0.035	−0.049	−0.010	0.005	0.069	0.104*
Q2	−0.025	−0.018	−0.060	0.002	0.099	0.124*
Q3	−0.085	−0.061	−0.054	0.054	0.156	0.241**
Q4	−0.105	−0.050	−0.049	−0.014	0.218	0.323**
Large	−0.116	−0.095	−0.056	0.046	0.215	0.331**
All	−0.074	−0.056	−0.046	0.019	0.154	0.228**

Panel B: Double sort on annual number of trades and ATC

Trades per year	ATC quintiles: Low	Q2	Q3	Q4	High	High − Low
Low	−0.080	0.011	−0.021	0.044	0.057	0.136*
Q2	−0.049	−0.036	−0.019	−0.012	0.123	0.172**
Q3	−0.040	−0.040	−0.031	0.024	0.092	0.132*
Q4	−0.107	−0.060	−0.106	0.034	0.216	0.324**
High	−0.092	−0.122	−0.054	0.007	0.268	0.360**

Notes. This table reports the mean adjusted diversification (ADIV) levels of investor groups, formed on the basis of portfolio size (PSize), adjusted trade clustering (ATC), and number of trades per year (TPY) variables. Portfolio diversification is measured using normalized variance. The normalized variance of a portfolio is defined as $\mathrm{NV} = \sigma_p^2/\bar{\sigma}^2$, where σ_p^2 is the variance of the given portfolio and $\bar{\sigma}^2$ is the average variance of all stocks in the portfolio. The peer group ADIV measure for each investor is defined analogously to the ATC and ADE measures using the negative of the normalized variance measure. In Panel A, the mean diversification measures are reported for investor groups formed by performing an independent double sort on portfolio size and the adjusted trade-clustering measures. In Panel B, the investor groups are formed by performing an independent double sort on number of trades per year and adjusted trade-clustering measures. We use the Kolmogorov-Smirnov test to examine the statistical significance of the differences in diversification measures.

*, ** Denote significance at 5% and 1% levels, respectively.

sure. Consistent with our main hypothesis, we find that the level of portfolio diversification increases with ATC. The mean adjusted diversification of investor portfolios in the highest and the lowest ATC quintiles are 0.154 and −0.074, respectively, and the differential of 0.228 is statistically significant at the 1% level. These univariate results suggest that the degree of trade clustering is positively related to the level of portfolio diversification.

For robustness, we perform two double sorts and examine the variation in the level of diversification as ATC varies within the investor subgroups. In the first case we use the ATC and the portfolio size as the sorting variables, and in the second cases we employ the ATC and the trades per year as the two sorting variables. These results are also reported in Table 4.

We find that the diversification level increases with ATC across all portfolio size quintiles (see Panel A) and across all trades per year quintiles (see Panel B). For instance, among large portfolios (highest portfolio size quintile), the mean ADIV is 0.215 in the highest ATC quintile and −0.116 in the lowest ATC quintile, and the differential of 0.331 is significant at the 1% level. Similarly, within the group of investors who trade most frequently (highest trades per year quintile), investors in the highest ATC quintile have a mean ADIV of 0.268, whereas those in the lowest ATC quintile have a mean adjusted diversification of −0.092. Again, the differential of 0.360 is significant at the 1% level.

4.3. Diversification Regression Estimates

To examine the incremental effect of ATC on investors' diversification decisions, we estimate a cross-sectional regression model, where the adjusted diversification measure of an investor is the dependent variable, and the ATC measure along with various portfolio and demographic variables are the independent variables. Our choice of portfolio and demographic attributes as control variables is motivated by the results in Goetzmann and Kumar (2008), who have identified them as determinants of portfolio diversification. Furthermore, the set of variables that are known to influence trade clustering (see §2.4) are employed as additional control variables. As before, the variables in the regression model are standardized, and we ensure that the estimates are robust to concerns about multicollinearity.

The regression estimates are reported in Table 5. All explanatory variables used in the regressions have been defined earlier (see Table 1), with the exception of the *local bias* variable. The local bias measure is the difference between the weighted distance of the actual investor portfolio from her location and the weighted distance of the market portfolio from her location.[9] We include this variable in our regression specification as a control variable because Goetzmann and Kumar (2008) find that investors with stronger local bias exhibit greater underdiversification.

When the ATC measure is the only independent variable, the coefficient estimate of ATC is strongly positive and significant (ATC estimate = 0.116, t-stat = 6.246). When we introduce demographic and portfolio characteristics as control variables in the regression model, the ATC estimate decreases but remains positive and statistically significant. The ATC coefficient estimate is 0.086 with a t-stat of 5.235. In addition, the

[9] The distance between an investor's location and her portfolio is defined as $D_{\mathrm{act}} = \sum_{i=1}^{N} w_i D_i$, where N is the number of stocks in the portfolio, w_i is the weight of stock i in the portfolio, and D_i is the distance between an investor's zip code and the zip code of a firm's headquarter. The distance between an investor's location and the market portfolio is defined in an analogous manner. See Coval and Moskowitz (2001) and Zhu (2002) for details of this measure. The results are qualitatively similar when we employ other related local bias measures in the regression specifications.

Table 5 Trade Clustering and Portfolio Diversification: Regression Estimates

Variable	Estimate	t-statistic	Estimate	t-statistic
Intercept	0.004	0.194	0.019	0.465
Adjusted trade clustering	0.116	6.246	0.086	5.235
Income			−0.007	−1.159
Log(age)			0.049	1.968
Professional dummy			0.005	1.011
Retired dummy			−0.057	−0.990
Portfolio turnover			−0.035	−1.679
Portfolio performance			0.030	0.743
Mutual fund ownership			0.041	2.019
Foreign dummy			0.053	3.134
Short sell dummy			0.017	1.743
Option dummy			−0.019	−1.348
Local bias			−0.093	−2.171
Number of stocks			0.028	1.415
Log(trades per year)			0.018	2.186
Portfolio size			0.028	1.247
Number of investors		21,679		7,569
Adjusted R^2		2.34%		13.70%

Notes. This table reports the estimates of cross-sectional regressions, where the average adjusted diversification (ADIV) measure of a household is the dependent variable. The adjusted trade-clustering (ATC) measure and a set of household characteristics and portfolio variables are used as independent variables. *Portfolio performance* is the risk-adjusted performance (Sharpe Ratio) of the household, and *local bias* is the difference between the weighted distance of an actual investor portfolio from her location ($\sum_{i=1}^{N} w_i D_i$, where N is the number of stocks in the portfolio, w_i is the weight of stock i in the portfolio, and D_i is the distance between an investor's zip code and the zip code of a firm's headquarter), and the weighted distance of the market portfolio from her location. Other independent variables have been defined in previous tables. Both independent and dependent variables have been standardized (mean is set to zero and standard deviation is one). The standard errors are corrected for heteroskedasticity.

coefficient estimates of the control variables are consistent with the results reported in Goetzmann and Kumar (2008). Comparing the magnitudes of the coefficient estimates, we find that local bias and trade clustering are the two strongest determinants of portfolio diversification.

For robustness, we use the RTC measure as the proxy for narrow framing and reestimate the diversification regression model. When RTC is the only independent variable in the diversification regression, the coefficient estimate increases from 0.116 to 0.129 (t-stat = 5.629). When other control variables are included in the regression specification, the RTC coefficient estimate is 0.093 with a t-statistic of 4.202. The RTC coefficient estimates indicate that the positive diversification–trade clustering relation is quite robust.

Collectively, the sorting results and the diversification regression estimates suggest that investors who execute more clustered trades and tend to make simultaneous trading decisions hold better-diversified portfolios than investors who execute separate trades and tend to make separate decisions. This evidence supports the second part of our main hypothesis, which posits that investors who adopt narrower decision frames hold relatively less-diversified stock portfolios.

5. Trade Clustering, Style Preferences, and Portfolio Performance

In this section, we examine the relation between adjusted trade clustering and portfolio performance. We consider both raw and risk-adjusted performance measures because the performance–trade clustering relation is likely to depend upon the choice of the performance measure. Investors who execute more clustered trades exhibit weaker disposition effects and hold relatively better-diversified portfolios. These investors who adopt broader decision frames would also be better positioned to examine the interactions among multiple portfolio decisions. In particular, they might be able to better assess the total risk of their portfolios. Consequently, trade clustering could be positively correlated with risk-adjusted portfolio performance. In contrast, investors who execute less-clustered trades and adopt narrower decision frames could earn higher raw returns because they prefer to hold riskier stocks. In this scenario, if riskier stocks earn higher average returns, trade clustering would be negatively related to raw portfolio performance.

To examine the relation between trade clustering and portfolio performance, we compute the ATC measure for each investor using all trades executed by the investor during the entire sample period and define ATC quintiles. We consider both raw and risk-adjusted performance measures and examine the average portfolio performance of investors in those five categories.[10] For each investor in our sample, we estimate several factor models, including the four-factor model (Fama and French 1993, Jegadeesh and Titman 1993, Carhart 1997), to measure her risk-adjusted performance. Table 6 reports the performance estimates, where for greater accuracy investors with fewer than 24 monthly observations are excluded from the analysis.

Consistent with the evidence in Barber and Odean (2000), we find that, on average, our sample of investors underperforms the common performance benchmarks. The mean four-factor alpha is −0.375, which translates into an annual, risk-adjusted underperformance of 4.50%. Examining the average portfolio characteristics across the ATC quintiles, we find that investors who execute more clustered trades hold less risky portfolios and earn lower raw returns. Consequently, the average Sharpe ratio does not vary

[10] The results are qualitatively similar when we consider ATC deciles instead of quintiles.

Table 6 Trade Clustering, Style Preferences, and Portfolio Performance

Performance measure	ATC quintiles Low	Q2	Q3	Q4	High	High − Low
Mean monthly return	1.251	1.227	1.228	1.216	1.122	−0.129*
Portfolio standard deviation	9.029	8.826	8.661	8.344	7.594	−1.435**
Sharpe ratio	0.101	0.101	0.103	0.105	0.104	0.003
Jensen's alpha	−0.127	−0.142	−0.166	−0.158	−0.217	−0.090*
Two-factor alpha	−0.433	−0.430	−0.441	−0.418	−0.432	0.001
Three-factor alpha	−0.483	−0.457	−0.431	−0.405	−0.353	0.130**
Four-factor alpha	−0.407	−0.382	−0.379	−0.362	−0.271	0.136**
RMRF exposure	1.221	1.197	1.204	1.185	1.116	−0.105**
SMB exposure	0.939	0.890	0.869	0.813	0.626	−0.323**
HML exposure	0.250	0.226	0.189	0.159	0.121	−0.129**
UMD exposure	−0.376	−0.351	−0.320	−0.307	−0.228	0.148**

Notes. This table reports the average portfolio performance and style preferences of investor groups formed by sorting along the adjusted trade-clustering (ATC) dimension. Using the ATC measure for the entire sample period, investors are ranked and five investor groups are defined. The performance measures for each investor portfolio are computed separately and the group averages are reported in the table. The following performance measures are reported: (i) mean monthly return, (ii) portfolio standard deviation, (iii) Sharpe ratio, and (iv) k-factor alpha measures ($k = 1, 2, 3, 4$). The k-factor alphas are estimated for each household by fitting a k-factor model to the sample period monthly returns time-series. The one-factor model contains only the market factor (RMRF); the two-factor model contains RMRF and SMB; the three-factor model contains RMRF, SMB, and HML; and the four-factor model contains RMRF, SMB, HML, and UMD. RMRF is the market return in excess of the risk-free rate, SMB is the size factor, HML is the value factor, and UMD is the momentum factor. The average factor exposures are also reported. They are estimated for each household by fitting a four-factor model to the sample period monthly returns time-series. Due to the possibility of cross-sectional dependence, we use bootstrapping to conduct the tests of statistical significance.

*, ** Denote significance at 5% and 1% levels, respectively.

considerably across the ATC quintiles. For instance, investors in the lowest ATC quintile earn a mean monthly return of 1.251% and have a mean portfolio standard deviation of 9.029%. In contrast, investors in the highest ATC quintile earn a lower mean monthly return (=1.122%), but they also have a lower mean portfolio standard deviation (=7.594%). The mean Sharpe ratios for the two groups are 0.101 and 0.104, respectively. This evidence is consistent with our diversification regression estimates, where we find that investors who execute more clustered trades hold less risky and better-diversified portfolios.

When we examine the mean risk-adjusted performance levels across the ATC quintiles, we find that the low-ATC investors continue to outperform high-ATC investors when we measure portfolio performance using Jensen's alpha. However, the low-ATC investors underperform high-ATC investors when we apply other asset-pricing models to define the performance benchmarks. For instance, the mean four-factor alpha for the lowest (highest) ATC quintile investors is −0.407 (−0.271). The alpha differential of 0.136% per month translates into an annual risk-adjusted performance differential of 1.632%.[11]

To identify the main source of the performance differences across the ATC quintiles, we examine whether investors' stock preferences vary across the ATC quintiles. Using the mean factor exposure estimates, we find that investors who execute less-clustered trades hold higher beta, smaller, higher book-to-market (B/M), and low-momentum stocks. This evidence might at least partly explain why the performance differential between the high- and the low-ATC investor groups switches sign when we introduce size and book-to-market factors to define the performance benchmarks.

In untabulated results, we find that the stock preference estimates are similar when we examine the actual portfolio holdings of investors in the low- and the high-ATC quintiles. For instance, compared to the weight in the aggregate market portfolio, the lowest ATC quintile investors overweight high beta (highest beta quintile) stocks by 15.27%, whereas the highest ATC quintile investors overweight them by 8.96%. Similarly, the lowest ATC quintile investors overweight smaller (lowest market-cap quintile) stocks by 17.02%, whereas the highest ATC quintile investors overweight them by 12.14%. The portfolio weights along other stock characteristics (B/M and 12-month momentum) also yield estimates that are consistent with investors' stock preferences as reflected by the mean factor exposures.

To better understand the relation between trade clustering and portfolio performance, we estimate performance regressions where the portfolio performance of an investor is the dependent variable. The independent variables are the adjusted disposition effect, the adjusted diversification, and the adjusted trade-clustering measures, along with the known determinants of portfolio performance. This set includes the investor's age, investment experience, the annual household income, a male dummy, a retired dummy, portfolio size, monthly portfolio turnover rate, and the portfolio dividend yield (e.g., Barber and Odean 2001, Korniotis and Kumar 2007). To account for potential cross-sectional dependence, we use robust standard errors adjusted for heteroskedasticity and clustering within zip codes.

Consistent with the sorting results, we find a negative performance–clustering relation when the mean portfolio return or the Jensen's alpha is the dependent variable (ATC coefficient estimates are −0.038 and −0.030 with t-statistics of −3.622 and −2.725, respectively) and a positive performance–clustering relation

[11] Due to the possibility of cross-sectional dependence in portfolio performance, we use bootstrapping to conduct the tests of statistical significance.

when the four-factor alpha is the dependent variable (ATC coefficient estimate = 0.032, t-statistic = 2.948). Furthermore, as expected, the ADE measure has a statistically negative coefficient estimate and the ADIV measure has a statistically positive estimate in both the raw and the risk-adjusted performance regressions.

Taken together, our performance results provide mixed evidence on the relation between trade clustering and portfolio performance. This relation depends upon the choice of the performance measure. It is negative when we consider the raw performance measure or the Jensen's alpha, but positive when we measure risk-adjusted performance using the three-factor alpha or the four-factor alpha.

6. Additional Robustness Checks

We conduct several additional tests to ensure that the observed positive (negative) relation between trade clustering and portfolio diversification (disposition effect) is robust. For brevity, the details of the robustness tests and the results are described in the online appendix (provided in the e-companion),[12] but a summary is provided below.

In our first robustness check, we perform Monte Carlo simulations to further eliminate the possibility of a purely mechanical relation between trade clustering and the disposition effect and portfolio diversification. Next, we show that low levels of trade clustering do not indicate superior information that might be associated with lower portfolio diversification (Ivković et al. 2008). We also consider the possibility that our trade-clustering measure might capture liquidity trading, transaction costs, passive limit orders, tax-motivated trades in December, or day trading, because these factors are likely to be associated with the disposition effect or portfolio diversification measures. We find similar results even after we control for the effects of these alternative sources of trade clustering.

To address the concern that we do not observe investors' entire portfolios, we use a compensated measure of portfolio diversification, where we assume that the unobserved part of an investor's portfolio is invested in the market portfolio. We also reestimate the diversification regression using a subsample of investors whose portfolios are large relative to their income levels, because for these investors we expect the unobserved portfolio components to be small. The results from these robustness tests are very similar to the reported results.

[12] An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

To examine whether our results are sensitive to the window size that defines "simultaneous" trades, we recompute trade clustering using a weekly rather than a daily time interval, and find similar results. The results are also very similar when we estimate the disposition effect and the diversification regressions for the two subperiods 1991–1993 and 1994–1996. In the last robustness test, we estimate change regressions and find that an increase in trade clustering is associated with a decrease in the disposition effect and an increase in portfolio diversification. Collectively, the robustness test results further indicate that the disposition effect–trade clustering and the diversification–trade clustering relations are robust and are unlikely to be mechanically induced.

7. Summary and Conclusions

This paper examines whether the framing mode influences the stock investment decisions of U.S. individual investors. Motivated by the extant experimental evidence, which suggests that separate decisions are more likely to be narrowly framed than simultaneous decisions, we propose trade clustering as a proxy for narrow framing. Using this framing proxy, we show that investors who execute more clustered trades exhibit weaker disposition effects and hold better-diversified portfolios. Because we use a narrow framing proxy instead of a direct framing measure, we conduct several robustness checks and show that the disposition effect–trade clustering and the diversification–trade clustering relations are robust and are not mechanically induced. We also show that investors who execute less-clustered trades exhibit a preference for small-cap and value stocks, and they earn higher raw returns but lower risk-adjusted returns.

Taken together, our results indicate that the framing mode is an important determinant of investors' stock investment decisions. This evidence complements the theoretical research on narrow framing (e.g., Barberis and Huang 2007) and contributes to an emerging literature that attempts to identify the fundamental determinants of behavioral biases (e.g., Graham et al. 2006, Barberis and Xiong 2008). Our evidence also suggests that narrow framing would have broader influence on investors' portfolio choices and trading decisions beyond its effect on risk attitudes (e.g., Benartzi and Thaler 1995, Gneezy et al. 2003, Barberis et al. 2006).

Although our study does not examine the relation between narrow framing and stock returns, our empirical results suggest that investors' framing choices are likely to have implications for stock returns. For instance, we find that investors' stock preferences vary systematically with the degree of trade clustering. This evidence suggests that the concentration of investors who are more likely to frame their decisions narrowly would vary with stock characteristics in a predictable manner. Thus, consistent with the theoretical predictions of Barberis and Huang (2001), those stocks might exhibit greater volatility and lower correlations with other stocks within the same category. We hope to examine these questions in our future research.

8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

Acknowledgments

The authors thank two anonymous referees, the associate editor, Hal Arkes, Brad Barber, Nick Barberis, Robert Battalio, Shane Corwin, Alex Edmans, Anand Goel, Olesya Grishchenko, Jeff Hales, David Hirshleifer, Steve Huddart, Pam Losefsky, Tim Loughran, Terrance Odean, Amiyatosh Purnanandam, Paul Schultz, Mark Seasholes, Juergen Symanzik, George Wu (the department editor), Ning Zhu, and seminar participants at the 2005 European Finance Association Meetings (Moscow), Korea Advanced Institute for Science and Technology, Korea University, Penn State University, and Seoul National University for helpful discussions and valuable comments. They also thank Itamar Simonson for making the investor data available to them and Terrance Odean for answering numerous questions about the investor database. The authors are responsible for all remaining errors and omissions.

References

Bailey, T., A. Gatrell. 1995. *Interactive Spatial Data Analysis*. Longman Scientific & Technical, Harlow, Essex, England.

Barber, B., T. Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *J. Finance* **55** 773–806.

Barber, B., T. Odean. 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *Quart. J. Econom.* **116** 261–292.

Barberis, N., M. Huang. 2001. Mental accounting, loss aversion, and individual stock returns. *J. Finance* **56** 1247–1292.

Barberis, N., M. Huang. 2007. Preferences with frames: A new utility specification that allows for the framing of risks. Working paper, Yale University, New Haven, CT.

Barberis, N., W. Xiong. 2008. What drives the disposition effect? An analysis of a long-standing preference-based explanation. *J. Finance*. Forthcoming.

Barberis, N., M. Huang, R. H. Thaler. 2006. Individual preferences, monetary gambles, and stock market participation: A case for narrow framing. *Amer. Econom. Rev.* **96** 1069–1090.

Benartzi, S., R. H. Thaler. 1995. Myopic loss aversion and the equity premium puzzle. *Quart. J. Econom.* **110** 73–92.

Carhart, M. M. 1997. On persistence in mutual fund performance. *J. Finance* **52** 57–82.

Coval, J. D., T. J. Moskowitz. 2001. The geography of investment: Informed trading and asset prices. *J. Political Econom.* **109** 811–841.

Dhar, R., N. Zhu. 2006. Up close and personal: An individual level analysis of the disposition effect. *Management Sci.* **52** 726–740.

Fama, E. F., K. R. French. 1993. Common risk factors in returns on stocks and bonds. *J. Financial Econom.* **33** 3–56.

Feng, L., M. S. Seasholes. 2005. Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Rev. Finance* **9** 305–351.

Gneezy, U., A. Kapteyn, J. Potters. 2003. Evaluation periods and asset prices in a market experiment. *J. Finance* **58** 821–837.

Goetzmann, W. N., A. Kumar. 2008. Equity portfolio diversification. *Rev. Finance*. Forthcoming.

Graham, J. R., C. R. Harvey, H. Huang. 2006. Investor competence, trading frequency, and home bias. Working paper, Duke University, Durham, NC.

Hirst, E. D., E. J. Joyce, M. S. Schadewald. 1994. Mental accounting and outcome contiguity in consumer borrowing decisions. *Organ. Behav. Human Decision Processes* **58** 136–152.

Ivković, Z., C. Sialm, S. Weisbenner. 2008. Portfolio concentration and the performance of individual investors. *J. Financial Quant. Anal.* Forthcoming.

Jegadeesh, N., S. Titman. 1993. Returns to buying winners and selling losers: Implications for market efficiency. *J. Finance* **48** 65–91.

Kahneman, D. 2003. Maps of bounded rationality: Psychology for behavioral economics. *Amer. Econom. Rev.* **93** 1449–1475.

Kahneman, D., D. Lovallo. 1993. Timid choices and bold forecasts: A cognitive perspective on risk taking. *Marketing Sci.* **39** 17–31.

Korniotis, G. M., A. Kumar. 2007. Does investment skill decline due to cognitive aging or improve with experience? Working paper, McCombs School of Business, University of Texas at Austin.

Lim, S. S. 2006. Do investors integrate losses and segregate gains? Mental accounting and investor trading decisions. *J. Bus.* **79** 2539–2573.

Linville, P. W., G. W. Fischer. 1991. Preferences for separating or combining events. *J. Personality Soc. Psych.* **60** 5–23.

Miller, G. A. 1956. The magical number seven plus or minus two: Some limits on our capacity for processing information. *Psych. Rev.* **63** 81–97.

Odean, T. 1998. Are investors reluctant to realize their losses? *J. Finance* **53** 1775–1798.

Read, D., G. Loewenstein. 1995. Diversification bias: Explaining the discrepancy in variety seeking between combined and separated choices. *J. Experiment. Psych.: Appl.* **1** 34–49.

Read, D., G. Loewenstein, M. Rabin. 1999. Choice bracketing. *J. Risk Uncertainty* **19** 171–197.

Redelmeier, D. A., A. Tversky. 1992. On the framing of multiple prospects. *Psych. Sci.* **3** 191–193.

Shefrin, H. M., M. Statman. 1985. The disposition to sell winners too early and ride losers too long. *J. Finance* **40** 777–790.

Simon, H. A. 1957. *Models of Man*: *Social and Rational*. John Wiley & Sons, New York.

Thaler, R. H. 1985. Mental accounting and consumer choice. *Marketing Sci.* **4** 199–214.

Thaler, R. H., E. J. Johnson. 1990. Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Sci.* **36** 643–660.

Tversky, A., D. Kahneman. 1981. The framing of decisions and the psychology of choice. *Science* **211** 453–458.

Tversky, A., D. Kahneman. 1986. Rational choice and the framing of decisions. *J. Bus.* **59** S252–S278.

Zhu, N. 2002. The local bias of individual investors. Working paper, International Center for Finance, Yale School of Management, New Haven, CT.