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Electronic Companion—"How Do Decision Frames Influence the Stock Investment Choices of Individual Investors?" by Alok Kumar and Sonya Seongyeon Lim, *Management Science*, DOI 10.1287/mnsc.1070.0845.

A. Online Appendix: Additional Robustness Tests

In this appendix, we conduct several additional tests to ensure that the negative relation between trade clustering and the disposition effect and the positive relation between trade clustering and portfolio diversification are robust.

A.1. A Mechanical Relation?

Although we use a peer group adjusted trade clustering and disposition effect measures and employ several control variables in our empirical analysis, one might still be concerned that the trade clustering and the disposition effect measures are mechanically related. We perform Monte Carlo simulations to mitigate those concerns.

We proceed as follows: First, for each investor, we keep the number of trades fixed but randomize the trading date and compute the trade clustering measure for the investor. Only the days on which the investor trades are used in the randomization experiment. We repeat the experiment 1,000 times and obtain the mean trade clustering measure for the investor, which is the "expected trade clustering" (ETC) measure obtained under the assumption that the investor executed her trades randomly.

Next, we compute an adjusted trade clustering measure by subtracting the expected trade clustering measure from the investor's actual trade clustering measure:

$$\mathrm{ATC}_i^{MC} = \mathrm{TC}_i - \mathrm{ETC}_i. \tag{1}$$

Last, we estimate the disposition effect regression using (i) the expected trade clustering measure (i.e., ETC_i) and (ii) the new adjusted trade clustering measure (i.e., ATC_i^{MC}). If the relation between trade clustering and the disposition effect is mechanically generated, the coefficient estimate of ETC_i would be negative and the coefficient estimate of ATC_i^{MC} would be statistically insignificant.

Our regression estimates indicate that ETC is *positively* related to ADE, i.e., investors with higher expected trade clustering exhibit stronger disposition effect. The ETC coefficient estimate is 0.124 with a t-statistic of 9.315. The relation between trade clustering and the disposition effect that we hypothesize is opposite to this observed relation. Importantly, when we re-estimate the disposition effect regression using the new adjusted trade clustering measure, the ATC coefficient estimate is somewhat stronger (ATC coefficient = -0.122, t-stat = -6.304).

We also estimate the diversification regression using the ETC_i and the ATC_i^{MC} measures. We find that ETC is *negatively* related to ADIV, i.e., investors with lower expected trade clustering hold better diversified portfolios. The ETC coefficient estimate is -0.081 with a t-statistic of -6.516. Again, the relation between trade clustering and portfolio diversification that we hypothesize is opposite to this observed relation. When we re-estimate the diversification regression using the new adjusted trade clustering measure, the ATC coefficient estimate is again found to be stronger (coefficient estimate = 0.124 with a t-statistic of 7.981). These regression estimates further indicate that the negative (positive) relation between trade clustering and the disposition effect (portfolio diversification) is unlikely to be mechanically induced.

A.2. Is Trade Clustering a Proxy for Superior Information?

It is possible that low TC investors hold concentrated portfolios because they have superior information about a small number of stocks. These investors may execute separate trades but take relatively larger bets on each trade to exploit their superior information. To examine whether trade clustering is a proxy for superior information, we use the mean k-day post-trade buy-sell return differential (PTBSD(k)) as a measure of superior information. Our choice is motivated by Odean (1999) and Barber and Odean (2001), who use a similar measure to identify the stock selection ability of investors. Specifically, investors who have superior stock selection ability are likely to buy stocks that outperform the stocks they sell.

We find that investors in the lowest ATC decile have worse stock selection ability. For instance, the 252-day PTBSD for the lowest (highest) ATC decile is -4.853% (-1.824%), and the difference of 3.028% is statistically significant (p-value < 0.01). The performance comparison indicates that low ATC investors have relatively worse stock selection ability compared to high ATC investors. Therefore, it does not appear that lower ATC is associated with superior information.

A.3. Is Trade Clustering a Proxy for Investors' Liquidity Needs?

One might be concerned that our trade clustering measure primarily captures liquidity induced trades. For instance, for a given portfolio size, relatively more diversified portfolios are likely to have smaller individual stock positions. Hence, investors with more diversified portfolios are likely to sell multiple positions simultaneously when faced with liquidity needs, which will lead to clustered trades.

We use the average trade size to control for the effects of liquidity on trade clustering. When we employ trade size as an additional control variable in the cross-sectional regression of portfolio diversification, the coefficient estimate of *Trade Size* is -0.159 which is statistically significant (t-stat $= -6.133$; adjusted $R^2 = 18.14\%$). However, the coefficient estimates of other explanatory variables, including the ATC variable (0.079 with a t-stat of 4.568), remain very similar (see Table A-1, Panel B, Line 1). The ATC coefficient estimate in the disposition effect regression remains similar as well (Panel A, Line 1; -0.113 with a t-stat of -6.445).

As an additional robustness check, we re-estimate the disposition effect and the diversification cross-sectional regressions using a trade clustering measure constructed from buy trades only. Clearly, buy trades would not reflect liquidity demands of investors. We find that, in the disposition effect cross-sectional regression (see Table A-1, Panel A, Line 2), the ATC estimate is -0.091 with a t-stat of -4.223 when ATC is used as an explanatory variable in conjunction with other control variables. Similarly, in the diversification cross-sectional regression (see Panel B, Line 2), the ATC estimate is 0.072 with a t-stat of 5.863. Taken together, these results indicate that our regression estimates are robust to concerns about liquidity induced trade clustering.

A.4. Is Trade Clustering a Proxy for Transaction Costs?

We address a possible concern that our trade clustering measure is a proxy for transaction costs rather than a proxy for narrow framing. Specifically, investors who face higher transaction costs might execute less clustered trades. In fact, we do find that investors with low trade clustering (see Table 6) seem to have a stronger preference for small, value stocks, which are likely to have higher transaction costs.

To examine whether our ATC measure proxies for transaction costs, we re-estimate the disposition effect and the diversification cross-sectional regressions, where we employ the portfolio's factor exposures (SMB exposure and absolute value of HML exposure) as additional control variables. Portfolios with a large positive SMB and extreme (both large negative and large positive) HML estimate are likely to have high transaction costs (e.g., Kumar and Lee (2006)) and, therefore, we use these factor exposures as a proxy for transaction costs. We find that, in the disposition effect cross-sectional regression (see Table A-1, Panel A, Line 3), the ATC estimate is -0.103 with a t-stat of -6.316 when ATC is used as an explanatory variable in conjunction with other control variables. Similarly, in the diversification cross-sectional regression (see Panel B, Line 3), the ATC estimate is 0.087 with a t-stat of 5.334. Taken together, these results indicate that our regression estimates are robust to concerns about the potential influence of transaction costs on trade clustering.

A.5. Is the Trade Clustering Measure Capturing Passive Limit Orders?

One might argue that our trade clustering measure is related to the order type (limit order versus market order). For instance, it is possible that passive limit orders submitted on separate days get executed on the same day when there are large market moves and when the market volatility is high. In this scenario, our trade clustering measure may be positively related to an investor's propensity to execute "passive" limit orders. A negative relation between trade clustering and investors' propensity to use limit orders is also possible. An investor's simultaneously-submitted limited orders may be executed over several days due to potential delays in the execution of limit orders. In either case, the choice of order type can influence trade clustering.

Our trading data do not allow us to differentiate between market orders and limit orders. However, previous studies (e.g., Harris (1991), Chung, Ness, and Ness (2002), Cooney, Ness, and Ness (2003)) suggest that trades executed at round dollars and half dollars are more likely to represent passive limit orders. Motivated by these earlier studies, for each investor in our sample, we obtain the proportion of all trades that are executed at round and half dollars and use this proportion (PLIMO) as a proxy for an investor's propensity to execute limit orders.

Examining the relation between adjusted trade clustering (ATC) and investors' propensity to execute limit orders (PLIMO), we find that ATC is only weakly correlated (correlation $= -0.190$) with PLIMO. This evidence suggests that investors who execute less clustered trades display a greater propensity to execute passive limit orders and contradicts the hypothesis that posits a positive relation between trade clustering and propensity to execute limit orders.

When we employ PLIMO as an additional control variable in the disposition effect cross-sectional regression, we find that the PLIMO coefficient is positive and statistically significant (coefficient estimate $= 0.065$, t-stat $= 5.156$). This suggests that investors with a greater propensity for executing limit orders exhibit higher disposition effect. More importantly, the ATC coefficient estimate is only marginally affected (coefficient estimate $= -0.102$, t-stat $= -5.477$) when PLIMO is employed as an additional control variable (see Table A-1, Panel A, Line 4). Thus, our disposition effect cross-sectional regression estimates are robust to concerns about the potential relation between trade clustering and order type.

A.6. Noisy Diversification Measure due to Unobserved Portfolio Positions

It is quite likely that investors in our sample hold accounts at other brokerage houses and we may be observing a fraction of their equity portfolios. Thus, our diversification measures may be noisy.

To examine the sensitivity of the trade clustering-diversification relation to the magnitude of the unobserved component in investors' equity portfolios, we re-estimate the diversification regression model (see Section 4.3) with a compensated measure of portfolio diversification. In this analysis, we assume that only $x\%$ of each investor's portfolio is observed and that the rest of the investor portfolio is invested in a well-diversified market portfolio. Using the four-factor time-series model, for different values of x, we compute the idiosyncratic risk (IR) of investor portfolios. The factor model is estimated for each investor portfolio using the monthly portfolio returns data, where the variance of the residuals from the four-factor model provides an estimate of a given portfolio's idiosyncratic risk.

Using IR as a compensated measure of portfolio diversification, we find that the ATC coefficient estimate is positive and significant (0.072 with a t-stat of 4.956) when we assume that $x = 100$ (see Table A-1, Panel B, Line 4). More importantly, the ATC coefficient estimate is only marginally lower (0.068 with a t-stat of 4.112) even when we assume that 50% of each investor's equity portfolio is unobserved, i.e., $x = 50$ (see Line 5). The ATC coefficient estimate is no longer significant when we assume that 80% of each investor's portfolio is unobserved.

As a final check, we re-estimate the diversification regression for the sub-sample of investors who hold larger portfolios relative to their respective income levels. Specifically, we only consider investors whose mean portfolio size is greater than or equal to their annual income, i.e., their size-to-income ratio or SIR is greater than or equal to one. It is very likely that the unobserved portfolio components would be small for this sub-sample of investors.

We find that the ATC coefficient estimate is positive, significant, and somewhat stronger than the one obtained using the full sample (the coefficient estimate is 0.093 with a t-stat of 7.153) for the large portfolio sub-sample (see Table A-1, Panel B, Line 6). The results are similar when other SIR cutoffs are used to define the large portfolio sub-sample. For instance, when SIR cutoff is two, the ATC coefficient estimate is 0.073 with a t-stat of 3.889. Taken together, these results indicate that the trade clustering-diversification relation is robust to concerns about our inability to observe the entire equity portfolios of sample investors.

A.7. Trade Clustering due to Tax-Motivated Selling in December

Previous studies (e.g., Odean (1998), Ivković, Poterba, and Weisbenner (2005)) have documented that the magnitude of tax-loss selling by the investors in our sample is most pronounced in the month of December. It is possible that our trade clustering measure primarily captures trade clustering resulting from potential tax-loss selling in December.

To examine the sensitivity of our estimates to tax-motivated trading in December, we measure ATC for each investor in our sample by excluding all trades executed in December. First, we examine the correlation between our original measure of adjusted trade clustering where we consider all trades (i.e., ATC_{all}) and the new measure of adjusted trade clustering where we exclude December trades (i.e., $\text{ATC}_{\text{nodec}}$). We find that the two ATC measures are strongly correlated (correlation = 0.940).

We also re-estimate the cross-sectional regression models of the disposition effect and portfolio diversification, where we use $\text{ATC}_{\text{nodec}}$ instead of ATC_{all} as one of the explanatory variables. The dependent variables in the cross-sectional regressions, namely, the disposition effect and the portfolio diversification level, are also computed by excluding December trades and end-of-month portfolio positions in December, respectively.

We find that the trade clustering coefficient estimate is only marginally different in the disposition effect and the diversification cross-sectional regression models. In the disposition effect cross-sectional regression (see Table A-1, Panel A, Line 5), the $\text{ATC}_{\text{nodec}}$ estimate is -0.098 with a t-stat of -6.091 when $\text{ATC}_{\text{nodec}}$ is used as an explanatory variable in conjunction with other control variables. Similarly, in the diversification cross-sectional regression (see Panel B, Line 7), the $\text{ATC}_{\text{nodec}}$ estimate is 0.091 with a t-stat of 6.097 when $\text{ATC}_{\text{nodec}}$ is used as an explanatory variable in conjunction with other control variables.

Our results are also similar when we use a trade clustering measure that only considers investors' buy trades. Since trade clustering using buy trades is not affected by tax-motivated selling in December, this provides additional evidence that our results are not driven by tax-motivated selling.

A.8. Do Clustered Trades Reflect Day Trading?

Our trade clustering measure might be contaminated by the presence of day traders in the sample. Day traders would have high trade clustering measure but their decisions need not necessarily correspond to a broader frame. We identify investors who are in the highest turnover decile as potential day traders, and re-estimate the regression models after excluding those potential day traders.

The sub-sample estimates indicate that the ATC coefficient estimate is still negative and significant (-0.104 with a t-stat of -6.427) in the disposition effect cross-sectional regression (see Table A-1, Panel A, Line 6). Furthermore, the ATC coefficient estimate is still positive and significant (0.089 with a t-stat of 6.024) in the diversification cross-sectional regression (see Panel B, Line 8). The estimates are remarkably similar even when we exclude 20% of investors with highest monthly portfolio turnover rate. These results indicate that our ATC estimates are robust to concerns about the possibility of day trading among investors in our sample.

A.9. "Joint" Trades and Trade Clustering

We examine the sensitivity of our results to the size of the window we employ to define simultaneous and temporally separated trades. We use a weekly measure of trade clustering for each investor where trades within a trading week are considered "simultaneous". The weekly trade clustering (WTC) measure is defined in an analogous manner to the daily trade clustering measure (see equation (1)):

$$\mathrm{WTC}_i = 1 - \frac{\mathrm{NTWKS}_i}{\mathrm{NTRADES}_i}. \tag{2}$$

NTWKS_i is the total number of weeks during which investor i trades stocks, and $\mathrm{NTRADES}_i$ is the total number of stock trades executed by investor i during the sample period. Similar to the daily TC measure, we obtain a peer group adjusted measure of WTC.

Examining the correlation between the daily and the weekly measures of trade clustering, we find that the two measures are strongly correlated (correlation = 0.813). Furthermore, we find that with the weekly trade clustering measure (i.e., WTC), the trade clustering coefficient estimate is only marginally different in the disposition effect and the diversification cross-sectional regression models.

In the disposition effect cross-sectional regression (see Table A-1, Panel A, Line 7), the WTC estimate is -0.102 with a t-stat of -6.552. Similarly, in the diversification cross-sectional regression (see Panel B, Line 9), the WTC estimate is 0.088 with a t-stat of 5.301. These regression estimates are very similar to the estimates we obtain using the daily trade clustering measure (see Tables 3 and 5). Collectively, these results indicate that our regression estimates are robust to the choice of the window used to define simultaneous and temporally separated trades.

A.10. Split Sample Tests

The compositions of investor portfolios change considerably during the six-year sample period. In particular, the average number of stocks in a portfolio increases almost monotonically during the sample period (Goetzmann and Kumar (2004)). As a result, our cross-sectional regression estimates based on six-year average measures may not accurately capture the disposition effect-clustering and diversification-clustering relations.

We take a closer look at the relation between trade clustering and the disposition effect and trade clustering and portfolio diversification using split sample tests. For each investor in our sample, we obtain the daily adjusted trade clustering measure for the 1991-93 and 1994-96 sub-periods. Furthermore, the explanatory variables that capture an investor's portfolio and trading characteristics are measured separately during the two sub-periods.

We find that the rank correlation between the adjusted trade clustering measures in the two sub-periods is strong (correlation = 0.585). We also re-estimate the cross-sectional regression models (see Sections 3.4 and 4.3 and the results in Tables 3 and 5) separately for the 1991-93 and 1994-96 sub-periods. Our estimation results indicate that the qualitative nature of the relation between trade clustering and the disposition effect and between trade clustering and portfolio diversification is remarkably similar across the two sub-periods.

During the 1991-93 sub-period, in the disposition effect cross-sectional regression (see Table A-1, Panel A, Line 8), the ATC estimate is -0.093 with a t-stat of -5.012 . Similarly, in the diversification cross-sectional regression (see Panel B, Line 10), the ATC estimate is 0.088 with a t-stat of 6.177 (adjusted $R^2 = 13.11\%$).

During the 1994-96 sub-period, in the disposition effect cross-sectional regression (see Panel A, Line 9), the ATC estimate is -0.089 with a t-stat of -4.921. Similarly, in the diversification cross-sectional regression (see Panel B, Line 11), the ATC estimate is 0.081 with a t-stat of 5.108 (adjusted $R^2 = 12.14\%$) when ATC is used as an explanatory variable in conjunction with other control variables. Taken together, these results indicate that our regression estimates are robust to concerns about inaccurate coefficient estimates due to the changing compositions of investor portfolios.

A.11. Regression Estimates with Change Measures

Our analysis so far has focused on the relations between ATC, ADE, and ADIV *levels.* In our final robustness test, we examine the relation between *changes* in ATC, ADE, and ADIV. We measure ATC, ADE, and ADIV for each investor during the first and the second halves of the sample period (1991-93 and 1994-96, respectively). Using the sub-period measures, for each investor i, we compute the change in ATC as $\Delta\mathrm{ATC}^{\mathrm{i}} = \mathrm{ATC}_2^{\mathrm{i}} - \mathrm{ATC}_1^{\mathrm{i}}$, the change in ADE as $\Delta\mathrm{ADE}^{\mathrm{i}} = \mathrm{ADE}_2^{\mathrm{i}} - \mathrm{ADE}_1^{\mathrm{i}}$, and the change in ADIV as $\Delta\mathrm{ADIV}^{\mathrm{i}} = \mathrm{ADIV}_2^{\mathrm{i}} - \mathrm{ADIV}_1^{\mathrm{i}}$. Similar to the disposition effect and diversification cross-sectional regression specifications described in Sections 3.4 and 4.3, we estimate two cross-sectional regressions, where ΔATC is the independent variable and ΔADE and ΔADIV are the dependent variables. The set of control variables employed are the same as those in the disposition effect and diversification cross-sectional regressions.

Our untabulated results indicate that the adjusted diversification level increases while the adjusted disposition effect decreases when there is an increase in the adjusted trade clustering measure. In the diversification cross-sectional regression, the coefficient estimate of ΔATC is 0.117 with a t-stat of 3.066. Furthermore, in the disposition effect cross-sectional regression, the coefficient estimate of ΔATC is -0.058 with a t-stat of -2.088. The evidence indicates that, for a given investor, her disposition effect decreases and her portfolio becomes more diversified when she increases the degree of trade clustering. Collectively, these results provide additional support for the hypothesized positive (negative) relation between trade clustering and portfolio diversification (disposition effect).

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Table A-1

Robustness Tests: Adjusted Trade Clustering Estimates

This table reports the adjusted trade clustering (ATC) coefficient estimates from our robustness tests. In Panel A, we report the ATC estimates from the disposition effect cross-sectional regressions with control variables (see Section 3.4 and Table 3) and in Panel B, we report the ATC estimates from the diversification cross-sectional regressions with control variables (see Section 4.3 and Table 5). The standard errors are corrected for heteroscedasticity.

Panel A: ATC Estimates in the Disposition Effect Regressions

Robustness Test	ATC Estimate	t-statistic	Adjusted R^2 (%)
Liquidity Trading: Test I (Section A.3)	−0.113	−6.445	12.96
Liquidity Trading: Test II (Section A.3)	−0.091	−4.223	11.34
Transaction Costs (Section A.4)	−0.103	−6.316	13.77
Passive Limit Orders (Section A.5)	−0.102	−5.477	12.25
Tax-Motivated Selling in December (Section A.7)	−0.098	−6.091	12.28
Day Trading (Section A.8)	−0.104	−6.427	11.77
Joint Trades (Section A.9)	−0.102	−6.552	12.03
Split Sample Test: 1991-93 (Section A.10)	−0.093	−5.012	11.68
Split Sample Test: 1994-96 (Section A.10)	−0.089	−4.921	11.03

Panel B: ATC Estimates in Diversification Regressions

Robustness Test	ATC Estimate	t-statistic	Adjusted R^2 (%)
Liquidity Trading: Test I (Section A.3)	0.079	4.568	12.33
Liquidity Trading: Test II (Section A.3)	0.072	5.863	12.82
Transaction Costs (Section A.4)	0.087	5.334	13.23
Idiosyncratic Risk as Div. Measure (Section A.6)	0.072	4.956	11.18
Compensated Div. Measure: 50% in Market (Section A.6)	0.068	4.112	8.13
Large Portfolio Sub Sample (Section A.6)	0.093	7.153	12.75
Tax-Motivated Selling in December (Section A.7)	0.091	6.097	12.86
Day Trading (Section A.8)	0.089	6.024	11.41
Joint Trades (Section A.9)	0.088	5.301	15.59
Split Sample Test: 1991-93 (Section A.10)	0.088	6.177	13.11
Split Sample Test: 1994-96 (Section A.10)	0.081	5.108	12.14