An Investor Behavior
and
Related Asset Pricing Distortions

by

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Calcutta. The city I owe some of my intellectual debt to.

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To the memory of

Professor Bhimasankaram Pochiraju.

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ABSTRACT

I document a stylized fact about stock buying behavior of investors. I empirically show that investors tend to buy riskier stocks following a realized loss. The risk measure that the investors seem to pay attention to is the market beta of the stocks. Thus, after a realized loss, investors buy higher beta stocks. This behavior is observed in institutional as well as individual investors but is more pronounced among individual investors with lower expertise, who on an average buy a new stock with up to 15% higher beta than that of the old stock they were holding. For an agent with utility consistent with prospect theory, this behavior emerges as the optimal response to her problem of maximizing utility within a mental account. Furthermore, this behavior can aggregate up during market downturns and cause pricing distortions in a direction similar to the beta anomaly. With this insight, I suggest a modification to the betting against beta trading strategy that can improve the Sharpe ratio more than twofold.

CHAPTER I

Introduction

The presence of psychological biases in economic decisions has been tested in low stake experimental settings. However, with the availability of individual investor data, it is possible to test many of those biases in the context of real-world high stake decisions. Most studies using investor data have paid attention to selling behavior of individuals. While the literature on the disposition effect – the tendency to sell profitable positions more easily than loss-making ones – studies when and why individuals sell stocks in the US (*Odean* (1998)) and Finnish (*Grinblatt and Keloharju* (2001)) data, *Ben-David and Hirshleifer* (2012) and *Hartzmark* (2014) study which stocks within their portfolio do individuals sell.

Individuals are known to hold under-diversified portfolios. *Van Horne et al.* (1975), *Kelly* (1995) and more recently *Polkovnichenko* (2005) document that households at any point in time hold an average of two to three stocks in their brokerage accounts. This small number of observable holding makes the study of stock selling behavior more tangible. In contrast, the number of stocks available to buy from is in thousands. In this thesis, I focus on what investors buy. More specifically I study whether investors look for stocks with different risk exposure when they have a different experience of profit or loss in the immediate past.

For a rational investor, a sunk loss or windfall gain in the past should not affect her future portfolio choice in an efficient market. In an efficient market[1] performance in the immediate past cannot be a predictor of future returns (*Fama* (1965)). Under standard utility, an individual should hold the market portfolio (*Markowitz* (1952)) at different leverages depending on her risk tolerance. Even when the risk tolerance changes the individual should change her leverage to obtain the best possible return.

However, studying stock transaction data from Finland, I find that after realizing a loss, investors buy stocks with market beta significantly higher than that of the old stocks they were holding. I corroborate the result in a sample of brokerage data from the US. Through the rest of the thesis, I refer to this behavior of acquiring higher beta stocks after a loss as the (beta) acquisition effect.

The empirical identification of the acquisition effect is the main result of the thesis and the subject matter of Chapter II. However, a significant criticism of empirically documenting such behavioral bias is the lack of theoretical understanding of such behavior. It is not sufficient to identify each behavioral bias in isolation. I attempt to motivate the acquisition effect in Chapter III theoretically. Under assumptions commonly used in investor behavior literature, I show that the acquisition effect emerges as the optimal response to an investor's problem where she is maximizing her utility over gains from each investment. The fourth and final chapter of the thesis deals with the economic significance of the acquisition effect. In Chapter IV, I show that the acquisition effect can aggregate up and cause testable pricing distortion that can be exploited in a trading strategy.

The empirical analysis in Chapter II starts with non-parametric estimation of the change in beta choice ($\Delta\beta = \beta_{new} - \beta_{old}$) as a function of profit (loss) realized from the last trade. I choose the non-parametric method primarily because of two reasons. The first is to observe whether there is any nonlinear pattern in the choice of beta as a function of the realized profit (loss). The second reason is to avoid imposing

[1]See *Malkiel and Fama* (1970) and *Dimson and Mussavian* (1998) for a discussion on the history of the theory of market efficiency.

any discontinuity if it does not occur naturally. From the result, where $\Delta\beta$ is plotted against realized dollar profit, the discontinuity around zero profit becomes clear (Fig. 2.1).

Next, I take a more traditional linear regression approach to control for multiple characteristics simultaneously. The result – jump in the choice of stock beta after a loss – remains consistent after controlling for the beta of the old stock, changes in idiosyncratic volatility, and lottery-like characteristics (MAX factor of *Bali et al.* (2011) and *Bali et al.* (2016)).

The tendency of individuals taking higher risk after a loss is not a novel finding. This tendency has been mentioned in the literature (*Black* (1976)) for a long time and has been observed in experimental setups (*Thaler and Johnson* (1990)). However, this phenomenon is not explained very well by standard utility maximization theories. Alternate theories with nonstandard preferences have explained investor behavior better than standard normative theories. Two such nonstandard theories – Prospect theory (*Kahneman and Tversky* (1979), *Tversky and Kahneman* (1992)) and mental accounting (*Thaler* (1985)) – intuitively seem to support the empirical finding of Chapter II. Using these two primary assumptions, I formalize this intuition in a model in Chapter III. Furthermore, I show that another widely studied investor behavior, the disposition effect can also be explained under the same theoretical framework.

The theoretical result reinforces the argument that the acquisition effect is behavioral. This then raises the question as to whether this behavior is economically significant or whether this behavior causes pricing distortions? The question is important because a probable market pricing distortion arising from aggregating an individual behavioral effect makes the effect an even more important phenomenon to study. I argue that the acquisition effect when aggregated across investors will lead to higher-than-usual demand for high beta stocks. Moreover, higher-than-usual demand for high beta stocks is the reason for the beta anomaly (high abnormal return of low beta stocks; *Jensen et al.* (1972)). So, rather than identifying a new pricing distortion, I am attributing an existing one viz. the beta anomaly, at least partially to the acquisition effect.

If indeed demand for high beta stocks can even partially be attributed to the acquisition effect, we can predict some time variation in it. Given that individuals demand high beta stocks after a loss, combined with the fact that a significant fraction of investors demonstrate a tendency to buy a stock immediately after selling one [2], I hypothesize that demand for high beta stocks will be higher on negative market return days and the day after. Thus high beta stocks should face buying pressure and generate higher than expected return on and immediately after a day with a low market return. This predictable return variation can be directly rested in stock returns data and can be utilized in a trading strategy. In Chapter IV I study the price predictability and incorporate it in a trading strategy.

[2] Investors appear to trade in clusters. Although on an average they trade once a quarter, almost 35% of sell transactions see a buy transaction within one day (Fig. 4.1). Investors seem to avoid leaving cash in their trading accounts, and all proceeds from a sell are seen to be immediately reinvested in an alternate stock.

CHAPTER II

Acquisition Effect

How does past performance in the stock market influence an investor's decisions in the future? If an investor is rational and if the market is efficient, past performance should not influence the investor's choice of her portfolio. The investors should always choose the tangency portfolio (*Markowitz* (1952)) at different levels of leverage, depending on her risk appetite. However, studying stock transaction data from Finland, I find that after realizing a loss, investors buy stocks with higher risk profile than of the old stocks they were holding. Furthermore, the measure of risk that these individual investors seem to be paying attention to is the market beta of the stock.

When I study the change in the choice of beta (between the old stock sold and the new stock bought) as a function of the holding period return of the old stock, a nontrivial pattern emerges. The choice of higher beta (Fig. 2.1) abruptly jumps up on the loss side, but does not continue to rise with increasing losses; on the profit side, the choice of beta remains indistinguishable from the beta of the old stock. This change in preference of beta is manifested almost like a step function that jumps on the negative side of the profit line. Through the rest of the chapter, I refer to this behavior of acquiring higher beta stocks after a loss as the (beta) acquisition effect.

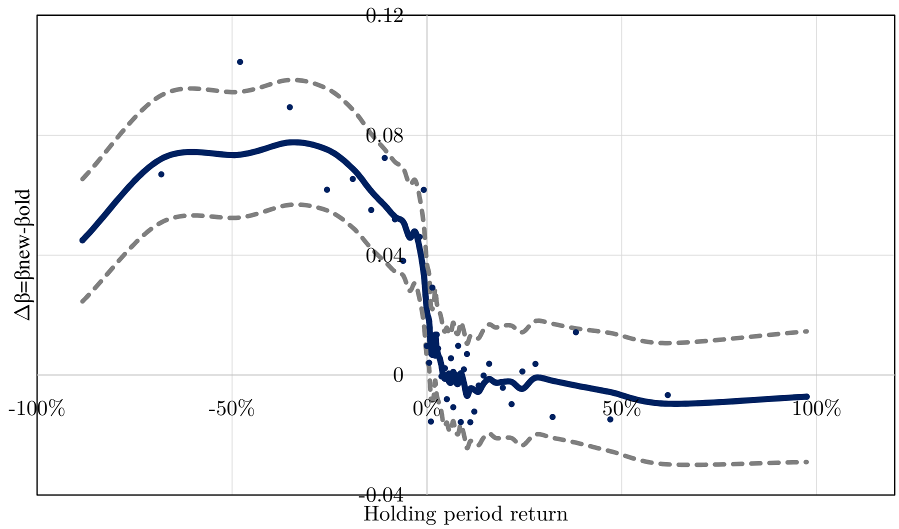


Figure 2.1: **Difference in Beta of Old Stock and the New Stock vs. Realized Return in Percentages**. The vertical axis is the difference in Beta computed as $\Delta\beta = \beta_{new} - \beta_{old}$. New beta being the beta of the stock bought and old beta being the beta of the stock sold. The horizontal axis is the realized profit from the buy-sell transaction in percentages. The solid line represents the moving average line through fifty estimates of average $\Delta\beta$ computed for bins (each bin having approximately equal number of observations) of profit. The dashed lines are 2 standard error confidence intervals.

2.1 Empirical Evidence of the Acquisition Effect

Using individual investor data, I study stock buying behavior – mainly whether the choice of the riskiness of a newly bought stock depends on the loss or gain experienced by the buyer in the immediate past. I start by describing the data, followed by the methods used and the results.

2.1.1 Data

This analysis uses stock transaction data from the Finnish stock exchange from the period January 2, 1995, to June 29, 2009. Return data between 1995 to 2009 was available for 292 stocks listed in the Finnish stock exchange. These stocks span almost 80% of all available transactions. The number of available stocks for which transactions are present vary across the sample period, averaging approximately 151 stocks every day.

Daily transaction data is available for individual account holders along with transaction price and transaction quantity. The time of a transaction, however, is not available. Thus, within a particular date, the sequence of transactions is unavailable. Also, the data suggest that a larger order placed by an investor on a single stock often got executed in multiple chunks with slightly different transaction prices. These were then registered as multiple transactions on the same stock by the same individual account holder on the same date. For each individual account, I aggregate multiple transactions in the same stock on the same date. After aggregation, an individual in my data-set can have at most one buy and one sell per stock per day.

In case of multiple transactions on the same stock by the same individual, the aggregate transaction price is determined as the quantity-weighted average transaction price. I explain this with an example. Suppose individual X sells 5, buys 10 and sells another10 shares of same the stock S, on the same date T, at prices $39, $40 and $41 respectively. In the aggregated data, the individual X will have one buy transaction of 10 shares of S at $40 and one sell transaction of 15 shares of S at $40.33, both on date T.

In all, there are 862,726 active accounts with at least one transaction in the observed period. There are 20,301,164 net transactions with an average of 23.53 transactions per account. The average length of an account is 5.3 years. The average number of stocks held by an individual at any point in time is 1.98, indicating that the average portfolio is under-diversified. The standard deviation of the number of stocks held is computed for each individual; the average of this standard deviations across all individuals is 0.81, and I refer to this as the average standard deviation. The average time between two transactions is .99 years while the corresponding average standard deviation is 1.03. The standard deviation points to a significant dispersion in the trading frequency of individuals while the mean indicates that the average individual investor trades quite infrequently.

The full sample consists of 862,726 unique accounts; however, due to the strict selection criteria described below, the final sample includes transactions from 76,713 accounts. The accounts in the final sample have relatively better-diversified portfolios, and they trade relatively more frequently. Although they comprise only 8.89% of the total number of accounts, they are responsible for 30.29% of total transactions. In Table C.1.2, I produce the summary statistics of the full-sample of accounts as well as the final sample.

Since the focus of the thesis is to study the stock buying behavior of individuals based on profit or loss realized in the immediate past, it is necessary to identify a realized profit or loss unambiguously before the buy transaction. Fig. 2.2 illustrates the sequence of trades that form a single data point in the empirical study.

$$\begin{array}{ccccc} \textit{buy } N_1 > 0 & & \textit{sell } N_2(N_1 \geq N_2 > 0) & & \textit{buy } N_3 > 0 \textit{ shares of} \\ \textit{shares of } A \textit{ (old stock)} & \dashrightarrow & \textit{shares of } A & \longrightarrow & \textit{new stock } B \\ \textit{at } t = t_1 & & \textit{at } t_2 > t_1 & & \textit{at } t_3 > t_2 \end{array}$$

Figure 2.2: **Transaction Sequence in Each Data Point:** An investor buys shares of stock A that has no preexisting balance at t_1. The investor then sells A, also referred to as the old stock, partially or fully at time t_2. This leads to an unambiguous realized profit or loss followed. The buy-sell transaction pair is followed by another buy transaction of a different stock B, referred to as the new stock at time t_3. There can be other transactions between time t_1 and t_2 but none between t_2 and t_3.

Each data point in the final sample of the analysis comprises three particular transactions, carried out by an individual investor in the following sequence. First, at time t_1 an investor buys a positive number of shares $N_1 > 0$ of a stock A, also referred to as the old stock. This transaction has to be a 'first buy'– which means that there should be no preexisting balance of stock A in the investor's account. The 'first buy' criterion helps identify buying price and thus realized profit can be estimated unambiguously. The second relevant transaction at time $t_2 > t_1$ is the one where the investor sells N_2 shares of her holdings in the old stock A, such that $N_1 \geq N_2 > 0$. In between time t_1 and t_2, there can be transactions in other stocks or additional buying of stock A. In case more of stock A is bought in between t_1 and t_2, the buying price is computed as a weighted average. Finally, the third transaction is buying of $N_3 > 0$ shares of new stock, B, at time $t_3 > t_2$. The time gap defined as $t_3 - t_2$ can be one month (21 trading days) unless otherwise stated.

2.1.2 Method and Results

The return from selling the old stock is computed as $\Pi_{\%} = P_2/P_1 - 1$, where P_2 and P_1 are the transaction prices of the old stock at times t_2 and t_1 respectively. Dollar profit is computed as $\Pi_{\$} = (P_2 - P_1)N_2$ where N_2 is the number of stocks sold at t_2.

Beta, volatility and idiosyncratic volatility are computed for each stock. The beta of a stock is computed as the ratio of the covariance of the stock return with the market return and the variance of the market return, $\beta_i = Cov(R_i, R_m)/Var(R_m)$ where R_i is the daily return of stock i and R_m is the market return. The market return, R_m is computed as the market capital weighted return of all available stocks and the maximum weight assigned to one stock is capped at 10%. Volatility is simply the square root of the variance $\sigma_i = \sqrt{Var(R_i)}$. Idiosyncratic volatility is computed as $IVOL_i = \sqrt{(\sigma_i^2 - \beta_i^2\sigma_m^2)}$ where σ_m is the volatility of the market return.

All statistics are estimated daily, using data from the past one year (250 trading days) not including the current day. The time series average of the daily market capital weighted beta is 0.99, and the volatility is 2.25%. Table (C.1.1) provides the summary statistics of the stocks. The difference in the choice of beta, $\Delta\beta = \beta_{new} - \beta_{old}$, estimated for the analysis, uses the betas estimated on date t_3 for both the new and the old stocks.

2.1.2.1 Non-Parametric Estimation

I use a non-parametric approach to estimate the difference in choice of beta as a function of realized holding period return from the old stock. The holding period return, $\Pi_{\%}$, realized by selling the old stock, is sorted into fifty bins or semi-percentiles, where each bin $j = 1 \ldots 50$ contains approximately an equal number of observations N_j. The median percentage profit $\Pi_{\%,j}^{med}$ for each bin is noted. For each bin, I compute the average jump in beta choice as $\overline{\Delta\beta}_j = \frac{1}{N_j} \sum_{i \in bin_j} \Delta\beta_i$. This computed $\overline{\Delta\beta}_j$ is plotted against $\Pi_{\%,j}^{med}$ for all j in Fig.(2.1). The figure demonstrates a clear jump in the choice of the beta of the new stock right when the investor incurs a loss.

The betas of the old and new stocks, rather than their differences, are plotted in Fig. (C.2.8). This plot demonstrates that the beta of the old stock has some interesting variation along the holding period return. It takes the shape of a valley around zero holding period return. So, small positive and negative returns are being realized from relatively lower beta stocks while high positive and negative returns are generally relatively from higher beta stocks.

A figure, similar to Fig (2.1) is obtained when the above exercise is carried out for the dollar profit $\Pi_{\$}$ rather than the percentage profit $\Pi_{\%}$. This is presented in Fig.(C.2.2).The non-parametric estimate of $\overline{\Delta\beta}$ as a function of dollar profit is also obtained after splitting the sample into less frequent trades and more frequent traders. The plots in Fig. C.2.3 and Fig. C.2.4 display very similar shapes but significantly different magnitudes of the jumps. Less frequent traders appear to choose a stock with 15% higher beta when they make a small loss, while the effect for higher frequency traders is around 7%.

A more formal non-parametric kernel regression (*Nadaraya* (1964); *Watson* (1964)) is carried out using a Gaussian kernel. In order to estimate the bandwidth h, I use a as rule of thumb (*Silverman*, 1986, p. 45-47):

$$h = 1.06 \times \frac{\sigma_\Pi}{n^{1/5}}$$

where σ_Π is the sample standard deviation of the independent variable, in this case the holding period return Π, and n is the sample size. This rule of thumb satisfies the two conditions necessary for the estimate to be consistent: $\lim_{n\to\infty} h = 0$ and $\lim_{n\to\infty} nh = \infty$. The non-parametric function $f(\Pi)$ at any profit (loss), Π can be estimated as:

$$\hat{f}(\Pi) = \frac{\sum_{i=1}^{n} \phi(\frac{\Pi - \Pi_i}{h}) \Delta\beta_i}{\sum_{i=1}^{n} \phi(\frac{\Pi - \Pi_i}{h})} \tag{2.1}$$

where $\phi()$ is the standard normal distribution. The estimated function is plotted for a series of profits (losses) around zero in Fig.(2.3). Similar to the previous exercise, here the discontinuity manifests as a sharp change in slope around the break even point.

Using a similar setup, I also plot the non parametric estimate corresponding to the difference in volatility, $\Delta\sigma = \sigma_{new} - \sigma_{old}$ and idiosyncratic volatility $\Delta IVOL = IVOL_{new} - IVOL_{old}$ as a function of the holding period profit (Fig. C.2.5b). This plot is most interesting in its lack of jump in $\Delta IVOL$. The lack of jump indicates that the investors might be choosing higher systematic risk or β rather than choosing more volatile stocks. The small increase in $\Delta\sigma$ for the negative return side is due to the jump in systematic risk. The increase is small because, for individual stocks, the idiosyncratic risk makes up a much larger part of the volatility as compared to the systematic risk.

The plot of $\Delta\sigma$ or $\Delta IVOL$ vs. realized return demonstrates a nontrivial hump shape. This is endogenous. The stocks generating small gains or small losses are of lower volatility than the stocks generating more extreme losses or gains. If the new

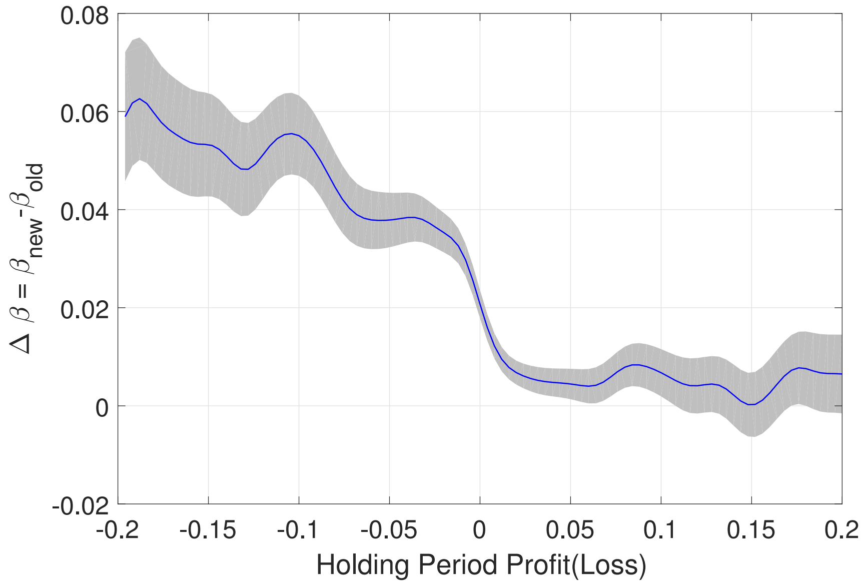


Figure 2.3: **Difference in Beta of Old Stock and the New Stock vs. Realized Return**. This is a plot of the non-parametric kernel regression function $\Delta\hat{\beta} = \hat{f}(\Pi)$, estimated for a range of values of profit around zero, $\Pi \in [-20\%, 20\%]$. The solid blue line represents the plot through the estimates while the gray area represents the two standard error confidence interval bootstrapped from a thousand re-sampling. The vertical axis is the estimated difference in Beta $\Delta\beta = \beta_{new} - \beta_{old}$. The horizontal axis is the realized profit from the buy-sell transaction during the holding period.

stock bought is of average volatility then the difference in volatility $(\sigma_{new} - \sigma old)$ should be positive for the small realized gains and losses and should be negative for large gains and losses. The argument is same for idiosyncratic volatility. This argument explains the hump shape. The finding suggests that the stocks sold and the stocks bought are often not comparable along important dimensions. Thus, a more traditional regression analysis is required, in which multiple characteristics can be controlled.

2.1.2.2 Linear Regression Estimation

The choice of higher beta stock in the loss domain, as demonstrated by the non-parametric estimation, can also be tested using a linear regression model:

$$\Delta\beta_i = C_0 + C_1\mathcal{D}_{\Pi_i<0} + C_2\Pi_i + C'X_i + \epsilon_i \tag{2.2}$$

where $\Delta\beta_i = \beta_{i,new} - \beta_{i,old}$ is the difference in beta, C_0 is the intercept, Π_i is the total holding period return, $\mathcal{D}_{\Pi_i<0}$ is an indicator variable which takes value 1 if $\Pi_i < 0$. The control variables are gathered as X_i. The set of control variables are varied across different regression specifications.

In order to subsume any effect of outliers, the regression can be carried out using a slightly altered specification with differences in log values of beta:

$$\Delta\log(\beta_i) = \log(\beta_{i,new}/\beta_{i,old}) = C_0 + C_1\mathcal{D}_{\Pi_i<0} + C_2\Pi_i + C'X_i + \epsilon_i$$

The results of the above regressions with varying set of controls are presented in Table 2.1.

The coefficient of interest is C_1 which captures the acquisition effect in terms of percentage increase in choice of beta after individuals realize a loss. As can be seen in Table 2.1, regressions (1) through (6) demonstrate a significant jump in the beta chosen after a loss. As seen in regression (1), after a loss, an individual investor chooses a stock with a beta on an average 7% higher than the beta of the old stock. The results from the linear regression are qualitatively similar to the non-parametric analysis. For example in Fig. 2.3 we see that after a loss the choice of beta increases on average by 0.04 to 0.06 units. This increase in beta is close to the fraction of the old beta as the mean beta is approximately equal to one.

In regression (2) I control for the log beta of the old stock while in regression (3) I

	$\Delta\log(\beta)$						$\Delta\log(IVOL)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathcal{D}_{\Pi<0}$	0.0684 (23.14)	0.0569 (19.91)	0.0542 (19.18)	0.01636 (5.61)	0.0496 (17.93)	0.0290 (11.26)	0.00278 (1.19)	-0.00251 (-1.89)
Π	0.00264 (1.84)	-0.00786 (-5.13)	-0.00671 (-4.53)	-0.00838 (-5.56)	-0.00171 (-1.56)	-0.00333 (-3.03)	0.000861 (1.19)	-0.00150 (-2.14)
$\log(\beta_{old})$		-0.650 (-253.70)	-0.682 (-262.71)	-0.794 (-272.67)	-0.794 (-282.79)	-0.872 (-307.45)	0.148 (94.95)	0.0217 (11.74)
$\log(\sigma_{old})$			0.203 (49.31)	0.198 (24.29)	0.170 (32.01)	0.155 (18.75)	-0.875 (-272.56)	0.0271 (3.68)
$\Delta\log(IVOL)$			0.255 (48.98)	0.234 (35.15)	0.234 (39.63)	0.211 (29.52)		
$\Delta\log(\beta)$							0.0583 (44.33)	0.0435 (30.07)
Const.	0.0362 (22.71)	-0.175 (-75.38)	0.552 (37.53)	0.511 (17.86)	0.394 (20.74)	0.198 (4.19)	-3.127 (-266.59)	-3.220 (-161.65)
Date F.E.				✓			✓	
Ind. F.E.					✓	✓		✓
Yr. F.E.						✓		✓
Obs.	546,448	546,448	546,448	546,448	546,448	546,448	554,436	554,436
Adj. R^2	0.001	0.336	0.350	0.423	0.438	0.476	0.405	0.469

t statistics in parentheses. Standard Error computed after individual level clustering.

Table 2.1: **Regression with Individual Investor Data.** The dependent variable in regressions (1) through (5) is $\Delta\log(\beta) = \log(\beta_{new}) - \log(\beta_{old})$ while that in (6) and (7) is $\Delta\log(IVOL) = \log(IVOL_{new}) - \log(IVOL_{old})$. $\mathcal{D}_{\{\Pi<0\}}$ is the dummy that takes value 1 when holding period return is negative, $\Pi < 0$. Π is included in the regression to absorb any trend. For various regressions I control for the log volatility and log beta of the old stock and also the difference in the log IVOL or difference in log betas where applicable. For different regressions, date, individual and year level fixed effects are also used. For all the regressions standard errors are computed by clustering at the individual level.

further include the log volatility of the old stock and the difference in log idiosyncratic volatility $\Delta log(IVOL)$. In regression (4) date level fixed effects are included. The date corresponds to t_3 in Fig.(2.2), which is the new stock purchase date. Regression (5) includes individual fixed effects. Regression (6) includes both individual and year fixed effects. The effect is this significant for the same individual trading inside the same year.

I test whether a jump, similar to that observed in the choice of beta, is observable in the idiosyncratic volatility of the chosen stocks. This result is presented in columns (7) and (8) of Table 2.1. Although the results can be argued to be statistically significant, they are much weaker, and in regression (8) the sign flips. The estimated coefficients (C_1) in regression (7) and (8) imply a change in IVOL of .28% and a -.25%, which are economically negligible.

In order to identify any non-linearity in the demand for beta, I take an approach similar to the non-parametric estimation. Semi percentiles (fifty bins) of the holding period return, Π are estimated. Median return, Π_j^{med} is also estimated for each bin j (where $j \in \{1, 2, \ldots, 50\}$). Fifty dummy variables are defined, one corresponding to each bin. An otherwise zero valued dummy variable, D_j takes the value of one if Π is within the corresponding bin j. A linear regression is set up as:

$$\Delta\beta_i = C_0 + C_1 D_1 + C_2 D_2 + \cdots + C_{49} D_{49} + C_\Pi \Pi + C_{\Pi'} \Pi_i \mathcal{D}_i + C' X_i + \epsilon_i \qquad (2.3)$$

The regression is carried out with year and individual fixed effects; additionally the volatility of the old stock and the change in idiosyncratic volatility are controlled for. The estimated value of C_j is plotted against Π_j^{med} for all $j \in \{1, 2 \ldots, 49\}$ in Fig.(C.2.7a). Similarly, a plot is obtained when the regression is carried out with $\Delta IVOL$ as the dependent variable, Fig.(C.2.7b).

The plots in Fig. C.2.7 include a 95% confidence interval where the standard error is estimated using date level clustering. The result is comparable to the non-parametric plots in Fig.(2.1) and Fig.(2.3). Even after controlling for important variations and fixed effects, and allowing the error to be clustered, the jump in the choice of beta around the break-even point is clear and statistically significant. Consistent with the nonparametric analysis, no significant jump is observed in the idiosyncratic volatility.

2.1.3 Interpretation & Extension of the Results

The nonparametric estimation identifies that there is a jump in the beta chosen after realizing a loss. This increase in beta chosen in the loss domain is not a trend.

Investors are not choosing incrementally higher beta after making increasingly larger losses, but the choice exhibits a discontinuous jump.

A closer look at the data helps to appreciate the nature of this jump. In table C.1.3, I list the average magnitude of this jump for different bins of dollar profit and loss for 'non-expert' individuals. The most substantial jump in the choice of beta is 0.20 units and is at the smallest loss bin – between zero and eleven dollars of loss. More substantial losses all see statistically significant jumps in beta around 0.15 units while on the profit side, the choice of beta is indistinguishable from the beta of the old stock. This jump cannot be explained by tax motivations, portfolio readjustments or any other mechanical reasons.

The table C.1.3 also lists the dollar size of the transaction corresponding to the newly bought stock. There is an expected increase in transaction size corresponding to more significant profit or loss bins. Otherwise, the transaction sizes are consistent across bins. The consistency of transaction size across bins alleviates the concern that the bin corresponding to the minimal losses (between zero and eleven dollars) comprises of some non-representative transactions where individuals may be experimenting with small sums of money, possibly in penny stocks. The phenomenon of the acquisition effect can thus be argued to be due to the behavior of investors and not due to some feature of the data.

To further support the hypothesis that the finding is indeed behavioral, I look at features commonly associated with behavioral biases. For example, sophisticated investors should be less prone to such behavior (*Dhar and Zhu* (2006), *Feng and Seasholes* (2005)). To check this, I categorize individuals in the data into two groups – 'experts' and 'non-experts'. I use three different measures to define expertise – frequency of trade, total observable investment size and the number of stocks held (diversity). I assume more frequent traders, people with bigger investment and more diverse portfolios are 'experts'. After splitting the sample along expertise determined by the frequency of trade, I estimate the choice of beta nonparametrically in the two separate samples. The plots in Fig. C.2.6 indicate that less sophisticated investors exhibit higher acquisition effect as expected. For the other two measures of expertise, the nonparametric plots have entirely overlapping confidence intervals and are thus inconclusive.

The inference about more expert traders exhibiting lower acquisition effect is statistically more conclusive in a linear regression setup.

$$\Delta\beta_i = C_0 + C_1\mathcal{D}_{\Pi_i<0} + C_2\Pi_i + C_e\mathcal{D}_{\Pi<0} \times \mathcal{D}_{exp} + C'X_i + \epsilon_i$$

The setup is similar to the one in Eq. 2.2. Additionally, an interaction term, $\mathcal{D}_{\Pi<0} \times \mathcal{D}_{exp}$, corresponding to negative profit and high 'expertise' is included in the linear regression as an explanatory variable. In all three measures of expertise, the coefficient ,C_e, corresponding to the interaction term takes a statistically significant negative value (Table C.1.13). The results suggest that, as expected, the acquisition effect is significantly lower among individuals with higher expertise.

Another clear measure of 'expertise' is being an institutional investor, as opposed to being an individual retail investor. A limited institutional investor data set is available and contains only 'non-financial' institutions. I estimate the acquisition effect among institutional investors, using a linear regression setup similar to the one used for individual investors. As observed from the results in table C.1.10 the effect is lower than what is observed in the sample of individual investors, albeit statistically significant. To check the difference in magnitude to the acquisition effect, I run a regression where the individual and institutional trading data are pooled. Indicator $\mathbb{I} = 1$ if the data is from an institute and is zero otherwise. In the regression, when the institute indicator is interacted with the negative return dummy, $\mathcal{D}_{\Pi<0} \times \mathbb{I}$, a negative coefficient is generally observed (Table C.1.11). The negative coefficient indicates that the effect is lower for institutes when compared to individuals.

One other factor strongly associated with cognitive behaviors of this nature is the effect of time. The time between the old stock being sold and the new stock being bought is referred to as the time gap. If the time gap is large, then we anticipate the acquisition effect to weaken, and this can be tested in the data. Before discussing the test results, it is worth pointing out that while individuals trade infrequently(on average approximately once a quarter), the gap between selling the old stock and buying a new one is surprisingly low (Fig. 4.1).

To test whether the magnitude of acquisition effect varies with the time gap, I run the regression on the individual investor data, allowing the time gap to be up to a year rather than the usual one month. I split the sample into three groups and run the regression individually on each sample. The first group corresponds to time gap within a quarter, in the second sample the time gap is above one quarter but within half a year and the third sample is for above half-year time gap. The coefficient corresponding to the negative profit dummy, which is a measurement of the acquisition effect, decreases from a highly statistically significant 2.12% in the first sample to a weakly significant 1.17% in the second sample to a statistically insignificant -0.15% in the third and final sample (Table C.1.13) . This change in coefficient across samples indicate that as the time gap increases, the acquisition effect weakens.

2.1.4 Robustness of the Results

Standard theories do not support the empirical identification of the acquisition effect. Hence it is essential to address concerns about the robustness of the results. Some main concerns about the result can be listed as i) endogeneity in the regression setup, ii) measurement of beta, iii) statistical significance or standard error estimation iv) choice of beta as the dependent variable as opposed to other stock characteristics correlated with beta, and v) whether the acquisition effect is specific to Finnish investors. I try to address the concerns below.

The endogeneity concern can be described as follows. If the realized losses in the sample are all coming from low beta stocks and investors go on to buy average beta stocks, the measured $\Delta\beta = \beta_{new} - \beta_{old}$ would appear high after a loss and low after a gain. To address this, I split the sample into three groups of low, medium and high initial beta stocks and carry out the nonparametric estimation on them separately. The plots presented in Fig. (C.2.9) are consistent with the primary finding. The groups of investors, with low and medium initial beta stocks, both demand higher beta stock after making a loss. The pattern is not the same for the group where initial beta is high. This difference in pattern is not unexpected since with already high initial beta holdings the scope for increasing beta any higher is limited. The same issue is also addressed in the linear regression setup by controlling for the beta of the old stock which does not affect the result (Table 2.1, C.1.4 and C.1.5).

The betas, used in the analysis, are estimated using daily returns from past one year. The betas of the old, as well as the new, stocks are measured at the same date t_3, the date of buying new stock in the sample. However, the results are robust to the betas being measured at t_2 or even one month before t_2. The consistency of the result, using betas measured at various times, ensures that the timing of measurement of beta is not affecting the results. I further run the regressions using a time-invariant whole sample beta for the stocks. The results in Table C.1.9 are consistent with the primary finding.

The statistical significance of the results is further challenged by estimating the standard errors clustered by different variables. Separate linear regression models are estimated with the errors clustered by date (Table 2.1), by the old stock sold, by the new stock bought and by the individual investor (Table C.1.4). Through all of these, the identification of the acquisition bias remains significant.

In order to ensure that the results are robust to the definition of the dependent variable, I estimate linear regressions with the level difference ($\Delta\beta$) as well as the log ratio of betas ($\Delta \log(\beta) = \log(\beta_{new}/\beta_{old})$. This log ratio measure handles the outliers better and drops any observation with a negative estimated beta. The results remain significant and improve slightly in magnitude (Table C.1.5).

The primary identification of the acquisition effect is with stock transaction data from Finland. The data covers all individuals in Finland trading in stocks listed in the Finnish stock exchange between 1995 to 2009. However, the behavior is not limited to Finnish individuals. The result is also verified in a smaller sample of data in the US. This data is obtained from a large brokerage house in the US[1] and it lists transactions by all its customers from 1991 to 1996. Computing the characteristics of the traded stocks after merging with CRSP, I carry out the standard linear regression analysis with several controls and fixed effects. The results presented in Table C.1.12 demonstrate that the acquisition effect is present among this set of US investors as well, although the magnitude and significance are both somewhat smaller when compared to the Finnish investors.

2.1.5 Factors Other than Beta

The choice of beta as the measure of risk, and the difference in betas being the dependent variable in the study needs to be justified both intuitively and econometrically. The intuitive explanation is provided in the next section. The challenge to providing the econometric justification comes from the fact that several other plausible measures of risk are correlated with the beta. Existing literature documents that individuals demand some of these other measures of risk.

Individuals are known to demand lottery-like stocks (*Kumar* (2009)) or stocks with high skewness (*Dijk et al.* (2014)) and high volatility or stocks with good past

[1]This data is the same as the one used in *Barber and Odean* (2000).

short-term performance as captured by the MAX5 factor (*Bali et al.* (2011)). The MAX5 factor, which measures the abnormal performance of a stock in the immediate past, also captures the lottery-like characteristics of a stock. Apart from demand for the aforementioned factors, if individuals buy stocks to gamble, they might also demand high volatility. Since skewness, lottery-like characteristics and volatility are all correlated with the beta, it would mechanically appear that the demand in any of these factors is a demand in high beta.

Another stock characteristic that is important to consider is momentum (*Jegadeesh and Titman* (1993)). Stocks that provided negative returns might well be the stocks with low momentum. Similarly, stocks that gave positive returns may be stocks with high momentum. Now, if an investor buys stock with average momentum, it would appear that the investor buys higher momentum after a loss and lower momentum stocks after a profit. Since momentum is weakly correlated with the beta, this might explain some of the results.

I check the influence of these characteristics on acquisition effect by running regressions in two directions. First, I run a regression with the standard change in beta $\Delta\beta$ as the dependent variable and the negative return dummy as the primary explanatory variable, controlling for the characteristic differences. Second, I run regressions with the change in these other characteristics as dependent variables with the negative return dummy as the co-variate, but here I control for the change in beta. In the first regression, I test whether the significance of the negative return dummy survives when these characteristics are controlled for. In the second set of regressions, I check if the negative return dummy explains any change in these characteristics in stocks when $\Delta\beta$ is controlled for. As an example I run the following regressions:

$$\Delta\beta \sim C_0 + C_1\mathcal{D}_{\Pi<0} + C_2\beta_{old} + \cdots + C_*\Delta MOM + \text{other controls}$$

$$\Delta MOM \sim C_0 + C_1\mathcal{D}_{\Pi<0} + C_2 MOM_{old} + \cdots + C_*\Delta\beta + \text{other controls}$$

where $\Delta MOM = MOM_{new} - MOM_{old}$ is the change in momentum. In the first regression, I would focus on the significance of C_1 – whether it diminishes when ΔMOM is introduced as a control – alternately I would check the significance of C_1 in the second regression with and without the $\Delta\beta$ control.

For the regressions, I compute MAX5, as defined in *Bali et al.* (2011), for each stock as the average of the top five returns in the past one month. Idiosyncratic volatility is computed from past one-year daily return and considering a one factor CAPM model. I also compute skewness form past one year's daily return. Momentum is computed as defined in *Jegadeesh and Titman* (2001) – past 12 months cumulative returns excluding the immediately previous month. Furthermore, to make the coefficients comparable across regressions, I normalize the variables beta, MAX5, momentum, skewness, etc. by their respective cross-sectional standard deviations.

The results for MAX5, momentum, skewness are presented in Table (C.1.7). It can be seen that change in momentum is the only factor that seems to have slight importance, which diminishes when change is beta is controlled for. Rather than checking the change in volatility, I check for the change in idiosyncratic volatility and the detailed analysis is presented in Table (C.1.6). Idiosyncratic volatility does not seem to have any influence of economic significance when the change in beta is controlled for.

I do not argue that beta is the only factor investors are paying attention to while buying a stock. There might as well be demands for volatile stocks, skewed stocks, and lottery-like stocks but the evidence suggests that even after controlling for those factors there is a statistically significant demand for higher beta stocks after a loss.

2.1.6 Why Beta?

From the empirical identification of the acquisition effect, it seems that individual investors intend to take higher risk after a loss. Also, individual investors are known to hold highly under-diversified portfolios (*Barber and Odean* (2000), *Goetzmann and Kumar* (2008)). The average investor in the Finnish data holds two stocks on average. In the more restricted sub-sample used for the primary analysis, this number is less than four stocks. So a natural question is – why do undiversified investors pay attention to beta, especially when we know that empirical evidence fails to support the CAPM? Also, why doesn't the investor look at volatility rather than beta?

Even if the market does not follow CAPM, if the market beta of a stock has any positive premium associated with it, there is an explanation why an individual should look at beta rather than volatility as a measure of risk. Suppose an individual has a change in preference and a higher threshold for volatility in her undiversified investment. So she might want to sell a stock and buy one which increases the volatility of her total holdings. To increase volatility, she has two options to choose from– higher beta or higher idiosyncratic volatility (IVOL). The investor can either choose a higher beta stock which comes with a higher mean return or, she can choose a higher IVOL stock which comes with the same mean return. Within the same total volatility, the investor should always prefer the choice that provides a higher mean return.

There are also some indirect evidence and some heuristic explanations about individual paying attention to beta. In *Barber et al.* (2015) the authors find that "investors attend most to market beta" when evaluating mutual funds and treat returns attributable to size, value, momentum, etc. as alphas. Similarly in *Berk and van Binsbergen* (2015), using mutual fund data, the authors conclude that "CAPM is the closest model to the model the investors use". In a survey of approximately four hundred CFOs, the authors in *Graham and Harvey* (2001) find that large firms rely heavily on the CAPM for project evaluation. These papers indicate that large investors and CFOs, who can be assumed to be experts when compared to individual investors, pay attention to the market beta as a measure of risk. If experts are seen as using beta as a measure of risk, it seems plausible that individuals use the same measure even when CAPM does not hold empirically.

A criticism of the above reasoning can be that retail investors do not have sufficient expertise to use the beta. Here it is worth pointing out that beta is not only the most talked about risk measure for stocks, but is also the only readily available measure of risk. Quick navigation through some of the most popular finance websites (Yahoo Finance, MSN Money, CNN Money, Google Finance, Market Watch, Seeking Alpha, AOL Finance, etc.) and the stock exchange websites (NYSE and NASDAQ) reveals that eight out of the top ten websites and both the exchange websites report beta of stocks. But, none provide information on volatility. Also, β is easy to compare; for example, a stock with a volatility of 24% does not immediately tell an investor whether it is a high or low volatility stock because the average volatility of a stock is not very well known. Additionally, the average volatility will vary with market conditions, and it also depends on the duration of the measurement. Beta, on the other hand, is known to have a benchmark of 1, so high or low β is much easier to conceive, and this benchmark does not depend on the market condition or the measurement duration.

CHAPTER III

Theory

In the previous chapter, I document the acquisition effect, where investors buy riskier stocks after a loss. Individuals taking higher risk after a loss is not a novel finding. Financial economists have had this intuition for a long time:

> "When things go badly, some people react by doubling their bets. They increase their exposure to risk in hopes of recouping their losses. ... It's a very common gambling strategy, and it's a very common philosophy of life." - *Black* (1976).

This behavior has been observed in experimental setups (*Thaler and Johnson* (1990)) but has not been explained very well by standard utility maximization theories. The documentation of an increase in risk appetite after a loss was one of the motivating factors for the development of the Prospect Theory (*Kahneman and Tversky* (1979)). In *Tversky and Kahneman* (1992), the authors calibrate a utility function which depends on gains and losses rather than their entire wealth. Further, the function is convex on the loss side, reflecting an individual's tendency to take more risk after a loss.

In this chapter, I use elements of prospect theory along with mental accounting (*Thaler* (1985)) to demonstrate that several investor behaviors, which appear puzzling under normative theories, can be explained as an optimal response of an investor's problem under certain assumptions widely used in behavioral finance. The two investor behaviors I attempt to explain are the acquisition effect and the disposition effect.

The disposition effect (*Shefrin and Statman* (1985), *Odean* (1998)) is the tendency of individuals to hold on to losers for too long and sellers too early. This behavior is closely related to the acquisition effect concerning how individuals code gains and losses in their mental account. I try to check whether the same theory can capture both the disposition effect and the acquisition effect within the same model.

Behavioral finance literature has attempted to model the disposition effect with ambiguous results. In *Barberis and Xiong* (2009), the authors set up a model where investors make adjustments to their portfolio – reallocating wealth between a risk and a risk-free asset – but realize their prospect theory utility at the end of T periods. The paper documents the disposition effect being rationalizable only when T is large. When the number of periods T is low, not only does disposition effect disappear but, the investor seems too risk averse to even participate in the stock market.

In *Hens and Vlcek* (2011) the authors argue that the question of whether to participate can be separated from the question regarding when the investor sells a stock given that she participates. The authors name this the ex-post disposition effect.

In this chapter, I assume market participation as given and then proceed to study when an investor endowed with a stock decides to sell it and subsequently what she decides to buy. Another significant departure from the frameworks in *Barberis and Xiong* (2009) and citehens2011does is concerning what is available to the investor once she decides to sell. In these two papers, the available assets are either a risk-free or a single risky asset. In my model, the invest chooses from a continuum of stocks with a range of beta and thus volatility. I explain the model and its assumption in details below.

3.1 The Model & Assumptions

I solve a two period model with $t \in \{-1, 0, 1\}$ which can be represented by the following diagram:

$$\begin{tikzcd}[row sep=tiny]
reference\ wealth & current\ wealth & future\ wealth \\
W_{ref} \arrow[r, "\{R_0\}"] & W_0 \arrow[r, "R_1"] & W_1 = W_0(1+R_1) \\
t=-1 & t=0 & t=1
\end{tikzcd}$$

Figure 3.1: **Sequence in the Model**

At $t = -1$, the agent started off with wealth W_{ref} invested in a stock and she will realize her profit (or potential loss) at $t = 1$. She does not pay continuous attention, but comes back to evaluate her investment at $t = 0$. At $t = 0$, the investor finds her current wealth to be W_0. At this point she has the option to change her investment at no transaction cost.

3.1.1 Assumptions

To write down the agent's problem formally I make a few assumptions:

3.1.1.1 Utility Function Consistent with Prospect Theory

The utility function, I assume in the model, is consistent with prospect theory. The realization utility (*Barberis and Xiong* (2012)) is derived from gains over a reference wealth, rather than consumption or the wealth itself, and can be written as:

$$\begin{aligned} V(W - W_{ref}) = &(W - W_{ref})^{\alpha} && \text{if} \quad W \geq W_{ref} \\ &-\lambda(-(W - W_{ref}))^{\alpha} && \text{if} \quad W < W_{ref} \end{aligned}$$

where $W - W_{ref}$ is the gain in wealth above reference wealth W_{ref}; $0 < \alpha \leq 1$ is the risk aversion/curvature parameter while $\lambda > 1$ is the loss aversion parameter. Unless otherwise mentioned, in this chapter I use parameter values as calibrated in

Tversky and Kahneman (1992) i.e. $\lambda = 2.25$ and $\alpha = .88$. With these parameters the plotted prospect theory utility function (Appendix Fig. (C.2.10) is concave in the profit domain, convex in the loss domain and has a kink at the break-even point.

The shape of the utility function captures investors' risk aversion in the domain of gains and risk preference in the domain of losses. They also have strong loss aversion, as reflected by the kink at the origin – so a loss hurts much more than the same amount of gain provides utility. The kink at zero return generates a first-order risk aversion in the utility function (*Barberis et al.* (2006)). This overall risk aversion checks individuals' preference for risk on the loss domain.

3.1.1.2 Rolling Mental Accounting

Mental accounting, as defined in *Thaler* (1985), is the process by which individuals break down their perception of utility from multiple sources into separate accounts. Mental accounting simplifies the problem of evaluating utility for the individual and leads the individual to look at each source of utility in isolation. This simplification is in contrast to what is expected of a rational agent, who should aggregate all such sources of utility to make rational decisions. The concept of mental account is incorporated in the prospect theory and is referred to as narrow framing.

Narrow framing or mental accounting (in the context of stock trading) means that, rather than evaluating gains and losses for the entire portfolio of their stock holdings, individuals derive utility from gains in each stock within their portfolio. The conventional mental accounting assumption implies that a mental account is opened when a stock is bought and that the mental account is closed when the stock is sold. However *Frydman et al.* (2016) hypothesizes that individuals often use rolling mental account. That is, individuals might sell a stock and not close the mental account but roll over the mental account to a newly bought stock. So the profit (loss) from the new stock may be benchmarked to the wealth invested in the old stock. Empirical results in *Frydman et al.* (2016) and the experimental finding in *Imas* (2016) backs up the hypothesis.

This assumption has the following implication for the model in this chapter. The diagram in Fig. (3.1) represents the problem of an agent within a rolling mental account. At time $t = 0$ the agent may sell the existing stock and buy a new stock. But rather than closing her old mental account after selling the old stock, she rolls it over to the new stock. So at time $t = 1$ the agent's utility, rather than being evaluated as $V(W_1 - W_{ref})$ will be evaluated as $V(W_1 - W_0)$. In the initial two-period model, I shall assume that investors always roll over their mental account. Later this assumption will be relaxed, and I will study the circumstances under which either of the two options is optimal: i) rolling over the old account to the new stock vs. ii) closing the old mental account and opening a new one.

3.1.1.3 Restrictions on Borrowing

I assume that the investor, within this two periods, commits to keeping her wealth in the mental account invested in some risky asset. Thus, at the time of decision at $t = 0$ neither does she park her money in the risk free-asset, nor does she take leverage. Within a particular mental account and during the two periods I model, the investor refrains from adding or withdrawing any sum of money. Thus if an agent sells the old stock at $t = 0$ and receives proceeds of W_0, she must invest the entire proceeds in another stock immediately.

This assumption is not inconsistent with empirical findings. I observe that, after selling a stock, investors tend to reinvest proceeds almost immediately in a new stock. They seem somewhat reluctant to park uninvested cash in the trading accounts. The tendency to quickly reinvest can be seen in Fig. 4.1 where a little above 35% of all sell-transactions are followed up with a buy-transaction on the next day, the number is 10% the day after and decreases exponentially.

This restricted borrowing assumption is not to say that investors never have access to any leverage. The agent might already have leveraged her wealth or assets. She also may have made some larger heuristic decision to allocate her total wealth between risky and risk-free assets. The assumption implies that leveraging or deleveraging is a slower moving decision and does not change as frequently as individuals trade stocks.

With the assumption that investors reinvest immediately I do not intend to argue that investors do not quit the market. In fact, after a certain period, investors learn their ability and are known to stop trading altogether if their performance has been consistently mediocre (*Seru et al.* (2010)). Since my study is on investor behavior, I mainly focus on investors who do not quit. These investors are observed to reinvest their proceeds from selling a stock rather quickly.

Broader decisions can be assumed to be impacted by several factors (like lifetime experience, macro events, employment situation, etc.) whereas the goal of the model here is to study short-term changes in risk preference arising from the experience of gain or loss in a stock in the immediate past. In the spirit of *Kahneman* (2011) the decision about taking leverage, allocating wealth between stock and bonds, or the decision to quit the stock market entirely may be categorized under slow thinking while the decision to take more risk after a loss in a single stock may be categorized as thinking fast.

3.1.1.4 Market Beta has Positive Premium

It is sufficient to assume that the investors believe stocks follow some factor model where market beta has a positive risk premium.

$$R_i - R_f = \alpha_i + \beta_i \lambda + \epsilon_i$$

where R_i is the return of any stock with market beta β_i, R_f is the risk-free rate and $\lambda > 0$ is the risk premium common to all stocks; α_i is the return unexplained by the model while ϵ_i is the idiosyncratic error. If α is zero and $\lambda = R_m - R_f$, then the above model is equivalent to CAPM. However, alphas of stocks are not zero. In fact, alphas of stocks are neither independent of betas nor are they randomly distributed in the cross-section. Alphas of individual stocks are known to vary inversely with betas. Low beta stocks have higher alphas, and high beta stocks have low alphas- this is the beta anomaly (*Friend and Blume* (1970)). This feature is captured well by the two-factor model:

$$
\begin{aligned}
& R_i - R_f = (1-\beta_i)(R_z - R_f) + \beta_i(R_m - R_f) + \epsilon_i \\
\text{or} \quad & R_i - R_z = \beta_i(R_m - R_z) + \epsilon_i
\end{aligned}
$$

where R_m is the return of the market and R_z is the return of a zero-beta portfolio with minimum variance.

The two-factor model was first motivated in *Jensen et al.* (1972) as a parsimonious solution to the cross-sectional dispersion of stock return. The cross-section of stock returns is not well explained by CAPM, because of the beta anomaly (*Friend and Blume* (1970)). The two-factor model resolves this by allowing higher beta stocks to have low alpha and lower beta stocks to have high alpha. This empirical two-factor model was later shown in *Black* (1972) to be the equilibrium model similar in spirit to CAPM but with restricted borrowing. This two-factor model reduces to CAPM if $\mathbb{E}(R_z) = R_f$.

When the model is calibrated I find that the return of the zero-beta portfolio is quite close to the return of the market portfolio, $\mathbb{E}(R_z) \approx \mathbb{E}(R_m)$. This similarity of returns is consistent with the fact that the empirically observed security market line is almost flat. The term $(1-\beta)(R_z - R_f)$ can be thought of as the alpha of a stock and consistent with data the term is inversely related to the sock's market beta.

It also suffices to assume that beta does not provide any risk premium and that idiosyncratic risk has negative premium. That high IVOL is associated with lower expected return has been documented in *Ang et al.* (2006) and *Ang et al.* (2009). For the analysis in this section, I will stick to the assumption of the 2-factor model and the CAPM.

Returns are assumed to be normally distributed, $R_m \sim \mathcal{N}(\mu_m, \sigma_m^2)$, $R_z \sim \mathcal{N}(\mu_z, \sigma_z^2)$ and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. This implies that any stock return is also normally distributed:

$$R \sim \mathcal{N}(\mu, \sigma^2)$$

where $\mu = (1-\beta)\mu_z + \beta\mu_m$ and $\sigma^2 = (1-\beta)^2\sigma_z^2 + \beta^2\sigma_m^2 + \sigma_\epsilon^2$. Under the CAPM, which is a special case of the two factor model, $\mu = (1-\beta)R_f + \beta\mu_m$ and $\sigma^2 = \beta^2\sigma_m^2 + \sigma_\epsilon^2$. Under either of these models, the choice of a stock by an investor can be simplified to the choice of the stock's market beta, β.

For the numerical analysis I calibrate parameters in the model from monthly CRSP data from 1965-2015. For the two factor model, I use $\mu_m = 0.87\%$, $\mu_z = .85\%$, $\sigma_m = 4.4\%$, $\sigma_z = 3\%$ and $\sigma_\epsilon = 4\%$. For CAPM, I use $R_f = 0.3\%$ and $\sigma_\epsilon = 9\%$, other parameters are similar.

3.1.2 The Agent's Problem

Standing at time $t = 0$, the agent now has to decide whether to change her investment. She chooses her optimal investment by picking beta. The problem can be written as:

$$\max_{\beta} \quad \delta\mathbb{E}(V(W_1 - W_{ref})) \tag{3.1}$$

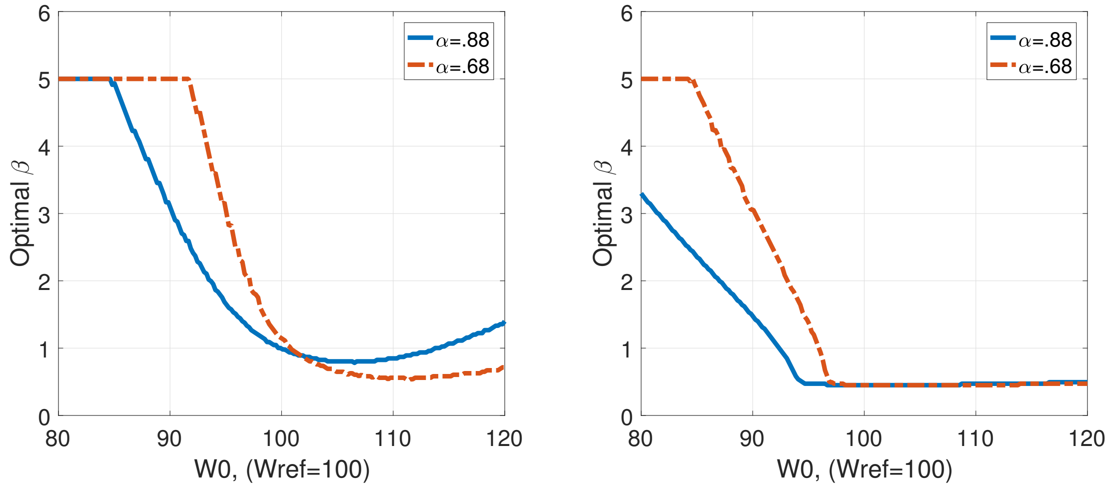
where next period wealth W_1 can be written as $W_1 = W_0(1 + R_1)$; W_0 is the current wealth, W_{ref} is the reference wealth, and δ is the time discount parameter. Due to the assumption about the market, the choice of stock with return R_1 boils down to a choice of beta β. The prospect theory utility function, defined over gains over a reference wealth is $V(.)$. The expectation operator is taken at time $t = 0$ when W_0 is known.

A more general version of this problem where the agent is given the choice of mental accounting decisions is solved in Section A.1.

3.1.3 Solution: Optimal Beta

The maximization problem can be solved analytically. But it requires a simplifying assumption – that the P.T. consistent utility is piece-wise linear. More precisely $\alpha = 1$ in Assumption (i). Using this simplification, the objective function in Eq. (3.1) can be written (Appendix B.1.1) in closed form and the first order condition (FOC) can be derived (Appendix B.1.2.1) from it in closed form as well. Furthermore, the second-order condition can be proved to hold (Appendix B.1.2.2). And finally, by studying the first order condition, it can be inferred that the optimal choice of beta rises steeply after a loss (Appendix B.1.2.3).

In order to obtain a more complete picture and without making any simplifying assumption, I solve problem (3.1) numerically. For the numerical solution I restrict the possible values of beta $\beta \in [0, 5]$. A surface plot (Appendix Fig. C.2.14) of the numerically estimated expected utility, $\mathbb{E}(V(W_1 - W_{ref}))$ as a function of β and W_0 with fixed reference wealth ($W_{ref} = 100$) displays significant variation along β and important but smaller variation along W_0. The optimal choice of beta is plotted against realized wealth W_0. Multiple plots (Fig. 3.2) are generated for different risk aversions and for market under CAPM and the 2-factor model.



(a) Stocks follow CAPM

(b) Stocks follow 2-Factor Model

Figure 3.2: **Optimal Beta vs. Current Wealth, $\mathbf{W}_0$** . The y-axis represents the choice of optimal beta for a given current wealth. The maximum value of beta is capped at 5, $\beta \in [-0.5, 5]$. The x-axis represents the current wealth. The reference wealth is fixed at $W_{ref} = 100$ while the current wealth is varied from $W_0 \in [80, 120]$ which is a profit (loss) range of $\pm$ 20%. The graphs are plotted for two different risk aversions; $\alpha = .68$ corresponds to higher risk aversion. Fig. (3.2a) corresponds to a market where stocks follow CAPM, while Fig. (3.2b) corresponds to the two-factor model.

The shape observed is consistent with the inference drawn from analytically studying the FOC and the empirically observed evidence. The optimal choice of beta after a loss is quite high and rises steeply with higher losses. This steepness seems to increase with higher risk aversion. The optimal choice of beta, however, does not seem to change much after profit. For example, under CAPM, at $W_0 = 90$ (10% below reference wealth) the optimal choice of stock seems to have a beta above three. After a gain, the optimal beta is around one and does not change much with increased gains.

3.1.4 The Alternate Problem

I try to incorporate an agents decision about her mental account within the model. In a similar two-period model, an agent can decide to roll over her mental account, or she can segregate her metal account. These two concepts need some clarification.

The agent had some reference wealth W_{ref}, and her current wealth is W_0. She will go on to choose some stock that would give her future wealth W_1. If she chooses to roll over her mental account, she will code her future gains with respect to original reference wealth W_{ref}. So her expected utility would be $\delta\mathbb{E}(V(W_1 - W_{ref}))$. If she chooses to segregate her mental account, then she has to close the current mental account and open a new one. By closing the mental account, she realizes a utility $V(W_0 - W_{ref})$ where all quantities are known and thus no expectation and by opening a new one she has a future expected utility $\delta\mathbb{E}(V(W_1 - W_0))$. The future expected utility has an updated reference point W_0 which is the wealth at the start of the mental account.

When the agent does not sell a stock, she automatically rolls over the mental account (continues the earlier account). The novel idea of rolling mental account is that it accommodates selling of one stock and buying of a new stock within the same mental account. However, it is reasonable to assume that segregation of mental account necessarily requires selling of one stock(closing a mental account) and buying a new stock (opening a new mental account).

The following model allows the agent to choose a mental accounting decision, but at the end of the two periods all mental accounts-rolled over or newly opened-should be closed, and the utilities from gains or losses should be realized. The mental accounting decision is over and above the decision to buy the optimal stock. The optimal stock being characterized by beta due to assumptions. The problem can be written as follows.

$$max \quad \{ \quad \underbrace{\max_{\beta} \quad \delta\mathbb{E}(V(W_1 - W_{ref}))}_{\text{roll over mental account}} \quad , \quad \underbrace{V(W_0 - W_{ref}) + \max_{\beta} \quad \delta\mathbb{E}(V(W_1 - W_0))}_{\text{segregate mental account}} \quad \}$$

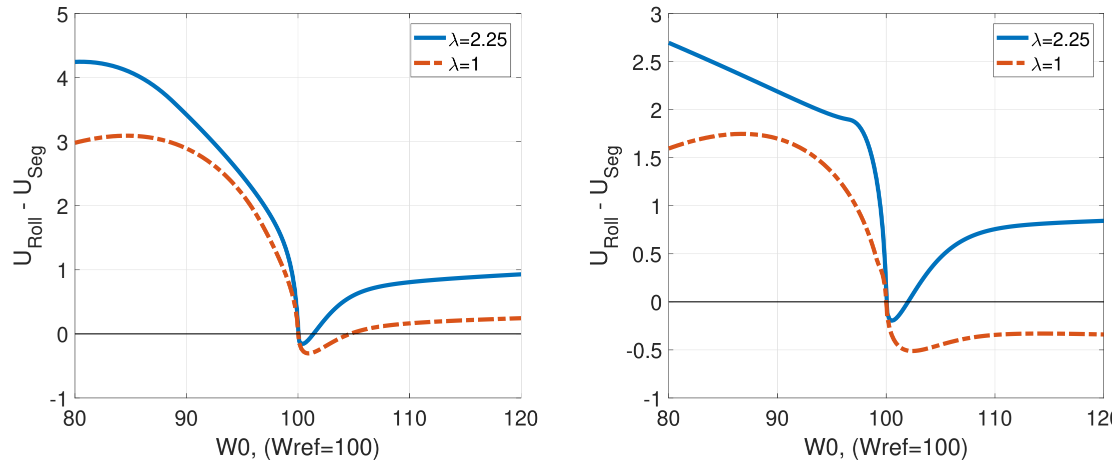
Just like the previous problem here also $W_1 = W_0(1 + R_1)$ where W_0 is the present wealth and R_1 is the return of the stock selected. The distribution of the stock return can be specified entirely by β, and due to the assumption, all other parameters in the distribution are constants. The reference wealth is the wealth an investor starts a mental account with. Thus, when the mental account is rolled over, reference wealth is W_{ref}, and when the mental account is segregated, the reference wealth is W_0. Like before, δ is the discount factor and $V(.)$ represents the prospect theory consistent utility function.

3.1.5 Solution to the Alternate Problem

I solve this problem numerically and in two parts. In the first part I study the individual's decision about mental account. Whether she wants to close her mental account or keep it open. In the second part I study the investors choice of stock. Given her current wealth and given a mental accounting decision I study the risk that is optimal for the investor.

3.1.5.1 Choice of Mental Account

I estimate the maximum utility with rolled over mental account, $\mathbb{U}^*_{roll} = \underset{\beta}{max} \quad \delta\mathbb{E}(V(W_1 - W_{ref}))$ and the maximum segregated utility $\mathbb{U}^*_{seg} = V(W_0 - W_{ref}) + \underset{\beta}{max} \quad \delta\mathbb{E}(V(W_1 - W_0))$ for a given W_0. I compute the utility difference $\Delta\mathbb{U} = \mathbb{U}^*_{roll} - \mathbb{U}^*_{seg}$ as a function of W_0. The plot in Fig(3.3) provides guidance as to whether the agent should roll over or segregate mental accounts based on present wealth.



(a) Stocks follow CAPM (b) Stocks follow 2-Factor Model

Figure 3.3: **Rolled Over–Segregated Utility vs. $\mathbf{W}_0$** . The y-axis represents the differnece in maximum rolled over Utility and Segregated utility, $\Delta\mathbb{U} = \mathbb{U}^*_{roll} - \mathbb{U}^*_{seg}$. The difference $\Delta\mathbb{U}$ is plotted against W_0. Whenever the plot is above the x-axis it implies that rolling is better otherwise segregating utility is optimal. The graphs are plotted for two different loss aversions; $\lambda = 2.25$ corresponds to higher loss aversion. Fig. (3.3a) corresponds to a market where stocks follow CAPM, while Fig. (3.3b) corresponds to the two-factor model.

The plots imply that irrespective of loss aversion parameter or assumption of the market model, it is optimal to roll over mental account when the agent is currently at a loss, $W_0 < W_{ref} = 100$. For a small range of profit – around 0 to 1% under the assumption of CAPM and about 0 to 2% holding period return under the two-factor model– it is optimal for the agent to segregate mental account when loss aversion is high. When loss aversion is low, it is optimal to segregate mental account for any profit.

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profit. The finding is indicative of the disposition effect.

The disposition effect, first identified in *Shefrin and Statman* (1985), documents that individuals are reluctant to sell stocks that are currently at a holding period loss and are willing to sell ones that are presently profitable. The conclusion from the theory is consistent with the disposition effect. The idea is also intuitive.

After a profit, an investor is on the concave side of the Prospect Theory utility function. Here the marginal utility realized from a further gain is small while that from a loss is large. The investor can change this situation by closing her mental account and starting a new one. Starting a new mental account resets the reference point and impacts the marginal utilities in two ways. First, it increases marginal utility from gains, since now small gains are coded on the steeper concave side of the utility. Second, this decreases marginal dis-utility from loss, since now losses are coded on the convex side of the utility function and thus hurt less. The above argument implies that the investor is optimally inclined to reset her reference point after a gain, which she can do by segregating her mental account – closing the existing account and opening a new one. As discussed earlier, closing an investor's mental account necessarily requires selling her existing stock.

Alternatively, after a loss, the investor is on the convex side of utility. Here, marginal utility from gains is high – because gains are coded on the steeper side of the convex utility – and dis-utility from losses is low – because losses are coded on the flatter side of the utility curve. Thus the investor likes the current position. If she closes the mental account, she would end up in a part of the utility function that codes gains on the concave side and thus give lower marginal utility and loses hurt more. It is optimal for the investor to not close this mental account. The current mental account can be preserved in two ways. The investor can keep holding the existent stock, or she can roll over the mental account to the new stock.

Thus the model predicts that after a gain the investor should optimally sell her existing stock while after a loss she might not sell the existing stock or she might roll over to a new mental account. This optimal behavior implies the disposition effect.

3.1.5.2 Choice of Risk

In this section I study the choice of the stock in conjunction with the mental accounting decision. Owing to the assumption about stock market, the choice of stock boils down to the choice of beta. I numerically estimate the optimal beta for both the rolled over mental account and the segregated mental account. Formally it can be written as follows.

$$\beta^R = \underset{\beta}{Argmax}\ \mathbb{U}_{Roll}(\beta)$$

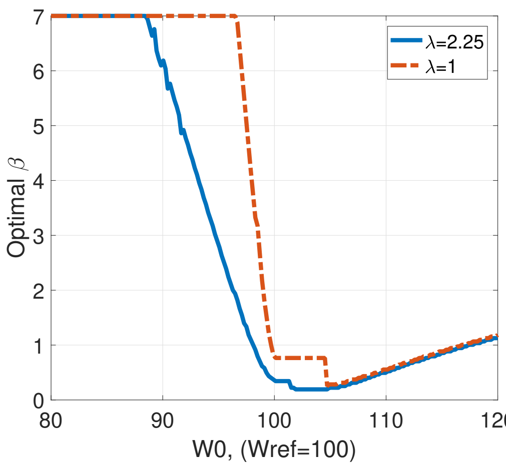
$$\beta^S = \underset{\beta}{Argmax}\ \mathbb{U}_{Seg}(\beta)$$

where $\mathbb{U}_{roll}(\beta) = \delta\mathbb{E}(V(W_1 - W_{ref})$ and $\mathbb{U}_{seg} = V(W_0 - W_{ref}) + \delta\mathbb{E}(V(W_1 - W_0)$.

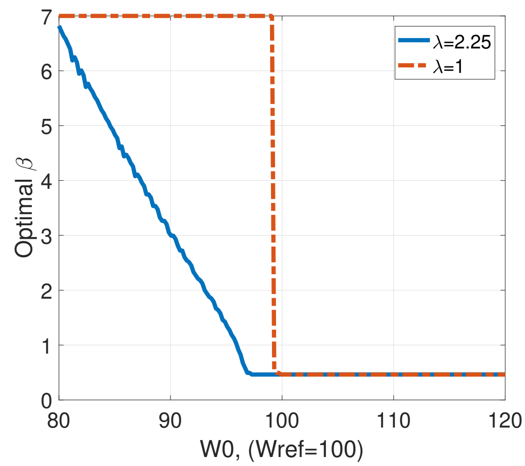
The optimal stock or optimal beta choice of an investor depends on whether the aggregated or segregated mental account provides higher utility. For given current wealth W_0 optimal beta β^* can be written as

$$\begin{aligned} \beta^* &= \beta^R \quad \text{if} \quad \mathbb{U}^*_{Roll} > \mathbb{U}^*_{Seg} \\ &= \beta^S \quad \text{otherwise} \end{aligned}$$

When β^* is plotted as a function of current wealth W_0, in Fig. 3.4, a pattern similar to that obtained in the earlier study can be observed. The demand for beta is stable on the positive side and varies very little while on the negative side it shoots up. The point of inflection where demand for beta shoots up is lower than the reference wealth but gets closer to reference wealth as loss aversion decreases. Loss aversion, graphically manifested as a kink at the zero return point, imposes a sort of risk-averse behavior on the investor. This risk aversion is especially pronounced around the zero-return point. With high loss aversion, the investor is reluctant to take risk after a small loss, which is close to the zero return point and thus makes the investor risk averse. It is only after the investor is deep into losses, where the convexity starts dominating the loss aversion, that the investor begins taking higher risk.



(a) Stocks follow CAPM



(b) Stocks follow 2-Factor Model

Figure 3.4: **Optimal Beta vs. Current Wealth $\mathbf{W}_0$** . The y-axis represents the choice of optimal beta for a given current wealth. The maximum value of beta is capped at 5, $\beta \in [-0.5, 7]$. The x-axis represents the current wealth. The reference wealth is fixed at $W_{ref} = 100$ while the current wealth is varied from $W_0 \in [80, 120]$ which is a profit (loss) range of $\pm$ 20%. The graphs are plotted for two different loss aversions; $\lambda = 2.25$ corresponds to higher risk aversion. Fig. (3.4a) corresponds to a market where stocks follow CAPM, while Fig. (3.4b) corresponds to the two-factor model.

When the choice of mental accounting is included in the problem of an investor, just like the solution to the problem without the choice of mental account, the optimal solution still indicates that buying of higher beta stock after a loss is the preferred choice. The result is consistent with experimental finding in *Thaler and Johnson* (1990) where the authors find that agents seem to segregate gains and integrate losses to evaluate lottery outcomes. This behavior of coding losses and gains was termed as *hedonic framing* in *Thaler* (1999). The model also supports the disposition effect qualitatively.

CHAPTER IV

Impact on Asset Price

Investor behavior not only allows us to understand why and when people trade but also helps us to understand how individuals perceive utilities. Insights into how individuals code utilities from gains or losses make it important for a financial economist to study such behavior. But, if a behavior is found to impact prices, then this finding makes it even more important to study the behavior. It becomes essential to understand how the behavior affects pricing and whether an arbitrageur can exploit this price impact.

I hypothesize that acquisition effect, where individual investors buy higher beta stocks after a loss, can aggregate up. When markets go down a lot of investors will be making losses, and if a sizable number of them subsequently go on to buy higher beta stocks, then this can cause aggregate demand pressure on high beta stocks. This demand pressure should cause short-term, but predictable, return movements. High beta stocks should see higher than usual returns when the market goes down or immediately after.

High beta stocks generating higher than usual returns when the market is going down is counter-intuitive because high beta stocks have high covariance with the market and when the market goes down these stocks are expected to go down more. If this counter-movement is significant, it should be testable in data in the form of time series predictability. Furthermore, an arbitrageur should be able to exploit such predictability in a trading strategy.

I study both the hypothesized predictability and the possibility of designing a trading strategy in this chapter. But both these phenomena are related to the timing to trade. Thus I first study the trade timing of individual investors.

4.1 When do Investors Trade?

The inference from the Chapter II is that investors buy riskier stocks after they make a loss. Does this behavior aggregate up? To respond to this, one needs first to answer – when do investors trade? More specifically when investors sell their loss-making stocks and when do they subsequently buy the next stock.

4.1.1 Selling Losers

If we assume that investors trade at the same rate each day irrespective of market returns[1], we can say that even mechanically, on negative market return days there will be a more significant percentage of investors selling stocks at a loss. This increased sell-trade volume can be observed in the US transaction data presented in Table 4.1.

Mk. Ret (vw)	No. days	Total Obs / day	Holding Ret	Obs / day
+ve	836	174.61	+ve	115.79
			-ve	58.81
-ve	657	179.7	+ve	109.75
			-ve	69.94

[1]Uniform trading rate across market condition is not true. In fact, trading volume spikes up on negative market return days and the day after. In the Finnish individual trading data, I find that daily stock selling rate increases by 8.5% on negative market return days and the day after that. For stocks making a loss, this number is 12.6%. In the CRSP data from 1926 to 2015, daily trading volume goes up by 15% on negative market return days and the day after. The corresponding rise in trading volume for the sample period 1991 to 2016 is 9%.

Mk. Ret (ew)	No. days	Total Obs / day	Holding Ret	Obs / day
+ve	1049	173.9	+ve	117.20
			-ve	56.69
-ve	444	183.81	+ve	103.52
			-ve	80.29

Table 4.1: **Stock Selling Depending on Market Returns.** The US transaction data is categorized into positive and negative return days. Only sell-transactions are presented in the table. The holding period return of the stocks being sold is also noted and categorized into negative and positive holding period returns. The upper panel represents dates split by value-weighted market return and the bottom panel slits observations according to equal-weighted market return.

In the US data, the average number of sell-transactions per day is slightly higher on negative market return days. Looking at holding period return, one can see that more stocks are sold at a profit than at a loss. More stocks sold at a profit is both due to the disposition effect and also the fact that market is generally upward moving so there are more stocks at a holding period profit than at a loss. However, stocks that are sold at a loss on negative market return days outnumber those sold on positive market return days. This difference is even higher when market return is defined as equal weighted. The data is represented graphically in Fig. (C.2.15).

The effect is at least partially mechanical. On negative market return days, the holding period returns of more stocks are mechanically negative. Thus, even if people sell stocks without paying attention to the holding period and sell stocks uniformly over time, on average more stocks will be sold at a loss on negative market return days. However, when I test this using a hazard model, I further find that the propensity to sell losing stocks increase on negative market return days. The result indicates that the effect is beyond mechanical.

4.1.2 A Hazard Model

A hazard model estimates, as a function of covariates, the time-varying hazard rate of an event. In this case, I assume the event to be selling a stock. A fair assumption being that as time goes to infinity the hazard rate becomes very high or the stock is sold surely.

The covariates covariates of a hazard model can be time-varying. In this case, covariates are dummy variables representing the sign of holding period return and the sign of market return and their interaction. The hazard model is written as Eq (4.1).

$$\lambda(t|X) = \lambda_0(t)e^{(\beta_1\mathbb{D}_{\{R_h<0\}}+\beta_2\mathbb{D}_{\{R_m<0\}}+\beta_3\mathbb{D}_{\{R_h<0\}}\times\mathbb{D}_{\{R_m<0\}})} \tag{4.1}$$

where $\lambda(t|X) = f(t|X)/\{1 - F(t|X)\}$ is the hazard rate or the instantaneous rate of selling the stock at time t, having not sold it till time t; $\mathbb{D}_{\{R_h<0\}}$ is an indicator variable which takes the value of one when the holding period return of the stock is negative and $\mathbb{D}_{\{R_m<0\}}$ is a similar indicator variable for negative market return. The parameter estimates of this model are presented in Table (4.2).

	(1)	(2)
$\mathbb{D}_{\{R_h<0\}}$	-0.55 (0.004)	-0.62 (0.005)
$\mathbb{D}_{\{R_m<0\}}$		0.08 (0.009)
$\mathbb{D}_{\{R_h<0\}} \times \mathbb{D}_{\{R_m<0\}}$		0.16 (0.006)

Table 4.2: **Estimates of Hazard Model.** The first model tests the presence of disposition effect or the sign of holding period return on the propensity to sell. The second model tests the effect of market return on the propensity to sell and its interaction with the holding period return. Values in parenthesis are standard errors.

The estimation of the first model tests the disposition effect. The negative coefficient associated with negative holding period return indicates that the propensity to sell a stock with positive holding period return is significantly higher than that of negative return stocks, which is the disposition effect.

In the second model, negative market return dummy has a positive and significant coefficient associated with it. This coefficient indicates that the propensity to sell any stock marginally increases when market returns are negative. This finding is also consistent with the aggregate volume data in CRSP which shows an increase in trading volume on negative market return days.

The interaction of negative market return and negative holding period return has a significant positive sign. The positive coefficient indicates that the propensity to sell negative stocks increases significantly more on negative market return days. Thus the observed increase in average sell-transaction of stocks at a loss on negative market return days is not just mechanical.

4.1.3 Buying After Selling

We have thus identified that there is an increased selling for stocks at a loss on negative market return days. The acquisition effect predicts that investors buy high beta stock after selling a stock at a loss. Combining the sell timing and the prediction from the acquisition effect leads to the next question – when do people buy a stock after selling one?

I observe that after selling a stock, investors buy a new stock quite promptly. Fig. 4.1 demonstrates this quick turnover where we can see that 36% of sell-transactions are followed by a buy transaction the following day.

For all the sell-transactions in the data, 77.75% have at least one following sell transaction within 1 and 21 days while 78.96% have at least one buy-transaction. In aggregate it seems plausible that on negative market return days, a more substantial number of investors realize a loss, and then they buy a new stock the next day. This new stock, due to the acquisition effect, is more likely to be a high beta stock. This

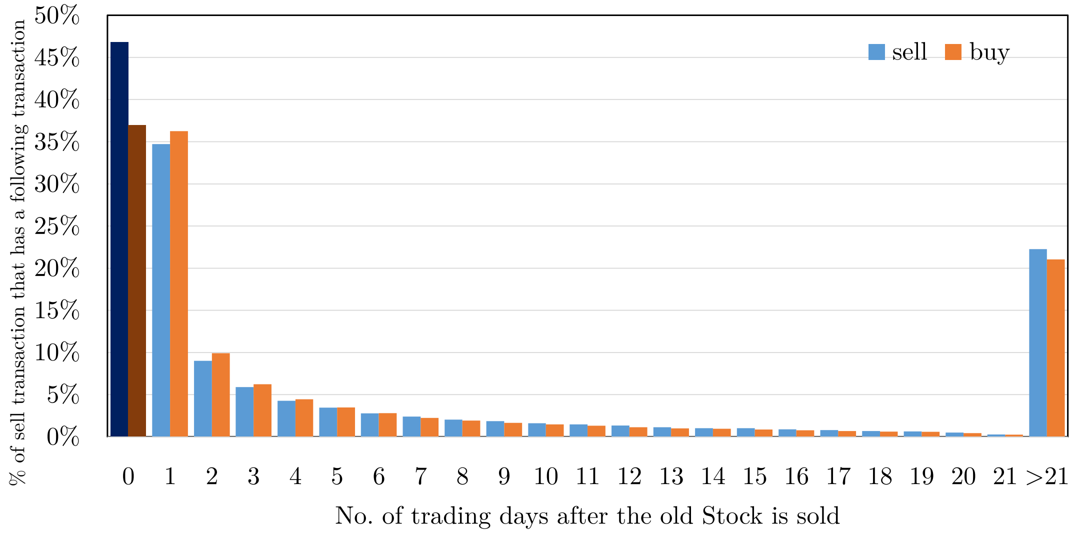


Figure 4.1: **Percentage of Sell Transaction with Following Trade vs. Days following Sell Transaction.** The number of days is counted as the number of trading days from a 'sell' transaction. The zero-day on the horizontal axis represents the number of sell-transactions that had another a buy or a sell by the same account holder, in a different stock, on the same date. So 46% of the sell-transactions in the data had another sell-transaction on the same date, and 37% had a buy-transaction. The rest of the numbers represent the number of trading days after which the same account holder made her first transaction after the initial sell. For this graph, I consider followup transaction up to a month(21 days). If a sell-transaction does not have a follow-up transaction within a month, it is grouped as > 21. From day 1 to day 21 and the > 21 sums up to 100% for both buy and sell transaction.
.

chain of trades – selling a loss-making stock on a negative market return day and subsequently buying a high beta stock – can create a predictable variation in demand for high beta stocks.

4.2 Return Predictability

Investors buy higher beta stocks immediately after selling a stock at a loss. Also, investors are more likely to sell a stock at a loss when the market goes down. If acquisition effect is strong enough, then there will be aggregate buying pressure on high beta stocks right after the market goes down, and this should be testable. More specifically we should see high beta stocks having a negative relation to lagged market return. Furthermore, consistent with the timing of the trades, the negative relation should be on a short horizon.

The empirical asset pricing literature has identified several short-term, time series predictability, and several explanations have been provided. Lack of trading is one of the reasons proposed for the presence of autocorrelation in stock and index returns. *Fisher* (1966) first identified the importance of asynchronous trading while *Scholes and Williams* (1977) showed the effect using a model of trading. Due to lack of trading, information may get incorporated slower and to a lesser degree than expected in a liquid market. This departure from a liquid market, *Scholes and Williams* (1977) argued, would result in underestimation of beta in the market model.

Dimson (1979) provides a solution to the problem of asynchronous trading by suggesting the use of lagged market return in regressions and subsequently aggregating the coefficients of up to five lagged market return as a better estimate of market beta. If due to lack of trading, market-wide information is incorporated slowly over a few days into a stock return, lagged market returns in the regression of the stock return will have positive coefficients. Aggregating the coefficients of market return and lagged market returns would raise the value of beta and adjust for the downward bias.

Another short-term predictability, related to the liquidity issue of asynchronous trading, arises from a bid-ask bounce. Consistent with *Roll* (1984), *French and Roll* (1986) finds that stock returns are negatively autocorrelated at the daily frequency. This negative autocorrelation arises due to low liquidity where stock prices alternately bounce between the bid and the ask-price on different days.

Momentum is another predictability detected at a longer frequency of three to twelve months (*Jegadeesh and Titman* (1993)) where past returns positively predict future return. But, at monthly frequency *Jegadeesh* (1990) detects negative autocorrelation.

The above-listed predictability either do not address the relation of a stocks return to lagged market return (cross-autocorrelation) or contradicts the hypothesis that this relation can be negative. To test the hypothesis of negative cross-autocorrelation, I would need to control for self-autocorrelation of stocks.

4.2.1 Regression

I test the hypothesis of a negative cross-autocorrelation of high beta stock returns with the market, especially when the lagged market return was low. I conduct the test both at daily, and monthly frequencies and I split the sample by the sign of lagged market return. But first I create twenty beta-sorted portfolios.

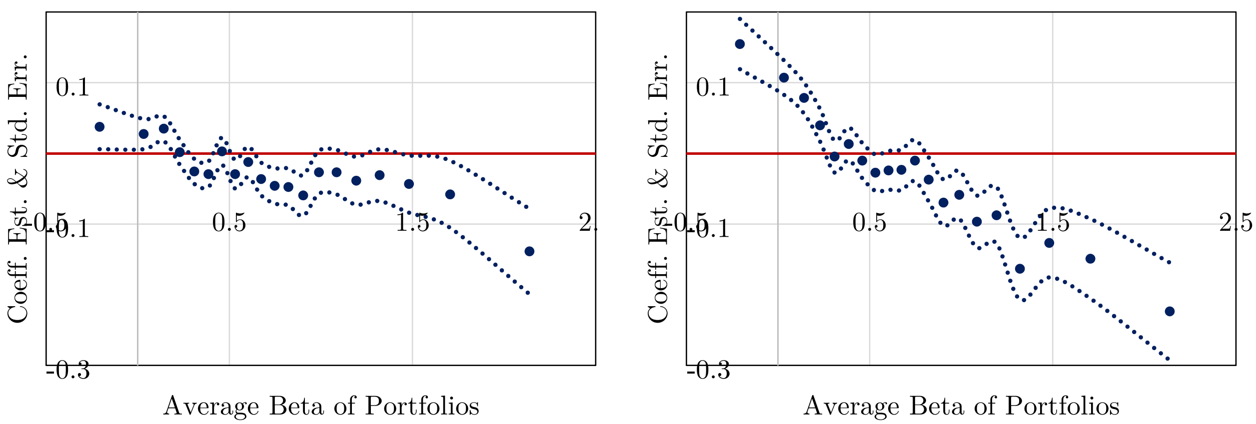
The betas are computed as backward-looking measures as would be available to an investor at the time. The betas for the daily analysis are calculated with past one year's daily return, not including the present date. Monthly returns are similarly computed using past three year's (36 month's) monthly return excluding the current month. I create twenty beta sorted portfolios every period such that each portfolio approximately has an equal number of stocks. Within each portfolio, the stocks are weighted according to their market capital. I run a regression on each portfolio separately across the entire time series from 1965-2016.

$$R_t^i = C_0 + C_1 \times R_{vw,t}^m + C_2 \times R_{vw,t-1}^m + C_3 \times R_{t-1}^i + \varepsilon_{i,t} \tag{4.2}$$

where R_t^i is the return on portfolio i at time t, $R_{vw,t}^m$ is the contemporaneous value-weighted market return, $R^m vw, t-1$ is the lagged value-weighted market return and R_{t-1}^i is the lagged return of portfolio i. Regressions are separately run for each portfolio and for two different samples. The first sample contains observations where the lagged market return is positive $R^m vw, t-1 \geq 0$ and the second sample contains observations where the lagged market return is negative.

The point estimates of twenty regressions each for positive and negative lagged market returns are presented in Tables C.1.18 and C.1.19 respectively. The tables demonstrate that the coefficient for lag market return after controlling for contemporary market return and lagged return of the portfolio has a negative coefficient for higher beta portfolios. The negative coefficients are larger in magnitude for the sample where the lagged market return is below zero. This feature is consistent with what i) the acquisition effect and ii) the trading behavior studied in this chapter suggests. A graph presents the tabulated results more intuitively.

I plot the estimated coefficient ($\hat{C}_2$) for twenty regressions corresponding to twenty beta-sorted portfolios against the average beta of each portfolio. The left panel in Fig (4.2) represent the regression estimated for positive lagged market return sample while the right panel corresponds to the sample where the lagged market return is negative.



(a) Positive Lagged Market Return

(b) Negative Lagged Market Return

Figure 4.2: **Regression Coeff. for Lagged (Daily) Market Return** Twenty beta sorted portfolios are created with daily adjustment. Each portfolio return is regressed against the value weighted contemporaneous market return, lagged market return and lagged return of the portfolio. The coefficient of interest is the one corresponding to lagged market return. I plot the lagged market return regression coefficients, corresponding to twenty regressions run on each portfolio, against the value-weighted average beta of each portfolio. Fig(4.2b) corresponds to the regression estimates in the sample where lagged market return was positive while Fig(4.2a) corresponds to the plots for the negative lagged market return sample.

The point estimates for positive market return are close to zero. Higher beta portfolios are slightly negative. For the sample corresponding to negative lagged market return, higher beta stocks show significantly negative coefficients. These coefficients imply that higher beta stocks seem to have a reverse relation to lagged market return, especially when the lagged market return was negative. A characteristically similar but statistically weaker result is obtained when the analysis is done for monthly data. The resulting graphs are presented in Fig C.2.17.

The predictability documented in this section should be exploitable using a trading strategy which I proceed to study next.

4.3 Trading Strategy

One of the most widely studied anomalies in asset pricing is the beta anomaly – high beta stocks provide a lower return than predicted by CAPM while low beta stocks provide a higher return. This was first documented in *Friend and Blume* (1970) and *Jensen et al.* (1972). There are several hypotheses regarding the reason for this anomaly, and they are often at odds. One consensus about beta anomaly is that there is a higher than usual demand for high beta stocks.

The explanation as to why there is higher demand is again varied. *Black* (1972) and more recently *Frazzini and Pedersen* (2014) argue that this demand is due to restrictions on borrowing. Individuals with higher risk tolerance cannot lever up the market portfolio and reach their risk tolerance optimally. Hence, they end up overweighing higher beta stocks in their portfolio.

Another prominent explanation is due to investor's demand for lottery-like stocks. In *Bali et al.* (2016) and *Bali et al.* (2011) the authors argue that individuals intrinsically demand stocks which provide lottery like returns. The demand for lottery-like stocks is also consistent with the finding of *Kumar* (2009). Since the lottery like characteristic of a stock is correlated with its market beta, the author argues that the lottery demand essentially translates to demand for higher beta stocks. Demand for stocks with lottery-like characteristics can thus explain the beta anomaly.

Irrespective of the reason for the higher demand of high beta stocks, a strategy to take advantage of the beta anomaly is to 'bet against beta'. Betting against beta (BAB) is a strategy popularized by *Frazzini and Pedersen* (2014)[2]. The BAB strategy suggests taking a short position in a diversified high beta portfolio and a long position in a levered up diversified low beta portfolio. The low beta portfolio being levered up to match the beta of the high beta portfolio. The long short positions cancel out most of the systematic risk while the diversification minimized the idiosyncratic risks. Since low beta stocks are empirically found to have higher alphas than high beta stocks, the BAB strategy generates positive returns at very low risk, thus yielding high Sharpe Ratio.

The acquisition effect suggests that there will be an overall higher demand for high beta stocks across time. From studying trade timing, I infer that this demand will be unusually high during market down movements. On the days when market return is negative or on the following days, demand pressure on high beta stocks will not let their prices decrease by as much as their market beta suggests. The prices might even increase. This predictable movement in returns of high beta stocks is verified in the previous section (Sec 4.2). Due to this predictable movement in high beta stocks, the betting against beta return (r^{BAB}) will be lower or even negative on those days. This prediction that the r^{BAB} should systemically vary with the market is counter-intuitive – because betting against beta is designed to be a market-neutral strategy – but not entirely new. The fact that r^{BAB} varies systematically with market return has been documented in *Cederburg and O'Doherty* (2016).

[2]The BAB strategy was initially proposed in 1969 by Fisher Black and Myron Scholes to Wells Fargo (*Mehrling* (2005)), but Wells Fargo decided not to implement it.

4.3.1 The Betting Against Beta Strategy

In order to observe whether r^{BAB} indeed weakens with a negative market return, I compute average r^{BAB} for days grouped into negative and positive market return days and also for days right after negative market return.

The BAB strategy I study at the beginning is not the classic monthly adjusted strategy in *Frazzini and Pedersen* (2014) but a daily adjusted one. Just like the original strategy, stocks are sorted into two portfolios. The high beta portfolio (H) has stocks with beta ≥ 1 while the low beta portfolio (L) has stocks having beta < 1. This sorting is done daily with market betas calculated with daily returns over past one year(252 days) leaving out the current date.

Within each portfolio, the stocks are weighted according to their ranks within the portfolio. The highest beta stock gets the highest weight in the H portfolio, and the lowest beta stock gets the highest rank in the L portfolio. Let there be n_H stocks in the high beta portfolio H, let their rank of the ith stock be denoted by $Z_i^H \in 1, 2 \ldots n_H$. The ranks are assigned in ascending order – highest rank stock being the highest beta stock. The sum of the ranks is $\sum Z_i^H = \sum_{i=1}^{n_H} i = n_H(1 + n_H)/2$. Then the weight assigned to stock i can be written as:

$$w_i^H = \frac{i}{n_H(1 + n_H)/2}$$

where the highest beta stock, with rank n_H, has weight $2/(1 + n_H)$ and the lowest beta stock has weight $2/n_H(1 + n_H)$.

The weights of the low beta portfolio can be defined similarly, except the ranks are assigned in descending order of beta. So the lowest beta stock has the highest rank and subsequently the highest weight in this portfolio.

The two corresponding portfolios with returns r^H and r^L can be thus created with the returns that can be expresses as in Eq (4.3).

$$r_t^H = \left(\sum_{i=1 \in H} w_i^H r_{i,t} \right) \tag{4.3}$$

where return of stock i at time t is $r_{i,t}$. The corresponding beta of H portfolio can be written as:

$$\beta_{t-1}^H = \left(\sum_{i=1}^{H} w_i^H \beta_{i,t-1} \right) \tag{4.4}$$

where the beta of stock i is $\beta_{i,t-1}$ is computed with information available till time $t-1$. Similarly the low beta portfolio can be formed and r^L and β^L can be estimated. Then at each date a self financing portfolio of r^L, weighted to the inverse of its beta is longed and a corresponding self financing high beta portfolio is shorted. Formally I can write the daily betting against beta return, r_t^{BAB} as:

$$r_t^{BAB} = \frac{1}{\beta_{t-1}^L} \left(r_t^L - r_t^f \right) - \frac{1}{\beta_{t-1}^H} \left(r_t^H - r_t^f \right) \tag{4.5}$$

where r_t^f is the risk free rate at time t.

To compute r^{BAB} empirically, I use only high market capital CRSP stocks listed in NYSE and NASDAQ. The daily adjusted portfolios are constructed with stocks which have been among the top thousand market capital stocks in the previous year. Further, I leave out stocks where market betas are estimated to be above 2 or below 0.3. With this data, I estimate the average daily return of the BAB strategy, $\overline{r^{BAB}} = \frac{1}{T} \sum_t r_t^{BAB}$, as .053% with an annualized Sharpe ratio of 1.21. When the sample is split into negative market return days, positive market return days and days after negative market return days, a clear pattern is observed. The negative market return day and the day after negative market return generates statistically significant negative average $\overline{r^{BAB}}$.

From Table 4.3, we can see that on negative market return days, the average

market return	#	$\overline{r^{BAB}}$	(std. err.)	Stdv. σ	Sharpe Ratio
All	23,386	0.0534%	(0.0046%)	0.7033%	1.2061
-ve	10,526	-0.025%	(0.0068%)	0.6996%	-0.5779
-ve^{+1}	10,526	-0.11%	(0.0068%)	0.6975%	-2.4928
-ve^{+2}	10,525	0.004%	(0.008%)	0.79%	0.08
+ve	12,860	0.118%	(0.0062%)	0.6997%	2.6772

Table 4.3: **Daily Adjusted Betting Against Beta.** Returns on the betting against beta strategy for different market return days. The first column indicated what the sign of market return was. $-ve^{+1}$ implies that the previous day was a negative market return day, while $-ve^{+2}$ implies that the day before the previous day was a negative market return day. The second column represents the number of days in the time series sample. In the third column, $\overline{r^{BAB}}$ represents the time series average of the daily betting against return. The fourth and the fifth column lists the standard error and the standard deviation of the average return. The last column is the Sharpe ratio which is annualized.

betting against beta return is -0.025% while on the day after negative market return the average rerun is -0.11%.

4.3.2 Dynamically Betting For and Against Beta

The estimates obtained in Table 4.3 make it clear that the r^{BAB} is lower on a negative market return day and the day after. This effect was anticipated from the time-varying demand for high beta stocks due to the acquisition effect. Since the return is negative on those days, just not trading on negative market return days or taking the opposite position will improve the performance of the trading strategy. But any strategy that depends on observing the current market return is a hypothetical one since this requires anticipation of which days will generate a negative market return. An alternative implementable strategy is to take a 'bet with beta' on days after the day market produces a negative return and to take the usual 'bet against beta' on other days. This alternative generates a daily return of 0.152% and an annualized Sharpe ratio of 3.50.

The predictable variation of r^{BAB} is not due to slow or asynchronous trading. As presented in Table 4.4, in the post-1990 sample the daily adjusted BAB strategy produces annualized Sharpe ratio of 2.69 while the recommended alternative BAB strategy generates Sharpe ratio of 3.25 The corresponding numbers for post-2000 data are 2.12 and 3.39.

Daily Sample	#	$\overline{r^{BAB}}^*$	(std. err.)	σ	S.R.	S.R.^{BAB}
1926-2016	23,386	0.152%	(0.0045%)	0.6887%	3.50	1.21
1991-2016	6,300	0.094%	(0.0066%)	0.5261%	2.84	2.72
2001-2016	3,773	0.108%	(0.008%)	0.492%	3.49	2.12

Table 4.4: **Daily Adjusted 'Modified' Betting Against Beta.** Returns on the modified daily adjusted BAB strategy for different samples. The first column indicated the range of the sample. The second column represents the number of days in the time series sample. In the third column, $\overline{r^{BAB}}^*$ is the time series average of the adjusted daily betting against return recommended due to time-varying demand for high beta stocks. The fourth and the fifth column lists the standard error and the standard deviation of the average return. The sixth column is the Sharpe ratio which is annualized while the seventh column is the Sharpe Ratio from the original betting against beta strategy with daily adjustments which is the benchmark.

I recognize that readjusting a portfolio daily is not practical. The exercise, however, remains important because it suggests significant variation in r^{BAB} as a function of lagged market return which is consistent with the acquisition effect. An investor can improve her performance from the BAB strategy by merely not trading on days immediately after observing negative market return days.

A more practical strategy will be a monthly adjusted one. But since, the demand pressure is short lived, at the monthly frequency the strategy cannot be improved upon as easily. The performance of the monthly BAB strategy on all months, on negative market return months, on months after negative market return months and positive market return months is listed in table C.1.17. The average returns, $\overline{r^{BAB}}$, demonstrate that at the monthly level, a strategy similar to the daily modified BAB – where we bet for beta or bet against beta based on the sign of last month's market return – will not work. However, the results are indicative of the presence of acquisition effect.

Quintile	#	$\overline{r^{BAB}}$	(std. err.)	Stdv. σ	Sharpe Ratio
Lowest	193	-0.175%	(0.361%)	5.013%	-0.121
Q2	200	0.299%	(0.301%)	4.252%	0.244
Q3	235	0.784%	(0.344%)	5.279%	0.515
Q4	204	1.196%	(0.264%)	3.77%	1.099
Highest	195	1.819%	(0.571%)	7.972%	0.791

Table 4.5: **Monthly Adjusted Betting Against Beta by Previous Month's Market Return.** Returns on the monthly adjusted betting against beta strategy is listed for different degrees of previous month's market return. The value weighted market return is grouped into quintile based on past 48 monthly value weighted market returns. The first column of the table indicates the quintile, the first row corresponds to the fist quintle which is for the lowest market return group. The second column represents the number of months in the time series sample. In the third column, $\overline{r^{BAB}}$ is the time series average of the monthly betting against return. The fourth and the fifth column lists the standard error and the standard deviation of the monthly average return. The last column is the Sharpe ratio which is annualized.

The average return on a monthly adjusted BAB strategy, $\overline{r^{BAB}}$ is 0.79% with an annualized Sharpe Ratio of 0.5. On the months where the market return is negative, the BAB return is -1.6% with a Sharpe Ratio of -1.24, and on the months after a negative market return month, the BAB return is a statistically insignificant 0.07% at a Sharpe Ratio of 0.05. Thus on months after a negative market return month, holding the market portfolio will improve the Sharpe ratio.

Although the demand pressure arising from the acquisition effect is short-lived, if the market return on a particular month is highly negative, this effect might spill over to the next month. It is thus necessary to look into the performance of the BAB strategy as a function of not just the sign but the degree of previous month's market return.

I categorize market return into quintiles, based on past 48 month's market return, on a rolling basis. The returns on the BAB strategy, listed according to the market return quintile of the previous month, is listed in Table 4.5.

The results in the table indicate that the return of the BAB portfolio is positively related to the market return of the previous month. For the lowest previous month market return quintile, the BAB strategy generates a negative return. Based on this result I recommend the following monthly trading strategy. If the last month's market return is in the lowest quintile of the previous four year's monthly returns, then hold a 'bet for beta' portfolio otherwise hold the regular BAB portfolio. This strategy generates an average return of 0.96% at a Sharpe Ratio of 0.62.

APPENDICES

APPENDIX A

Choice of Mental Account

I attempt to motivate theoretically that both the disposition effect and the acquisition effect are rationalizable under the assumption that investors make choices of mental account.

A.1 Choice of Mental Account

If the agent has a choice of mental account, then the choices can be defined as:

(i) Rolled Over Mental Account: She can choose to roll over or aggregate her mental account such that her reference point is still W_{ref} and she may look for new investment (which requires selling the old stock and buying a new one), or she may continue with the old one.

(ii) Segregate Mental Account: She can choose to close her mental account and start a new one. To close the account, she must sell the old stock and thus realize her profit of a loss. This generates a burst of realization utility (*Barberis and Xiong* (2012)). To start the new mental account, she must buy a new stock and reset her reference wealth to current wealth W_0.

The problem of the agent with such choices can be written as:

$$max \quad \{ \quad \underbrace{\max_{\beta} \quad \delta\mathbb{E}(V(W_1 - W_{ref}))}_{\text{rolled over mental account}} \quad , \quad \underbrace{V(W_0 - W_{ref}) + \max_{\beta} \quad \delta\mathbb{E}(V(W_1 - W_0))}_{\text{segregated mental account}} \quad \}$$

The first expression above represents utility due to aggregated mental account, U_{Agg} while the second one is due to segregated mental accounts, U_{Seg}. The first term in the second expression can be interpreted as the burst of realization utility as defined in *Barberis and Xiong* (2012).

Claim: Aggregating utility is better after a small loss while segregating is better after a small gain.

Proof:

Aggregating mental account implies no present realized utility, maintaining the old reference wealth and discounted future expected utility.

$$\begin{aligned} U_{Roll} &= \delta\mathbb{E}\left(V(W_1 - W_{ref})\right) \\ &= \delta W_{ref}^{\alpha}\mathbb{E}\left(V(R_1(1+R_0)+R_0)\right) \end{aligned} \tag{A.1}$$

Segregated mental account implies a current realization of the gain (or loss), change in reference wealth to the current wealth and a discounted future expected utility.

$$\begin{aligned} U_{Seg} &= V(W_0 - W_{ref}) + \delta\mathbb{E}\left(V(W_1 - W_0)\right) \\ &= W_{ref}^{\alpha}V(R_0) + \delta W_{ref}^{\alpha}(1-R_0)^{\alpha}\mathbb{E}\left(V(R_1)\right) \end{aligned} \tag{A.2}$$

Here $V(.)$ is the prospect theory (P.T.) consistent utility functio; U_{Roll} and U_{Seg} are the expected utilities from aggregating or segregating the mental accounts in the two period setup. δ is the time discount factor of utility. W_{ref} is the reference wealth which is also the initial wealth at time $t = -1$, $W_0 = (1 + R_0)W_{ref}$ is wealth at time

$t = 0$ and $W_1 = (1 + R_1)W_0$ is wealth at $t = 1$. The expectation operator $\mathbb{E}(.)$ is applied at $t = 0$ such that everything upto $t = 0$, including R_0 and W_0 is known.

The future wealth is due to a stock selected from a market that follows a 2-factor model, $R_1 = (1 - \beta)R_z + \beta(R_m - R_z) + \epsilon$. Due to this model a particular stock is completely specified by its beta. Also U_{Agg} and U_{Seg} are both functions of β.

Let the optimal stock after aggregating mental account be represented by β^A and that after segregated mental account be represented by β^S. They can be formally defined as:

$$\beta^R = \underset{\beta}{Argmax}\; U_{Roll}(\beta) \tag{A.3}$$

$$\beta^S = \underset{\beta}{Argmax}\; U_{Seg}(\beta)$$

Stock beta is restricted to be within reasonable bounds $\beta \in [\underline{\beta}, \overline{\beta}]$.

For the same realized wealth W_0, if a stock with risk factor β is chosen, the difference in utility can be written as:

$$\begin{aligned}
\Delta\mathbb{U}(\beta, W_0) &= (U_{Roll}(\beta) - U_{Seg}(\beta)) \\
&= [\delta\mathbb{E}\left(V(W_1 - W_{ref})\right) - V(W_0 - W_{ref}) - \delta\mathbb{E}\left(V(W_1 - W_0)\right)] \qquad \text{(A.4)} \\
&= W_{ref}^{\alpha}\left[\delta\mathbb{E}\left(V(R_1(1 + R_0) + R_0)\right) - \delta(1 + R_0)^{\alpha}\mathbb{E}\left(V(R_1)\right) - V(R_0)\right] \qquad \text{(A.5)}
\end{aligned}$$

where α is the curvature (risk aversion) parameter of the P.T. consistent utility. When $W_0 = W_{ref}$ i.e. $R_0 = 0$, we have $U_{Roll} = U_{Seg}$ or $\Delta\mathbb{U}(\beta, W_{ref}) = 0$.

Since $W_0 = W_{ref}(1 + R_0)$, in order to study $\frac{\partial \Delta \mathbb{U}}{\partial W_0}$ around $W_0 = W_{ref}$ (small loss/small gain), it is sufficient to study $\frac{\partial \Delta \mathbb{U}}{\partial R_0}$ around $R_0 = 0$.

$$\frac{1}{W_{ref}^{\alpha}} \frac{\partial \Delta \mathbb{U}}{\partial R_0} = \delta \mathbb{E} \left(V'(R_1(1 + R_0) + R_0)(1 + R_1) \right) - \delta\alpha(1 + R_0)^{\alpha-1} \mathbb{E} V(R_1) - V'(R_0) \tag{A.6}$$

where $V'(.)$ represents the derivative of the utility function.

$$\begin{aligned} V'(R_0) = \left[\frac{\partial V(R)}{\partial R}\right]_{R=R_0} \quad &= \frac{\alpha}{R_0^{1-\alpha}} \quad \text{if} \quad R_0 > 0 \equiv W_0 > W_{ref} \\ &= \frac{\lambda\alpha}{-R_0^{1-\alpha}} \quad \text{if} \quad R_0 < 0 \equiv W_0 < W_{ref} \end{aligned}$$

where $0 < \alpha < 1$, $\lambda > 1$. Thus with R_0 near zero,marginal utility $V'(R_0)$ takes a very large and positive value. Formally:

$$\begin{aligned} \lim_{R_0 \to 0^+} V'(R_0) &= +\infty \\ \lim_{R_0 \to 0^-} V'(R_0) &= +\infty \end{aligned}$$

The first and the second term of the derivative (Eq. A.6) are finite for values around $R_0 = 0$ and so the third term dominates. Using the above and the fact that $\frac{\partial \Delta \mathbb{U}}{\partial W_0} = \frac{1}{W_0} \frac{\partial \Delta \mathbb{U}}{\partial R_0}$, I write:

$$\lim_{W_0 \to W_{ref}} \frac{\partial \Delta \mathbb{U}}{\partial W_0} = -\infty \tag{A.7}$$

Let $W_0 = W_{ref} + \omega$, where ω is a nonzero number which can be considered small compared to W_{ref}. The I can write an approximate taylor expansion as:

$$
\begin{aligned}
\Delta\mathbb{U}(\beta, W_{ref} + \omega) &\approx \Delta\mathbb{U}(\beta, W_{ref}) + \omega \left[\frac{\partial \Delta\mathbb{U}}{\partial W_0}\right]_{W_0 = W_{ref}} \\
&\approx \qquad 0 \qquad + \omega \left[\frac{\partial \Delta\mathbb{U}}{\partial W_0}\right]_{W_0 = W_{ref}}
\end{aligned}
\tag{A.8}
$$

If $|W_0 - W_{ref}|$ is small, using Eq. (A.7) and Eq. (A.8) I can write:

$$
\begin{aligned}
\Delta\mathbb{U}(\beta, W_0) > 0 \quad \text{if} \quad W_0 < W_{ref} \\
\Delta\mathbb{U}(\beta, W_0) < 0 \quad \text{if} \quad W_0 > W_{ref}
\end{aligned}
$$

Expanding $\Delta\mathbb{U}$ I can write:

$$
\begin{aligned}
U_{Roll}(\beta) \quad &> \quad U_{Seg}(\beta) \quad \text{if} \quad W_0 < W_{ref} \quad \forall \quad \beta \in [\underline{\beta}, \overline{\beta}] \\
U_{Roll}(\beta) \quad &< \quad U_{Seg}(\beta) \quad \text{if} \quad W_0 > W_{ref} \quad \forall \quad \beta \in [\underline{\beta}, \overline{\beta}]
\end{aligned}
$$

Since β^A and β^B are the utility maximizing choices under aggregation and segregation respectively, using Eq. A.3 I can write:

$$
\begin{aligned}
U_{Roll}(\beta^R) \quad &> \quad U_{Seg}(\beta) \quad \text{if} \quad W_0 < W_{ref} \quad \forall \quad \beta \in [\underline{\beta}, \overline{\beta}] \\
U_{Roll}(\beta) \quad &< \quad U_{Seg}(\beta^S) \quad \text{if} \quad W_0 > W_{ref} \quad \forall \quad \beta \in [\underline{\beta}, \overline{\beta}]
\end{aligned}
$$

The above proof holds for 'small' profits and losses. For similar inference for more significant gains and losses I solve the model numerically in Chapter III. ■

APPENDIX B

Expected Utility Maximization

B.1 Expected Utility Maximization

Future wealth of an individual investor is given by:

$$W_1 = W_0(1 + R_1) \tag{B.1}$$

where W_0 is the starting wealth, R_1 is the return on the stock invested in. Utility obtained from the wealth depends on reference wealth W_{ref} and is consistent with the prospect theory. To derive a closed form solution the utility function is simplified to be piecewise linear:

$$\begin{aligned} V(W_1 - W_{ref}) =& W_1 - W_{ref} && \text{if} \quad W_1 > W_{ref} \\ & -\lambda(-(W_1 - W_{ref})) && \text{if} \quad W_1 \leq W_{ref} \end{aligned}$$

where the loss aversion parameter is greater than one, $\lambda > 1$. Stocks are selected from a market that follows a two factor model:

$$R_1 = (1 - \beta)R_z + \beta R_m + \epsilon$$

where $R_m \sim \mathcal{N}(\mu_m, \sigma_m^2)$ is the market return and $R_z \sim \mathcal{N}(\mu_z, \sigma_z^2)$ is the return of a minimum variance zero beta portfolio. This model, due to *Jensen et al.* (1972), has been shown to fit the data better and can explain the lower than expected slope of the one factor CAPM model. By setting zero beta return to a non random risk free rate, $R_z = R_f$ this model directly reduces to CAPM.

With the above assumptions, I can write $R_1 \sim \mathcal{N}(\mu, \sigma^2)$, where $\mu = \mu_z + \beta(\mu_m - \mu_z)$ while $\sigma^2 = \beta^2\sigma_m^2 + (1-\beta)^2\sigma_z^2 + \sigma_\epsilon^2$.

B.1.1 Expected Utility

Within a mental account a gain is not with respect to starting wealth but with respect to the reference point, $W_1 > W_{ref}$. Using Eq. (B.1) I write:

$$\begin{aligned} W_1 = W_0(1 + R_1) &> W_{ref} \\ \implies R &> \frac{W_{ref}}{W_0} - 1 = g \quad \text{(say)} \end{aligned}$$

Now the expected utility can be written as:

$$\begin{aligned} \mathbb{E}V &= \int_{-\infty}^{\infty} V(W_1 - W_{ref}) f(R) dR \\ &= \int_{-\infty}^{g} \lambda(W_1 - W_{ref}) f(R) dR + \int_{g}^{\infty} (W_1 - W_{ref}) f(R) dR \\ &= \int_{-\infty}^{g} (\lambda - 1)(W_1 - W_{ref}) f(R) dR + \int_{-\infty}^{\infty} (W_1 - W_{ref}) f(R) dR \end{aligned}$$

where $f(R)$ is the density function of R.

Plugging in the expression of W_1 from eq (B.1) the above integration can be rewritten.

$$\begin{aligned}\mathbb{E}V =&(\lambda-1)W_0\int\limits_{-\infty}^{g} Rf(R)dR \\ &+(\lambda-1)(W_0-W_{ref})F(g)+W_0(1+\mu)-W_{ref}\end{aligned} \tag{B.2}$$

Let $r=(R-\mu)/\sigma\sim\mathcal{N}(0,1)$ which implies $f(R)=\phi(r)/\sigma$ and $F(g)=\Phi(\gamma)$ where $\phi()$ and $\Phi()$ are the pdf and cdf of standard normal distribution and $\gamma=\dfrac{g-\mu}{\sigma}$.

$$\begin{aligned}\int\limits_{-\infty}^{g} Rf(R)dR &= \int\limits_{-\infty}^{\gamma}(\mu+\sigma r)\frac{\phi(r)}{\sigma}\sigma dr \\ &= \mu\Phi(\gamma)-\sigma\int\limits_{-\infty}^{g}\phi'(r)dr \\ &= \mu\Phi(\gamma)-\sigma\phi(\gamma)\end{aligned}$$

where I use the result $\phi'(x)=d\phi(x)/dx=-x\phi(x)$. The above result can be used in Eq (B.2) and after rearranging terms:

$$\mathbb{E}V=\{W_0(1+\mu)-W_{ref}\}(1+(\lambda-1)\Phi(\gamma))-(\lambda-1)\phi(\gamma)W_0\sigma \tag{B.3}$$

A more intuitive form of the expected utility can be written as:

$$\begin{aligned}\mathbb{E}V &= \{W_0(1+\mu)-W_{ref}\} \\ &\quad +(\lambda-1)\left[\Phi(\gamma)\{W_0(1+\mu)-W_{ref}\}-\phi(\gamma)W_0\sigma\right]\end{aligned}$$

where the first term is the expected utility of a risk neutral agent and the second term is due to loss aversion. Te second term due to loss aversion can be shown to be always negative. If we assume it to be positive, then we can write:

$$
\begin{aligned}
&\Phi(\gamma)\{W_0(1+\mu) - W_{ref}\} \geq \phi(\gamma)W_0\sigma \\
\implies &\Phi(\gamma)\{-\gamma\sigma W_0\} \geq \phi(\gamma)W_0\sigma \\
\implies &-\gamma \geq \frac{\phi(\gamma)}{\Phi(\gamma)} = -\mathbb{E}(r|r<\gamma) \\
\implies &\mathbb{E}(r|r<\gamma) \geq \gamma \quad \text{(unfeasible)}
\end{aligned}
$$

Hence as intuition suggests, the loss aversion term is always negative and thus the expected utility of a loss averse agent is lower than that of a risk neutral agent.

B.1.2 The Maximization Problem

If the market follows the two factor model or simply CAPM, a stock is completely characterized by its beta. So beta is the only choice variable is necessary:

$$
\underset{\beta}{max} \qquad \mathbb{E}V(W_1 - W_{ref})
$$

where W_{ref} is the reference wealth, $W_1 = W_0(1+R_1)$ is the future wealth, and the market risk factor, beta is bounded within plausible values, $\beta \in [\underline{\beta}, \overline{\beta}]$.

B.1.2.1 First Order Condition

Using the expected utility expression derived before (Eq.B.3), the expression of the first order condition can be written as:

$$
\begin{aligned}
\frac{\partial \mathbb{E}V}{\partial \beta} =& W_0(\mu_m - \mu_z)\left(1 + (\lambda-1)\Phi(\gamma)\right) + \left(W_0(1+\mu) - W_{ref}\right)(\lambda-1)\phi(\gamma)\frac{d\gamma}{d\beta} \\
&+ W_0(\lambda-1)\sigma\gamma\phi(\gamma)\frac{d\gamma}{d\beta} - W_0(\lambda-1)\phi(\gamma)\frac{d\sigma}{d\beta}
\end{aligned}
$$

In the second term I replace $W_0 - W_{ref} = -W_0 g$ and in the third term I use $\sigma\gamma = (g-\mu)$; after gathering terms, the coefficient corresponding to $\frac{d\gamma}{d\beta}$ becomes zero.

$$\frac{\partial \mathbb{E}V}{\partial \beta} = W_0(\mu_m - \mu_z)\left(1 + (\lambda - 1)\Phi(\gamma)\right) - W_0(\lambda - 1)\phi(\gamma)\frac{d\sigma}{d\beta} \tag{B.4}$$

where $g = \frac{W_{ref}}{W_0} - 1$ and $\gamma = (g-\mu)/\sigma = \left(\frac{W_{ref}}{W_0} - (1+\mu)\right)/\sigma$ as defined earlier.

B.1.2.2 Second Order Condition

The expression for the second order condition (SOC) can be derived as:

$$\frac{\partial^2 \mathbb{E}V}{\partial \beta^2} = W_0(\mu_m - \mu_z)(\lambda - 1)\phi(\gamma)\frac{d\gamma}{d\beta} + W_0(\lambda - 1)\gamma\phi(\gamma)\frac{d\gamma}{d\beta}\frac{d\sigma}{d\beta} - W_0(\lambda - 1)\phi(\gamma)\frac{d^2\sigma}{d\beta^2} \tag{B.5}$$

Both γ and σ being functions of β, their relevant derivatives can be written as:

$$\frac{d\gamma}{d\beta} = -\frac{\gamma}{\sigma}\frac{d\sigma}{d\beta} - \frac{1}{\sigma}(\mu_m - \mu_z) < 0 \quad \text{if} \quad \mu_m > \mu_z \tag{B.6}$$

$$\frac{d\sigma}{d\beta} = \frac{\beta(\sigma_m^2 + \sigma_z^2) - \sigma_z^2}{[\beta^2\sigma_m^2 + (1-\beta)^2\sigma_z^2 + \sigma_\epsilon^2]^{1/2}} > 0 \quad \text{if} \quad \beta > \frac{\sigma_z^2}{\sigma_m^2 + \sigma_z^2} \tag{B.7}$$

$$\frac{d^2\sigma}{d\beta^2} = \frac{\sigma_m^2\sigma_z^2 + \sigma_z^2\sigma_\epsilon^2 + \sigma_\epsilon^2\sigma_m^2}{[\beta^2\sigma_m^2 + (1-\beta)^2\sigma_z^2 + \sigma_\epsilon^2]^{3/2}} > 0 \tag{B.8}$$

Mean return of the market can be safely assumed to be above the mean return of the zero beta portfolio, so inequality B.6 is plausible. *Jensen et al.* (1972) estimates $\sigma_z \approx .5\sigma_m$, so for the inequality (B.7) to hold we need β to be greater than approximately 0.2 which is realistic. Finally the inequality B.8 holds without condition.

Eq.(B.5) can be rewritten as:

$$\begin{aligned}\frac{\partial^2 \mathbb{E}V}{\partial \beta^2} &= W_0(\lambda-1)\phi(\gamma)\frac{d\gamma}{d\beta}\left[(\mu_m-\mu_z)+\gamma\frac{d\sigma}{d\beta}\right] - W_0(\lambda-1)\phi(\gamma)\frac{d^2\sigma}{d\beta^2} \\ &= W_0(\lambda-1)\phi(\gamma)\frac{d\gamma}{d\beta}\left[\qquad -\sigma\frac{d\gamma}{d\beta}\qquad\right] - W_0(\lambda-1)\phi(\gamma)\frac{d^2\sigma}{d\beta^2}\end{aligned}$$

where the third equality is due to Eq. (B.6). Thus the SOC can be expressed as:

$$\frac{\partial^2 \mathbb{E}V}{\partial \beta^2} = -\sigma W_0(\lambda-1)\phi(\gamma)\left[\frac{d\gamma}{d\beta}\right]^2 - W_0(\lambda-1)\phi(\gamma)\frac{d^2\sigma}{d\beta^2} \quad < \quad 0 \tag{B.9}$$

where the inequality can be established using Eq. (B.8). The sign of the SOC implies that any interior solution by equating the FOC to zero is a maximum point.

B.1.2.3 Solution to the Maximization Problem

Claim: The optimal choice of beta after a loss is higher than that after a gain.

Proof: From Eq. (B.4) the FOC expression of the maximization problem is:

$$\frac{\partial \mathbb{E}V}{\partial \beta} = W_0\left[(\mu_m-\mu_z)\left(1+(\lambda-1)\Phi(\gamma)\right) - (\lambda-1)\phi(\gamma)\frac{d\sigma}{d\beta}\right]$$

Informally the proof can be argued just from the FOC expression. The first term in side the braces, $(\mu_m-\mu_z)\left(1+(\lambda-1)\Phi(\gamma)\right)$ is positive and monotonically decreasing in W_0. It is positive because the mean market return can be safely assumed be higher than mean return of the zero beta portfolio, $\mu_m > \mu_z$, $\lambda > 1$ and the cdf is always positive, $\Phi(\gamma) > 0$. It is monotonically decreasing because $\Phi(\gamma)$ is monotonically increasing in γ and $\gamma = \left(\frac{W_ref}{W_0} - (1+\mu)\right)/\sigma$ is monotonically decreasing in W_0. The fist term takes it's maximum possible value $(\mu_m-\mu_z)\lambda$ as $W_0 \to 0$.

The second term, $-(\lambda-1)\phi(\gamma)\frac{d\sigma}{d\beta}$, is negative and non-monotonic in W_0 (increases in absoloute value till $W_0 = \frac{W_{ref}}{1+\mu}$ and then decreases). It is negative because of the negative sign that precedes it; the three factors in the term are all positive. Loss version is assumed greater than one, $\lambda > 1$, pdf is by definition always positive, $\phi(\gamma) > 0$ and volatility increases with beta $\frac{d\sigma}{d\beta} > 0$ (Eq. B.7). It is non-monotonic in W_0 due to $\phi(\gamma)$ which is non-monotonic in W_0. Also as $W_0 \to 0$ this second term takes the value of zero. The second term takes its maximum possible absolute value at $W_0 = \frac{W_{ref}}{1+\mu}$.

So for lower values of W_0, i.e., when the agent is running at a loss, the first term is positive and dominates while the second term is close to zero. So marginal expected utility with respect to beta, $\frac{\partial \mathbb{E}V}{\partial \beta}$, is positive. Positive marginal utility with respect to beta implies that, for high losses, the optimal solution to the optimization problem (3.1) should be to increase beta until the FOC holds. Since the SOC holds unconditionally, increasing beta will gradually decrease the marginal utility until the FOC holds.

More formally, we can derive the change in optimal solution with respect to profit or loss. For the optimal beta β^*, the FOC expression is zero. The optimal beta which is a function of W_0, $\beta^*(W_0)$. Also γ is a function of both β and W_0 individually and $\dfrac{d\sigma}{d\beta}$ is a function of β. For optimal beta, I write γ^* and $\left[\dfrac{d\sigma}{d\beta}\right]_{\beta=\beta^*}$. At the optimal the FOC equation can be written as:

$$\text{or} \quad (\mu_m - \mu_z)\left(1 + (\lambda - 1)\Phi(\gamma^*)\right) - (\lambda - 1)\phi(\gamma^*)\left[\frac{d\sigma}{d\beta}\right]_{\beta=\beta^*} = 0 \tag{B.10}$$

Now differentiating the expression in Eq. (B.10) with respect to W_0 we get:

$$\Delta\mu(\lambda - 1)\phi(\gamma^*)\frac{d\gamma^*}{dW_0} + (\lambda - 1)\gamma\phi(\gamma^*)\frac{d\gamma}{dW_0}\left[\frac{d\sigma}{d\beta}\right]_{\beta=\beta^*} - (\lambda - 1)\phi(\gamma)\frac{d}{dW_0}\left(\left[\frac{d\sigma}{d\beta}\right]_{\beta=\beta^*}\right) = 0$$

where $\Delta\mu = \mu_m - \mu_z$. The expression can be further simplified as:

$$\frac{d\gamma^*}{dW_0}\left(\Delta\mu + \gamma^*\left[\frac{d\sigma}{d\beta}\right]_{\beta=\beta^*}\right) - \frac{d\beta^*}{dW_0}\left[\frac{d^2\sigma}{d\beta^2}\right]_{\beta=\beta^*} = 0 \tag{B.11}$$

We know that $\gamma = \left[\frac{W_{ref}}{W_0} - 1 - (1+\mu)\right]/\sigma$, where μ and σ are both functions of β; so we can write:

$$\begin{aligned}\frac{d\gamma^*}{dW_0} &= \frac{\partial\gamma^*}{\partial W_0} + \left[\frac{\partial\gamma}{\partial\beta}\right]_{\beta=\beta^*}\frac{d\beta}{dW_0} \\ &= -\frac{1}{\sigma}\frac{W_{ref}}{W_0^2} + \left[\frac{\partial\gamma}{\partial\beta}\right]_{\beta=\beta^*}\frac{d\beta}{dW_0} \end{aligned} \tag{B.12}$$

Using Eq. (B.12) in Eq. (B.11) and gathering terms, we can write:

$$\frac{d\beta^*}{dW_0} = \frac{-\frac{1}{\sigma}\frac{W_{ref}}{W_0^2}\left(\Delta\mu + \gamma^*\left[\frac{d\sigma}{d\beta}\right]_{\beta=\beta^*}\right)}{\frac{d^2\sigma}{d\beta^2} - \left(\Delta\mu + \gamma^*\left[\frac{d\sigma}{d\beta}\right]_{\beta=\beta^*}\right)\left[\frac{d\gamma}{d\beta}\right]_{\beta=\beta^*}}$$

Using Eq (B.6) the denominator of the above expression can be simplified and I write:

$$\frac{d\beta^*}{dW_0} = \frac{-\frac{1}{\sigma}\frac{W_{ref}}{W_0^2}\left(\Delta\mu + \gamma^*\left[\frac{d\sigma}{d\beta}\right]_{\beta=\beta^*}\right)}{\frac{d^2\sigma}{d\beta^2} + \sigma\left[\frac{d\gamma}{d\beta}\right]^2_{\beta=\beta^*}} \tag{B.13}$$

So the denominator is always positive and the sign of the derivative depends on the numerator. Expanding the numeration using expression for γ and $\frac{d\sigma}{d\beta}$ from Eq.(B.7) I can write:

$$\begin{aligned}\frac{d\beta^*}{dW_0} &< 0 \quad \text{if} \quad W_0 < \frac{W_{ref}}{1+\mu_z - \Delta\mu\mathbb{K}} = W_* \quad \text{say} \\ &\geq 0 \quad \text{o/w.}\end{aligned} \tag{B.14}$$

where $\mathbb{K} = \dfrac{\sigma_z^2(1-\beta^*) + \sigma_\epsilon^2}{\beta^*(\sigma_m^2 + \sigma_z^2) - \sigma_z^2}$. The above inequality holds if $\beta^* > \frac{\sigma_z^2}{\sigma_m^2+\sigma_z^2}$ which empirically is ≈ 0.2 and thus plausible. Also if β^* is in the neighborhood of one, then $\mathbb{K} \approx 0.5$, and we can safely assume $\Delta\mu = \mu_m - \mu_z$ to be greater than zero and small[1]. So $W_* < W_{ref}$ but is also very close to reference wealth.

So the optimal beta is increasing when $W_0 < W_*$ and due to the factor $\frac{W_{ref}}{W_0^2}$ in Eq (B.14) the rate of increase in optimal beta grows steeper with larger losses (smaller W_0). By similar reasoning the slope grows flatter with larger profits (larger W_0). We can also write:

$$\lim_{W_0 \to 0} \frac{d\beta^*}{dW_0} = \infty$$
$$\lim_{W_0 \to \infty} \frac{d\beta^*}{dW_0} = 0$$

where $\lim W_0 \to 0$ represents extreme loss and $\lim W_0 \to \infty$ represents extreme profit. ■

[1] $\Delta\mu$ also represents the slope of the security market line.

APPENDIX C

Tables & Figures

C.1 Tables

No. of Stocks	Ret.	Vwret.	Beta	Stdv.	Std. Err.	Vol.
150.81	0.075%	0.08%	0.99	0.41	0.03	0.026

Table C.1.1: **Summary of Stocks**. I compute all statistics for each day of the available data from January 1995 to July 2009. Equal-weighted time series averages are reported. The first column is the average number of stocks traded per day. The second column is the time series average of the equal-weighted daily average return of all stocks – I compute the return of an equal weighted portfolio of stocks each day and then take the time series average. The third column is a similar measure of average return but market capital weighted rather than equal-weighted. The fourth column is the time series average of the daily market capital weighted average beta of all stocks. The fifth column is the time series average of the daily computed cross-sectional standard deviation of the betas of stocks, and the last one is a similar measure but with an average standard error rather than standard deviation. The last column is the average volatility of the available stocks.

No. of Acc.	Avg. No. of Trans.	Avg. Len. of Acc.(yrs.)	Avg. No. of Stocks	Avg. Stdv. of # Stocks	Avg. Trans. Gap (yrs.)	Avg. Stdv. of Trans. Gap
862,726	23.53 (0.49)	5.31 (0.005)	1.98 (0.002)	0.81 (0.001)	.99 (0.002)	1.03 (0.002)
Statistics for the Subsample Used in this Paper						
76,713	80.16 (0.65)	6.89 (0.013)	3.75 (0.01)	1.65 (0.005)	0.26 (0.001)	0.43 (0.002)

Table C.1.2: **Summary Statistics of Individual Investors**. The first column is the number of individual accounts in the data; the second column is the average number of transactions that are carried out by each account holder over the entire period, the third column is the average of observable lengths of the accounts. The fourth column is the average number of stocks simultaneously held in an individual account over its lifespan. The standard deviation of the number of stocks held is measured for each individual. The average standard deviation reported in the fifth column is the average across all individual accounts. The sixth column is the average gap between two transactions made by an individual; the standard deviation of the transaction gap is again measured for each individual. The average standard deviation across all individuals is reported in the final column. The upper row represents the statistics for the entire sample available, while the lower row of the table is the same statistics but for the final sample .

Profit Range ($)	Avg. New Trans.($)	$\Delta\beta$	(std. err.)
-3448 to -1600	7,803.46	6.58%	(0.025)
-1600 to -950	6,802.31	8%	(0.026)
-950 to -625	5,938.63	12.19%	(0.03)
-625 to -435	5,362.54	13.2%	(0.031)
-435 to -305	4,963.16	12.02%	(0.031)
-305 to -220	4,486.50	18.7%	(0.031)
-220 to -156	4,111.86	13.04%	(0.033)
-156 to -110	3,798.44	16.9%	(0.032)
-110 to -75	3,459.07	13.6%	(0.036)
-75 to -49	3,262.13	15.2%	(0.04)
-49 to -28	2,804.46	14.43%	(0.035)
-28 to -11	2,701.87	13.11%	(0.032)
-11 to 0	3,608.72	19.36%	(0.038)
0 to 10	2,581.81	5.89%	(0.033)
10 to 20	2,735.26	4.21%	(0.03)
20 to 28	2,812.49	4.33%	(0.037)
28 to 36	2,849.04	12.18%	(0.037)
36 to 45	3,287.50	8.8%	(0.034)
45 to 54	3,219.62	1.22%	(0.034)
54 to 63	2,989.87	4.49%	(0.033)
63 to 72	3,416.57	-0.45%	(0.03)
72 to 84	3,400.98	1.59%	(0.035)
84 to 95	3,751.87	5.64%	(0.033)
95 to 105	3,597.32	-2.75%	(0.032)
105 to 119	3,741.09	3.75%	(0.035)
119 to 130	4,265.39	2.78%	(0.027)
130 to 145	3,712.48	2.01%	(0.031)
145 to 160	4,265.39	-2.32%	(0.03)
160 to 176	3,712.48	6.5%	(0.029)
176 to 196	4,086.83	5.69%	(0.031)
196 to 212	4,479.65	3.48%	(0.028)
212 to 234	4,423.03	3.73%	(0.027)
234 to 256	4,752.44	1.29%	(0.029)
256 to 284	4,586.37	1.98%	(0.027)
284 to 312	4,836.31	7.08%	(0.027)
312 to 346	5,356.10	3.68%	(0.027)
346 to 385	5,023.96	4.34%	(0.026)
385 to 427	5,314.16	6.68%	(0.027)
427 to 480	5,620.90	5.3%	(0.025)
480 to 538	5,574.97	2.99%	(0.025)
538 to 605	6,255.16	4.78%	(0.023)
605 to 700	6,434.87	3.75%	(0.023)

Table C.1.3: **Choice of Higher Beta as a Function of Profit (Low Skill Individuals).** This table contains the data that goes into the plot of Fig. C.2.3. The first column is the range of realized profit (loss) from the last trade, while the second column represents the increase in choice of beta in buying the new stock. The third column is the standard errors of estimated beta difference. some of the rows have been left out lack of space and will me made available in online appendix.

$\Delta\beta$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\mathcal{D}_{\Pi<0}$	0.0489	0.00847	0.0260	0.0384	0.0294	0.0568	0.0409	0.0217	0.0577	0.0425	0.0269
	(16.79)	(4.55)	(2.66)	(4.17)	(5.75)	(9.24)	(9.36)	(6.76)	(21.15)	(23.13)	(15.93)
Π	0.00952	-0.00529	-0.00569	-0.00750	-0.00696	0.0112	0.00390	0.0000651	0.00406	-0.00292	-0.00197
	(6.00)	(-4.46)	(-1.94)	(-2.56)	(-2.09)	(4.95)	(2.81)	(0.06)	(2.79)	(-3.12)	(-2.76)
$\mathcal{D}_{\Pi<0} \times \Pi$	-0.0309	0.0184	-0.000617	0.00932	0.0141	-0.0486	-0.0125	-0.00452	-0.0251	0.00808	0.00619
	(-3.60)	(4.41)	(-0.07)	(1.72)	(2.13)	(-2.68)	(-1.04)	(-1.03)	(-2.45)	(3.30)	(3.55)
σ_{old}	-15.64	-1.054	-0.239	5.210	-1.759	-12.98	2.822	7.342	-8.539	3.891	-1.907
	(-41.24)	(-4.95)	(-0.26)	(5.72)	(-2.40)	(-6.84)	(1.50)	(3.71)	(-73.60)	(31.20)	(-13.05)
$\Delta IVOL$	-7.148	-0.548	1.540	1.537	-1.369	-6.511	4.747	8.021	-3.623	2.072	-1.079
	(-28.65)	(-2.47)	(1.07)	(1.69)	(-1.33)	(-2.64)	(2.75)	(3.92)	(-26.35)	(15.58)	(-7.74)
β_{old}		-0.723		-0.458	-0.621		-0.750	-0.904		-0.684	-0.785
		(-218.92)		(-7.44)	(-16.87)		(-25.52)	(-54.15)		(-219.58)	(-282.89)
Constant	0.493	0.723	0.0457	0.291	0.522	0.411	0.621	0.704	0.281	0.530	0.747
	(43.88)	(112.60)	(1.65)	(4.64)	(6.91)	(7.46)	(9.70)	(3.69)	(81.27)	(129.77)	(25.24)
Fx. Eff.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
	–	–	–	–	Year	–	–	Year	–	–	Year
S.E. Clust.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
Obs.	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436
Adj. R^2	0.113	0.425	0.195	0.269	0.348	0.280	0.665	0.739	0.080	0.361	0.437

t statistics in parentheses

Table C.1.4: **Regressions with Beta Difference as Dependent Variable.** The dependent variable in all regressions is the difference is beta, $\Delta\beta = \beta_{new} - \beta_{old}$. The main dependent variable of interest is the dummy variable $\mathcal{D}_{\{\Pi<0\}}$ that takes the value of one when holding period return Π is negative. The return variable Π and an interaction term $\mathcal{D}_{\{\Pi<0\}} \times \Pi$ are included to absorb any linear trend that is allowed to be different in the profit and loss domains. The volatility of the old stock, σ_{old}, change in idiosyncratic volatility $\Delta IVOL$ and the beta of the old stock β_{old} is also controlled for. Additionally fixed effect(s) are also absorbed and standard errors are clustered by mentioned variables. 'Date' implies the date corresponding to the new stock bought, 'Old(New) St' implies the old(new) stock, 'Inv.' implies individual investors and 'Year' corresponds to the year in which the new stock is bought.

$\Delta \log \beta$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\mathcal{D}_{\Pi<0}$	0.0690	0.0138	0.0329	0.0508	0.0401	0.0863	0.0659	0.0399	0.0806	0.0605	0.0397
	(15.43)	(4.20)	(2.94)	(4.44)	(5.41)	(10.82)	(12.15)	(8.13)	(20.57)	(19.66)	(13.61)
Π	0.0155	-0.00615	-0.00866	-0.0110	-0.0105	0.0219	0.00950	0.00232	0.00758	-0.00285	-0.00249
	(5.35)	(-4.04)	(-1.94)	(-2.61)	(-2.20)	(4.79)	(3.40)	(1.09)	(3.26)	(-1.98)	(-2.14)
$\mathcal{D}_{\Pi<0} \times \Pi$	-0.0427	0.0303	0.00375	0.0172	0.0226	-0.0720	-0.0168	-0.00476	-0.0326	0.0163	0.0151
	(-3.74)	(3.87)	(0.28)	(2.11)	(2.44)	(-3.09)	(-1.21)	(-0.83)	(-2.68)	(2.64)	(2.91)
σ_{old}	-16.39	3.957	-0.0895	7.827	0.821	-13.54	6.177	15.34	-9.361	7.892	3.024
	(-26.93)	(11.29)	(-0.06)	(5.54)	(0.36)	(-6.75)	(2.81)	(7.35)	(-53.62)	(42.21)	(12.46)
$\Delta \log(IVOL)$	0.0512	0.270	0.350	0.330	0.227	0.114	0.458	0.649	0.160	0.341	0.257
	(4.66)	(24.61)	(5.01)	(6.89)	(4.30)	(1.36)	(6.25)	(8.37)	(23.41)	(51.45)	(36.28)
β_{old}		-1.057		-0.655	-0.881		-1.067	-1.296		-0.993	-1.143
		(-131.83)		(-4.97)	(-7.83)		(-31.43)	(-45.65)		(-187.60)	(-223.08)
Constant	0.520	0.894	0.0520	0.404	0.711	0.429	0.819	0.937	0.310	0.705	1.000
	(28.98)	(83.26)	(1.29)	(3.17)	(7.66)	(7.36)	(9.97)	(5.59)	(59.36)	(114.52)	(25.48)
Fx. Eff.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
	–	–	–	–	Year	–	–	Year	–	–	Year
S.E. Clust.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
Obs.	546448	546448	546448	546448	546448	546448	546448	546448	546448	546448	546448
Adj. R^2	0.080	0.334	0.206	0.263	0.311	0.230	0.537	0.597	0.070	0.298	0.346

t statistics in parentheses

Table C.1.5: **Regressions with Log Ratio of Beta as Dependent Variable.** The dependent variable in all regressions is the log ratio or the difference in the log beta of the new stock from that of the old stock $\Delta \log(\beta) = \log(\beta_{new}/\beta_{old}) = \log(\beta_{new}) - \log(\beta_{old})$. The main dependent variable of interest is the dummy variable $\mathcal{D}_{\{\Pi<0\}}$ that takes the value of one when holding period return Π is negative. The return variable Π and an interaction term $\mathcal{D}_{\{\Pi<0\}} \times \Pi$ are included to absorb any linear trend that is allowed to be different in the profit and loss domains. The volatility of the old stock, σ_{old}, change in log of the idiosyncratic volatility $\Delta \log(IVOL)$ and the beta of the old stock β_{old} is also controlled for. Additionally fixed effect(s) are also absorbed and standard errors are clustered by mentioned variables. 'Date' implies the date corresponding to the new stock bought, 'Old(New) St' implies the old(new) stock, 'Inv.' implies individual investors and 'Year' corresponds to the year in which the new stock is bought.

$\Delta IVOL$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\mathcal{D}_{\Pi<0}$	0.000107	0.000260	0.000228	0.000216	0.000123	-0.000280	-0.000412	-0.000132	-0.000185	-0.000198	-0.0000925
	(1.33)	(3.78)	(1.59)	(1.65)	(0.85)	(-1.84)	(-3.23)	(-1.76)	(-2.98)	(-3.75)	(-2.03)
Π	-0.0000440	0.0000338	-0.000152	-0.000150	-0.0000285	-0.000436	-0.000385	-0.0000863	-0.000337	-0.000274	-0.0000646
	(-1.81)	(1.29)	(-1.64)	(-1.62)	(-0.78)	(-5.37)	(-5.73)	(-3.63)	(-4.80)	(-4.71)	(-2.13)
$\mathcal{D}_{\Pi<0} \times \Pi$	0.00101	0.000728	0.000900	0.000892	0.000895	0.00129	0.00107	0.000489	0.000882	0.000628	0.000332
	(2.64)	(2.31)	(2.20)	(2.19)	(2.28)	(3.87)	(3.86)	(3.19)	(3.13)	(3.12)	(2.27)
σ_{old}	-0.785	-0.824	-0.321	-0.325	-0.714	-0.567	-0.615	-0.926	-0.561	-0.623	-0.872
	(-170.14)	(-180.90)	(-5.86)	(-6.79)	(-21.24)	(-24.20)	(-30.18)	(-80.65)	(-145.52)	(-167.23)	(-262.19)
$\Delta\beta$	-0.00273	-0.000314	0.000754	0.000827	-0.000733	-0.00244	0.00349	0.00444	-0.00150	0.00118	-0.000573
	(-32.48)	(-2.45)	(1.07)	(1.63)	(-1.37)	(-3.68)	(2.45)	(3.02)	(-24.92)	(16.56)	(-7.50)
β_{old}		0.00483		0.000371	0.00222		0.00804	0.0104		0.00588	0.00472
		(36.08)		(0.30)	(4.42)		(6.24)	(9.29)		(73.19)	(55.31)
Constant	0.0234	0.0201	0.00937	0.00916	0.0178	0.0170	0.0110	0.0161	0.0167	0.0132	0.0204
	(169.71)	(143.71)	(5.71)	(4.45)	(15.24)	(24.32)	(7.73)	(7.45)	(144.80)	(125.74)	(45.14)
Fx. Eff.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
	–	–	–	–	Year	–	–	Year	–	–	Year
S.E. Clust.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
Obs.	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436	554,436
Adj. R^2	0.409	0.426	0.314	0.314	0.391	0.531	0.570	0.748	0.338	0.364	0.479

t statistics in parentheses

Table C.1.6: **Regressions with Idiosyncratic Volatility Difference as Dependent Variable.** The dependent variable in all regressions is the difference is idiosyncratic volatility of the new stock from the old stock $\Delta IVOL = IVOL_{new} - IVOL_{old}$. The main dependent variable of interest is the dummy variable $\mathcal{D}_{\{\Pi<0\}}$ that takes the value of one when holding period return Π is negative. The return variable Π and an interaction term $\mathcal{D}_{\{\Pi<0\}} \times \Pi$ are included to absorb any linear trend that is allowed to be different in the profit and loss domains. The volatility of the old stock, σ_{old}, change in idiosyncratic volatility $\Delta IVOL$ and the beta of the old stock β_{old} is also controlled for. Additionally, fixed effect(s) are also absorbed, and standard errors are clustered by mentioned variables. 'Date' implies the date corresponding to the new stock bought, 'Old(New) St' implies the old(new) stock, 'Inv.' implies individual investors and 'Year' corresponds to the year in which the new stock is bought.

	$\Delta\beta_z$		ΔMOM_z		ΔSKW_z		$\Delta MAX5_z$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathcal{D}_{\Pi<0}$	0.0888	0.0931	0.0428	0.0269	-0.0114	0.00203	-0.000168	-0.000315
	(4.20)	(6.21)	(6.62)	(3.13)	(-1.75)	(0.33)	(-0.72)	(-1.34)
Π	-0.00594	-0.00732	-0.00779	-0.00796	0.000875	-0.00166	-0.00000130	-0.0000730
	(-1.97)	(-1.03)	(-3.31)	(-3.00)	(0.77)	(-1.02)	(-0.09)	(-1.59)
$\beta_{old,z}$	-0.813	-0.792						
	(-49.48)	(-39.75)						
ΔSKW_z		-0.274						
		(-3.71)						
ΔMOM_z		0.0958						
		(2.13)						
$MOM_{old,z}$			-0.725	-0.682				
			(-34.98)	(-30.83)				
$SKW_{old,Z}$					-0.914	-0.894		
					(-73.21)	(-57.20)		
$MAX5_{old}$							-0.769	-0.743
							(-38.94)	(-34.24)
$\Delta\beta_z$				0.0238		-0.0490		0.000637
				(2.19)		(-3.67)		(2.04)
Constant	2.945	2.903	0.783	0.359	0.235	0.301	0.0256	0.0259
	(3.17)	(3.35)	(1.58)	(1.02)	(1.50)	(0.77)	(8.44)	(11.25)
Obs.	554,436	553,959	570,630	553,959	605,297	554,434	611,138	554,436
$Adj.(R^2)$	0.437	0.451	0.406	0.437	0.552	0.567	0.426	0.436

t statistics in parentheses, Ind. and Yr. Fixed Effects, Std. Err. clustered by date

Table C.1.7: **Regressions with Difference of Stock Characteristics correlated with Beta as Dependent Variable.** The dependent variables are differences in different stock characteristics scared by the scross sectional standard deviation of the characteristics. The first two regressions have $\Delta\beta_z$ as the dependent variable, which is the difference in the beta of the new and the old stock scaled by cross-sectional standard deviation of beta. Regressions (3) and (4) have change in momentum as the dependent variable, where momentum is computed as past twelve month's cumulative return excluding the previous month. Regressions (5) and (6) have scaled change in skewness as the dependent variable while the last two regressions have the standard deviation scaled change in max factor as the dependent variable.

$\Delta\beta$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathcal{D}_{\Pi<0}$	0.0498	0.0484	0.0605	0.0289	0.0290	0.0177	0.0181
	(6.51)	(6.99)	(7.09)	(5.06)	(4.98)	(3.49)	(6.10)
Π		0.00205	0.00930	-0.00584	-0.00588	-0.00639	-0.000130
		(1.36)	(4.06)	(-3.05)	(-3.00)	(-3.34)	(-0.12)
$\mathcal{D}_{\Pi<0} \times \Pi$		-0.0111	-0.0386	0.0145	0.0157	0.0159	-0.00436
		(-1.54)	(-2.53)	(2.71)	(2.94)	(3.12)	(-1.01)
σ_{old}			-9.754	-1.220	-2.270	-2.336	7.334
			(-6.23)	(-1.06)	(-0.48)	(-0.51)	(3.70)
β_{old}				-0.663	-0.657	-0.644	-0.898
				(-29.02)	(-16.39)	(-15.52)	(-51.75)
$\Delta IVOL$					-1.365	-4.711	6.941
					(-0.30)	(-0.94)	(3.23)
$\Delta MAX5$						2.630	0.859
						(3.48)	(2.47)
Constant	-0.187	-0.187	0.0725	0.561	0.584	0.578	0.699
	(-0.85)	(-0.85)	(0.28)	(2.03)	(1.69)	(1.71)	(3.70)
Fixed Effect	Year –	Year –	Year –	Year –	Year –	Year –	Year, Stock
Obs.	554,440	554,436	554,436	554,436	554,436	554,436	554,436
Adj. R^2	0.007	0.007	0.045	0.341	0.342	0.355	0.740

t statistics in parentheses

Table C.1.8: **Regressions with Different Control Variables.** The dependent variable in all regressions is the difference is beta, $\Delta\beta = \beta_{new} - \beta_{old}$. The main dependent variable of interest is the dummy variable $\mathcal{D}_{\{\Pi<0\}}$ that takes the value of one when holding period return Π is negative. In regression (2), the return variable Π and an interaction term $\mathcal{D}_{\{\Pi<0\}} \times \Pi$ are included to absorb any linear trend that is allowed to be different in the profit and loss domains. The volatility of the old stock, σ_{old} is further controlled for in regression (3) while the beta of the old stock β_{old} in included in regression (4). Regression (5) incrementally adds the difference in idiosyncratic volatility $\Delta IVOL$ to the list of controls. Regression (6) includes the change in the MAX factor. All the regressions include year level fixed effects where year corresponds to the year the new stock is bought. Regression (7) includes stock level fixed effects, where the stock corresponds to the new stock bought. All standard errors are computed using stock level clustering.

	$\Delta\beta_{ws}$						$\Delta IVOL_{ws}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathcal{D}_{\Pi<0}$	0.0441	0.0195	0.0189	0.00868	0.0170	0.0121	0.000202	-0.000111
	(14.60)	(9.07)	(9.22)	(4.05)	(10.13)	(8.65)	(1.85)	(-2.00)
Π	0.000552	0.000233	0.000205	-0.0000130	0.000261	0.000188	-0.00000198	0.00000306
	(7.97)	(2.40)	(1.77)	(-0.08)	(4.36)	(4.41)	(-0.82)	(1.84)
$\beta_{old,ws}$		-0.625	-0.610	-0.681	-0.808	-0.854	-0.00125	-0.00291
		(-191.11)	(-179.30)	(-260.98)	(-289.46)	(-365.64)	(-7.96)	(-12.25)
$\sigma_{old,ws}$			-1.251	-2.901	-2.344	-3.433	-0.867	-0.944
			(-19.50)	(-68.56)	(-37.96)	(-66.10)	(-235.44)	(-246.46)
$\Delta IVOL_{ws}$			-2.648	-3.451	-2.959	-3.515		
			(-48.13)	(-83.32)	(-55.22)	(-74.98)		
$\Delta\beta_{ws}$							-0.00660	-0.00715
							(-32.26)	(-29.19)
Const.	0.0188	0.470	0.498	0.605	0.674	0.861	0.0282	0.0296
	(8.95)	(200.33)	(166.78)	(284.48)	(243.45)	(31.22)	(198.65)	(42.08)
Date F.E.				✓			✓	
Ind. F.E.					✓	✓		✓
Yr. F.E.						✓		✓
Obs.	617656	617656	617656	617656	617656	617656	617656	617656
Adj. R^2	0.003	0.289	0.300	0.348	0.428	0.457	0.499	0.556

t statistics in parentheses. Standard Error computed after individual level clustering.

Table C.1.9: **Regression with Difference in Whole Sample Beta as Dependent.** The dependent variable in regressions (1) through (6) is $\Delta\beta_{ws} = \beta_{ws,new} - \beta_{ws,old}$ while that in (7) and (8) is $\Delta IVOL_{ws} = IVOL_{ws,new} - IVOL_{ws,old}$. β_{ws} and $IVOL_{ws}$ are computed from the whole sample of stock returns from 1995 to 2009, rather than from past data on a rolling basis. $\mathcal{D}_{\{\Pi<0\}}$ is the dummy that takes value 1 when holding period return is negative, $\Pi < 0$. Π is included in the regression to absorb any trend. For various regressions, I control for the volatility and beta of the old stock and also the difference in the IVOL or difference in betas where applicable. For different regressions, date, individual and year level fixed effects are also used; but only the individual and year level can be used together. For all the regressions standard errors are computed by clustering at the individual level.

$\Delta\beta$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\mathcal{D}_{\Pi<0}$	0.0320	0.00470	0.0202	0.0363	0.0230	0.0574	0.0455	0.0230	0.0458	0.0476	0.0302
	(3.28)	(0.60)	(1.45)	(2.30)	(2.00)	(7.58)	(6.28)	(4.71)	(4.14)	(5.32)	(3.63)
Π	0.0139	-0.00808	-0.00649	-0.00997	-0.00958	0.0190	0.00488	0.00131	0.00897	-0.00568	-0.00588
	(2.00)	(-1.90)	(-1.07)	(-1.58)	(-1.53)	(2.33)	(0.99)	(0.41)	(1.33)	(-0.80)	(-0.90)
$\mathcal{D}_{\Pi<0} \times \Pi$	-0.166	0.0452	0.0229	0.0775	0.0530	-0.179	0.00896	0.00259	-0.136	0.118	0.0888
	(-4.94)	(1.72)	(0.58)	(2.22)	(1.64)	(-3.77)	(0.28)	(0.13)	(-3.72)	(3.87)	(3.07)
σ_{old}	-24.11	2.679	0.586	7.942	1.555	-17.48	4.131	11.49	-12.90	6.390	1.845
	(-33.15)	(4.93)	(0.45)	(7.08)	(1.09)	(-10.09)	(1.59)	(5.56)	(-26.92)	(12.95)	(2.78)
$\Delta IVOL$	-7.785	2.994	5.464	5.174	2.048	-5.720	7.384	12.11	-1.810	4.969	2.485
	(-14.87)	(6.58)	(2.44)	(3.52)	(1.25)	(-2.55)	(3.99)	(5.68)	(-3.19)	(9.22)	(4.22)
β_{old}		-0.769		-0.544	-0.665		-0.809	-0.966		-0.784	-0.850
		(-96.21)		(-7.34)	(-14.58)		(-39.50)	(-59.97)		(-79.40)	(-87.56)
Constant	0.716	0.654	0.0376	0.304	0.468	0.523	0.634	0.593	0.400	0.555	0.598
	(35.22)	(46.62)	(1.00)	(4.83)	(7.91)	(11.00)	(9.42)	(3.78)	(29.81)	(42.97)	(11.93)
Fx. Eff.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
	–	–	–	–	Year	–	–	Year	–	–	Year
S.E. Clust.	Date	Date	Old St.	Old St.	Old St.	New St.	New St.	New St.	Inv.	Inv.	Inv.
Obs.	42,464	42,464	42,464	42,464	42,464	42,464	42,464	42,464	42,464	42,464	42,464
Adj. R^2	0.180	0.459	0.221	0.303	0.364	0.336	0.714	0.779	0.097	0.398	0.454

t statistics in parentheses

Table C.1.10: **Regressions with Beta Difference as Dependent Variable using Institutional Investor Data.** The dependent variable in all regressions is the difference is beta, $\Delta\beta = \beta_{new} - \beta_{old}$. The main dependent variable of interest is the dummy variable $\mathcal{D}_{\{\Pi<0\}}$ that takes the value of one when holding period return Π is negative. The return variable Π and an interaction term $\mathcal{D}_{\{\Pi<0\}} \times \Pi$ are included to absorb any linear trend that is allowed to be different in the profit and loss domains. The volatility of the old stock, σ_{old}, change in idiosyncratic volatility $\Delta IVOL$ and the beta of the old stock β_{old} is also controlled for. Additionally, fixed effect(s) are also absorbed, and standard errors are clustered by mentioned variables. 'Date' implies the date corresponding to the new stock bought, 'Old(New) St' implies the old(new) stock, 'Inv.' implies individual investors and 'Year' corresponds to the year in which the new stock is bought. The data used here is only from individuals categorized as 'non-individuals'.

$\Delta\beta$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathcal{D}_{\Pi<0}$	0.0490	0.0478	0.0616	0.0299	0.0301	0.0183	0.0185
	(6.98)	(7.53)	(7.69)	(5.39)	(5.19)	(3.58)	(6.05)
$\mathcal{D}_{\Pi<0} \times \mathbb{I}$	0.0143	0.0141	-0.00972	-0.0245	-0.0263	-0.0243	-0.00886
	(0.76)	(0.76)	(-0.59)	(-2.02)	(-2.84)	(-2.71)	(-1.86)
Π		0.00198	0.00959	-0.00598	-0.00602	-0.00650	-0.000103
		(1.32)	(4.15)	(-3.10)	(-3.03)	(-3.37)	(-0.09)
$\mathcal{D}_{\Pi<0} \times \Pi$		-0.0103	-0.0404	0.0153	0.0164	0.0165	-0.00430
		(-1.46)	(-2.56)	(2.85)	(3.02)	(3.20)	(-0.95)
σ_{old}			-10.16	-1.185	-2.068	-2.128	7.627
			(-6.26)	(-1.02)	(-0.43)	(-0.46)	(3.85)
β_{old}				-0.665	-0.660	-0.646	-0.902
				(-29.07)	(-16.09)	(-15.22)	(-52.60)
$\Delta IVOL$					-1.146	-4.596	7.194
					(-0.24)	(-0.89)	(3.36)
$\Delta MAX5$						2.726	0.891
						(3.50)	(2.51)
Constant	-0.163	-0.163	0.103	0.554	0.573	0.567	0.682
	(-0.79)	(-0.79)	(0.42)	(2.09)	(1.71)	(1.73)	(3.70)
Fixed Effect	Year –	Year –	Year –	Year –	Year –	Year –	Year, Stock
Obs.	596,913	596,900	596,900	596,900	596,900	596,900	596,900
Adj. R^2	0.007	0.007	0.047	0.343	0.343	0.357	0.743

t statistics in parentheses

Table C.1.11: **Pooled Regressions of Individual and Institutional Investor Data with Different Control Variables.** The dependent variable in all regressions is the difference is beta, $\Delta\beta = \beta_{new} - \beta_{old}$. The main dependent variable of interest is the dummy variable $\mathcal{D}_{\Pi<0}$ that takes the value of one when holding period return Π is negative. In addition, there is an interaction variable $\mathcal{D}_{\Pi<0} \times \mathbb{I}$ where $\mathbb{I}$ is an indicator variable hat takes the value of one if the data is from an institute as opposed to an individual. In regression (2), the return variable Π and an interaction term $\mathcal{D}_{\Pi<0} \times \Pi$ are included to absorb any linear trend that is allowed to be different in the profit and loss domains. The volatility of the old stock, σ_{old} is further controlled for in regression (3) while the beta of the old stock β_{old} in included in regression (4). Regression (5) incrementally adds the difference in idiosyncratic volatility $\Delta IVOL$ to the list of controls. Regression (6) includes the change in the MAX factor. All the regressions include year level fixed effects where year corresponds to the year the new stock is bought. Regression (7) includes stock level fixed effects, where the stock corresponds to the new stock bought. All standard errors are computed using stock level clustering.

	$\Delta\beta$					$\Delta IVOL$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathcal{D}_{\Pi<0}$	0.0319	0.0614	0.0168	0.0155	0.0124	0.000107	0.0000806
	(4.30)	(6.51)	(2.47)	(2.27)	(1.84)	(0.67)	(0.50)
Π	-0.00139	-0.00149	-0.000298	-0.000253	-0.000582	0.00000401	0.00000158
	(-1.61)	(-1.58)	(-0.50)	(-0.43)	(-0.94)	(0.20)	(0.08)
$\mathcal{D}_{\Pi<0} \times \Pi$	0.0413	0.102	-0.0102	-0.0231	-0.00987	0.00102	0.000804
	(1.46)	(2.96)	(-0.44)	(-0.99)	(-0.43)	(1.51)	(1.21)
β_{old}			-0.903	-0.901	-0.912		0.00229
			(-180.45)	(-178.41)	(-184.39)		(11.80)
σ_{old}				-0.464	1.613	-0.920	-0.935
				(-2.62)	(4.22)	(-90.67)	(-88.88)
$\Delta IVOL$					2.459		
					(7.39)		
$\Delta\beta$							0.00138
							(7.72)
Constant	0.0116	0.00564	1.245	1.257	1.146	0.0292	0.0279
	(3.79)	(2.20)	(173.71)	(150.23)	(71.34)	(94.26)	(65.68)
Individual F.E.		✓	✓	✓	✓		✓
Year F.E.					✓		✓
Observations	149,196	149,196	149,196	149,196	149,196	149,196	149,196
Adjusted R^2	0.000	0.004	0.440	0.440	0.448	0.444	0.451

t statistics in parentheses. Standard Error computed after individual level clustering.

Table C.1.12: **Regressions Using US Investor Data with Different Control Variables.** The data is a set of individual investors' transactions, obtained from a large US brokerage firm. This dataset is the same one used in *Barber and Odean* (2000). For the first five regressions, the dependent variable is the difference is beta, $\Delta\beta = \beta_{new} - \beta_{old}$. For the next two regressions, the dependent variable is the difference in idiosyncratic volatility $\Delta IVOL = IVOL_{new} - IVOL_{old}$. The main dependent variable of interest is the dummy variable $\mathcal{D}_{\Pi<0}$ that takes the value of one when holding period return Π is negative. The second regression absorbs individual level fixed effect. The beta of the old stock is controlled for in regression (3) while additionally the volatility of the old stock is controlled for in regression (4). Regression (5) incrementally adds the difference in idiosyncratic volatility $\Delta IVOL$ to the list of controls along with year fixed effect. The last two regressions check whether there remains some jump in the residual volatility after controlling for some of the usual characteristics..

$\Delta\beta$	Sophistication Wealth	Diversity	Frequency	Time Gap <1Q	1Q-2Q	>2Q
$\mathcal{D}_{\Pi<0}$	0.0268	0.0358	0.0389	0.0264	0.0167	0.00600
	(15.86)	(11.04)	(5.37)	(15.20)	(0.85)	(0.19)
$\mathcal{D}_{\Pi<0} \times \mathcal{D}_{wlt}$	-0.0267					
	(-1.77)					
$\mathcal{D}_{\Pi<0} \times \mathcal{D}_{div}$		-0.0125				
		(-3.30)				
$\mathcal{D}_{\Pi<0} \times \mathcal{D}_{frq}$			-0.0130			
			(-1.75)			
β_{old}	-0.785	-0.784	-0.785	-0.779	-0.913	-0.939
	(-282.92)	(-282.85)	(-282.89)	(-270.43)	(-33.59)	(-20.46)
σ_{old}	-1.924	-1.926	-1.925	-1.869	-2.573	-2.261
	(-13.18)	(-13.20)	(-13.19)	(-12.31)	(-1.40)	(-0.49)
$\Delta IVOL$	-1.077	-1.076	-1.077	-0.951	-2.188	-2.750
	(-7.72)	(-7.72)	(-7.72)	(-6.50)	(-1.30)	(-0.63)
Constant	0.747	0.747	0.747	0.748	0.857	0.631
	(25.25)	(25.25)	(25.24)	(23.74)	(2.47)	(0.96)
Fixed Effect	Year Inv.	Year Inv.	Year Inv.	Year Inv.	Year Inv.	Year Inv.
Observations	554,440	554,440	554,440	516,618	27,112	10,710
Adjusted R^2	0.437	0.437	0.437	0.431	0.673	0.831

t statistics in parentheses, standard errors clustered at investor level.

Table C.1.13: **Acquisition Effect with Different Investor Sophistication and Time Gaps.** The dependent variable in all six regressions is $\Delta\beta = \beta_{new} - \beta_{old}$. The main independent variable of interest is $\mathcal{D}_{\{\Pi<0\}}$, which is the dummy that takes value 1 when the total return is negative, $\Pi < 0$. The entire sample corresponds to the 'larger sample' described in data section where the date between the selling of old stock and buying of the new stock, defined as the date gap, is allowed to be up to one year, 250 trading days. The first three regressions identify variation in the acquisition effect based on 'sophistication' of investors. The dummy variables $\mathcal{D}_{wlt}$, $\mathcal{D}_{div}$ and $\mathcal{D}_{frq}$ corresponds to one if the individual is determined to have higher observable wealth, more diversified portfolio or the individual is a more frequent trader. Larger wealth, more diversified portfolio and higher frequency of trade are assumed to be proxies of investor sophistication. The sophistication dummy variable is interacted with the profit dummy $\mathcal{D}_{\{\Pi<0\}} \times \mathcal{D}_*$ to estimate the effect difference. In the last three regressions, the sample is split into three groups. The first sample is where data gap with within one quarter or 60 trading days. The second sample is where the date gap is between one and two quarters, and the third split is for one is more than two quarters. The date gap being the time between the old stock being sold and the new stock being bought. The control variables include beta and volatility of the old stock and difference in idiosyncratic volatility between new and old stock. The fixed effects include individual-level fixed effect and year fixed effect. The values in parenthesis are t-statistics, and all standard errors are estimated after clustering at the investor level.

Group	Obs. Prob.	Bench. Prob	Diff
all	0.58	0.09	0.48
	(0.0003)	(0.00005)	(0.00029)
Stock	0.4	0.11	0.29
	(0.00172)	(0.00074)	(0.00177)
Ind.	0.45	0.06	0.38
	(0.00057)	(0.00006)	(0.00057)
Ind. & Stock	0.51	0.09	0.42
	(0.0004)	(0.00005)	(0.0004)

standard error in parentheses.

Table C.1.14: **Comparing Observed & Benchmark Probabilities.** Each buy observation in the Finnish data has two additional measures. First is a dummy variable X that indicates whether the stock bought is among the familiarity set of the individual at that time. The second measure is a benchmark probability P that a random stock bought would mechanically be part of the familiarity set. The benchmark probability is computed such that the probability of choosing any stock is proportional to the trading volume of that stock on that day. The average of the dummy variable is thus the observed probability and the average of the benchmark. Under the null, the dummy X is an outcome of a Bernoulli distribution with probability P. I present the average X, the average P and the average $X - P$. The first row corresponds to average taken over the entire sample. For the second row, the three averages are calculated first for each stock and then averaged over all stocks. This gives each stock equal weight and ensures that the result is not driven by a single stock that trades the most. The third row similarly is averaged for individuals first and the final row is averaged first for each combination to individual and stock.

Cross-Sec Stdv		
All Stocks	Fam. Sets	Diff
0.40	0.35	-0.05
(0.0015)	(0.002)	(0.0015)

standard error in parentheses.

Table C.1.15: **Cross-Sectional Dispersion of Betas.** Betas are estimated from backward looking daily returns of past one year for each Finnish stock. Each day the cross-sectional standard deviation of beta is estimated from all stocks traded that day. The average of all these standard deviations is presented as the first value. Each day, a familiarity set can be constructed for each individual in the Finnish transaction sample. The cross-sectional standard deviation of stocks within each familiarity set is estimated. This estimates when averaged across all individuals on a particular date should ideally provide an unbiased estimate of the cross sectional standard deviation of all available stocks. Time series average of the cross sectional standard deviation measured within familiarity sets is presented as the second value. The third value is the average of the difference of the two measures at each date. The standard errors are presented in parenthesis.

$\Delta\beta$	(1)	(2)	(3)	(4)	(5)	(6)
$\mathcal{D}_{\Pi<0}$	0.0576	0.0494	0.0431	0.0351	0.0117	0.0244
	(12.45)	(13.55)	(11.36)	(9.67)	(3.58)	(7.08)
$\mathcal{D}_{fam}$	0.001	0.002	0.002	0.002	0.002	0.002
	(0.41)	(0.49)	(0.49)	(0.51)	(0.49)	(0.50)
$\mathcal{D}_{fam} \times \mathcal{D}_{\Pi<0}$	0.0139	0.00707	0.00746	0.00866	0.000693	0.000972
	(2.93)	(1.54)	(1.64)	(1.95)	(0.18)	(0.24)
β_{old}		-0.519	-0.559	-0.686	-0.743	-0.789
		(-108.44)	(-114.44)	(-148.51)	(-235.68)	(-186.63)
σ_{old}			3.929	3.306	-0.691	-1.847
			(12.22)	(10.85)	(-3.25)	(-6.66)
$\Delta IVOL$			2.175	1.967	-0.251	-0.868
			(8.55)	(8.16)	(-1.15)	(-3.75)
Constant	-0.0617	0.339	0.263	0.390	0.583	0.710
	(-17.77)	(59.96)	(31.85)	(47.87)	(79.54)	(16.70)
Fx. Eff.				Inv.	Year	Inv. Year
Observations	488,472	488,472	488,472	488,472	488,472	488,472
Adjusted R^2	0.015	0.269	0.276	0.380	0.444	0.454

t statistics in parentheses, standard errors clustered by date of new stock bought

Table C.1.16: **Checking Interaction of Familiarity with Acquisition Effect.** The dependent variable in all six regressions in this table is change in beta. The set of covariates are standard from the previous regressions except for the indicator representing familiarity and its interaction with the negative return dummy. The familiarity indicator$\mathcal{D}_{fam}$ takes the value of one when the stock bought is familiar ti the investor and is zero otherwise.

market return	#	$\overline{r^{BAB}}$	(std. err.)	Stdv. σ	Sharpe Ratio
All	1,063	0.785%	(0.167%)	5.427%	0.501
-ve	407	-1.553%	(0.215%)	4.344%	-1.238
-ve^{+1}	407	0.070%	(0.251%)	5.062%	0.048
+ve	656	2.235%	(0.216%)	5.527%	1.400

Table C.1.17: **Monthly Adjusted Betting Against Beta.** Returns on the betting against beta strategy for different market return months. The first column indicated what the sign of market return was. $-ve^{+1}$ implies that the previous month was a negative market return month. The second column represents the number of months in the time series sample. In the third column, $\overline{r^{BAB}}$ is the time series average of the monthly betting against return. The fourth and the fifth column lists the standard error and the standard deviation of the monthly average return. The last column is the Sharpe ratio which is annualized.

Port.No.	*Intercept*	*Mkt.Ret.*	*Lag(Mret)*	*lag(Ret)*
0	0.0024 (0.0001)	0.0335 (0.0142)	0.0375 (0.0158)	-0.0244 (0.0132)
1	0.0012 (0.0001)	0.1496 (0.0095)	0.0272 (0.0107)	0.0891 (0.0137)
2	0.001 (0)	0.2353 (0.0076)	0.0348 (0.0088)	0.0372 (0.0131)
3	0.0009 (0)	0.299 (0.0073)	0.0016 (0.0088)	0.0956 (0.0128)
4	0.0009 (0)	0.3679 (0.0067)	-0.0256 (0.0088)	0.0856 (0.0127)
5	0.0008 (0)	0.4356 (0.0065)	-0.0293 (0.009)	0.0861 (0.0129)
6	0.0007 (0)	0.4927 (0.0067)	0.0027 (0.0096)	0.0369 (0.0127)
7	0.0007 (0)	0.58 (0.0063)	-0.0295 (0.0101)	0.077 (0.0129)
8	0.0008 (0)	0.6406 (0.0063)	-0.0122 (0.0108)	0.0168 (0.0129)
9	0.0006 (0)	0.7046 (0.0064)	-0.0362 (0.0115)	0.0756 (0.0131)
10	0.0006 (0)	0.7664 (0.0064)	-0.0459 (0.0124)	0.0655 (0.0133)
11	0.0006 (0)	0.8425 (0.0064)	-0.0475 (0.0131)	0.0498 (0.0133)
12	0.0004 (0)	0.9023 (0.0068)	-0.0594 (0.0144)	0.074 (0.0135)
13	0.0003 (0)	0.9725 (0.0067)	-0.0267 (0.0152)	0.0355 (0.0134)
14	0.0003 (0)	1.0534 (0.0064)	-0.0266 (0.0157)	0.0384 (0.013)
15	0.0001 (0)	1.1603 (0.0064)	-0.0386 (0.0169)	0.0555 (0.013)
16	-0.0001 (0)	1.2678 (0.0072)	-0.0308 (0.0183)	0.042 (0.0128)
17	0 (0)	1.4125 (0.008)	-0.0433 (0.0202)	0.0243 (0.0127)
18	-0.0005 (0.0001)	1.6093 (0.0103)	-0.0579 (0.0237)	0.0425 (0.0125)
19	-0.0009 (0.0001)	1.9305 (0.0152)	-0.1387 (0.0301)	0.0919 (0.0128)

Standard Error statistics in parentheses.

Table C.1.18: **Regression of Portfolio Returns on Lagged (Positive) Market Return.** Twenty beta sorted portfolios are created with daily adjustment. Beta being calculated from backward looking daily return of past one year. The daily return of each beta sorted portfolio is regressed on the contemporaneous market return, the lagged market return and the lagged return of the portfolio. The first column in the table represents the portfolio number. Portfolio 0 being the lowest beta portfolio and Portfolio 19 being the highest beta portfolio. A regression is run corresponding to each portfolio and the results are presented in rows. The first column is the intercept the second is the coefficient corresponding to the market return, which closely resembles the beta and is increasing in the portfolio number. The third column is the coefficient corresponding to market return. The final column has the autogression coefficient. Standard Errors are presented below each estimate.

Port.No.	*Intercept*	*Mkt.Ret.*	*Lag(Mret)*	*lag(Ret)*
0	0.001	0.0307	0.1545	-0.0022
	(0.0001)	(0.0139)	(0.0177)	(0.015)
1	0.0005	0.1614	0.1072	0.0586
	(0.0001)	(0.0091)	(0.0121)	(0.0145)
2	0.0004	0.2633	0.0783	0.1052
	(0)	(0.0078)	(0.011)	(0.015)
3	0.0003	0.3273	0.0396	0.1016
	(0)	(0.0076)	(0.0114)	(0.0155)
4	0.0001	0.405	-0.0045	0.096
	(0)	(0.007)	(0.0113)	(0.0157)
5	0.0001	0.4507	0.0132	0.0625
	(0)	(0.0067)	(0.0115)	(0.0155)
6	0.0001	0.5248	-0.0103	0.0754
	(0)	(0.0069)	(0.0124)	(0.0159)
7	0.0001	0.5887	-0.0272	0.069
	(0)	(0.0064)	(0.0128)	(0.0156)
8	0.0001	0.6498	-0.024	0.0524
	(0)	(0.0066)	(0.0137)	(0.0157)
9	0.0002	0.7184	-0.0232	0.0585
	(0)	(0.0065)	(0.0143)	(0.0154)
10	0.0001	0.7715	-0.0101	0.0327
	(0)	(0.0064)	(0.0146)	(0.0152)
11	0.0001	0.8265	-0.037	0.048
	(0)	(0.0065)	(0.0155)	(0.0152)
12	0.0001	0.9245	-0.0696	0.0798
	(0)	(0.0065)	(0.0164)	(0.015)
13	0.0001	0.972	-0.0585	0.0577
	(0)	(0.0065)	(0.0169)	(0.0151)
14	0	1.0707	-0.0964	0.0576
	(0)	(0.0065)	(0.0184)	(0.0155)
15	0.0002	1.1738	-0.0875	0.0509
	(0)	(0.0067)	(0.0199)	(0.0156)
16	0.0003	1.281	-0.1632	0.0846
	(0)	(0.0071)	(0.0218)	(0.0158)
17	0.0004	1.4138	-0.1268	0.0587
	(0)	(0.0082)	(0.0243)	(0.0159)
18	0.0006	1.6199	-0.149	0.0391
	(0.0001)	(0.0105)	(0.0281)	(0.0161)
19	0.0012	1.9344	-0.2236	0.0643
	(0.0001)	(0.0149)	(0.0345)	(0.0158)

Standard Error statistics in parentheses.

Table C.1.19: **Regression of Portfolio Returns on Lagged (Negative) Market Return.** Twenty beta sorted portfolios are created with daily adjustment. Beta being calculated from backward looking daily return of past one year. The daily return of each beta sorted portfolio is regressed on the contemporaneous market return, the lagged market return and the lagged return of the portfolio. The first column in the table represents the portfolio number. Portfolio 0 being the lowest beta portfolio and Portfolio 19 being the highest beta portfolio. The first column is the intercept the second is the coefficient corresponding to the market return, which closely resembles the beta and is increasing in the portfolio number. The third column is the coefficient corresponding to market return. The final column has the autogression coefficient. Standard Errors are presented below each estimate. The results are presented for regression run for the CRSP sample between 1965-2016 where the lagged value weighted market return was negative.

C.2 Figures

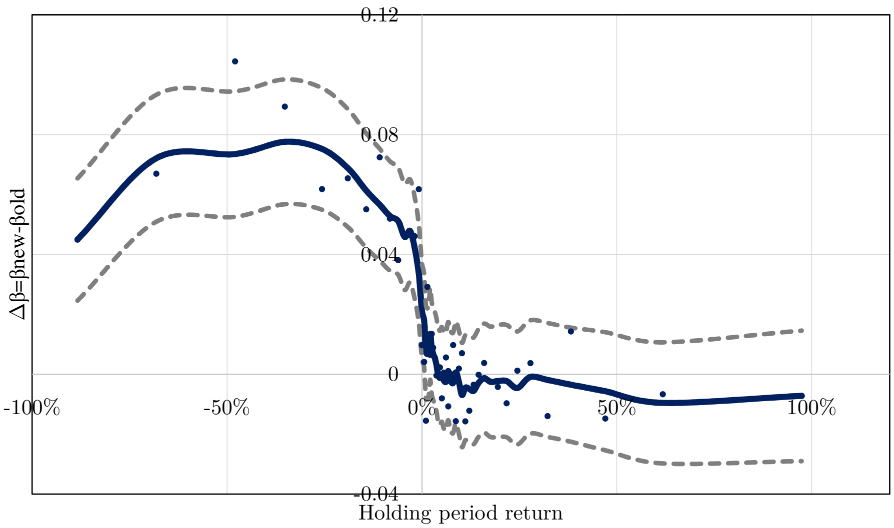


Figure C.2.1: **Difference in Beta of Old Stock and the New Stock vs. Realized Return in Percentages**. The vertical axis is the difference in Beta computed as $\Delta\beta = \beta_{new} - \beta_{old}$. The horizontal axis is the realized profit from the buy-sell transaction in percentages. The solid line represents the moving average line through fifty nonparametric estimates of $\Delta\beta$ while the dotted lines are 2 standard error confidence intervals.

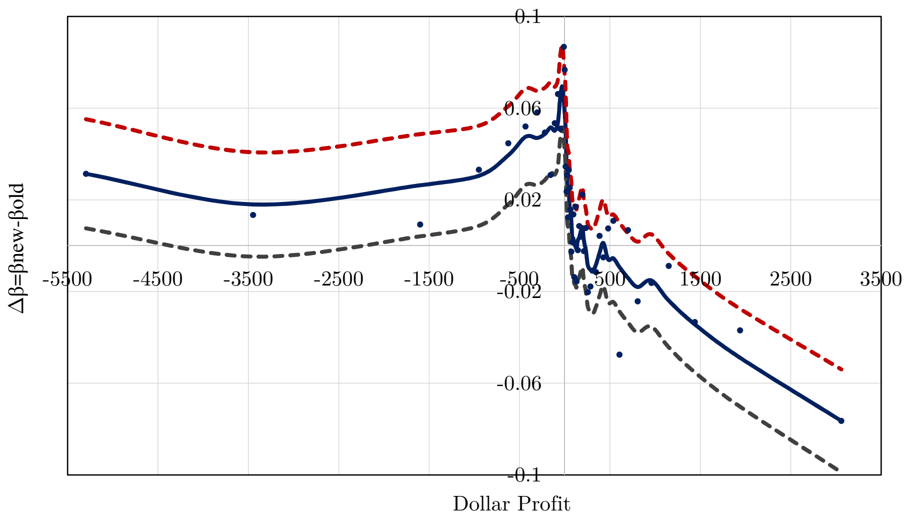


Figure C.2.2: **Difference in Beta of New Stock and the Old Stock vs. Realized Return in Dollar Amounts**. The vertical axis is the average of the difference in Beta $\overline{\Delta\beta}$ for each bin, where $\Delta\beta = \beta_{new} - \beta_{old}$. The horizontal axis is the realized profit from the buy-sell transaction in dollar amounts. The solid line represents the moving average line through fifty estimates of $\overline{\Delta\beta}$ while the dotted lines are two standard error confidence intervals.

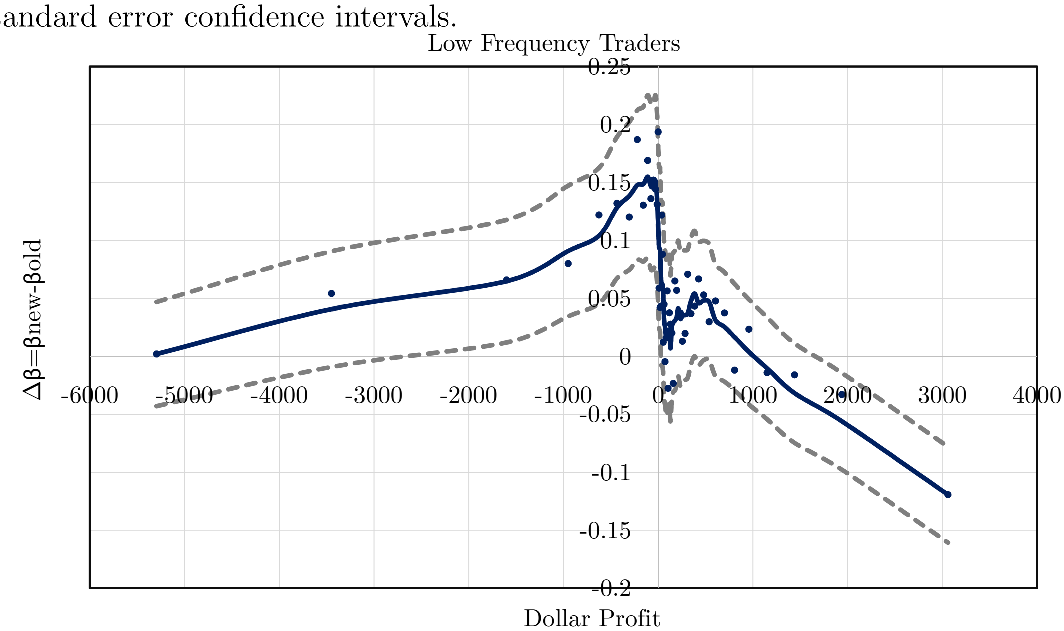


Figure C.2.3: **Difference in Beta (Less Frq. Traders) vs. Realized Return in Dollar Amounts**. $\Delta\beta$ plotted against dollar profits for individual traders who trade relatively less frequently. The entire sample of individual traders is split into two groups of higher and lower frequency traders.

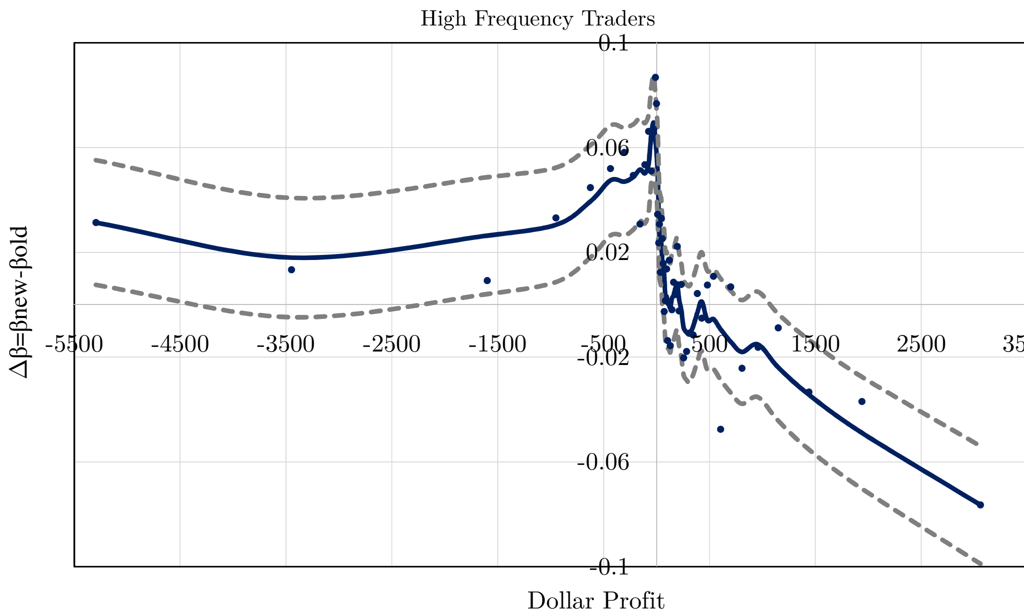
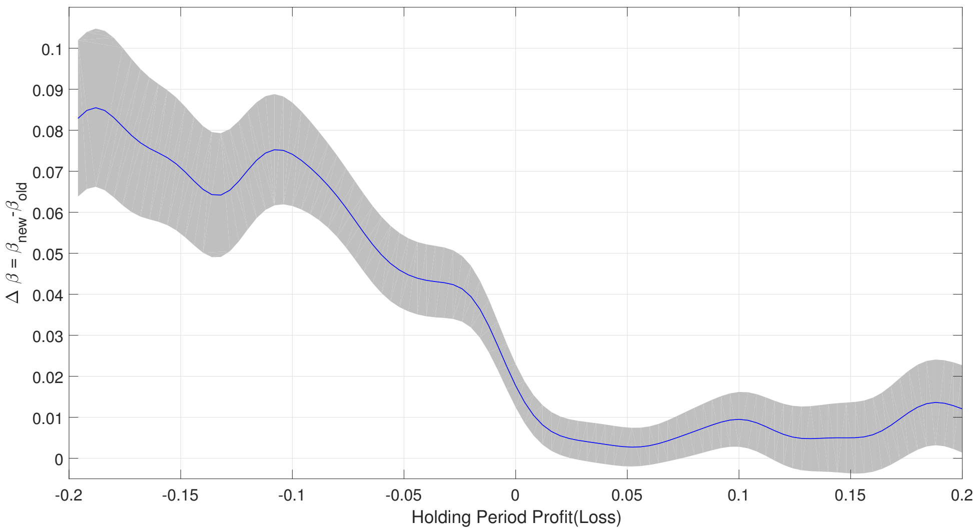
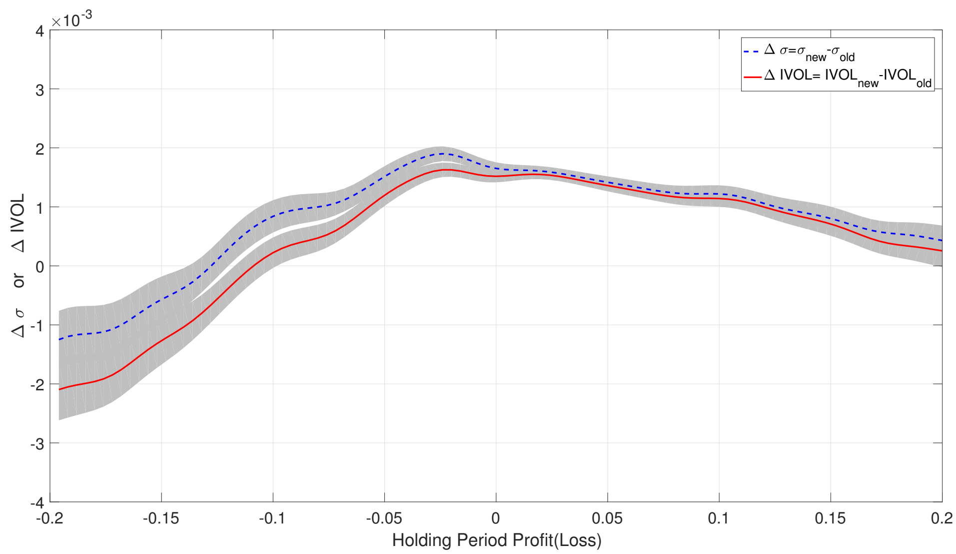


Figure C.2.4: **Difference in Beta (More Frq. Traders) vs. Realized Return in Dollar Amounts**. Exactly same as previous graph now for individual investors who trade more frequently.



(a) Difference in market risk, $\Delta\beta$



(b) Difference in volatility, $\Delta\sigma$ and difference in idiosyncratic volatility, $\Delta IVOL$

Figure C.2.5: **Difference in β, σ and $IVOL$ vs Holding Period Profit.** The x-axis in both the figures represent holding period profit of the old stock, Π. The graphs are plotted for profit range $Pi \in [-20\%, 20\%]$. Fig. C.2.5a represents the non parametric kernel regression estimate of the function $\hat{f} : \Pi \in [-20\%, 20\%] \mapsto \Delta\hat{\beta} \in \mathbb{R}$ where $\Delta\beta = \beta_{new} - \beta_{old}$. In Fig. C.2.5b similar non parametric kernel estimates are plotted for the change in volatility $\Delta\sigma$ (blue dashed line) and change in idiosyncratic volatility $\Delta IVOL$ (red solid line).

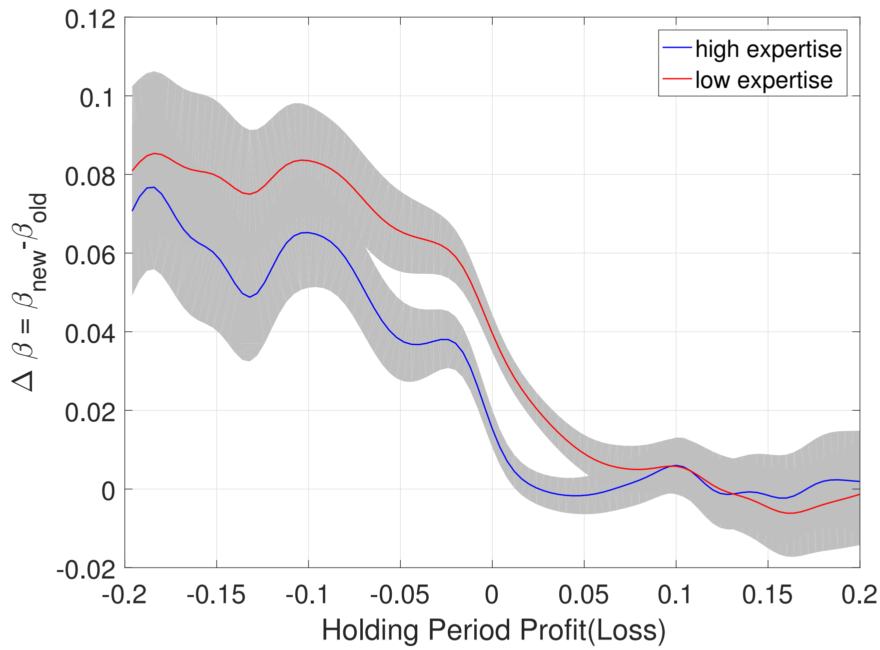
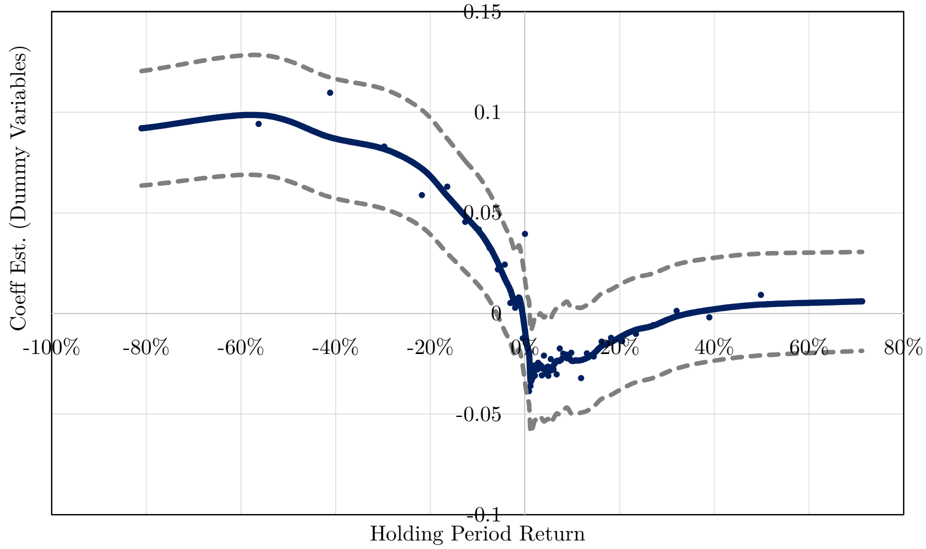
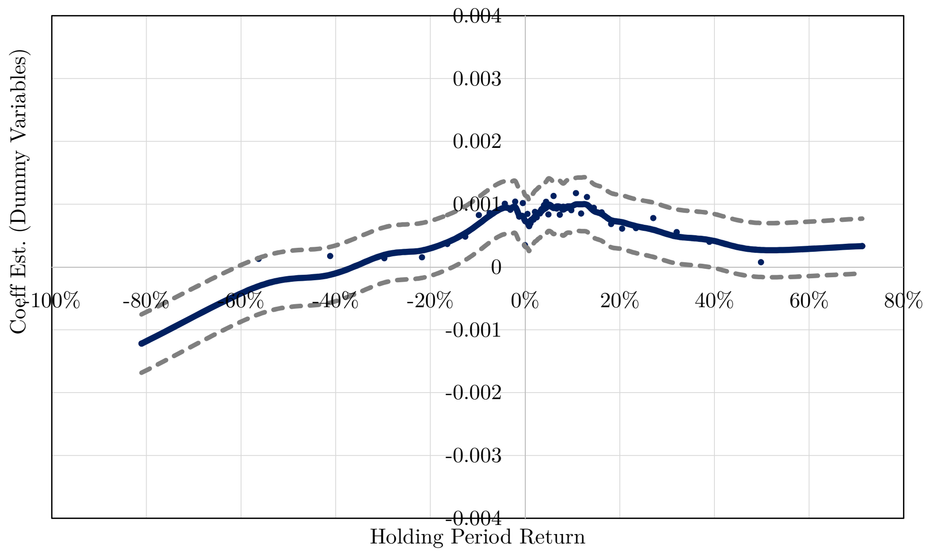


Figure C.2.6: **Difference in Acquisition Effect for Different Expertise Levels**. The red and the blue lines represents the low and high expertise investors respectively. Expertise here being measured by how frequently an individual trades, more frequent is assumed to be signal of higher expertise. The shaded area around the lines represent bootstrapped confidence intervals.



(a) Difference in market risk, $\Delta\beta$ as the dependent variable.



(b) Difference in idiosyncratic volatility, $\Delta IVOL$ as the main dependent variable.

Figure C.2.7: **Plot of Regression Estimates**. Semi percentiles of the holding period return is estimated and fifty dummy varies are assigned, one to each bin. The top figure, Fig. (C.2.7a) represents the coefficient plot corresponding to the regression where $\Delta\beta = \beta_{new} - \beta_{old}$ is the dependent variable. Similarly, the bottom plot, Fig (C.2.7b) corresponds to $\Delta IVOL$. Year and individual level fixed effects are included in the regressions. The volatility of the old stock and any linear trend is controlled for. Additionally for regression corresponding to $\Delta\beta$, $\Delta IVOL$ is controlled for and vice versa. The dots in the figures are coefficient estimates corresponding to forty nine of the fifty dummy variables plotted against the median return of each semi percentile.The solid blue line is a smoothed moving average plot through the coefficient estimates and the dashed lines correspond to 95% confidence interval.

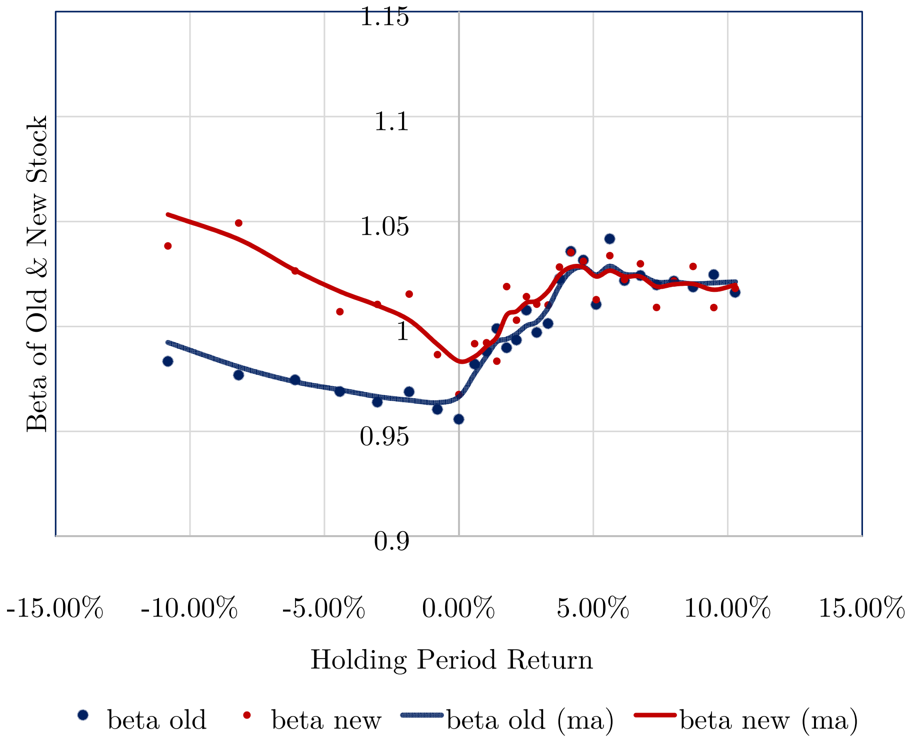


Figure C.2.8: **Old Beta & New Beta vs. Holding Period Return**. The beta of the stock sold and the beta of the stock bought are plotted against the holding period return of the stock sold. The red dots represent the average old beta for a particular bin of holding period return. The blue dots represent average beta of the new stock for each bin of the holding period return. The solid lines are smoothed moving average plots which are a weighted average of neighborhood points. It weights two points on each side of the bin concerned; so five points in all with weights 0.1, 0.2, 0.4, 0.2 and 0.1 with the maximum weight given to the central point. The vertical axis is the beta of stocks measured from past one year daily returns, and the horizontal axis is the holding period return in percentages.

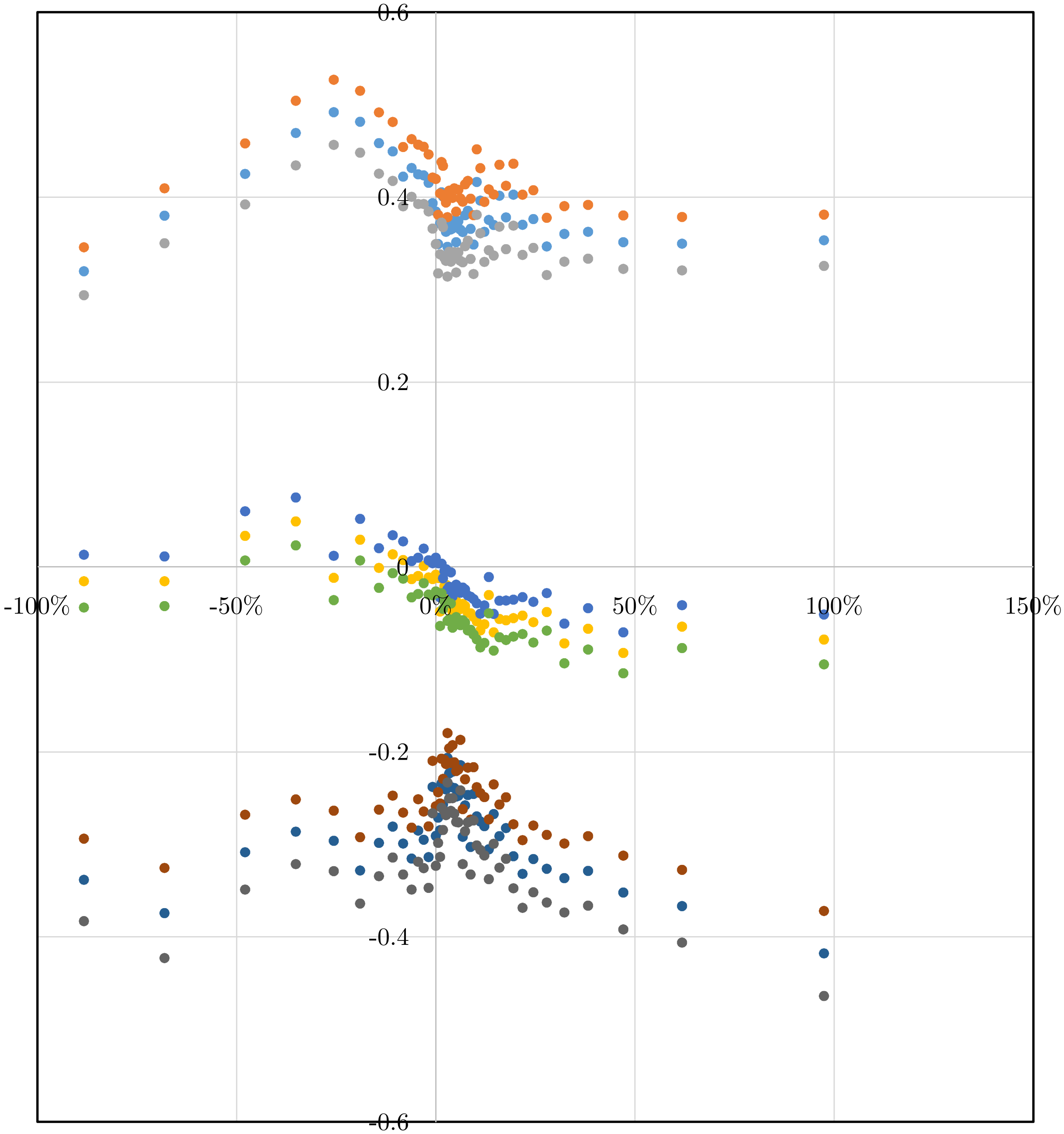


Figure C.2.9: **Beta Difference Across Different Initial Beta Holdings**. The three plots in this graph corresponds to three different levels of beta for the initial stock. The top plot is for low initial beta stock, the middle one is for medium initial beta and the bottom one is for high initial beta stocks. The vertical axis is $\Delta\beta$ and horizontal axis is return in percentages.

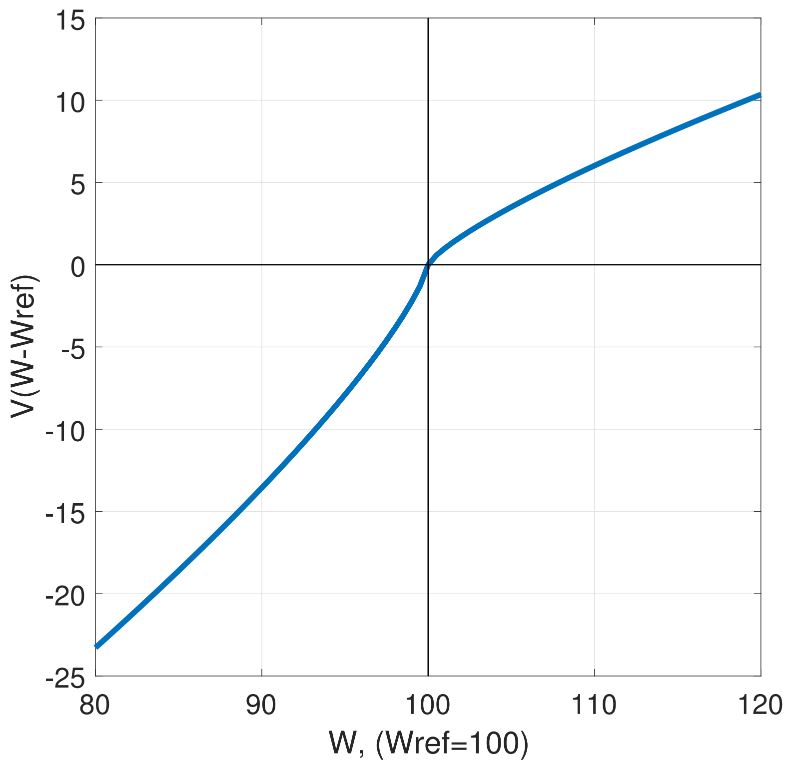


Figure C.2.10: **Prospect Theory Utility Function** A utility function, $V(W - W_{ref})$, consistent with the prospect theory (*Kahneman and Tversky* (1979)) can be defined as $V(W - W_{ref}) = (W - W_{ref})^{\alpha}$ for $W \geq W_{ref}$ and $V(W - W_{ref}) = -\lambda(-(W - W_{ref}))^{\alpha}$ for $W < W_{ref}$. W is the wealth from which utility is to be gained while W_{ref} is the reference wealth. α is the curvature parameter which takes positive values less than one. So the function is concave in the positive domain and convex in the negative domain. λ is the loss aversion parameter which takes positive and greater than one value. Loss aversion implies that a loss hurts much more than a gain of similar magnitude provides utility. The graph is plotted for wealth $W \in [80, 120]$ with reference wealth $W_{ref} = 100$; parameter values used for this figure are $\alpha = 0.78$ and $\lambda = 2.25$. The curvature parameter is set different than that calibrated in *Tversky and Kahneman* (1992) to accentuate the shape which otherwise looks quite flat.

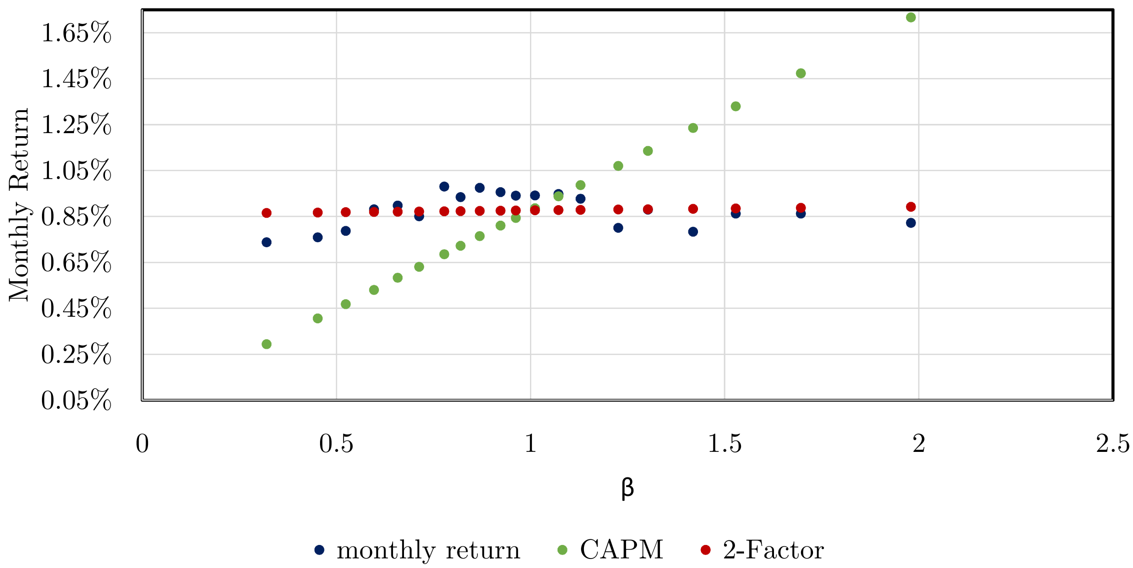


Figure C.2.11: **Cross Section of Market Return and the 2-Factor Model** I use the top 1000 stocks by market capital from CRSP from 1965-2016 and sort them into twenty beta sorted groups every month. Beta's are computed on a rolling basis using monthly returns of past thirty-six months, not including the current month. Twenty corresponding portfolios are formed weighing stocks within each group according to their market capital. The monthly return of the twenty portfolios are plotted against the beta of the portfolios in blue dots. The expected stock return according to the CAPM is plotted in green. The expected returns according to a calibrated 2-factor model is plotted as red dots.

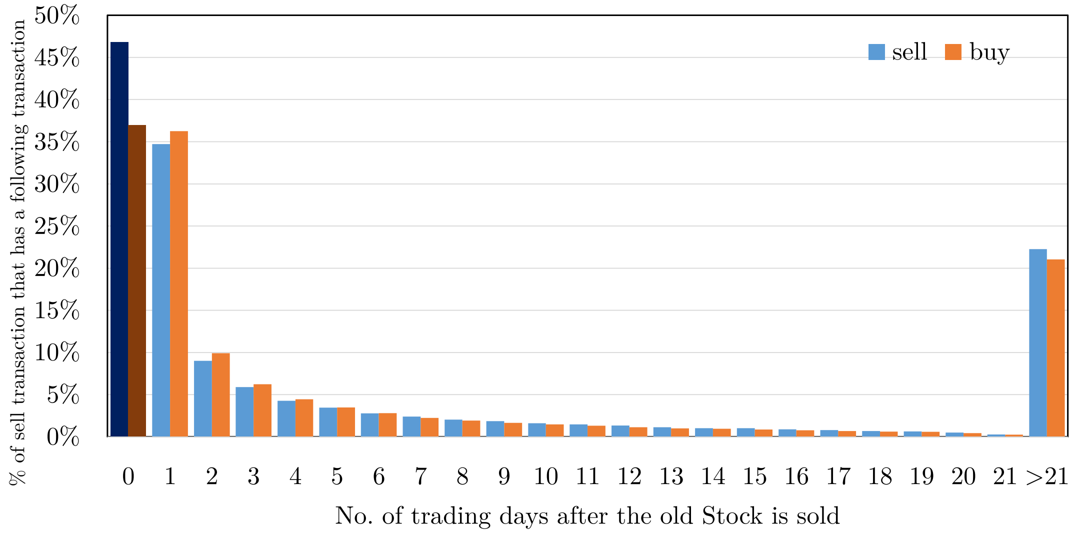


Figure C.2.12: **Percentage of Sell Transaction with Following Trade vs. Day of following Trade.** The number of days are counted as the number of trading days from the 'sell' transaction of the buy-sell pair in the data. The zero-day on the horizontal axis represents the number of sell-transactions that had another a buy or a sell by the same account holder, in a different stock on the same date. So 46% of the sell-transactions in the data had another sell-transaction on the same date, and 37% had a buy transaction. The rest of the numbers represent the number of trading days after which the same account holder made her first transaction after the initial sell. For example, 34.72% of all sell-transactions are followed by a sell-transaction on the next day while a buy-transaction follows 36.24%. Similarly, 9% of all sell transactions saw the next transaction two days later, and it was a sell, while 9.89% saw the next transaction as a buy, two days later. For this graph, I consider followup transaction up to a month(21 days). If a sell-transaction does not have a follow-up transaction within a month, it is grouped as > 21. From day 1 to day 21 and the > 21 sums up to 100% for both buy and sell transaction. Also of all the sell-transactions in the data, 77.75% have at least one following sell transaction within 1 and 21 days while 78.96% have at least one buy.
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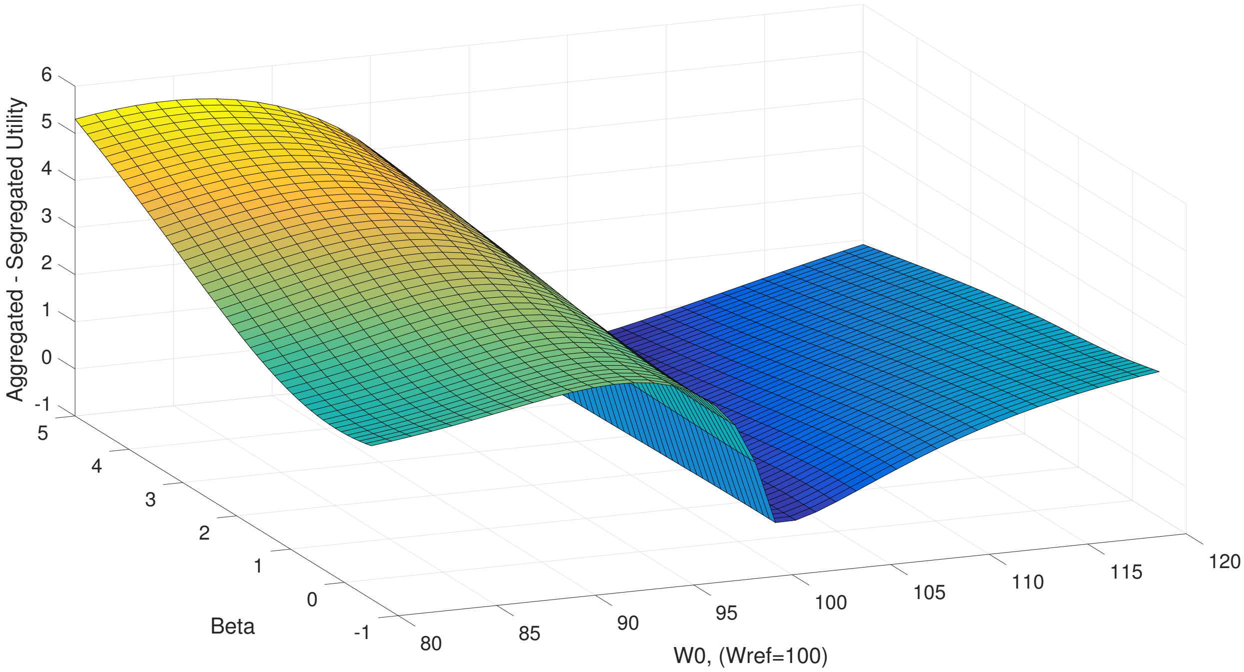


Figure C.2.13: **Utility Difference Plotted Against Beta and Current Wealth.** ($\Delta\mathbb{U} = U_{Agg} - U_{Seg}$ vs. $\beta \times W_0$). The utility difference, $U_{Agg} - U_{Seg} = [\delta\mathbb{E}(V(W_1 - W_{ref}))] - [V(W_0 - W_{ref}) + \delta\mathbb{E}(V(W_1 - W_0))]$, depends on future wealth $W_1 = W_0(1+R_1)$, current wealth W_0 and reference wealth W_{ref}. I assume the time period to be monthly and thus assume away the time discount of utility, $\delta = 1$. The reference wealth is fixed at hundred, $W_{ref} = 100$. Stock is picked from a continuum consistent with CAPM: $R_1 - R_f = \beta(R_m - R_f) + \epsilon$. The market return and the idiosyncratic error both follow normal distributions, $R_m \sim \mathcal{N}(\mu, \sigma_m^2)$, $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. Parameters, $\mu = 0.87\%$, $R_f = 0.3\%$, $\sigma_m = 4.4\%$ and $\sigma_\epsilon = 9\%$ are calibrated using monthly US stock data from CRSP between 1960 and 2015. Surface plots are generated for current wealth from 80 to 100, which implies a profit range of $\pm 20\%$. Beta is allowed in range $\beta \in [-0.5, 5]$. The points in the surface with Z-axis value above zero implies $U_{Agg} > U_{Seg}$, and thus aggregated mental account utility is more profitable than the segregated counterpart.

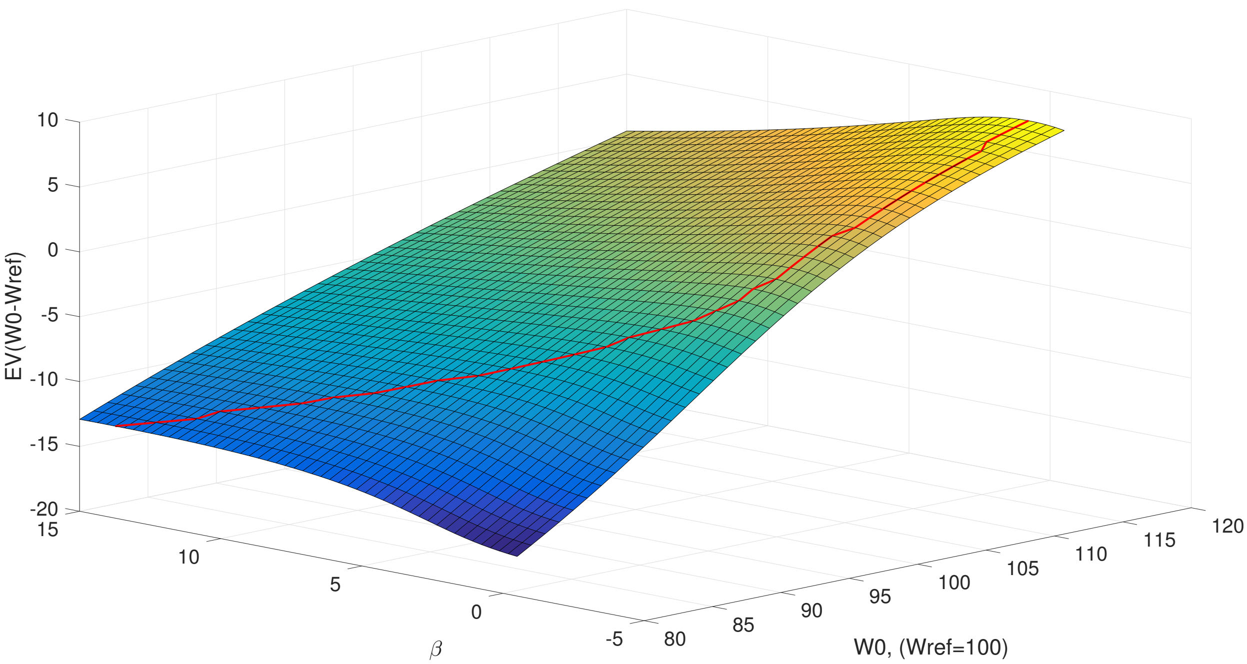
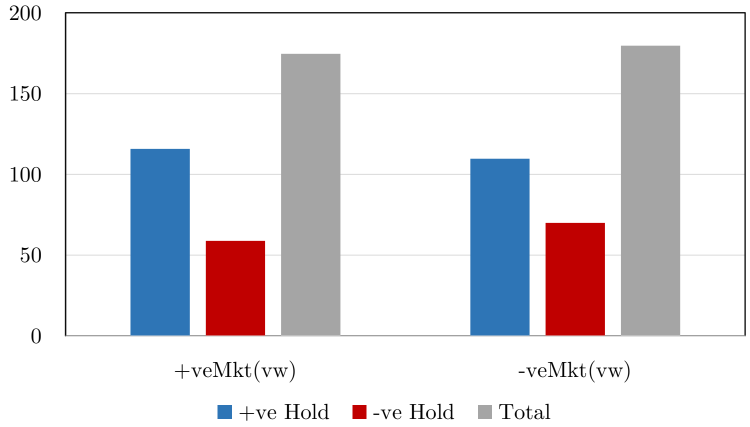
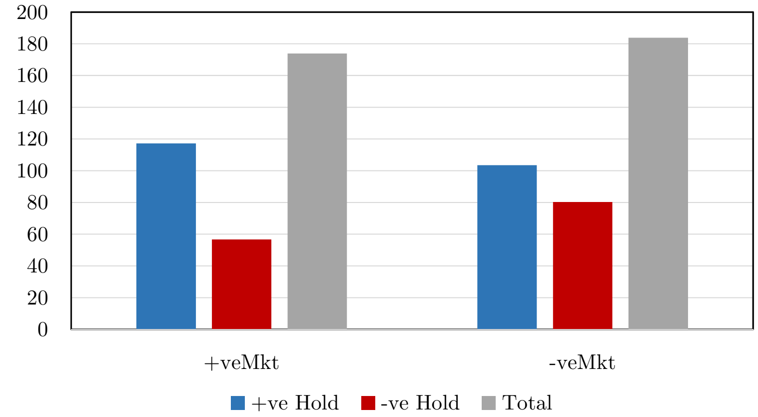


Figure C.2.14: **Expected Utility plotted against Choice of Beta and Current Wealth.** One period ahead expected utility $\mathbb{E}(V(W_1^* - W_{ref}))$ depends on future wealth W_1^* due to optimally chosen beta β, reference wealth $W_{ref} = 100$ standardized to one hundred and current wealth W_0 . The red locus along the surface represents the future expected wealth due to optimally β for a given current wealth W_0. Plots are generated for current wealth from 80 to 100, keeping the reference wealth at 100, which implies a profit range of ±20%. Beta is allowed in range $\beta \in [-0.5, 5]$.

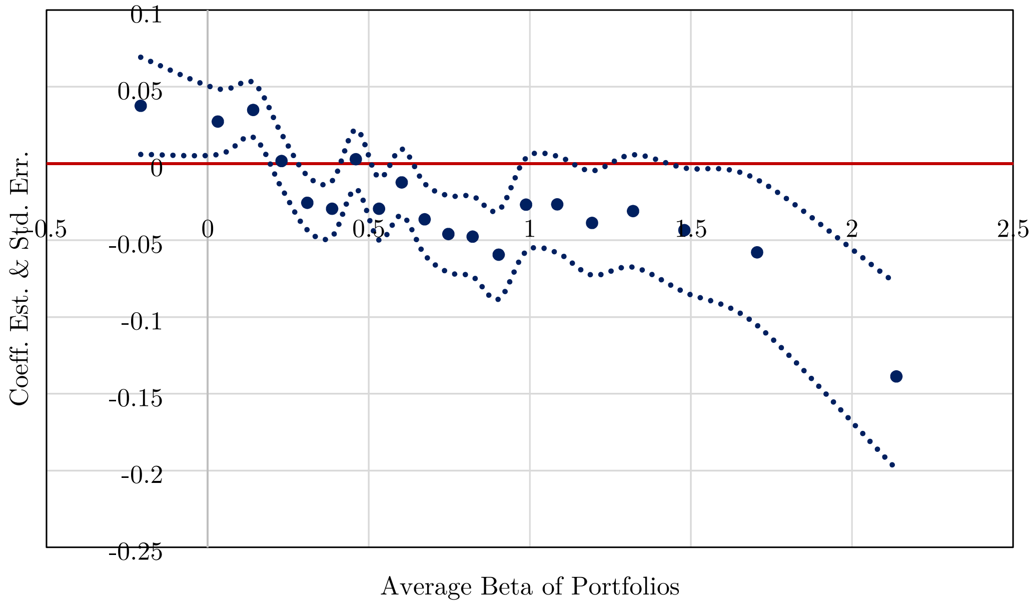


(a) VW Market Return



(b) EW Market Return

Figure C.2.15: **Trading Volume in US Brokerage Transaction Data**. The y-axis represents the average number of sell transactions per day in the US brokerage data. The days are split into positive and negative market return days. Within the market return each sell transaction is categorized according to Fig. (C.2.15a) corresponds to the sell volumes being split according to value weighted market return, while Fig. (C.2.15b) corresponds to the market return being measured as equal weighted.



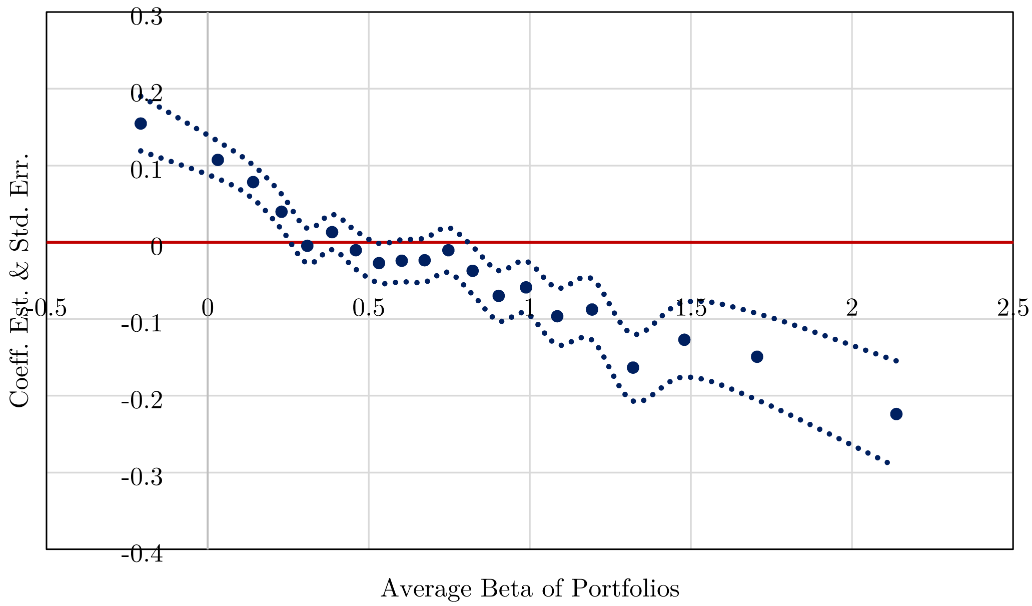


Figure C.2.16: **Regression Coeff. for Lagged (Positive) Market Return** Twenty beta sorted portfolios are created with daily adjustment. The betas are computed from backward looking returns (past one year daily returns or past three years monthly) from 1965-2016 in the CRSP database. Each portfolio return is regressed with the value weighted contemporaneous market return, lagged market return and lagged return of the portfolio. The coefficient of interest is the one corresponding to lagged market return. I plot the regression coefficients corresponding to twenty regressions run on each portfolio and plot it against the value weighted mean beta of each portfolio. This graph corresponds to the estimate where the sample was selected where lagged market return was positive. The upper figure is for daily data, the lower figure is for monthly data.

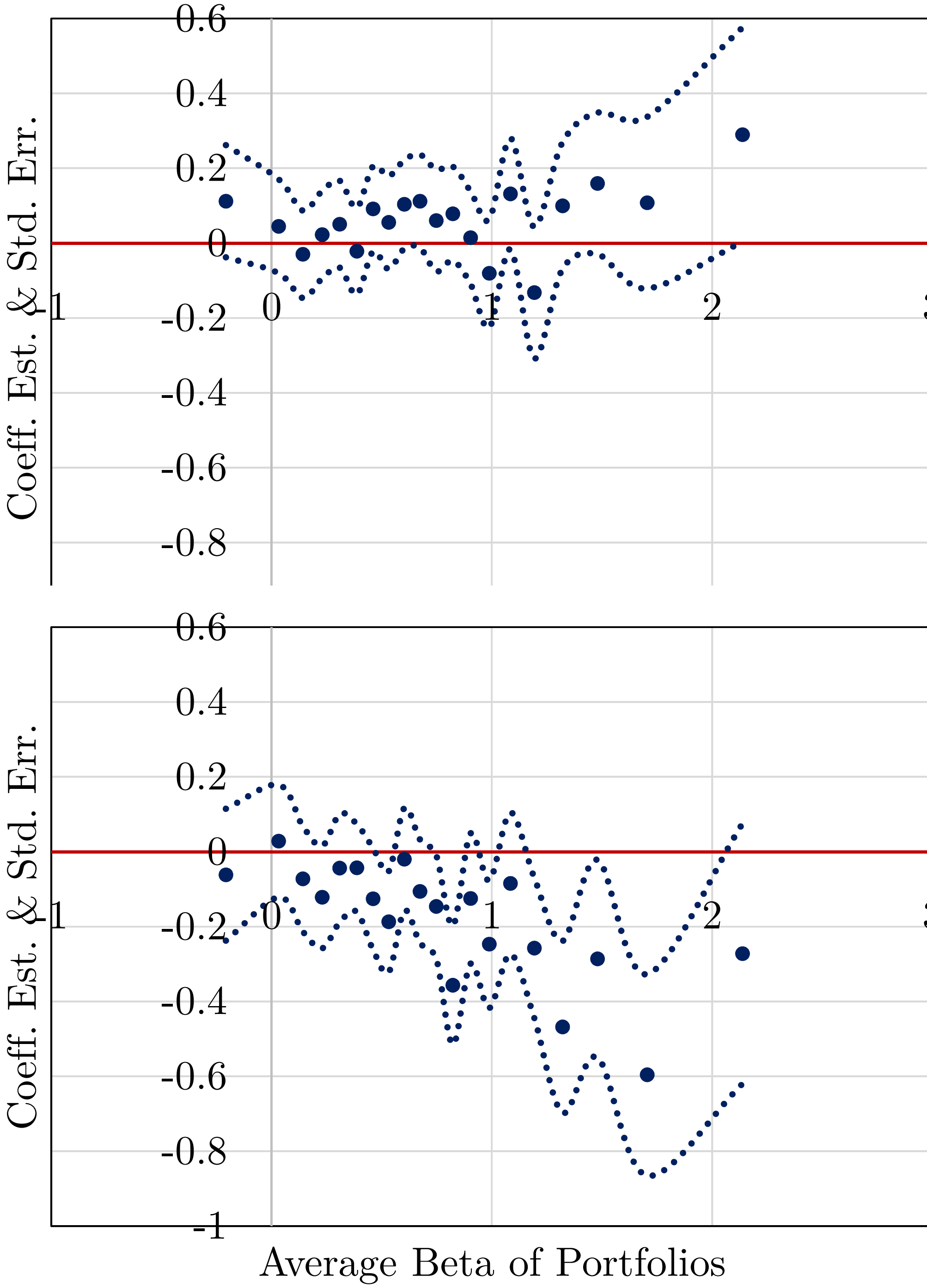


Figure C.2.17: **Regression Coeff. for Lagged (Negative) Market Return** Twenty beta sorted portfolios are created with daily adjustment. The betas are computed from backward looking returns (past one year daily returns or past three years monthly) from 1965-2016 in the CRSP database. Each portfolio return is regressed with the value weighted contemporaneous market return, lagged market return and lagged return of the portfolio. The coefficient of interest is the one corresponding to lagged market return. I plot the regression coefficients corresponding to twenty regressions run on each portfolio and plot it against the value weighted mean beta of each portfolio. This graph corresponds to the estimate where the sample was selected where lagged market return was negative. The upper figure is for daily data, the lower figure is for monthly data.

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