Essays in Behavioral Finance

Anders Anderson

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to my surprise

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Acknowledgments

In the literature on cognitive psychology, overconfidence has been shown to be task dependent. More precisely, it is in tasks that people consider difficult that one is more likely to find stronger evidence of overconfidence. I must dispute this stylized fact. During the work on this thesis, which I have found very difficult, I have been underconfident. Many times I doubted if I would ever complete it. Now I am very close, and will soon find out if the pain of writing this thesis was worth the pleasure of submitting it. This will be my very own experiment on loss aversion. In the meanwhile, I would like to acknowledge those around me who pushed me through this process.

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which has become a lasting one, is of a person with a very sharp intellect and an unusually wide range of skills. I cannot hold Paul responsible for the content of my essays, but only hope that some of his brilliance spilled over onto me.

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Stockholm, April 2004

Anders Anderson

Introduction and Summary

Economists have traditionally tended to describe the optimal choices of rational individuals. The goal of normative economics is to give advice to improve people's imperfect choices. As Keynes (1932) put it: "If economists could manage to get themselves thought of as humble, competent people, on a level with dentists, that would be splendid!" This is no easy feat, and how successful economists have been over the past seventy years is debatable. Some take their advice very seriously; others still fear economists more than dentists.

A large body of experimental evidence, starting with Allais (1953), reveals that individuals do not behave according to normative economics. Behavioral finance applies cognitive psychology to finance to explain these deviations, as cognitive psychology examines human internal processes, mental limitations, and the way in which the processes are shaped by the limitations. Human beings apply rules of thumb, or heuristics, to make decisions, which is often a smart way of dealing with the complexities of reality, but one that may also lead to errors. The central controversy surrounding behavioral finance is whether these errors apply more generally than found in experiments. Some people ask if individuals behave differently when stakes are much higher, and when they are able to interact and learn. I acknowledge these questions, and believe they give us even more reason to study, rather than to ignore, the behavioral approach.

Behavioral finance has gained ground in recent years; new economic theories have been formulated to incorporate aspects of human behavior. In addition, new and detailed data on individuals' financial decisions have spurred the emergence of an important body of empirical work. For non-academics,

the surging interest in behavioral finance is perhaps due to the dramatic developments in world stock markets over the last decade. Most people consider the fast run-up in stock prices in the 1990s, which subsequently ended with a sharp decline beginning in the year 2000, to be an irrational phenomenon. From a historical perspective, however, bubbles and crashes are not new. Many speculators during the Dutch tulip mania in the 17th century, and investors in Internet stocks in the early 2000s, had the same unpleasant experiences. Isaac Newton was one of the many investors who lost a fortune when the infamous South Sea bubble burst in early 18th century England. He was quoted as saying: "I can calculate the motion of heavenly bodies, but not the madness of people." My goal in this thesis is not to take on the challenge that Newton failed, but to analyze and document three instances where psychology may be valuable in explaining common investor behavior.

Each of the three essays investigates different aspects of behavioral finance. In the first essay, I analyze a portfolio choice problem when investors are *loss averse*, rather than expected utility maximizers. The second essay relates individual portfolio performance for a group of online traders to two cognitive biases: *overconfidence* and *availability*. The final essay documents to what extent aggregate mutual fund flows can be associated with returns, in a search for *price-pressure* effects and *positive feedback trading*. A more detailed description of each essay is given below.

"One For the Gain, Three for the Loss" explores a portfolio choice problem when investor preferences are given by the celebrated *prospect theory* of Kahneman and Tversky (1979). The value function in this model has three distinct features: (*i*) risky outcomes are defined over gains and losses; (*ii*) there is risk aversion in the domain of gains and risk loving in the domain of losses; and (*iii*) losses loom larger than gains suggested by a steeper curvature in the domain of losses. The last property is referred to as loss aversion, and Tversky and Kahneman (1992) find in experiments that people value losses about twice as much as gains. I derive indifference curves in mean-standard deviation space for loss-averse investors when returns are normally distributed. The normality assumption creates a mapping between model parameters and the investment opportunity set given by standard mean-variance analysis, as proposed by Markowitz (1952). The model is then calibrated to historical re-

turn data for various assumptions regarding the set of admissible risky assets. I find that the pain of a loss must be greater than *three* times the pleasure of a gain for investors to hold finitely leveraged portfolios. For lower rates of loss aversion, the allocation to risky assets is *infinite*. The results have two general interpretations. Either the equity premium measured in historical data is higher than expected, or people are more loss averse to real world gambles than experiments have found.

In "All Guts, No Glory: Trading and Diversification among Online Investors," I explore the cross-sectional portfolio performance for a large sample of investors at an online discount brokerage firm during the period May 1999 to March 2002. The data reveal that investors, on average, hold undiversified portfolios, have a strong preference for risk, and trade aggressively. The observed behavior is difficult to reconcile with rationality, but is consistent with theories of overconfidence and availability bias, as documented in the psychology literature by, e.g., Kahneman, Tversky and Slovic (1982). I measure portfolio performance and explain the cross-sectional variation using investors' turnover, portfolio size and degree of diversification. I find that portfolio size is important when determining the negative effect of turnover on performance. High turnover is harmful to investors' performance, and those with small portfolios pay higher fees in proportion to their transactions. Overall, investors in the top turnover quintile lose 95 basis points per month compared with those who do not trade. The number of different stocks in the portfolio has a positive effect on performance, which confirms that diversification could be a useful proxy for investor sophistication. The quintile of investors who are most diversified outperform those who are least diversified by 38 basis points per month within any given industry. A panel regression confirms that the two measured effects of turnover and diversification are separate and distinct. The measured effects are also helpful in explaining the overall result: Investors underperform the market by around 8.5% per year on average.

In the final essay, "Equity Mutual Fund Flows and Stock Returns in Sweden," I use time series methods to characterize the relation between unexpected flows to equity mutual funds and returns on the Swedish stock market. Black (1986) refers to small and uninformed investors who trade on sentiment

rather than information as "noise traders." If mutual fund flows are a measure of such investor sentiment, we may find them correlated with lagged and concurrent stock returns. I find no evidence of investors chasing returns and only weak signs of the stock market reacting to shocks originating from flows in monthly data. I do find that unexpected flows and returns are strongly positively correlated within the month. Depending on specification, a positive one-standard deviation shock to unexpected flows corresponds to a monthly excess return of between 1.2% and 1.8% above the mean, measured on a value-weighted index. Unexpected flows also have a distinct effect on the market return when regressed along with the world stock market return, term structure, retail sales, and industrial production growth.

References

Allais, Maurice, 1953, Le comportement de l'homme rationnel devant le risque, critique des postulates et axiomes de l'ecole americaine, *Econometrica* 21, 503–546.

Black, Fischer, 1986, Noise, *Journal of Finance* 41, 529–543.

Kahneman, Daniel, Paul Slovic, and Amos Tversky (eds), 1982, *Judgement under Uncertainty: Heuristics and Biases* (Cambridge University Press: Cambridge, U.K.).

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–292.

Keynes, John M., 1932, *Economic Possibilities for our Grandchildren* (Harcourt Brace: New York, N.Y.).

Markowitz, Harry, 1952, Portfolio selection, *Journal of Finance* 7, 77–91.

Tversky, Amos, and Daniel Kahneman, 1992, Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297–323.

Chapter I

One For the Gain, Three for the Loss

I hate losses. Nothing ruins my day more than losses.
—Gordon Gecco, in *Wall Street*

1 Introduction

One of the most important areas in financial research is asset allocation. Finance academia has long taken a prescriptive approach, explaining what people *should* do. Markowitz (1952) showed that investors with preferences defined over the expected return and variance will choose *efficient* portfolios: those that yield the highest expected return for a given variance. Mean-variance efficiency is consistent with expected utility maximization when the utility function is quadratic or when returns are normally distributed. Since the normal distribution is completely characterized by its mean and variance, Ingersoll (1987) conjectures that all expected utility maximizers who possess an increasing and concave utility function defined over wealth will optimize by choosing efficient portfolios.

Behavioral finance is based on a positive, or descriptive, approach: that is, what people *actually* do. A large body of empirical evidence, starting with Allais (1953), reveals that individuals deviate systematically from expected

[0] I would like to thank Paul Söderlind, Magnus Dahlquist, Peter Englund, Chris Leach, and Iñaki Rodríguez-Longalera for useful comments and suggestions.

utility maximization in experimental settings. Rabin (2000) shows that expected utility may also deliver implausible theoretical results. If a person equipped with a concave utility function defined over wealth rejects a 50/50 gamble of winning \$550 or losing \$500, this person must also reject a 50/50 gamble of losing \$10,000 or winning \$20 million. This follows from the rather extreme curvature of the utility function when it is scaled to wealth.

A family of utility functions that can make sensible predictions about both large and small scale risks is one that displays *first-order* risk aversion.[1] First-order risk aversion means that a utility function possesses local risk aversion, in contrast to standard preferences that are smooth and locally risk neutral. Here, I will consider one of the best known models within this family, namely prospect theory, developed by Kahneman and Tversky (1979). The value function in this model has three distinct features: (*i*) risky outcomes are defined over gains and losses; (*ii*) there is risk aversion in the domain of gains and risk loving in the domain of losses; and (*iii*) losses loom larger than gains suggested by a steeper curvature in the domain of losses. The last property is referred to as *loss aversion*.

This paper explores the well-known, one-period asset allocation problem under the assumptions that preferences are specified by prospect theory and returns are normally distributed. The last assumption enables us to derive useful properties of the indifference curves, which are found to be linear in mean-standard deviation space in two special cases: (*i*) when the prospective utility is zero, and (*ii*) at the asymptote of an indifference curve. These properties create a mapping between model parameters and the investment opportunity set, and mean-variance efficiency applies.

The main result is that loss aversion must be high compared with estimates found in the experimental literature for individuals to hold plausible portfolios. The allocation to risky assets is *infinite* for loss aversion parameters lower than about three when the model is calibrated to historical data. This result is robust to several assumptions regarding the investment opportunity set. Moreover, the allocation scheme is similar even when the normality assumption is relaxed and returns are drawn from the set of realized observations.

[1] Barberis, Huang, and Thaler (2003) stress that utility functions with first-order risk aversion also have difficulty in explaining attitudes to large *and* small-scale risks unless risks are also regarded in isolation, rather than added to the overall portfolio.

The general conclusion is therefore similar to those found in other asset pricing studies: historical returns are more attractive than can be explained by reasonable model parameters. In addition, the linearity of the indifference curves has the undesirable feature that the allocation decision is highly sensitive to the parameters of the model—especially in the range in which the allocation to stocks is high.

The outline of the paper is as follows. Section 2 describes prospect theory and discusses how it has been applied to portfolio theory in the previous literature. Section 3 derives the model under the assumption of normally distributed returns, and shows how parameters can be inferred from the Sharpe ratio. Section 4 revisits the standard one-period portfolio choice problem for investors that have prospect theory preferences. By calibrating the model to historical data, we obtain parameter estimates under various assumptions regarding the investment opportunity set. Section 5 concludes.

2 Prospect theory and portfolio choice

Kahneman and Tversky (1979) describe prospect theory with a value function which determines how individuals evaluate outcomes. We can write the value function for a random variable x as

$$V^{\alpha}(x) \equiv V_{+}^{\alpha}(x) - \lambda V_{-}^{\alpha}(x) \tag{1}$$

where

$$V_{+}^{\alpha}(x) \equiv \max\{x, 0\}^{\alpha},$$

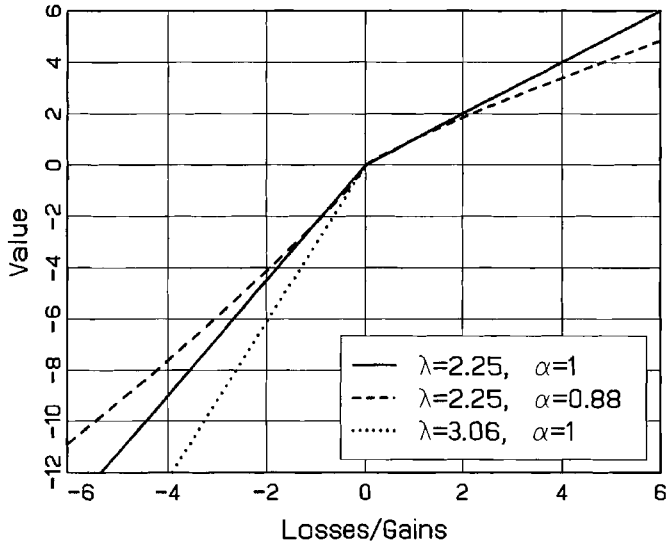
and

$$V_{-}^{\alpha}(x) \equiv \max\{(-x), 0\}^{\alpha},$$

such that gains (+) and losses (−) are measured from a reference point which here is set to zero, but could differ depending on the context being analyzed. The theory states that the reference point should reflect the correct aspiration level. For instance, if a sure gain is attainable, the individual will regard all outcomes below the certain gain as losses.

The parameter λ determines how much the individual dislikes losses. Tver-

Figure 1: The value function in prospect theory
The value function is displayed for three sets of parameter values. There are two cases when the loss-aversion parameter, λ, is 2.25 and the exponent α either takes the value 1 or 0.88 (solid and dashed lines). The third example displays the case when λ is 3.06 and α equals 1 (dotted line).



sky and Kahneman (1992) find that people on average value losses about twice as high as gains. From experimental data, they infer that average λ is 2.25. They also find that individuals exhibit risk aversion when faced with gambles defined strictly over gains, and the opposite, i.e. risk seeking, when facing only losses. They find that a curvature parameter α of 0.88 in both gains and losses is a good proxy for this behavior. Figure 1 illustrates the value function for the benchmark parameters explored in this paper. The curvature obtained by setting $\lambda = 2.25$ and $\alpha = 0.88$ is depicted by a dashed line that can be compared with the solid line when $\alpha = 1$ (the dotted line displays the case in which $\lambda = 3.06$ and is a parameter value included for later reference).

Prospect theory has attracted wide interest from economists because it quantifies the observed human behavior found in the experimental laboratory. Among the first to apply prospect theory to portfolio choice problems were Benartzi and Thaler (1995), who suggested a behavioral explanation to

Mehra and Prescott's (1985) "equity premium puzzle."[2] Rather than assuming a consumption based model, Benartzi and Thaler suggest that individuals exhibit *myopic loss aversion* which is a variant of loss aversion combined with *mental accounting* (Kahneman and Tversky, 1983). They show that if stocks are evaluated in the short term (irrespective of actual holding period), they will be less attractive than if evaluated in the long term. The intuition for this result is closely related to time diversification. The probability that the stock investment will yield a loss decays with time (even if the magnitude of losses increases). It is then crucial to determine at which frequency stocks are evaluated by the investor to implement the theory. The authors argue that a one-year evaluation period is reasonable, as people generally file tax returns once a year, and individuals, as well as institutions, scrutinize their investments more carefully at the end of the year. When they calculate prospective utility for an all-bond and all-stock portfolio, they find that when $\lambda = 2.77$ and $\alpha = 1$, the investor is indifferent between these two portfolios. The equity premium over bonds is thus explained by investors' aversion to incurring losses in the short term.

Barberis, Huang, and Santos (2001) develop an asset pricing framework where utility is defined directly over changes in wealth as well as consumption. The preference component over wealth is similar to prospect theory, but the value function is linear with the additional feature that *previous* losses and gains affect the rate of current loss aversion. This *house money effect*, originally proposed by Thaler and Johnson (1990), attempts to capture that individuals are found to shift their attitude towards risk depending on prior outcomes. A previous gain acts to cushion subsequent losses, making the investor more tolerant towards risk. A previous loss acts as to increase loss aversion, thereby inducing more conservative risk preferences. The authors show that this model can generate a reasonable risk-free rate together with risky returns that exhibit high mean and volatility as well as predictability from consumption data for reasonable parameter values. A crucial component for these results is not only that investors have preferences over changes in wealth, but that there is time-variation in loss aversion.

[2]The puzzle refers to the rather extreme parameter for constant relative risk aversion (CRRA) required to explain the high premium of stock returns over interest rates when consumption data is smooth.

Time dependence can also be induced by allowing the reference point to follow dynamic updating rules. Berkelaar, Kouwenberg, and Post (2003) analyze optimal portfolio strategies for loss-averse investors in continuous time where the reference point is adjusted by the stochastic evolution of wealth adjusted by the risk-free rate. They show that there is, in fact, an equivalence between introducing a dynamic updating rule and a shift in the static reference point. Gomes (2003) explores the demand for risky assets with prospect theory preferences in a two-period equilibrium model where the reference point adjusts in a similar manner. He finds theoretical support for the empirical observation of positive correlation between trading volume and stock return volatility. Ang, Bekaert, and Liu (2003) consider the related concept of *disappointment aversion* developed by Gul (1991), which is a one-parameter extension of the standard CRRA framework, but in which losses are weighted higher than gains. They find more reasonable parameter values for risk-aversion when investors are averse to losses.

The papers that are most closely related to the work here are applications in which prospect theory preferences are related to mean-variance portfolios. Sharpe (1998) analyzes the selection of mutual funds with respect to asymmetric definition of risk used in the *Morningstar* mutual fund ratings. The ratings are related to prospect theory since risk is measured by separating positive from negative outcomes.[3] He finds that indifference curves associated with the ratings imply a linear relation in mean-standard deviation space when returns are normally distributed, and this in turn produces a discrete ranking of funds. Levy and Wiener (1998) develop a framework in which stochastic dominance rules are related to optimal portfolios for investors with prospect theory preferences. Levy and Levy (2004) use this framework to show that mean-variance portfolios and those obtained by prospect theory are closely related under very general distributional assumptions for returns. In particular, they show that they coincide exactly for the part of the efficient set associated with decreasing Sharpe ratios when returns are normally distributed.

Rather than solely relying on numerical methods, as Benartzi and Thaler, or stochastic dominance rules, as applied by Levy and Levy, this paper derives

[3]Other related concepts are semivariance and downside risk, explored by, e.g., Porter (1974) and Fishburn (1977).

and develops the results of Sharpe for indifference curves. Even if some of the theoretical insights are not new to the literature, the main contribution lies in showing how parameters can be recovered analytically and quite simply from data. In particular, it is possible to analyze the quantitative implications of the model with virtually no constraints on the number of admissible assets.

3 Loss aversion and normally distributed returns

The expectation of the value function in equation (1) can be written

$$EV^{\alpha}(x) = EV_{+}^{\alpha}(x) - \lambda EV_{-}^{\alpha}(x), \tag{2}$$

which hereafter is referred to as the *prospective utility*. The expectation in the more extensive form of prospect theory described in Tversky and Kahneman (1992) allows for non-linear transformations of the objective probabilities. This case will not be considered here due to reasons of tractability, but will be discussed with respect to the results obtained. In general, prospective utility in (2) can be stated

$$EV^{\alpha}(x) = \int_{0}^{\infty} x^{\alpha} dF_x - \lambda \int_{-\infty}^{0} (-x)^{\alpha} dF_x, \tag{3}$$

where F_x is the cumulative density function associated with x. Assume now that $x \sim N(\mu, \sigma)$ and consider the case when $\alpha = 1$. As Figure 1 illustrates, $\alpha = 1$ means that the value function is two-piece linear, so we name this case *pure* loss aversion.

We can identify the prospective utility in (3) as a combination of a lower and upper censored normal distribution. Let $s \equiv \mu/\sigma$. Standard results from statistics allow us to write

$$EV_{+}^{1}(x) = \Phi(s)\left(\mu + \sigma\Omega_{+}\right)$$

and

$$EV_{-}^{1}(x) = -\Phi(-s)\left(\mu + \sigma\Omega_{-}\right),$$

where $\Omega_+ \equiv \phi(-s)/\Phi(s)$ and $\Omega_- \equiv -\phi(-s)/\Phi(-s)$, commonly known as the inverse Mills ratio, and where ϕ and Φ denote the standard normal probability density function and cumulative distribution function. Therefore, (3) can be written

$$EV^1(x) = \mu\left[\Phi(s) + \lambda\Phi(-s)\right] + \sigma(1-\lambda)\phi(-s). \tag{4}$$

By inspection, we see that the expectation of the value function has three arguments: the loss-aversion parameter λ, the mean μ, and the standard deviation σ. When $\alpha = \lambda = 1$, equation (4) reduces to μ. This is rather trivial, since we take the expectation of a normally distributed random variable, but have arranged it in two parts. In other words, an individual with parameters $\alpha = \lambda = 1$ is risk-neutral.

To prove that all portfolios chosen under pure loss aversion are mean-variance efficient, it is sufficient to show that the derivative of the value function for the mean is strictly positive, and the derivative with respect to the standard deviation is strictly negative. The derivative with respect to the mean is

$$\frac{dEV^1(x)}{d\mu} = \Phi(s) + \lambda\Phi(-s),$$

which is strictly positive and increasing in the loss-aversion parameter λ. Again, we see that the derivative is one when $\lambda = 1$. We also note that the same holds when $\sigma \to 0$, and therefore $s \to \infty$, irrespective of λ. The intuition is that if there is no risk of a loss, the prospective value is just a positive constant, μ. The derivative with respect to the standard deviation is

$$\frac{dEV^1(x)}{d\sigma} = (1-\lambda)\phi(-s),$$

which is strictly negative for λ greater than one.[4] The derivative approaches the constant $(1-\lambda)\phi(0) \approx (1-\lambda)(0.4)$ as variance goes to infinity. A higher value of λ therefore suggests a higher sensitivity to prospective utility in both cases.

Mean-variance efficiency follows directly from the properties of the derivatives as long as $\lambda > 1$, because the normal distribution is completely charac-

[4] I remind the reader that $\Phi(-x) = 1 - \Phi(x)$ and $\phi(-x) = \phi(x)$. The inner derivatives of s cancel in both cases, which is not trivial. See Appendix A for details.

terized by its two first moments.[5]

3.1 Solutions to the parameter for loss aversion

The key results of this paper build on the characteristics of the indifference curves in mean-standard deviation space. In order to do so, we fix prospective utility to some constant V in equation (2) and solve for the loss-aversion parameter λ to obtain

$$\lambda_V^\alpha(\mu,\sigma) \equiv \lambda(V,\alpha,\mu,\sigma) = \frac{EV_+^\alpha(x)}{EV_-^\alpha(x)} - \frac{V}{EV_-^\alpha(x)}. \tag{5}$$

In the general case, λ is a function of the level of utility V, the concavity/convexity parameter α, and the first two moments of the normal distribution. Even if we hold V and α fixed, it is not easy to characterize a solution to an indifference curve by inspection of equation (5).

Let us therefore begin by making a simplifying assumption in which prospective value is zero. The economic meaning is that we are now measuring the certainty equivalent for all pairs of means and standard deviations that are worth zero for the loss-averse individual. We see that the second term of equation (5) drops out of the expression, such that we can write the parameter for loss aversion as

$$\lambda_0^\alpha(s) \equiv \lambda(V=0,\alpha,s) = \frac{EV_+^\alpha(x)}{EV_-^\alpha(x)} = \frac{\int_0^\infty x^\alpha dF_x(\mu,\sigma)}{\int_{-\infty}^0 (-x)^\alpha dF_x(\mu,\sigma)}, \tag{6}$$

which is in fact only a function of the mean-standard deviation ratio s. This is not clear in equation (6), but as we can standardize the normal distribution by substituting

$$x = (y\sigma + \mu),$$

[5]Levy and Levy (2004) give the exact conditions under which prospect theory investors choose efficient portfolios in cases in which α is not one.

such that $dx = \sigma dy$, we can rewrite equation (6) as

$$\lambda_0^\alpha(s) = \frac{\int_{-s}^{\infty} (y\sigma + \mu)^\alpha \, dF_y(0,1)}{\int_{-\infty}^{-s} (-y\sigma - \mu)^\alpha \, dF_y(0,1)} = \frac{\int_{-s}^{\infty} (y + s)^\alpha \, dF_y(0,1)}{\int_{-\infty}^{-s} (-y - s)^\alpha \, dF_y(0,1)}, \tag{7}$$

where the last equality is obtained by multiplying $\sigma^{-\alpha}$ in both the numerator and denominator. This proves that prospective utility—for fixed parameters—is only a function of s when it is zero, and means that the solution to $\lambda_0^\alpha(s)$ is given by a ray in mean-standard deviation space.

We could do some preliminary comparative statics immediately. A decrease in $\lambda_0^\alpha(s)$ is obtained either by a lower s, or a lower parameter value for α. The intuition for the first case is straightforward, because a lower mean or higher standard deviation makes a gamble less attractive. An investor must be *less* loss averse to be indifferent to such a change. The result for α relies on the assumption that the distribution mean is greater than the value of the reference point. As can be seen in Figure 1, an α below one means that a given loss *and* gain is weighted less. But when the mean is greater than zero, positive outcomes are more likely. This means that a lower α makes a given distribution less attractive. A lower α must therefore be offset by a lower λ in order to keep the individual indifferent to the change.

It is straightforward to recover the $\lambda_0^\alpha(s)$ associated with a particular ray in mean-standard deviation space. As we have an exact correspondence, we can solve equation (7) by numerical integration for any given s.

In the special case in which $\alpha = 1$, we can rewrite equation (7) in terms of previously defined distribution density function

$$\lambda_0^1(s) \equiv \lambda\,(V = 0, \alpha = 1, s) = \frac{\phi(-s) + s\Phi(s)}{\phi(-s) - s\Phi(-s)}, \tag{8}$$

which is commonly referred to as the *gain-loss* ratio. The gain-loss ratio is considered in Bernardo and Ledoit (2000) and related to their approach to asset pricing in incomplete markets. They show that limits to the gain-loss ratio put restrictions on the maximum to minimum values of the pricing kernel, which in turn provide bounds on asset prices. A high gain-loss ratio implies loose

bounds and in the limit, as the gain-loss ratio approaches infinity, we obtain the arbitrage-free bounds.

Here, we see that we can think of the gain-loss ratio in terms of how loss averse an individual can be and still be indifferent between a normal distributed gamble and the status quo of zero prospective utility. Equation (8) shows that $\lim_{s\to 0} \lambda_0^1(s) = 1$ and $\lim_{s\to\infty} \lambda_0^1(s) = \infty$. An arbitrage opportunity arises when the expected loss is zero and the expected gain is positive. The parameter for loss-aversion, λ, is then infinite so the interpretation is that one would have to be infinitely loss averse not to take an arbitrage opportunity within this setting. When $\lambda = 1$, expected gains equals expected losses, which is the intuition for risk neutrality.

The case in which V is different from zero is more difficult to generalize. We can, however, characterize the slope of an indifference curve associated with infinite standard deviation. This case is important, because it means that we could retrieve the parameters associated with the asymptote of an indifference curve in mean-standard deviation space. With this objective, it is sufficient to prove that the second term in (5) becomes infinitely small as σ goes to infinity, while holding s constant. But this was, in fact, already done in equation (7), because the denominator can be written

$$EV_-^\alpha(x) = \sigma^\alpha \int_{-\infty}^{-s} (-y-s)^\alpha \, d\Phi_y.$$

Since it is assumed that $\alpha \in (0,1]$ we see that $\lim_{\sigma\to\infty} EV_-^\alpha = \infty$ for any fixed ratio s and it will grow faster as α approaches one. As the second ratio of equation (5) goes to zero, we have the result that an indifference curve for fixed model parameters at *any* level of prospective utility will converge to the same slope, namely the one determined by the gain-loss ratio.

We have then obtained two special cases when indifference curves are linear and determined by the Sharpe ratio: when prospective utility is zero, and as standard deviation goes to infinity. For the intermediate cases, we need to rely on a numerical method. These cases are important, because we want to ensure that solutions are unique as well.

Figure 2: Indifference curves and slopes

Figures 2A and 2B display indifference curves in mean-standard deviation space along with associated slopes for different levels of prospective utility when $\alpha = 1$. The dashed line in Figure 2A corresponds to the Capital Allocation Line ("CAL") spanning feasible allocation to the equity premium which is labelled "EQP." Figures 2C and 2D repeat the main analysis when $\alpha = 0.88$.

Figure 2A:
Indifference curves, $\lambda = 2.25, \alpha = 1.00$

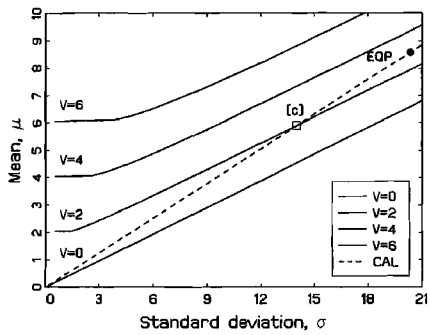


Figure 2B:
Slopes, $\lambda = 2.25, \alpha = 1.00$

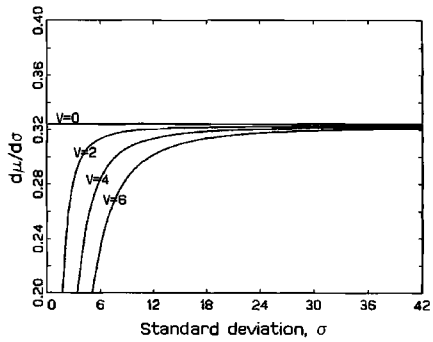


Figure 2C:
Indifference curves, $\lambda = 2.25, \alpha = 0.88$

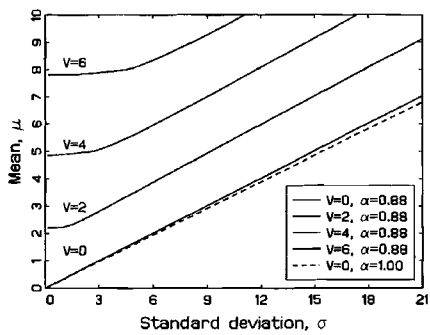
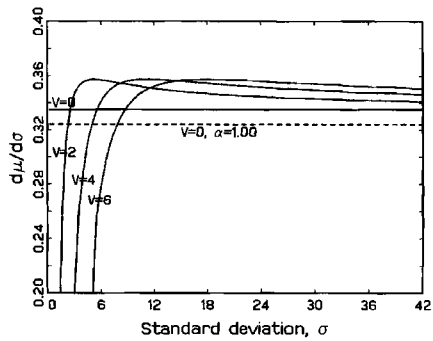


Figure 2D:
Slopes, $\lambda = 2.25, \alpha = 0.88$



3.2 Indifference curves

An indifference curve can be obtained by finding the σ that solves equation (3) implicitly for a constant level of prospective value V, a pair of fixed model parameters λ and α, and a given μ. Repeating this exercise for different values of μ, we can trace out a curve in mean-standard deviation space. To solve this problem, a numerical method is applied in which the difference between the prospective value and the constant is minimized.

Figures 2A and 2B plot four indifference curves along with their deriva-

tives when prospective value V is 0, 2, 4 and 6, while keeping loss-aversion, λ, fixed at our benchmark value of 2.25.

The exact linearity does not hold in general for arbitrary values of V, but the numerical derivatives of Figure 2B suggest that the slopes of the indifference curves converge relatively fast as standard deviation increases. More importantly, they are convex, which guarantees that there is an unique mapping between an indifference curve and any allocation along a straight line in mean-standard deviation space. We have already noted in equation (4) that $\lim_{\sigma \to 0} \Phi_s = 1$ and $\lim_{\sigma \to 0} \phi_s = 0$. This means that the point of intersection of the vertical axis in mean-standard deviation space implies $V = \mu$.[6]

Figures 2C and 2D plots indifference curves when $\alpha = 0.88$. When $V = 0$, the curve is exactly linear but somewhat steeper than when $\alpha = 1$ (dashed line), which confirms the previous comparative statics. When $V > 0$, the numerical derivatives in Figure 2D reveal not only that convergence is slower when $\alpha < 1$, but that there is an inflection point. Hence, there could be two portfolios along a straight line in this space that yield the same level of prospective utility, such that the solution is not unique. The intuition for this result is that we are considering an investor who displays an element of risk-seeking in the domain of losses. An increase in the standard deviation increases the probability of a loss. The first-order effect of this is negative because losses are weighted higher than gains through the parameter λ. The second-order effect is positive because both marginal gains and losses are weighted less when $\alpha < 1$.

The inflection point is potentially problematic for finding unique solutions to model parameters. In the results that follow, we will only rely on the asymptotic characterization, meaning that the indifference curves converge to the same slope as when $V = 0$ for any model parameters. This could only be done as long as we can rule out other solutions along that particular indifference curve.

[6] In general, this point is given by the solution to μ in the equation $V = \mu^{\alpha}$.

4 Calibrating the model to return data

The objective now is to take the derived features of prospect theory to data. Table 1 summarizes the moments for three asset classes that are used for the analysis: Cash, Bonds and Stocks. These assets correspond to the 30-day U.S. Treasury Bill, a long-term U.S. government bond, and the S&P 500 stock index. We consider both real and nominal, as well as annual and monthly returns in what follows. These data, which cover the period 1926 to 2001, are obtained from Ibbotson Associates and are widely used in the asset pricing literature.

The first case we analyze is when Cash is riskless, and there is only one risky asset. It is shown that this assumption implies a binary choice of risky assets, such that we can derive pairs of parameters λ and α, that correspond to a point of indifference. This is not true in the general case when there exists a universe of risky assets, because the investment opportunity set is then concave. The following subsections reveal which parameters can be associated with different assumptions regarding admissible assets.

4.1 One risky asset: the equity premium

The linearity directly delivers an understanding of why portfolio optimization within the prospect theory framework is sensitive to its specification.[7] Figure 2A provides a graphical tool for an intuitive means of thinking about this problem in the case of one risky asset. More formal proof of the set of attainable portfolio weights under the same assumption is found in Ang, Bekaert, and Liu (2003) and also Levy, De Giorgi, and Hens (2003).

Assume that the investor derives positive value only for outcomes over and above the risk-free interest rate, and that assets are evaluated on an annual basis. This can be thought of as the vertical axis at the origin of Figure 1 is set to the yearly T-bill rate, rather than zero. Further, the investment opportunity set is the yearly equity premium with Sharpe ratio denoted s. The loss-averse investor is therefore restricted to holding Cash, from which she will derive zero utility, or invest into Stocks, which is associated with risky prospective

[7]Sharpe (1998) finds discrete choices with respect to *Morningstar* rankings of mutual funds, and Aït-Sahalia and Brandt (2001) find that the implied market-timing behavior of loss averse investors is aggressive.

Table 1: The distribution of returns

The label "Cash" refers to the U.S. 30-day Treasury Bill, a long-term U.S. government bond index is labelled "Bonds" and "Stocks" is the S&P 500 stock return. Real returns have been geometrically inflation-adjusted. There are 76 annual and 912 monthly observations in the sample. Bera-Jarque is a joint test of skewness and kurtosis under the null of normality. The rejection probability is reported for each asset individually as well as for a portfolio consisting of 50% of the labelled asset and 25% in each of the other two. Data from Ibbotson Associates.

	Panel A: Real annual returns, 1926-2001			Panel B: Nominal annual returns, 1926-2001			Panel C: Real monthly returns, 01/1926-12/2001		
	Cash	Bonds	Stocks	Cash	Bonds	Stocks	Cash	Bonds	Stocks
Arithmetic mean, %	0.82	2.69	9.40	3.86	5.69	12.65	0.06	0.21	0.76
Standard deviation, %	4.07	10.56	20.36	3.16	9.36	20.24	0.53	2.31	5.67
Skewness	-0.51	0.75***	-0.12	0.88**	1.24***	-0.30	-1.81***	0.55***	0.52***
Excess kurtosis	3.16**	0.15	-0.41	0.60	1.95***	-0.27	16.62***	4.33***	9.81***
Individual Bera-Jarque prob.	<0.01	<0.01	0.75	<0.01	<0.01	0.52	<0.01	<0.01	<0.01
Portfolio Bera-Jarque prob.	0.65	0.86	0.60	0.85	0.20	0.50	<0.01	<0.01	<0.01
Correlation with Cash	1.00	-	-	1.00	-	-	1.00	-	-
Correlation with Bonds	0.58	1.00	-	0.24	1.00	-	0.32	1.00	-
Correlation with Stocks	0.11	0.24	1.00	-0.03	0.16	1.00	0.08	0.19	1.00

Rejection levels from a double sided t-test for skewness and excess kurtosis equal to zero at the 10%, 5%, and 1% level are marked (*), (**), and (***).

utility. This portfolio allocation problem can be stated

$$\max_{w} = EV^{\alpha}[wEQP], \tag{9}$$

where w is the weight and the equity premium is denoted EQP and refers to the first two moments of the yearly return for Stocks, subtracted with the yearly return on Cash displayed in Table 1. According to these data, the annual Sharpe ratio for real stock returns during the period 1926 to 2001 was 0.42.

The set of solutions to this allocation problem is almost trivial when exploring indifference curves in Figure 2A along with the dashed, implied Capital Allocation Line (CAL). Consider the portfolio allocation of roughly 70% stocks that is denoted point (c). An investor who weights losses at 2.25, as in this case, will derive a utility of 2 for this portfolio. But this is not the maximum utility attainable. In fact, if this investor could borrow, there would be no limit to the weight she would like to put into equities. Conversely, if the indifference curves were steeper than the CAL—when loss aversion is sufficiently high—the investor would always choose a zero allocation.[8]

When the inverse of (6), $s(h^{-1}(\lambda_0^{\alpha})) = s_{EQP}$, the indifference curve and the CAL are parallel, such that the loss-averse investor is indifferent to holding Cash and Stocks. There is no need to derive this complicated inverse, because we can simply plug in s_{EQP} in (6) and obtain $\lambda_0^1(s_{EQP}) = 2.89$, $\lambda_0^{0.88}(s_{EQP}) = 2.79$ and $\lambda_0^{0.70}(s_{EQP}) = 2.61$.

The formal solution set to the problem stated in equation (9) in the case $\alpha = 1$ is therefore

$$w = \begin{cases} 0 & \text{for } \lambda_0^1 > 2.89, \\ [0, \infty) & \text{for } \lambda_0^1 = 2.89, \\ \infty & \text{for } \lambda_0^1 < 2.89. \end{cases} \tag{10}$$

It is easy to generalize the mapping between model parameters and the Sharpe ratio by using the point of indifference implied by the solution in (10). Figure 3A plots which Sharpe ratio is associated with zero prospective utility.

[8]The investor never short stocks in this setting, which also follows from mean-variance efficiency.

Figure 3: Sharpe ratios and loss-aversion

The mapping between model parameters and the Sharpe ratio when prospective utility is zero is plotted in two ways. The direct relation between λ_0^α is plotted in Figure 3A, and the indirect relation obtained by the implied Sharpe ratio for different time periods is plotted in Figure 3B. The solid line labelled "Realized" in Figure 3B is obtained by drawing from the set of realized monthly returns for different period lengths, as opposed to assumed independent returns. The regions "Accept" and "Reject" in both graphs mark the areas in which prospective is positive and negative, under and above the lines that indicate the points of indifference.

Figure 3A: Sharpe ratios

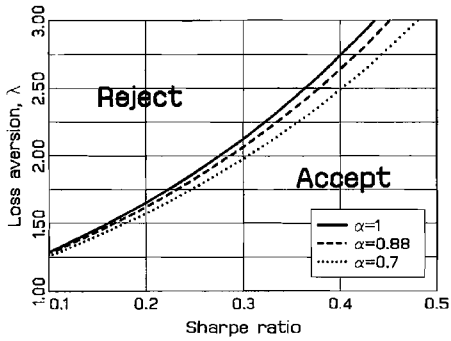
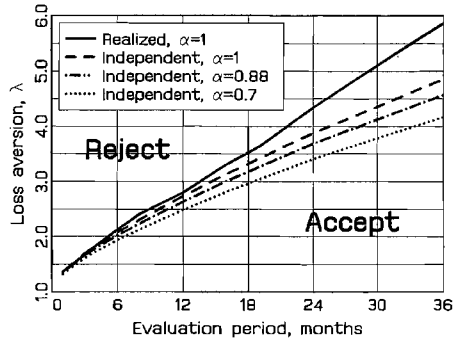


Figure 3B: Time periods



The regions labelled "Reject" and "Accept" mark the areas where this investor derives negative and positive utility, thereby finding it less or more preferable to the risk-free alternative.

Let us again consider the benchmark case when $\lambda = 2.25$ and $\alpha = 0.88$ together with a Sharpe ratio of 0.42. Figure 3A shows that the point implied by this parameter constellation is situated quite far in the acceptance region. The empirical Sharpe ratio is fairly in line with Benartzi and Thaler (1995), who report that a value for λ of 2.77 when $\alpha = 1$ yields about the same prospective utility for stocks as bonds evaluated by realized, yearly returns. We can conclude that the stock market is quite a favorable gamble for most loss averse investors, conditional on the parameters given by Kahneman and Tversky.

Alternatively, we may interpret the results as suggesting that the expected equity premium is lower than what has been realized during the period. If we calculate the equity premium consistent with $\lambda = 2.25$ and $\alpha = 0.88$ we obtain around 6.7% rather than the 8.6% measured historically. Whichever way one looks at the problem, a reasonably loss averse individual has been more than compensated for the risk she has been exposed to in the stock market given these assumptions.

4.2 Myopic loss aversion

The derived relation between loss aversion and Sharpe ratios directly demonstrates the willingness of time diversification, or myopic loss aversion. The scale independence holds between mean and variance, but not standard deviation. The Sharpe ratio rises when several periods of returns are aggregated. It is important here to stress that "time" in our analysis should be interpreted as an evaluation period rather than an actual holding period as pointed out by Benartzi and Thaler (1995). The theory at hand suggests that even a long-term investor could be exposed to narrow framing, such that the portfolio is evaluated frequently. A short evaluation period therefore makes this investor sensitive to short-term losses, given by the associated lower Sharpe ratio.

If we ignore compounding, the Sharpe ratio s can be scaled with a constant T such that

$$s_T = \mu T / \sigma \sqrt{T}. \tag{11}$$

This relation would naturally hold exactly if we assumed continuously compounded returns. However, our investor is assumed to derive utility over simple returns, rather than the logarithm of returns. Therefore, we keep this convention in what follows.[9]

To investigate the effect of assuming different time horizons for evaluation, Figure 3B plots the loss aversion parameter that is associated with zero prospective utility—similarly to Figure 3A. The solid line traces out the points of indifference for λ when $\alpha = 1$ when actual t-period returns are drawn from the sample of monthly returns. When one-month and twelve-month evaluation periods are considered, the Sharpe ratio is given exactly by the mean and standard deviation in panel C and A of Table 1. Therefore, an evaluation period of one year corresponds to $\lambda = 2.89$, which was the value found in Figure 3A. Figure 3B plots this relation for time periods up to 36 months. As we are drawing from the set of realized monthly returns, this methodology allows for mean-reversion. More precisely, if variances grow disproportion-

[9]There is a subtle but important difference here. If a one-period simple return is normally distributed, a two-period return is not. This is because only sums of normals, not products, are themselves normally distributed. It is also a fact that returns are bounded at -100%, which can make inferences suspect when approximating returns with normal distributions. All results regarding the Sharpe ratios and limits of parameters also apply for the case of continuously compounded returns.

ately slower than the mean when we increase the evaluation period, we will account for negative serial correlation. The Sharpe ratio is then higher in the presence of mean-reversion than independent returns, which in turn implies a larger acceptance region for λ_0^α.

As a benchmark, the dashed line in Figure 3B traces out the same relation when returns are assumed to be independent. We see that there is little difference between the solid and dashed lines when we consider time horizons up to one year. However, as the time horizon increases, the solid line showing actual returns is steeper. This is in line with the evidence suggesting some negative serial correlation in the sample for return horizons of over one year.

The solid and dashed lines show that the driving force behind the increasing demand for stocks is not due to mean-reversion, because the positive relation remains.[10] Rather, it is the decreasing probability of a loss that gives this result through a rising Sharpe ratio. Yet, we should be a bit careful in making direct comparisons with traditional models of portfolio choice. Here, we are following a descriptive approach where we look at the impact of narrow framing, rather than determining the allocation for an actual investment horizon.

The value of α plays a minor role for allocation when the evaluation period is short. Again, it is the parameter for loss aversion that is most important for the results. For a one-month evaluation period, an individual must weight losses to gains by a ratio equal to or below 1.3 in order to find the stock market alternative more attractive. This is close to being risk-neutral. The evaluation period associated with our benchmark parameters, $\lambda = 2.25$ and $\alpha = 0.88$, is seven months. As the evaluation period increases, an individual must be extremely loss averse to be indifferent to a zero-bet and the stock market—especially if she believes that stock returns mean-revert.

The evaluation period itself is therefore at least as important for the allocation decision as loss aversion, and it is impossible to analyze the two independently without either fixing the evaluation period or restricting the value of λ^α. But this is possible in experiments. Gneezy and Potters (1997) find that individuals are more likely to accept gambles that are presented as pack-

[10] It is well known that mean reversion produces an increase in the demand for risky assets even for power utility functions. See, for instance, Campbell and Viceira (2002).

ages of repeated lotteries of the same kind, rather than as isolated gambles. Thaler, Tversky, Kahneman, and Schwartz (1997) study the effects of myopia when allocating between stocks and bonds. The hypothesis is that individuals who evaluate gambles between a stock and a bond fund—and have to commit themselves for several periods—allocate a higher share to the more risky stock fund. The authors argue that the experiment broadly confirms that a reasonable evaluation period is twelve months on average. Therefore, annual returns will be assumed in the subsequent analysis.[11]

4.3 Portfolio analysis

By assuming normally distributed asset returns, standard mean-variance analysis applies, and we can make use of many well-known results from efficient set mathematics. In particular, we can recover the weights for any portfolio along the mean-variance frontier. This is promising, since we have discovered an exact mapping between the Sharpe ratio and the parameters of the model in two cases: when prospective utility is zero, and at the asymptote of the indifference curve.

Although the asymptote of the efficient set for most purposes is fairly uninteresting, it will, in this setting, provide a lower bound on the estimate for our model parameters. This is so for the same reason as in the one risky asset case, namely that *too* low a level of loss aversion implies unbounded portfolios, and this is a feature that we want to avoid.

We can exploit the revealed facts about investor preferences and apply them to portfolio investments, following Ingersoll (1987). Let $\mathbf{z}$ be a vector of sample means with corresponding covariance matrix $\mathbf{\Sigma}$. We can express the maximum Sharpe ratio of the efficient set as

$$Z = \hat{\sigma}\sqrt{\mathbf{z}'\mathbf{\Sigma}^{-1}\mathbf{z}} \equiv \hat{\sigma}\sqrt{C}, \tag{12}$$

where Z and $\hat{\sigma}$ are the portfolio mean and standard deviation. The weight vector for this portfolio is $\mathbf{w} = \mathbf{\Sigma}^{-1}\mathbf{z}/\mathbf{1}'\mathbf{\Sigma}^{-1}\mathbf{z}$. Hence, the slope in mean-standard deviation space associated with (12) is $\sqrt{C}$, and we can directly solve

[11] The mean allocation to stocks was roughly 40-45% when returns were evaluated on a six week basis in this experiment. In the yearly condition, the mean allocation to stocks rose to 70%.

for a unique λ_0^α.

Furthermore, it can be shown that the asymptote of the efficient set follows

$$Z = B/A + \hat{\sigma}\sqrt{(D/A)}, \tag{13}$$

where $B \equiv \mathbf{1}'\mathbf{\Sigma}^{-1}\mathbf{z}$, $A \equiv \mathbf{1}'\mathbf{\Sigma}^{-1}\mathbf{1}$, $\mathbf{1}$ is the unit vector and $D \equiv AC - B^2$. The slope of the asymptote is $\sqrt{(D/A)}$. Per definition, the indifference curve tangent to this slope has no finite solution with respect to the weights.

4.3.1 Real returns

Let us first consider the case when there are three risky assets: Stocks, Bonds and Cash from which we use annual real returns as specified in panel A of Table 1. Cash is often regarded a safe asset, but we may think of it here as risky, due to inflation uncertainty.

Figure 4A plots the mean-variance frontier associated with these data. The slope of the maximum Sharpe ratio, $\sqrt{C}$, is 0.492 and marked by the point (d) in Figure 4A. We can immediately identify this point lying along the indifference curve associated with zero prospective utility, and we obtain $\lambda_0^1(0.492) = 3.45$. This portfolio consists of 44% Cash, 17% Bonds and 39% Stocks—a quite conservative allocation in line with the relatively high rate of loss aversion. The benefit of the methodology here becomes clear when we note that we will optimize by choosing exactly the same portfolio for parameters $\lambda_0^{0.88}(0.492) = 3.30$ and $\lambda_0^{0.7}(0.492) = 3.07$. Again, we see that there must be a significant change in α in order to lower the required rate of loss aversion. The indifference curve associated with these pairs of parameters is indicated by a dotted line that is exactly tangent to point (d) in Figure 4A.

Point (d) is interesting for another reason. It is the point at which expected weighted losses and gains are exactly equal. We can draw a direct conclusion that any portfolio left of point (d) on the frontier in Figure 4A is associated with negative prospective utility. The only way to obtain such a portfolio on the frontier is by increasing the slope of the indifference curve, and hence λ. Such an indifference curve must inevitably have a negative intercept, and therefore be associated with negative utility. This may seem counter-intuitive, as we move into a region of *safer* assets in the traditional framework. It is,

Figure 4: Portfolio optimization: Cash, Bonds and Stocks

The mean-variance frontiers are obtained from data in Table 1 when all three assets—Cash, Bonds and Stocks—are risky. Real returns are plotted in Figure 4A, and nominal returns in Figure 4B. The dashed line plots the asymptote of the efficient set and the dotted line where prospective utility is zero. Loss aversion is infinite at the minimum-variance portfolio as indicated by the dash-dotted line. The indicated values for λ associated with the slopes assume that $\alpha = 1$.

Figure 4A: Real returns

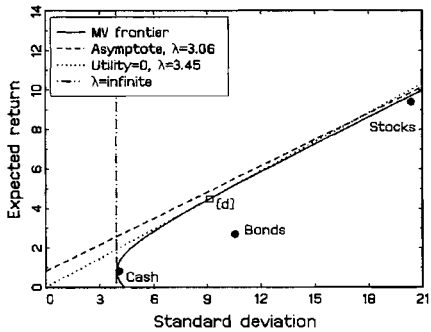
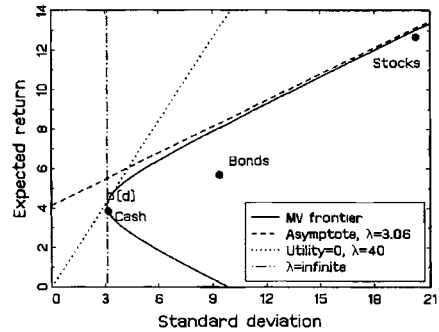


Figure 4B: Nominal returns



however, a property of the model. The Stock investment is attractive, and the only way a conservative portfolio is held is if loss aversion is high. Another way of grasping the same intuition is to note that the probability of a loss decreases, so it must be more heavily weighted than gains as we move down the frontier.

This argument can be taken to the extreme. From mean-variance analysis, we can obtain the minimum variance portfolio, indicated by the dash-dotted line. At this point, λ approaches infinity, and prospective value minus infinity. The intuition is that, locally, there is no trade-off between standard deviation and mean, just a change in the mean. Under such circumstances, one must be infinitely loss averse not to accept a marginal increase in the mean.

The asymptote of the boundary of the efficient set is calculated to 0.444, and traced out by the dashed line in Figure 4A. This point will be associated with the maximum, bounded prospective utility attainable, because the investor could not be better off and still own a portfolio with finite weights. By noting this fact, we label the parameter value associated with the asymptote $V_{\max}$ and find that $\lambda^1_{V\,\max} = 3.06$.

When α is set to the value of 0.88, we obtain $\lambda^{0.88}_{V\,\max} = 2.94$; when $\alpha = 0.7$ the parameter drops to $\lambda^{0.7}_{V\,\max} = 2.75$. The indifference curves associated with

the asymptote for the cases considered do not intersect the frontier. This is important, because we would otherwise mistakenly obtain a parameter value that is associated with another feasible portfolio.

4.3.2 Nominal returns

Some authors, including Benartzi and Thaler (1995), argue that nominal rather than real returns should be used in describing investor behavior. The reason for this is that individuals exhibit money illusion and that everyday return data are reported in nominal rather than real terms. Cash could also be risky in nominal terms in this case, because the investor derives utility from inflation, which is uncertain. A descriptive approach must acknowledge these potentially important deviations from traditional investment analysis.

The distribution for nominal returns can be found in panel B of Table 1. We see that when inflation is added, Cash—not Stocks—is the asset with the highest Sharpe ratio. Nominal returns also have a slightly different covariance structure, which in turn will alter the investment opportunity set. In what follows, we will explore how these alterations affect the previous conclusions.

The higher Sharpe ratio is indicated by the indifference curve tangent to point (d) in Figure 4B. This exactly captures the intuition that the probability of a loss in nominal terms is more unlikely than in real terms. A loss averse individual caring about nominal losses would be much more inclined to take on more risk in the traditional meaning for given parameters. In fact, the slope suggests that an individual can weight losses to gains in the neighborhood of 40:1 and still derive positive utility from choosing a portfolio among the available assets.

We could adjust this estimate for α as we did earlier and find that $\lambda_0^{0.88} = 35$ and $\lambda_0^{0.70} = 29$. The argument can be rephrased by recovering the weights for this portfolio. It consists of 88% Cash, 5% Bonds and 7% Stocks, making it a much more conservative portfolio than that defined over real returns. Therefore, we see that an upward shift of the mean of the distribution will inevitably alter the allocation for given parameters. On the other hand, if we are concerned about the relatively high rate of loss aversion that constitutes its lower bound, it is the asymptote of the efficient set that is of interest. Figure 4B shows that the slope of the asymptote is virtually unchanged for

nominal returns, and therefore we would still be unable to find a finite portfolio for $\lambda^1_{V\,\max}$ below 3.06. Therefore, the earlier conclusion also holds for alternative values of α—the limiting parameters are virtually unchanged for nominal compared to real returns.

4.3.3 No correlation

Experimental evidence offered by Kroll, Levy, and Rapoport (1988) show that individuals pay little or no attention to the correlation between assets. Benartzi and Thaler (2001) find that investors follow the *1/n-strategy*—naively splitting their investments in equal proportions over investment alternatives. Even though such a strategy is somewhat at odds with the utility approach here, it may suggest that correlation considerations are of secondary importance to the allocation decision.

We can easily simulate the case when asset returns are regarded as being independent. When all elements but the diagonal of the variance-covariance matrix are zero, we have taken away all correlation. Hence, it is only the individual assets' mean and variance that can determine the allocation decision. Repeating the analysis above for nominal returns and zero correlation in Figure 5A, we actually obtain somewhat higher parameter values: $\lambda^1_{V\,\max} = 3.18$ and $\lambda^{0.88}_{V\,\max} = 3.04$. Therefore, the parameters associated with the opportunity set considered here are not sensitive to assumptions regarding covariance.

4.3.4 Two risky assets: Bonds and Stocks

In Figure 5B we assume that Cash is risk-free, and the investor derives prospective utility for returns in excess of the risk-free rate (i.e. the bond and stock premium). Here, we obtain $\lambda^1_{V\,\max} = 2.31$ and at the point where prospective utility is zero we have $\lambda^1_0 = 3.06$. Even if the investor here need not to be as loss averse to have a finite portfolio as in the three assets case, there may be another source of concern. Since holding Cash gives zero prospective utility, it is difficult to argue that the investor would optimize by choosing any other mixture of Bonds and Stocks than those given between point (d) and the asymptote of the frontier. Points on the frontier below (d) are all associated with negative prospective utility, and are thus clearly inferior to holding

Figure 5: Portfolio optimization: alternative assumptions
5A diplays the mean-variance frontier obtained by uncorrelated nominal returns. In 5B there are two risky assets, where the loss averse investor optimizes over the Bond and Stock premium. The dashed line plots the asymptote of the efficient set and the dotted line where prospective utility is zero. The indicated values for λ associated with the slopes assume that $\alpha = 1$.

Figure 5A: No correlation

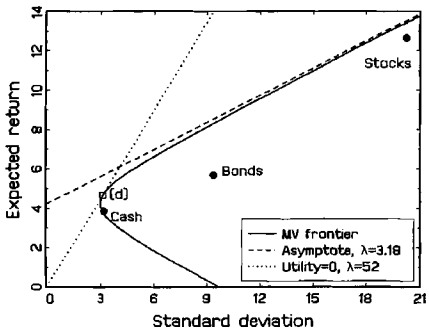
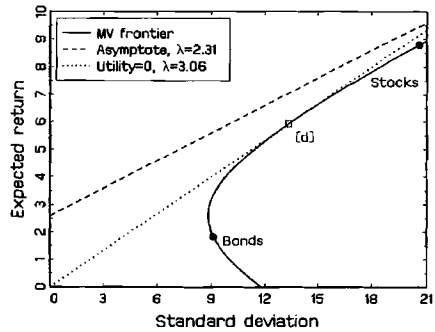


Figure 5B: Bonds and Stocks



Cash. Under these assumptions, an investor with loss aversion higher than 3.06 holds only Cash; at this point she switches to a roughly 40%/60% composition of a Bond/Stock portfolio, and successively weights Stocks higher as loss aversion is lowered further.

Canner, Mankiw, and Weil (1997) find an *asset allocation puzzle*, in which common portfolio advice cannot be rationalized with portfolio weights obtained from traditional portfolio theory. The advice is to have a lower weight in bonds relative to stocks as the weight to stocks increases, but standard theoretical models imply constant or increasing relative weight for bonds.[12] The results obtained here could partly describe this type of advice, but not all. Most importantly, common investment advice also recommends that some Cash is held throughout different levels of risk. We could not explain portfolios consisting of all three assets nor portfolios consisting mainly of Bonds using prospect theory under this set of assumptions.

The allocations using prospect theory when Stocks and Bonds are risky and Cash risk less could describe why stock market participation is low, but another potential drawback is the sensitivity to model parameters. We would

[12]It is easy to envision the case in which the dotted line in Figure 5B represents a capital allocation line in standard portfolio theory, where point (d) is the optimal tangency portfolio. The bond-to-stock ratio is constant for all allocations along this line.

only observe different portfolio compositions for a very narrow parameter range of λ_0^1. Figure 5B shows that this range is between 2.31 and 3.06.

4.3.5 Skewness and Kurtosis

Realized stock returns may not be well described by a normal distribution. This will matter if investors have preferences over higher moments, and more specifically, over skewness and kurtosis. As can be seen in Table 1, the null of normality for all asset returns can be rejected when measured on a monthly basis, but the evidence is not as clear for the yearly frequency.[13] Before going into detail on what the distributions here imply for the portfolio decision at hand, let us see if we can understand in what way skewness and kurtosis could matter.

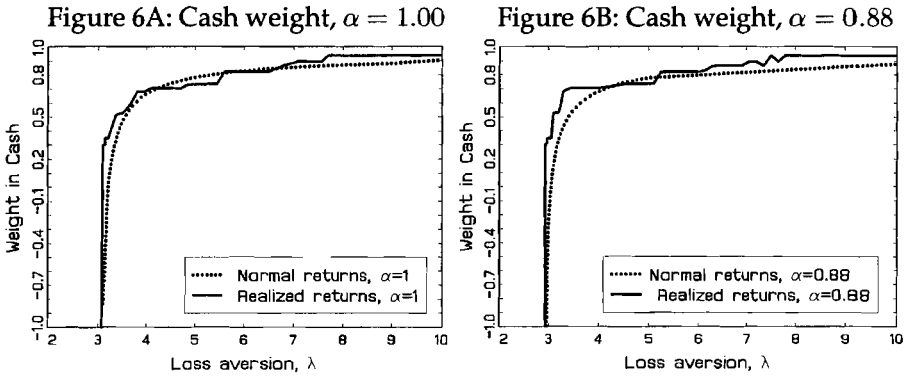
Skewness explains the asymmetry of a distribution. Positive skewness implies that large negative outcomes become more unlikely, while the reverse is true for positive outcomes. In principle, preferences over skewness may be applicable to a much wider family of utility functions than the one considered here. In particular, Harvey and Siddique (2000) formally incorporate co-skewness in an asset pricing model and show that investors indeed command a higher risk premium on average compared when only mean, variances and covariances matter. The intuition for why skewness matters in the case of pure loss aversion is clear. When losses are weighted higher than gains, investors like skewness since extreme losses are less likely than extreme gains. But when there is risk-seeking in the domain of losses, it is no longer as easy to generalize this result.

A measure of excess kurtosis above zero means that the distribution is leptokurtic—or has fatter tails than that of a normal distribution. Intuitively, kurtosis should be disliked by loss averse investors for the same reason as above. Pure loss aversion will always punish investments that increase the probability of a loss.

The negative skewness of yearly stock returns in Table 1 therefore indicates that Stocks should be less attractive than Bonds. At the same time, Stocks have less excess kurtosis than Bonds and Cash, and it is not easy to arrive at any

[13] This feature is well known; see, e.g., chapter 1 of Campbell, Lo, and MacKinlay (1997).

Figure 6: Portfolio weights: realized returns vs. normally distributed returns
Portfolio weights for Cash, Bonds and Stocks are recovered by a numerical optimization procedure for two cases. The dotted lines trace out the portfolio weight in Cash when drawing 1,000,000 returns from a multivariate normal distribution corresponding to that of the means and covariance matrix of the data in Panel A of Table 1. The solid line plots the weight when drawing returns in triplets from the realized distribution of Cash, Bonds and Stocks. The difference between Figure 6A and 6B is that α is either 1 or 0.88.



definite conclusion on how the loss averse investor ranks the investments.

We could continue to use the same framework even if assets are not normally distributed. In fact, we could replicate a very wide range of distributions as mixtures of different normal distributions.[14] Therefore, if we knew *which* mixture of normal distributions results in the distribution for an asset, we would be able to calculate utility. Unfortunately, this is no easy task, and even if we were able to calculate prospective utility, it is not obvious which way to quantify the results.

Instead, a numerical method is applied (details are given in Appendix B). We can search for the weights that optimize the realized returns and compare them with the portfolios obtained by assuming normality. There are only 76 realized yearly returns—and as an example—only 24 of them were years in which Stocks yielded a loss.[15] It is therefore more difficult to get precise estimates of the weights when we vary the parameter for loss aversion, than when

[14]Equation (2) can be expressed simply as a weighted average of the prospective utility measured over a set of (individually) normally distributed gambles

$$EV^{\alpha}(P) = \rho_1 EV^{\alpha}(P_1) + \rho_2 EV^{\alpha}(P_2) + \ldots + \rho_N EV^{\alpha}(P_N),$$

where ρ_i is the weight for each of the N normal distributions.

[15]To preserve the covariance structure, the realized returns are drawn in triplets.

we draw 1,000,000 returns in the normal case. However, it certainly gives us a good indication of how serious a crime we have committed by following the normal assumption. Figure 6A and 6B plot the weights to Cash under the assumption of normality along with the corresponding weights when realized returns are used.

The general shape of the dotted and dashed lines confirms the rather extreme sensitivity in the region of lower λ's where leverage is high. From a descriptive viewpoint, the parameter for loss aversion must be contained within quite a narrow range over the population for us to observe a wide spectrum of portfolio holdings where people choose portfolios other than the most extreme.

The lowest value for which the numerical algorithm converged for $\alpha = 1$ was 3.03 in the case when realized real returns were used, as opposed to 3.08 when they were drawn from a normal distribution. Similarly, in Figure 6B—when $\alpha = 0.88$—the parameters are 2.94 compared to 2.95.[16] These similar results are likely due to the fact that it is much harder to reject normality for portfolios than for individual assets. The Bera-Jarque test for portfolios in Table 1 tests normality for portfolios consisting of 50% of the labelled asset and an equal proportion of 25% in the remaining two. Normality can not be rejected for any of the portfolios in the case of yearly returns.

The discreteness of using realized returns is apparent along the solid line connecting the point estimates for the Cash weights. Even if there certainly are differences in allocation to Cash in this region, they are within a narrow parameter range where leverage is high. The general shape of the allocation scheme does not imply that the normality assumption is too restrictive.

4.3.6 Summary of results

In summary, we have studied portfolio allocation under five sets of assumptions. In four instances, the investment opportunity set varied, but returns were assumed to be normally distributed. In the last instance, the normality assumption were relaxed. The associated parameter limits for the asymptote

[16]The difference between the lowest theoretical and numerical parameter values when the normal assumption is applied should only be interpreted as an effect of very weak concavity in the range close to the asymptote, and therefore numerical solutions are difficult to obtain.

Table 2: Summary of results

Panel A reports the lowest value for the loss aversion parameter λ that could be achieved under the assumptions regarding the investment opportunity set considered in the main text. Panel B reports the λ in case where prospective utility is zero.

Panel A: Asymptotic λ					
Scenarios	Real	Realized*	Nominal	No correlation	B & S premium
α=1.00	3.06	3.03	3.06	3.18	2.31
α=0.88	2.94	2.94	2.94	3.04	2.24
α=0.80	2.85	2.81	2.85	2.96	2.19
α=0.70	2.75	2.73	2.75	2.85	2.13
s	0.444	0.447	0.444	0.459	0.334
Panel B: λ at 0 prospective utility					
Scenarios	Real	Realized**	Nominal	No correlation	B & S premium
α=1.00	3.45	3.42	40	52	3.05
α=0.88	3.30	3.37	35	45	2.92
α=0.80	3.20	3.30	32	42	2.84
α=0.70	3.07	3.27	29	37	2.74
s	0.492	0.490	1.405	1.500	0.442

*) The parameters reported are the lowest for which convergence was achieved. **) Parameters are averaged between last positive and first negative value of prospected utility when moving over the grid of optimal λ.

of the investment opportunity set and values when prospective utility is zero are presented in Table 2. The limit of λ is around 3 when $\alpha = 1$ for all scenarios when all three assets span the frontier. This is a considerably higher value than previously proposed in the experimental literature, as illustrated by the dotted line in Figure 1. Weak non-linearity, introduced by reasonable values of α, does not change this conclusion in any significant way. It is also worth emphasizing here that we have derived parameters for the asymptote. These portfolios are infinitely leveraged and are therefore only of theoretical interest. To obtain *reasonable* portfolios, we must either have even *higher* loss aversion or greater curvature (lower α). It is also clear that the curvature of the value function must be rather extreme to make any significant difference in the portfolios held. The case in which Bonds and Stocks are evaluated separately from Cash can explain low stock market participation, but also suffers

from a discrete allocation feature. A loss averse investor will switch to a mixture of Bonds and Stocks, but will never hold a portfolio consisting of Bonds and Cash.

Due to the model's close relation to the Sharpe ratio, there is duality in the results with respect to the frequency for which the assets are evaluated. A shorter evaluation period makes a risky portfolio less attractive for a loss averse investor. This means that any given set of parameters could pin down a specific solution if the evaluation period can be determined freely. A shorter evaluation period will make the asymptotic parameters of Table 2 lower, but not change the general discovery that *some* bound will exist.

5 Conclusion

We have found that it generally takes higher levels of loss aversion than proposed in the previous literature to find bounded solutions to asset allocation problems. This result can have several explanations.

Individuals may be less loss averse to small-stake gambles than to real-life investments. A common argument is that laboratory payoffs are too small to support any larger-sized generalizations of actual behavior (see, e.g., Campbell and Viceira, 2002, p. 9). If this is the case, it could well be that actual loss aversion is higher than we have seen in these studies.[17]

We may also have good reasons to believe that the measured historic equity premium is higher than expected. Fama and French (2002) find that stock returns after 1951 seem to be much higher than indicated by dividend discount models. The simple interpretation is that stock returns yielded surprisingly high returns in the latter half of last century. The reason is that a decline in the discount rate produces large capital gains. If the sample is "contaminated" with capital gains, we are likely to overestimate the expected return on stocks. Fama and French argue that the expected equity premium should be in the range of 2.55% to 4.32% for this time period. The analysis here indicates that only a marginally lower equity premium—around 6.7% compared

[17] In fact, most of the experiments referred to in Kahneman & Tversky (1979, 1992) used hypothetical payoffs.

to 8.6%—is consistent with the benchmark parameters suggested by Kahneman and Tversky.

Dynamic applications, such as those by, for instance, Barberis, Huang, and Santos (2001), and Gomes (2003), are able to generate parameter estimates that are closer to those of Kahneman and Tversky, due to the additional concavity that is imposed when reference points adjust. It is possible that the static approach considered here is less suited for describing actual investor behavior. On the other hand, dynamic models are complicated and difficult to solve analytically even for two assets, and it is not always clear whether they deliver insights that are not captured by a static model.[18] The theoretical results presented here may provide useful tools for solving allocation problems in the case of a much broader universe of assets.

Investors in this model are rational, meaning that they assess the correct objective probabilities of outcomes. Based on experimental evidence, Tversky and Kahneman (1992) consider the case in which objective probabilities are transformed when judging the likelihood of events, where extreme outcomes are considered more likely than the actual frequency at which they occur. These transformations have the potential power to explain many observed behavioral anomalies, such as why risk-averse individuals buy lottery tickets with very low expected value. Essentially, transforming the probabilities means that the distribution from which returns are evaluated is not normally distributed, and is therefore not considered in this paper. But Levy and Levy (2004) show that even this case is equivalent to mean-variance optimization for a large segment of the efficient set. Therefore, parameters associated with a certain portfolio may change, but there is less concern that the solutions are not optimal in a mean-variance context.

The discussion above assumes that prospect theory is a relevant description of individual behavior, but this has been contested. Levy and Levy (2002) find that when experimental subjects are faced with mixed bets, i.e., when outcomes are not restricted to the positive or the negative domain, there is much less support for the general S-shaped value function as depicted in Figure 1. This implies that prospect theory, although useful in explaining some contexts

[18] Berkelaar, Kouwenberg, and Post (2003) show that there is a link between a static and dynamic reference point when prospective utility is defined over final wealth.

of observed behavior, may not be well suited for arbitrary generalizations.

One advantage of prospect theory is that it translates into more conventional assessments of preferences. Perhaps it could be useful in communicating risk in a more intuitive way. We have found that if the pain of a loss is less than three times the pleasure of a gain, you should not be reluctant to invest in stocks. For most people, this provides far more intuition than most standard measures of risk.

Appendix A: Derivatives of the value function

We have the value function

$$EV^1(x) = \mu[\Phi(s) + \lambda\Phi(-s)] + \sigma[(1-\lambda)\phi(-s)]. \tag{A1}$$

In what follows we note that $F = \Phi(x)$, $f = \phi(x)$, $f' = -x\phi(x)$. Further, we have that $\phi(-x) = \phi(x)$ and $\Phi(-x) = 1 - \Phi(x)$. By applying these rules to (A1) we can write the derivatives of the value function as follows:

$$\begin{aligned}
\frac{dEV(x)}{d\mu} &= [\Phi(s) + \lambda\Phi(-s)] + \mu\left[\phi(s)\frac{1}{\sigma} - \lambda\phi(-s)\frac{1}{\sigma}\right] \\
&\quad -\sigma(1-\lambda)\phi(-s)\frac{\mu}{\sigma}\cdot\frac{1}{\sigma} \\
&= [\Phi(s) + \lambda\Phi(-s)] \\
&\quad +(1-\lambda)\phi(s)\frac{\mu}{\sigma} - (1-\lambda)\phi(-s)\frac{\mu}{\sigma} \\
&= \Phi(s) + \lambda\Phi(-s).
\end{aligned} \tag{A2}$$

Similarly, for the derivative with respect to the variance we get

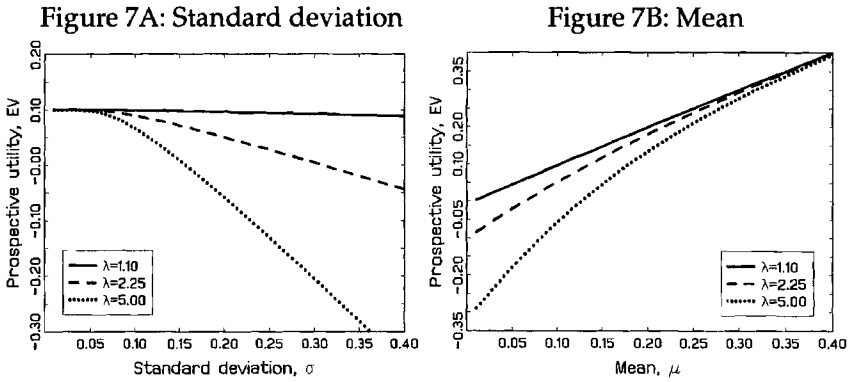
$$\begin{aligned}
\frac{dEV(x)}{d\sigma} &= -\mu\phi(s)\frac{\mu}{\sigma^2} + \mu\lambda\phi(-s)\frac{\mu}{\sigma^2} + (1-\lambda)\phi(-s) \\
&\quad +\sigma(1-\lambda)\phi(-s)\frac{\mu}{\sigma^2}\cdot\frac{\mu}{\sigma} \\
&= -(1-\lambda)\phi(s)\frac{\mu^2}{\sigma^2} \\
&\quad +(1-\lambda)\phi(-s) + (1-\lambda)\phi(-s)\frac{\mu^2}{\sigma^2} \\
&= (1-\lambda)\phi(s).
\end{aligned} \tag{A3}$$

Figure 7A illustrates that there is little change between the expected value and prospective utility when the parameter for loss aversion, λ, is close to 1. The investor who is close to risk-neutral will experience less disutility than the more loss averse investor when standard deviation increases.

A similar argument applies to Figure 7B, where the standard deviation is constant but the mean changes. The more loss-averse an investor is, the more powerful the impact on utility for an increase in the mean. A loss-neutral investor with $\lambda = 1$ will have a one-to-one mapping between increases of the

Figure 7: Derivatives of the value function

In Figure 7A, the mean is held fixed at 10% while standard deviation is varied from 1% to 40%. In Figure 7B, the standard deviation is held constant at 20% while varying the mean in the same interval.



distribution's mean and prospective utility.

Appendix B: Numerical optimization

To retrieve portfolio weights, we reformulate equation (3) in discrete form and maximize prospective utility. The optimal weights then solve

$$\begin{aligned} \max_{\mathbf{w}} EV^{\alpha}(Z) &= \max_{\mathbf{w}} \left[\frac{1}{N} \sum_{n=1}^{N} \left(V_{+}^{\alpha}(Z_n) - \lambda V_{-}^{\alpha}(Z_n) \right) \right] \\ \text{s.t. } \mathbf{w}'\mathbf{1} &= 1, \end{aligned} \tag{B1}$$

given the parameters λ and α, where $\mathbf{w}$ is a vector of weights, and $\mathbf{1}$ is the unit vector. The portfolio return Z_n is partitioned into gains

$$V_{+}^{\alpha}(Z_n) \equiv \max\{\mathbf{w}'\mathbf{R}_n, 0\}^{\alpha},$$

and losses

$$V_{-}^{\alpha}(Z_n) \equiv \max\{-\mathbf{w}'\mathbf{R}_n, 0\}^{\alpha}.$$

Here, $\mathbf{R}_n$ is either the n yearly return observations in sample, or n draws from a multivariate normal distribution with means and covariance matrix from panel A in Table 1. In the latter case, the method inevitably involves choosing an n that is large enough to provide a high degree of accuracy in the parameter estimates for $\mathbf{w}$. The obvious trade-off is a slower convergence of the optimization routine. There are 1,000,000 draws which should provide sufficient precision in the point estimates, although this is not formally investigated. Barberis (2000) also uses 1,000,000 draws and argues that his model provides fairly stable estimates above 100,000 draws. The similar estimates between the numerical and theoretical parameter values obtained in the results here confirm this claim.

References

Aït-Sahalia, Yacine, and Michael W. Brandt, 2001, Variable selection for portfolio choice, *Journal of Finance* 56, 1297–1351.

Allais, Maurice, 1953, Le comportement de l'homme rationnel devant le risque, critique des postulates et axiomes de l'ecole americaine, *Econometrica* 21, 503–546.

Ang, Andrew, Geert Bekaert, and Jun Liu, 2003, Why stocks may disappoint, Working Paper, NBER, Cambridge.

Barberis, Nicholas, 2000, Investing for the long run when returns are predictable, *Journal of Finance* 55, 225–264.

———, Ming Huang, and Tano Santos, 2001, Prospect theory and asset prices, *Quarterly Journal of Economics* 116, 1–53.

Barberis, Nicholas, Ming Huang, and Richard H. Thaler, 2003, Individual preferences, monetary gambles and the equity premium, Working Paper, University of Chicago.

Benartzi, Shlomo, and Richard H. Thaler, 1995, Myopic loss aversion and the equity premium puzzle, *Quarterly Journal of Economics* 91, 79–99.

———, 2001, Naive diversification strategies in defined contribution savings plans, *American Economic Review* 91, 427–465.

Berkelaar, Arjan, Roy Kouwenberg, and Thierry Post, 2003, Optimal portfolio choice under loss aversion, Working Paper, Erasmus University Rotterdam.

Bernardo, Antonio E., and Olivier Ledoit, 2000, Gain, loss and asset pricing, *Journal of Political Economy* 108, 144–172.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton University Press: Princeton, N.J.).

Campbell, John Y., and Luis M. Viceira, 2002, *Strategic Asset Allocation: Portfolio Choice for Long-Term Investors* (Oxford University Press: Oxford).

Canner, Niko, N. Gregory Mankiw, and David N. Weil, 1997, An asset allocation puzzle, *American Economic Review* 87, 181–191.

Fama, Eugene F., and Kenneth R. French, 2002, The equity premium, *Journal of Finance* 57, 637–659.

Fishburn, Peter C., 1977, Mean-risk analysis with risk associated with below-target returns, *American Economic Review* 67, 116–126.

Gneezy, Uri, and Jan Potters, 1997, An experiment on risk taking and evaluation periods, *Quarterly Journal of Economics* 112, 631–645.

Gomes, Francisco, 2003, Portfolio choice and trading volume with loss-averse investors, *Forthcoming in the Journal of Business.*

Gul, Faruk, 1991, A theory of disappointment aversion, *Econometrica* 59, 667–686.

Harvey, Campbell R., and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263–1295.

Ingersoll, Jonathan E. Jr., 1987, *Theory of Financial Decision Making* (Rowman & Littlefield: Totowa, N.J.).

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.

———, 1983, Choices, values and frames, *American Psychologist* 39, 341–350.

Kroll, Yoram, Haim Levy, and Amnon Rapoport, 1988, Experimental tests of the separation theorem and the capital asset pricing model, *American Economic Review* 78, 500–519.

Levy, Haim, Enrico De Giorgi, and Thorsten Hens, 2003, Prospect theory and the CAPM: A contradiction or coexistence?, Working paper, Institute for Empirical Research in Economics, University of Zurich.

Levy, Haim, and Moshe Levy, 2002, Prospect theory: Much ado about nothing?, *Management Science* 48, 1334–1349.

———, 2004, Prospect theory and mean-variance analysis, *forthcoming in Review of Financial Studies*.

Levy, Haim, and Zvi Wiener, 1998, Stochastic dominance and prospect dominance with subjective weighting functions, *Journal of Risk and Uncertainty* 16, 14–163.

Markowitz, Harry, 1952, Portfolio selection, *Journal of Finance* 7, 77–91.

Mehra, Rajnish, and Edward C. Prescott, 1985, The equity premium puzzle, *Journal of Monetary Economics* 15, 146–161.

Porter, R. Burr, 1974, Semivariance and stochastic dominance: A comparison, *American Economic Review* 64, 200–204.

Rabin, Matthew, 2000, Risk aversion and expected utility theory: A calibration theorem, *Econometrica* 68, 1281–1292.

Sharpe, William F., 1998, Morningstar's risk-adjusted ratings, *Financial Analysts Journal* Jul-Aug, 21–33.

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

Thaler, Richard H., Amos Tversky, Daniel Kahneman, and Alan Schwartz, 1997, The effect of myopia and loss aversion on risk taking - an experimental test, *Quarterly Journal of Economics* 112, 647–661.

Tversky, Amos, and Daniel Kahneman, 1992, Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297–323.

Chapter II

All Guts, No Glory: Trading and Diversification among Online Investors

Investing is a "loser's game," in which the winner is often the investor who makes the fewest errors.
—Charles D. Ellis

1 Introduction

The stock market boom of the late 1990s is, by most standards, unprecedented in stock market history. Even if many companies in traditional industries were valued at historical highs, the market was given an extra boost by sky rocketing prices stemming from the newly emerging information technology sector. Interest in the stock market surged. A new category of financial intermediaries, namely online brokers, provided low-cost stock market access that was mainly aimed at small investors. The Stockholm Stock Exchange reports that, in 1997, these companies accounted for 1% of the value and 3% of the transactions on the exchange. By 2000, this had risen to 4% of the value and 18% of the transactions. These aggregate figures suggest that online brokers have attracted a clientele of small investors that trade actively. In March 2000 the

[0] I would like to thank Magnus Dahlquist, Peter Englund, and Paul Söderlind for helpful comments and suggestions. I especially thank the online broker, who wishes to remain anonymous, and *Finansinspektionen* for providing me with the data.

market peaked, and then entered into a bear market that was to become one of the worst ever. These turbulent times provide the data for this study on the investor performance of a group of online traders.

This paper aims to quantify and measure the relative effects on performance of investment behavior. Since online investing is fairly new, there exists little previous research on the performance of online traders, even though they are predicted to grow in number (see Barber and Odean, 2001b for a survey). Online investors are well suited for studying individual investor behavior, since intermediation between the broker and the investor is kept at a minimum. Individual investors are also more likely to suffer from behavioral biases than investment professionals; overconfident investors are likely to trade more vigorously and hold undiversified portfolios.

The data were made available by an online broker and cover all transactions since the start in May 1999 up to and including March 2002. The 324,736 transactions in common stocks are distributed over 16,831 investors who enter sequentially. The investors are, on average, relatively young, predominantly male, and aggressive traders.

The average turnover rate implies that investors buy and sell their portfolio more than twice a year. The 20% that trade the most turn their portfolios around about seven times a year. In addition, investors are not well diversified. The median number of stocks in the portfolio is two, and 18% of the investors hold only one stock.

The investors in this sample show a preference for risk in general, and technology stocks in particular. The average beta is above 1.4, and among the investors who only hold one stock, 80% choose a stock belonging to the technology industry. In contrast, among the investors who hold four or more stocks, the average technology sector weight is only 55%. Diversification is therefore not only related to idiosyncratic risk, but to industry selection as well. Furthermore, I find evidence that investors who are more highly diversified systematically hold stocks that perform better *within* industries on average. This effect remains when accounting for differences in portfolio risk and size, and suggests that investment skill is related to the degree of diversification.

I propose a method for retrieving individual, monthly portfolio returns

directly from transaction data that is new to the literature of individual investor performance. Portfolio returns are measured relative to *passive returns*, which are the returns of the portfolio investors held at the beginning of the month, and therefore exclude monthly trading. It is found that most of what is lost due to trading can be related to fees, or 32 basis points per month compared with a total of 37. Investors in the top trading quintile lose around 95 basis points per month compared with those who do not trade. This result, however, is primarily driven by investors with small portfolios who are more sensitive to fixed fees. The average investor spends around 3.8% per year of their portfolio wealth on fees; this is more than twice the charge of a standard mutual fund.

Figure 1A shows that the equally-weighted mean of the market-adjusted return is -2.07% per month. In this paper I show how to decompose the return into the three parts discussed: the component due to the choice of industry, intra-industry selection—"stock-picking," and trading.

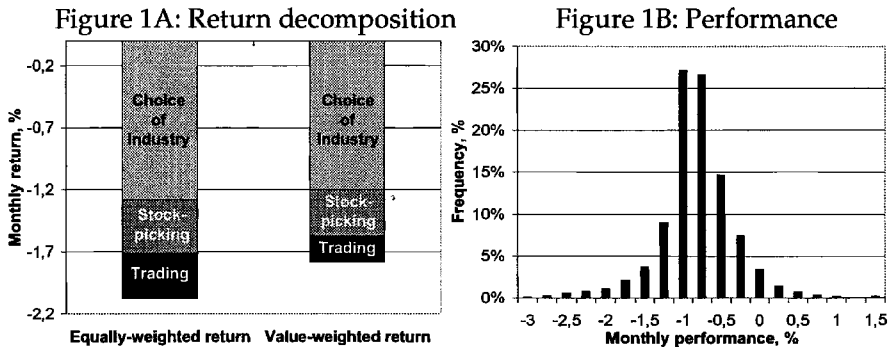
The choice of industry is most important in explaining the return difference to the market, reflecting the heavy tilt toward technology stocks and bad market timing. This may simply reflect investors' preferences for high risk. Risk is likely to be less of a problem when measuring stock-picking ability. The investors lose 43 basis points per month from choosing stocks that underperform any given industry on average. Trading costs are roughly equally important; 37 basis points per month are lost compared with the passive portfolio held at the beginning of the month. The value-weighted return suggests that fees, in small transactions and for small portfolio sizes, drive this result.

In addition to the uni-dimensional effects of trading and stock selection documented above, the main contribution of this paper lies in quantifying the relative importance of these characteristics for investor performance taken together.

Figure 1B shows the frequency distribution of investors' average performance, generated from estimates in a panel regression. The average performance here is a function of investors' turnover, size of portfolio and number of stocks held. It is possible to generate quite substantial cross-sectional variation in abnormal performance from the data by using these characteristics. The average underperformance is 74 basis points (or around 8.5% in annual-

Figure 1: Summary of key results

Figure 1A depicts the equally and value-weighted mean of a decomposition of the monthly market-adjusted return. The bar labelled "Choice of industry" refers to the return difference between the market and the chosen industry. "Stock-picking" measures the deviation from the individual stocks selected and the industry benchmark. "Trading" measures the return difference between the portfolio that includes trading and the portfolio held at the beginning of the month. Figure 1B displays a histogram of the 16,831 investors' monthly abnormal performance generated by the coefficient estimates of panel regression Model V in Table 8.



ized terms). The poor performance is likely to be due to the fact that these investors' portfolios are *too small*, that they trade *too much* and are *less* experienced *on average* compared with other stock market participants. An additional percentage increase in turnover hurts investor performance by 1.7 basis points per month. Investors whose portfolio values are twice as high as the sample average gain an additional 11 basis points. Similarly, investors who hold one stock more than average, i.e., four rather than three, perform 7 basis points better. The characteristics are also related to risk; investors that are older, women, trade more, and are more diversified all take less systematic risk.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical foundations of trading and stock selection, as well as the previous empirical evidence, within the framework of individual investor behavior. Section 3 presents the transaction data. Section 4 begins by explaining how portfolio returns are retrieved from transactions and then presents the results. Section 5 concludes.

2 Trading and stock selection

This paper links individual investor performance to both trading behavior and portfolio strategies. Explaining the findings by rational behavior is not unproblematic, given the overall poor performance of investors' portfolios.

The first question that arises is: Why do these individuals trade in such vast quantities? The no-trade theorem states that prices fully reflect information and when new information arrives, it is immediately incorporated into prices. If this were the case, there would be no trading at all.

But there may be informational asymmetries that drive trading. Grossman and Stiglitz (1980) derive an equilibrium from when the marginal benefits and costs of trading equate. Varian (1989) shows that trading can occur if investors have different priors of a risky assets mean. While this may explain why trading occurs, it offers little explanation as to what drives the priors. If differences in information drive trading, we would expect to see such investors compensated for the cost. The available evidence from individual investors in fact suggests the opposite: trading erodes returns. Heaton and Lucas (1996) propose that individuals trade in financial assets to buffer idiosyncratic income shocks in order to smooth consumption over time. Even if this provides another fully rational explanation for trading, it is difficult to see why this insurance should be valued at such high transaction costs. Investors could instead trade in mutual funds at a much lower cost.

The trading behavior of individual investors has often been attributed to overconfidence, as proposed by De Long, Shleifer, Summers, and Waldmann (1990), Kyle and Wang (1997), Daniel, Hirshleifer, and Subrahmanyam (1998), among others. In the psychology literature, overconfidence serves as a label—at least from a theoretical viewpoint—of two broad classes of cognitive biases.

The first, and most common, definition of overconfidence is the tendency for individuals to understate the uncertainty regarding their own estimates. When experimental subjects are asked to form confidence bounds around their point estimates, the outcome typically falls outside of the bound much more often than expected if people were well calibrated. This phenomenon is found to be task dependent, meaning that the evidence is strongest in tasks

that subjects find difficult.[1]

The second manifestation of overconfidence is that people are unrealistically optimistic about their own ability. In a classic survey among students, Svensson (1981) finds that 82% rank themselves to be among the 30% of drivers with the highest driving safety. Such a belief can be linked to the concept of priors mentioned above, because it implies that individuals may overstate the significance of the information they may acquire. Furthermore, Langer and Roth (1975) find that individuals tend to ascribe success to their own ability and failure to bad luck. Such an *illusion of control* is therefore closely related to overconfidence.

In financial models, overconfident investors are those who hold unrealistic beliefs of how high their returns will be and how precisely these can be estimated. It is reasonable to believe that overconfidence may be more prevalent among individual investors, since money management is regarded as a difficult task for most people. In addition, feedback in terms of relative performance is very noisy, and therefore the ability to learn from behavior is low. In the previous literature, overconfidence has primarily been associated with excessive trading, but in principle, it could also lead to a lack of diversification. Investors overestimating the significance of the information they obtain regarding a particular stock may feel that investing in this stock is more attractive than investing in a more diversified portfolio.

In the previous literature on individual investor performance, Schlarbaum, Lewellen, and Lease (1978) match purchases to sales and find that a round-trip transaction costs around 3.5% in commissions. Investors in their sample more than compensate for this cost in their trading. These results have been contested by Barber and Odean (2000), who point out that if investors are more likely to realize gains than losses, this methodology is likely to produce overly favorable estimates of investor returns.[2]

Barber and Odean (2000), in contrast, measure returns from position statements, implicitly assuming that all trades are conducted at the end of the month, and estimate trading costs separately. They find that the average

[1]For a review of these results, see McClelland and Bolger (1994).

[2]This argument relies on the findings of Shefrin and Statman (1985), Weber and Camerer (1998), and Odean (1998) that investors hold on to the losers and sell the winners in their portfolios.

round-trip trade costs approximately 3% in commissions and 1% on the bid-ask spread for a round-trip transaction. An aggregated portfolio consisting of the top quintile of active traders loses as much as 6.5% annually compared to the market due to these costs.

A related result by Barber and Odean (2002) is that online investors significantly underperform a size-matched sample of investors who did not go online. They find that young men with high portfolio turnover are more likely to go online—and once they do—trade even more. They attribute this finding to three factors. First, it is argued that men are more overconfident than women, and will therefore be more likely to switch to online trading. Second, there is an illusion of control; in other words, investors who go online falsely perceive risk to be lower when they are able to monitor their portfolio instantly. Third, they propose that another psychological concept—*cognitive dissonance*—can reinforce trading activity. Cognitive dissonance occurs when individuals rationalize a behavior on the basis of prior beliefs. If the belief is that high performance is associated with intense trading activity and constant monitoring of the portfolio, it is precisely this behavior that such individuals will show.

Glaser and Weber (2003) conduct a survey among investors at an online broker, and are therefore able to test directly how different measures of overconfidence relate to trading volume. They find evidence that trading volume is related to the second manifestation of overconfidence, rather than the first: investors who believe they are above average trade more.

Overconfidence can explain trading behavior and lack of diversification, but not *which* stocks investors choose to buy. To gain a better understanding of investment strategies, we borrow a different concept from the psychology literature, namely the availability heuristic. Individuals have a clear tendency to underestimate risks when the context is familiar or available. Slovic, Fischhoff, and Lichtenstein (1982) find that individuals underestimate by far the risk of dying of common diseases, but overestimate the risk of rare and dramatic accidents. Even if accidents are rare, they attract much more attention when they occur. It is thus easy to attribute too much weight to such casual observations.

Odean (1999) reports that investors, on average, sell stocks that outper-

form those they buy at a cost of around 3% per year. This cannot easily be explained by overconfidence, but is attributed to investors following naive investment strategies. Barber and Odean (2003) argue that people's buying behavior of stocks is subject to an availability bias, as stocks bought are more likely to have had an extreme return performance (positive *and* negative) or have had high media coverage. Benartzi and Thaler (2001) suggest another form of availability bias when choosing among mutual funds: the *1/n-heuristic*. They find that the number of funds available for selection determines the allocation, with investors naively splitting their investments in equal proportions across the funds. These examples provide evidence of systematic effects on buying behavior and should therefore be added to the previous evidence on the reluctance to sell losers.

It is still not clear in what ways naive strategies erode performance, unless they are negatively correlated with return patterns. Grinblatt and Keloharju (2000) find that the degree of sophistication matters for performance. They argue that households are likely to be less sophisticated investors and find that they trade to the opposite of investment professionals, such as institutions. In their sample, households act contrarian, and on average, lose from having such a strategy.

From the results cited here, it is tempting to generalize about private investors, who as Coval, Hirshleifer, and Shumway (2003) put it; "are often regarded as at best uninformed, at worst fools." However, they do find persistence in the performance of the top ten percent of most successful traders. This serves as an important reminder that not all private investors perform poorly, even if many do.

3 Data

An important advantage of studying an online broker is that the orders are placed directly by the investors. Although it is possible to place orders over the telephone as well, this constitutes a very small part of the transactions. There is therefore little direct interaction between the investor and the broker, which could otherwise be a source of concern when making inferences about performance across various investor groups. A drawback is that such

investors cannot be regarded as being representative of any other group than online investors in general. As low fees are the main form of competition for online brokers when attracting customers, active traders are likely to be self-selected.

There are no tax exemptions for any accounts, as there are for the Keogh or 401(k) scheme in the U.S., where taxes are deferred. Furthermore, Swedish tax rules do not distinguish between the holding period of stocks, as is common in many countries. The tax rate is a flat 30% rate for the net of all realized gains and losses for private investors. It is therefore possible to aggregate all portfolio holdings across individuals, even if they in some cases possess more than one account.

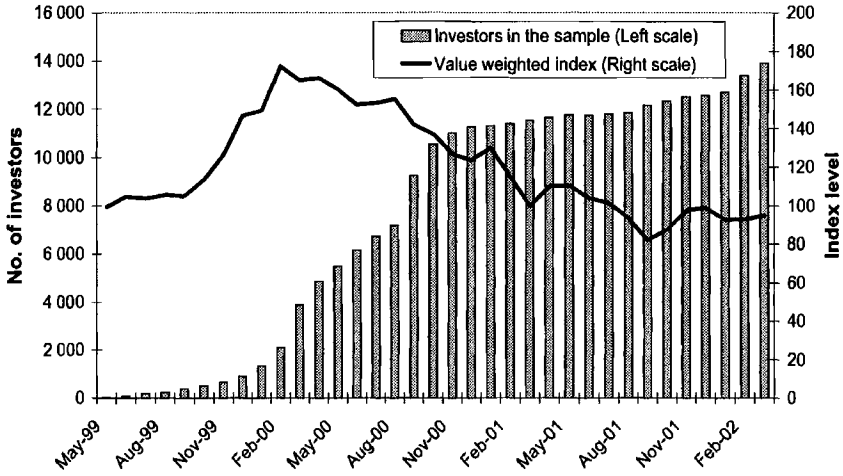
The transaction file includes all trades in common Swedish stock for all customers at an Internet brokerage firm from the time it was established. The data stretches from mid-April 1999 until the end of March 2002, or 35 calendar months.[3] This file contains transaction prices, volumes and fees for each traded stock, as well as an individual identification tag that shows account number, age and gender for each trade. In addition, data are collected on closing prices for 521 distinct stock ticker names corresponding to the transaction file.[4]

From the original sample of 340,612 transactions distributed over 20,799 investors, I make the following exclusions: Accounts owned by minors, those under the age of 18 in the first year of trading, are excluded as it is unclear if they are independently managed. Portfolios worth less than or equal to SEK 1,000 in the first month are excluded, since apart from their being small, there is also very little trading in these portfolios. These small portfolios are not likely to be important for the investor, and the very fact that they are not traded may indicate that they are also judged by the investor as being too small. Finally, I exclude investors that trade but never owned a portfolio at month-end in the sample for selectivity reasons. An investor enters the sample by either buying or depositing stocks. When categorizing investors by trad-

[3]In effect, I exclude all April 1999 transactions from the sample in order to get full calendar months of data. However, I calculate the portfolios held at the end of April 1999, and thus any positions from this period are included in the data.

[4]I include stocks from all official listings in Sweden. The prices were collected from *OM Stockholmsbörsen, Nordic Growth Market, Aktietorget* and *Nya Marknaden*.

Figure 2: Investors in the sample and the price level of stocks
The price path of the Swedish value-weighted index is plotted with a solid line (right scale) where the price is normalized to 100 on the last of April 1999. The bars denote the number of investors active in the sample each month (left scale).



ing activity, the first month is excluded if there were no deposits, because it may not be representative of how active the trader is.[5] By excluding these observations, we obtain a sample which is hereafter referred to as non-entering observations.

The fact that investors enter sequentially is displayed by Figure 2, along with the price level of a value-weighted Swedish stock index. There were 900 investors active in the sample at the end of 1999. By the end of 2000, the number of investors had grown to 11,261 and by 2001 they were 12,569. At most, which was in the last month of the sample, there were 13,917 investors active at the same time. Even if the pace at which investors entered is interesting in itself, it is not possible to know if they were new in the stock market or if they were experienced traders that switch between brokers.

There are 2,914 investors leaving before the sample period ends, but the attrition rate is relatively stable around the mean of 1.4% per month.[6] This is

[5]We do not wish to distinguish between an investor who begins her career by depositing stocks—and therefore records a zero turnover—and an investor buying the same portfolio, who will record a turnover of 50%.

[6]The stable attrition rate supports the hypothesis that most investors leave for exogenous reasons and there are only 41 instances in which investors go bankrupt, i.e., record a return of -100%.

roughly four times as high as that found by Brown, Goetzmann, Ibbotson, and Ross (1992) in a sample of U.S. mutual funds. Odean (1999) analyzes active accounts at the beginning of his sample period and find that 55% of the accounts fall out of the sample during the seven-year period in his study, which suggests a mean attrition rate of around 0.65% per month. When investors leave the sample, but are not replaced, there could potentially be a survivorship bias in favor of more successful investors that continue trading. The sample under consideration here contains all investors, and we could therefore measure the effect survivorship has on performance. However, it is clear that the data set across investors, for the most part, covers the bear market that followed the peak of the stock market boom in March 2000.

3.1 Sample summary

A description of the 324,736 transactions and 16,831 investors in the sample is presented in Table 1. There are 287,723 buy and sell transactions and 37,013 deposits and redemptions in all.

The average purchase is lower than the average sale, but as the number of purchases exceeds sales, the total value purchased is larger than the value sold. It is likely that part of this difference is attributable to new investors coming into the sample, thereby net investing in the market.

There is a great deal of skewness in the transactions, as evidenced by the mean being higher than the 75th percentile in all cases. This has implications for fees, as they are fixed within certain value brackets.[7] Therefore, small trades will be costly if measured as an average per transaction as in Table 1. This is illustrated by the fact that the mean purchase and sale fees are 1.69% and 1.94% measured on an average trade basis, whereas the value-weighted fees, obtained by dividing total trade value by the sum of fees, are as low as 0.20% and 0.16%, respectively. The median trade implies that a round-trip transaction costs around 1%. The sharp differences in value and trade weighted fees alone suggest that there may be considerable differences in per-

[7]The standard fee charge in Swedish kronor, is SEK 89 (approx. USD 10) for each transaction. For each 200,000 interval of trade value above 20,000, there is an additional charge of SEK 119. However, for the most active investors, with more than 75 trades per quarter, the charge is only 5 basis points of the value of the trade, or a minimum of SEK 79 per transaction.

Table 1: Data Description: Transactions and Portfolios

Descriptive statistics of the transaction data are displayed in Panel A. The purchases and sales fees are averaged over the number of trades. Portfolio size in Panel B is determined by the first observation of total capital (as defined in the main text) for each investor. The mean turnover, number of observations, trades, stocks and technology weight are first averaged for each investor over the months they appear in the sample. USD 1 corresponds to about SEK 9 during the sample period.

Panel A: Transactions							
	No. of Obs.	Mean	Standard deviation	25th Percentile	Median	75th Percentile	Total value (MSEK)
Purchases, SEK	169,471	51,128	187,622	4,500	12,400	39,000	8,664.71
Purchases, fee in %		1.69	3.71	0.22	0.61	1.56	17.43
Sales, SEK	118,252	69,922	224,441	7,052	19,750	59,400	8,268.47
Sales, fee in %		1.94	12.48	0.16	0.48	1.12	13.34
Deposits	30,543	44,071	266,988	2,755	9,550	25,800	1,346.07
Redemptions	6,470	40,360	259,436	1,577	4,560	22,300	261.13
Panel B: Monthly portfolios							
	No. of Obs.	Mean	Standard deviation	25th Percentile	Median	75th Percentile	Total value (MSEK)
Portfolio obs.	265,342	15.77	8.44	8	18	23	n/a
Portfolio size	16,831	92,347	418,549	6,200	17,700	53,750	1,554.30
Turnover, SEK	16,831	74,392	846,646	616	2,532	11,281	16,963.95
Turnover, %	16,831	17.93	35.72	2.94	6,90	17.68	n/a
Number of trades	16,831	1.19	3.51	0.16	0.44	1.00	n/a
Number of stocks	16,831	3.30	2.95	1.38	2.36	4.00	n/a
Technology weight, %	16,831	66.52	35.09	38.28	78.41	100.00	n/a
Panel C: Investor demographics							
	No. of Obs.	Mean	Standard deviation	25th Percentile	Median	75th Percentile	Proportion, %
Age, All	16,831	38.95	12.35	29	37	48	100.00
Age, Men	13,768	38.43	12.20	29	36	47	81.80
Age, Women	3,063	41.24	12.74	31	39	51	18.20

formance depending on the size of the trades, which ultimately is related to portfolio size.

There are 16,831 investors in the sample from which 265,342 portfolios are reconstructed. To obtain a measure of portfolio size that is unrelated to investor returns, the first monthly observation of portfolio capital is used.[8] Portfolio size varies substantially between investors: the mean is SEK 92,347, and the median SEK 17,700.

The median for portfolio size in this sample is close to the figures from *Statistics Sweden* for the overall population. The median Swede owned Swedish stocks worth between SEK 20,000 and SEK 15,000 at the end of 1999 and 2001 respectively, but the corresponding average is much higher at SEK 319,000 and SEK 183,000.[9] The relative difference between the means and medians between time periods indicates that new investors enter the market. Between these dates, the share of the population that owned individual stocks rose from 16% to almost 22%. This is an unobserved variable in the sample, but it does suggest that a fair share of the investors studied here are new to the stock market.

The median investor in the sample holds an average of 2.33 stocks. The higher mean suggests that there are a minority of investors with a much higher degree of diversification across holdings. That the mean and median investor holds few stocks may not be so surprising given the relatively small value of the portfolio. In fact, roughly 18%, or 3,030 investors, hold only one stock. This feature of the data implies that the idiosyncratic component of individual portfolio returns is high.

The sample consists of 82% men, making it similar to the sample of online traders in Barber and Odean (2002). However, the median age is considerably lower. The median age of all investors is 37, with no significant difference in the age distribution between men and women. Therefore, the composition of investors broadly supports the hypothesis of Barber and Odean (2001a) that overconfidence is related to gender. If overconfident investors tend to self-

[8]Portfolio capital includes the value of the portfolio at the beginning of the month as well as the value of any net purchases during the month. Portfolio capital is formally defined in Appendix A.

[9]The sharp difference between medians and means is even more extreme because the nationwide statistics include entrepreneurs who own very large stakes in their companies.

select in becoming clients at online brokers, we may then expect to find them to be young and predominantly male.

Turnover is measured by dividing the total value of monthly trades by two times the value of the portfolio holdings each month. The average monthly turnover for each investor is almost 18%. The annualized turnover would therefore be 216%, implying that these investors flip their portfolios more than twice a year. By comparison, the Swedish stock market average turnover between 1999 and 2002 is around 62%.[10] This implies that turnover among the investors considered here is more than four times as high as the market in general. We also find considerable cross-sectional variation in trading, as the median investor only turns around 7.5% of the portfolio. Even if the median investor's turnover is much lower at an average yearly turnover rate of 90%, it is still well above the overall market mean.

Portfolio composition is analyzed with respect to industry classification.[11] The companies are categorized into nine industries: telecommunications, information technology, finance, health care, industrials, consumer goods, media, raw materials and services. Portfolio holdings are largely concentrated in two industry sectors: telecommunications and information technology, combined and hereafter referred to as technology. The median investor holds an average of 71% technology stocks, which represents a clear overweight of the sector. The technology sector has a predominant role as it represented between 34% and 48% of the value-weighted Swedish market index. On a relative basis, the mean investor in the sample allocates twice the weight to technology compared to the technology index weight.[12]

The strong tilt towards these stocks among investors can have several explanations. First, technology stocks are riskier, and investors may prefer to take higher risk. But rational investors diversify their portfolios to avoid idiosyncratic risk; they typically do not choose only one stock. Second, it is reasonable to assume that companies in the technology industry on average

[10]This measure is constructed by dividing the value of all trades at the Stockholm Stock Exchange by two times the value of outstanding stock at year-end.

[11]The industry classification is made by *Affärsvärlden*, who also produce the value-weighted index used here.

[12]This measure is obtained by dividing the investors weight by the overall technology sector index weight, each month. It is not reported separately, because the results are similar to that of the absolute weight, which in turn are easier to interpret.

are smaller, and investors prefer small stocks. But the evidence for this is not very clear. The median company for the consumer goods, media and services industries are equally small or even smaller. Third, during this period, the technology sector offered a wider set of companies that investors could choose from. There is slightly more support for this, since only one other sector contains close to an equal number of stocks—industrials. This feature is relevant if investors follow the 1/n-heuristic as suggested by Benartzi and Thaler (2001). Fourth, it is important to keep in mind that during the Internet frenzy, new companies entered the stock market at an unprecedented pace. It is possible, or even likely, that the news flow was biased towards the technology sector. Barber and Odean (2003) also propose that naive investors select stocks that have experienced extreme price movements. This could also explain why risky technology stocks are overrepresented in the sample.

Naive investors may therefore react to signals that are unrelated to information for several reasons. But the rational principle of diversification could be contrasted with naive strategies. Sophisticated investors, who are less overconfident and prone to react to noise, are more likely to be better diversified than those following naive strategies. A preliminary investigation of such systematic effects of investor behavior can be studied in the correlations reported in Table 2.

Quite naturally, the number of stocks held and the value of the portfolio are highly positively correlated, as are turnover and the number of trades. The fact that age and portfolio value is positively related can be an indication that portfolio value in turn is correlated with (unobservable) overall wealth. Age and technology weight are negatively related, suggesting that stocks within this industry are more popular among younger investors.

Two correlations are more interesting than others. The first is portfolio value, which is positively correlated with both the number of trades and turnover. This is in contradiction to the common apprehension that trading is most frequent among small investors. The second finding is a substantial negative correlation between the number of stocks in the portfolio and the technology weight. There is, of course, a binary choice of industry when few stocks are held, such that diversification must by necessity be related to stock holdings. What is not so obvious, as the negative correlation suggests, is that

Table 2: Correlations: Individual characteristics
The table reports non-parametric Spearman correlations for 16,831 individual investor characteristics given in Table 1, excluding non-entering observations. All values are significantly different from zero at the 1% level, except the correlation between age and turnover which has a p-value of 9%.

	Portfolio size	Turnover	Number of trades	Number of stocks	Technology weight	Age
Portfolio size	1.00	-	-	-	-	-
Turnover	0.09	1.00	-	-	-	-
Number of trades	0.17	0.82	1.00	-	-	-
Number of stocks	0.24	0.10	0.31	1.00	-	-
Technology weight	-0.04	0.03	-0.02	-0.22	1.00	-
Age	0.08	0.01	0.04	0.15	-0.11	1.00

investors *on average* choose a lower technology sector exposure when holding more stocks. This indicates that investors pursue different strategies depending on portfolio composition.

The positive correlation between portfolio turnover and size, and the negative correlation between technology weight and diversification, suggest a general pattern. To analyze these two features of the data in more depth, the investors are sorted into quintiles formed on the basis of these variables.

3.2 Turnover and portfolio size

Given the major differences in median and mean fees, the performance of small investors is likely to suffer due to their small-sized trades. Hence, it may be important to control for portfolio size when looking at performance. I apply a two-pass sorting procedure. In the first pass, the investors are sorted by turnover into five groups that contain approximately 3,366 investors each. In the second pass, each turnover quintile is sorted into five equally sized subquintiles.[13] There are then about 673 investors in 25 groups in the turnover/portfolio size dimension. Table 3 displays the means of turnover and size

[13]This sorting procedure is therefore similar to that used by, e.g., Fama and French (1992) when exploring the book-to-market and size effect.

Table 3: Quintiles sorted by turnover and portfolio size

Investors are first sorted into quintiles based on their average turnover, excluding entering observations. A second sorting is conducted on portfolio value, thereby partitioning each turnover quintile into five sub-quintiles based on portfolio size. Panel A and B report the means of turnover in percent per month and portfolio size in SEK. USD 1 corresponds to about SEK 9 during the sample period.

	Turnover, quintiles					
	(Low) 1	2	3	4	(High) 5	All
	Panel A: Mean turnover, monthly %					
Portfolio size 1 (Small)	0.00	1.24	4.27	10.26	41.56	11.47
Portfolio size 2	<0.01	1.37	4.12	10.43	48.05	12.79
Portfolio size 3	<0.01	1.36	4.18	10.37	53.22	13.83
Portfolio size 4	0.00	1.30	4.20	10.43	62.89	15.76
Portfolio size 5 (Large)	<0.01	1.20	4.19	10.81	87.43	20.74
All	<0.01	1.29	4.19	10.46	58.63	14.92
	Panel B: Mean portfolio size, SEK					
Portfolio size 1 (Small)	2,882	3,592	3,444	3,555	4,223	3,539
Portfolio size 2	5,142	8,346	8,268	9,449	12,432	8,727
Portfolio size 3	9,801	18,304	18,284	20,799	30,341	19,506
Portfolio size 4	22,049	44,489	41,540	45,988	76,944	46,201
Portfolio size 5 (Large)	174,725	542,453	341,642	311,246	548,729	383,808
All	42,907	123,401	82,612	78,185	134,618	92,347

for each group. The main difference in trading activity between investors is that those in the lowest turnover quintile hardly ever trade, while those in the highest quintile trade extensively. Those who trade the most have a turnover of almost 59% per month, which on a yearly basis means that they buy and sell their portfolio almost seven times. In fact, the investors in the top turnover quintile account for more than 60% of the trades.

Among the investors in turnover quintile 5, those with the largest sized portfolios trade significantly more than all other groups. Among these investors, turnover is almost 90% per month. This, in turn, drives the overall result that the quintile with the largest portfolio size has the highest turnover rate. Comparing the overall means of turnover in Table 1 and Table 3, it falls from 18% to 15% when only the non-entering observations are included.

Portfolio size is also unevenly distributed across individuals. The mean size of the smallest quintile is around 100 times smaller than the largest quin-

Table 4: Quintiles sorted by technology weight and number of stocks
Investors are first sorted into quintiles based on the average number of stocks in their portfolio. A second sorting is done on the investors' average technology weight, thereby partitioning each diversification quintile into five sub-quintiles based on the average technology weight. Panel A and B report the means of the number of stocks held and the technology weight in percent.

	Diversification quintiles: Number of stocks held					
	(Few) 1	2	3	4	(Many) 5	All
	Panel A: Mean number of stocks					
Technology weight 1 (Low)	1.00	1.65	2.43	3.71	8.65	3.49
Technology weight 2	1.02	1.72	2.48	3.71	8.35	3.45
Technology weight 3	1.00	1.54	2.48	3.70	7.78	3.30
Technology weight 4	1.00	1.74	2.50	3.71	7.43	3.28
Technology weight 5 (High)	1.00	1.60	2.19	3.49	6.65	2.99
All	1.01	1.65	2.42	3.66	7.77	3.30
	Panel B: Mean technology weight, %					
Technology weight 1 (Low)	0.06	7.44	13.08	14.97	13.63	9.83
Technology weight 2	91.15	53.81	49.14	45.70	36.08	55.17
Technology weight 3	100.00	89.96	79.51	68.43	54.06	78.39
Technology weight 4	100.00	100.00	97.02	87.38	71.83	91.24
Technology weight 5 (High)	100.00	100.00	100.00	99.30	90.93	98.04
All	78.22	70.22	67.73	63.14	53.30	66.52

tile. The investors with the lowest trading activity clearly have smaller portfolios, around half the value of the overall sample. The data also suggest that those who trade the most have larger portfolios compared with the other size matched turnover quintiles.

3.3 Diversification and technology weight

An identical approach is used to investigate how stock diversification is related to investors technology weight. Investors are first sorted by the number of stocks held and then by the technology weight. Table 4 reveals that the mean number of stocks held among the 20% of investors that are least diversified is close to one. In the top quintile, they hold around eight stocks. Those who have a lower technology weight also have slightly more stocks than those who have the highest weight—3.49% compared with 2.99%.

The most striking result is found in Panel B, where the mean technology

weight decreases monotonically with the number of stocks held from 78% to 53%. This means that four out of five investors who hold only one stock choose one in the technology sector. Consequently, there is strong evidence of a systematic effect of diversification that goes beyond that of simply holding stocks of different companies. Investors with more stocks in their portfolio choose to be less exposed to the technology sector. This suggests that investment strategies differ between groups of investors, and implies that there are underlying differences in behavior that could be related to investment skill.

4 Results

The previous data analysis reveals considerable cross-sectional variation in trading and diversification that may be helpful in explaining performance. At the outset, we may expect that excessive trading erodes performance, but the prior of how diversification should affect performance is not very clear. A random strategy—where investors hold a few stocks selected at random—should be related to idiosyncratic risk only, and be unrelated to mean returns. But this is true only if the strategy and associated expected returns are independent. Overconfident investors who follow naive investment strategies will underestimate risk, and their forecasts for expected returns will be overly favorable. Such investors are not only likely to take more systematic risk, but may also be less skilled in choosing which stocks to select. In this case, performance may vary with diversification. Overconfident investors who hold undiversified portfolios could be less skilled in choosing which stocks to select.

To facilitate such comparisons, the results are presented in two parts. The first part begins by reviewing how portfolio returns are constructed from transaction data and proposes a return decomposition. The market adjusted return can be split into components that are designed to identify the returns that can be associated with investor turnover and industry selection. The return differences are evaluated separately over the quintiles in these dimensions, as in the previous section. The second part presents a panel regression model. The individual characteristics are incorporated at the same time, such that we obtain marginal effects of those found in the first part.

4.1 Investor returns

The data are available in transaction form, from which portfolios are reconstructed. The key issue, when defining returns, is to identify the payoff and the corresponding capital that can be associated with it.[14] Only a brief summary of the method is presented here, without going into any details of the definitions. A more exhaustive explanation of how portfolio excess returns are calculated from transaction data is given in Appendix A. Three returns are used in the analysis: excess passive return, $R^P_{i,t}$; total excess return, $R_{i,t}$; and industry excess return, $R^{Ind}_{i,t}$. Each of them is explained below.

Passive excess return refers to the return of the portfolio held by investor i at date $t-1$, i.e., the beginning of the month. The payoff is calculated for each stock as the price change during month t times the number of stocks held at date $t-1$. The payoffs are then summed over all stocks in the portfolio, and normalized into a return by the value of the total position. This value, which is the required capital to finance the portfolio, is referred to as *position capital*. We denote the passive excess return adjusted with the 30-day T-bill rate $R^P_{i,t}$.

When investors trade, the payoff is calculated as follows for each stock. Suppose a transaction in a certain stock for an individual takes place at date d, which is at some point during month t. If the trade is a purchase and the stock is held throughout month t, the net proceeds are calculated from date d to t, and conversely, if it is a sale of a stock owned at date $t-1$, from $t-1$ to d. As is shown in Appendix A, intra-month transactions for each stock can be aggregated and averaged, so the net effect applies to what has already been stated. The sum of the payoffs over each stock in the portfolio is the value change of the portfolio during month t.

The key now is to identify the capital components associated with trading. The minimum capital requirement for each investor is assumed to be the position capital measured at date $t-1$. If purchases exceed sales, in cases requiring additional funds, these funds are added to the capital base and labelled *trading capital*.[15] Total capital is thus the sum of position capital and trading capital.

[14] A related approach has been applied by Linnainmaa (2003), who investigates daytrades. However, the method considered here defines payoffs and required capital quite differently.

[15] Note that the timing of sales and purchases matters for the definition of the capital base. Consider a sale and a purchase of the same value. If the purchase precede the sale, capital is required whereas there is no effect if it were the other way around.

The portfolio return is in excess of the interest rate, which is adjusted for in the following way. Reducing the total payoff with the cost of position capital is straightforward, because this is the minimum cost for financing this portfolio. However, when there is trading, investors can be net sellers or net buyers. Interest is added to the payoff if they are net sellers, and deducted if they are net buyers. The interest associated with trading involves calculating the cash balance for each investor at each point in time during the month. This "fictitious cash account" therefore assures that net buyers or net sellers are charged or compensated for cash-flows at the going 30-day interest rate.[16] The resulting *total excess return* is denoted $R_{i,t}$, and includes all trades between $t-1$ and t. Therefore—if there is no trading—$R^P_{i,t}$ coincides with $R_{i,t}$.

The return measure does not include dividends. This exclusion will bias the returns measured here downwards. However, this bias is expected to be small. The overall market paid little in dividends during the period, and especially the growth firms held by the investors in the sample. For this reason, the market return used as benchmark does not include dividends.

The third and last return needed for the analysis is the *industry excess return*, $R^{Ind}_{i,t}$, constructed as follows. The industry weights for the portfolio the investor holds at date $t-1$ are calculated. The industry return is the weighted average of the excess returns on the nine industry indexes, and therefore tracks the index composition of each investor's portfolio.

4.1.1 A simple return decomposition

The decomposition aims to clarify the return difference between a passive strategy (excluding trading) and an active strategy (including trading) as well as how a passive strategy relates to various benchmarks. By using the three returns, we can offer the following definitions. *Market-adjusted return* is defined as

$$\Delta IM_{i,t} \equiv R_{i,t} - R_{M,t},$$

[16] The effect on returns stemming from the interest rate, however is small due to the high volatility of stock returns.

where $R_{M,t}$ is the excess return of the value-weighted market benchmark. *Trade-adjusted return* is defined as

$$\Delta IP_{i,t} \equiv R_{i,t} - R^P_{i,t},$$

and serves as an approximation of the contribution of active trading. Passive return can be thought of in this setting as an own-benchmark return in the same spirit as proposed by Grinblatt and Titman (1993), who investigate the performance of mutual funds. They argue that any asset pricing model is sensitive to its particular assumptions, but the own-benchmark can serve as an intuitive and appealing means of comparison. Grinblatt and Titman use yearly and quarterly fixed portfolios when defining the benchmark portfolio. Here, passive return is defined on a monthly basis. Investors in this sample have a much higher turnover than mutual fund managers, and there is enough variation in a month to enable interesting comparisons. Passive return serves as a natural benchmark when investigating if rebalancing is profitable for investors. It should be noted that when there is no portfolio observation at the beginning of the month, we cannot observe a passive return. To make investor returns comparable with or without trading, only non-entering observations will be considered. More importantly, measured trading costs can be difficult to interpret if the first purchased portfolio is included. A buy-and-hold investor needs to buy the portfolio at some stage, but transaction costs are averaged over a very long time.

Market-adjusted industry return is written

$$\Delta INDM_{i,t} \equiv R^{Ind}_{i,t} - R_{M,t},$$

which is a measure of the return contribution stemming from the choice of industry compared to the market benchmark. It follows by construction that if an investor holds the market value weights, the difference is zero.

Industry-adjusted passive return is defined as

$$\Delta PIND_{i,t} \equiv R^P_{i,t} - R^{Ind}_{i,t},$$

and measures the difference between the actual portfolio held at the beginning

of the month and a portfolio that tracks the return of the chosen industries. This can be interpreted as a measure of how well investors can select stocks *within* industries. Consider an investor who owns two stocks, but in different industries. Even if the industries underperform the market, the selected stocks might still outperform the chosen industries. This is exactly what is captured by the industry-adjusted passive return.

By using the definitions above, we can express the market-adjusted return as the sum of three components: the trade-adjusted return, the market-adjusted industry return, and the industry-adjusted passive return

$$\Delta IM_{i,t} = \Delta IP_{i,t} + \Delta INDM_{i,t} + \Delta PIND_{i,t}.$$

Furthermore, it follows that we are also able to define the *market-adjusted passive return* as

$$\Delta PM_{i,t} \equiv \Delta IM_{i,t} - \Delta IP_{i,t} = \Delta INDM_{i,t} + \Delta PIND_{i,t} = R^P_{i,t} - R_{M,t},$$

which then completes the link between the five definitions and three returns. Table 5 displays the results of this decomposition in four ways: returns with or without fees, and by weighing returns equally or with total capital.

The average investor in the sample had a monthly return of -3.38%, which implies an annualized excess return of a substantial -34%. The strong negative return indicates that investors, on average, have experienced very high losses. This can partly be explained by the fact that investors enter the market sequentially, as illustrated by Figure 2. The large number of investors who entered the sample late inevitably faced a weaker stock market.

The market-adjusted return makes a crude adjustment for such effects. Still, investors lose between 1.8% to 2.1% per month compared to the market, including fees. The equally-weighted means of the trade-adjusted return reveal that 32 basis points can be explained by fees alone. In annualized terms, 32 basis points per month means that the average investor paid around 3.8% per year of her portfolio value in fees. This is more than twice the annual fee charged by most mutual funds. Further, the effect of value-weighting investors on fees is clear, implying that large investors pay less in fees expressed as a percentage of the portfolio return.

Table 5: Investor mean returns: A simple decomposition

The market-adjusted return is decomposed into three parts. The trade-adjusted return measures the effect of rebalancing. The difference between the market-adjusted return and the trade-adjusted return is labelled the market-adjusted passive return, which in turn has two components: The market-adjusted industry return measures the contribution stemming from industry selection with respect to the market, and the industry-adjusted passive return measures stock-picking ability within industries. There are 251,879 non-entering observations in the sample from which averages of 16,831 investor mean returns are constructed. The means for investor portfolio returns are weighted equally or with total capital as defined in the text. The effect of including or excluding fees is presented separately.

Returns, monthly %			With fees		Without fees	
Operation	Definition	Comment	Value-weighted	Equally-weighted	Value-weighted	Equally-weighted
None	Portfolio excess return, $R_{i,t}$	Investor total excess return.	-3.05 (0.05)	-3.38 (0.05)	-2.97 (0.05)	-3.07 (0.05)
None	Market-adjusted return, $\Delta IM = R_{i,t} - R_{M,t}$	Total return including monthly rebalancing in excess of market.	-1.78 (0.05)	-2.08 (0.05)	-1.70 (0.05)	-1.76 (0.05)
-	Trade-adjusted return, $\Delta IP = R_{i,t} - R^{P}_{i,t}$	Trading contribution from rebalancing.	-0.21 (0.02)	-0.37 (0.02)	-0.13 (0.02)	-0.05 (0.02)
=	Market-adjusted passive return, $\Delta PM = R^{P}_{i,t} - R_{M,t}$	Buy-and-hold return in excess of market.	→		-1.57 (0.05)	-1.71 (0.05)
-	Market-adjusted industry return, $\Delta INDM = R^{Ind}_{i,t} - R_{M,t}$	Industry contribution to buy-and-hold return.	→		-1.20 (0.02)	-1.28 (0.02)
=	Industry-adjusted passive return, $\Delta PIND = R^{P}_{i,t} - R^{Ind}_{i,t}$	Stock selection contribution to buy-and-hold return.	→		-0.37 (0.04)	-0.43 (0.04)

Mean standard errors in parentheses. All variables are significantly different from zero at the 1% level or lower, except equally-weighted ΔIP without fees, which is significant at the 5% level.

There is a small but still negative difference in the trade-adjusted return even when fees are excluded. This is evidence that investors on average do not beat their own-benchmark defined by the portfolio held at the beginning of the month. The trade-adjusted mean when investors are value-weighted actually implies that large-sized investors lose more than median investors when fees are excluded. The fee itself only explains some 8 basis points of the total 21 points.

The difference between the market-adjusted return and the trade-adjusted return can be further analyzed and decomposed into two parts. Both of these are defined for passive portfolios, such that they are free from trading. Hence there is no need for a separate analysis with respect to fees.

The market-adjusted industry return shows the difference between the market return and the particular choice of industries. Most of what can explain the deviations from the market return is embedded here. Investors have chosen to invest in industries that have underperformed relative to the

market, which is most likely a direct consequence of the strong tilt towards technology stocks. As this simple decomposition does not include any risk-adjustment, this effect might very well be a result of investors choosing higher systematic risk.

Risk is likely to be less problematic when evaluating the industry-adjusted passive return, as there is considerably less variation in risk within industries than between. The industry-adjusted passive return reveals that the investors on average lose around 43 basis points from choosing stocks that underperform any chosen industry. This is interesting, as it suggests that individuals may systematically choose stocks that underperform. Furthermore, the somewhat higher value-weighted return indicates that this pattern is more predominant among investors with small portfolios.

If we assume that all systematic risk is captured by industries, the decomposition suggests that investors underperform the market by around 80 basis points. In this case, trading and stock selection are roughly equally important. To examine these two features of the data in more depth, the following sections report the returns associated with the corresponding quintiles of Table 3 and Table 4.

4.1.2 Returns: Trading and portfolio size

We will now look more closely at how the trade-adjusted return is related across investor groups. The mean return is calculated for each of the 25 groups of investors defined in Section 3.2. This is also done for all investors in each quintile in the two dimensions, and finally for the whole sample. Table 6 reports the mean returns corresponding to the sample partition in Table 3. Associated standard errors are given in parentheses.

As there is virtually no trading in the lowest turnover quintile, there can be no deviation from the own-benchmark, and so the passive return equals the total return. This means that the difference in the first column of Table 6 is zero. It is clear that when trading activity increases, performance declines. The most active traders underperform their benchmark portfolio by 95 basis points compared with only 52 for traders in the fourth quintile. This general effect seems to be valid for all portfolio sizes, but the smallest investors contribute most to this general pattern.

Table 6: Mean trade-adjusted returns

The trade-adjusted return measures the difference between the total portfolio return and the passive return, which is the portfolio held at the beginning of the month. The return is reported with fees in Panel A, and without fees in Panel B. There are approximately 673 investors in each sub-quintile corresponding to the partition in the turnover and portfolio size dimensions in Table 3.

	Turnover quintiles					
	(Low) 1	2	3	4	(High) 5	All
Panel A: ΔIP, Trade-adjusted returns including fees, monthly %						
Size 1 (Small)	0.00	-0.20***	-0.53***	-1.22***	-2.01***	-0.79***
	(0.00)	(0.02)	(0.02)	(0.13)	(0.35)	(0.08)
Size 2	<0.01	-0.13***	-0.37***	-0.59***	-0.87***	-0.39***
	(<0.01)	(0.03)	(0.03)	(0.07)	(0.26)	(0.06)
Size 3	<0.01	-0.09***	-0.20***	-0.40***	-0.78***	-0.29***
	(<0.01)	(0.02)	(0.03)	(0.09)	(0.28)	(0.06)
Size 4	0.00	-0.06***	-0.15***	-0.28***	-0.51***	-0.20***
	(0.00)	(0.01)	(0.03)	(0.06)	(0.17)	(0.04)
Size 5 (Large)	<0.01	-0.01	-0.06***	-0.11***	-0.59***	-0.15***
	(<0.01)	(0.01)	(0.03)	(0.05)	(0.12)	(0.03)
All	<0.01	-0.10***	-0.26***	-0.52***	-0.95***	-0.37***
	(<0.01)	(<0.01)	(0.01)	(0.04)	(0.11)	(0.02)
Panel B: ΔIP, Trade-adjusted returns excluding fees, monthly %						
Size 1 (Small)	0.00	-0.05**	-0.07*	-0.21*	0.31	-0.01
	(0.00)	(0.02)	(0.04)	(0.12)	(0.33)	(0.07)
Size 2	<0.01	-0.04	-0.13***	-0.12*	0.11	-0.04
	(<0.01)	(0.03)	(0.03)	(0.07)	(0.26)	(0.05)
Size 3	<0.01	-0.03	-0.06**	-0.08	-0.17	-0.07
	(<0.01)	(0.02)	(0.03)	(0.09)	(0.28)	(0.06)
Size 4	0.00	-0.02*	-0.06**	-0.11*	-0.17	-0.07*
	(0.00)	(0.01)	(0.03)	(0.06)	(0.17)	(0.04)
Size 5 (Large)	<0.01	0.01	-0.01	-0.01	-0.42***	-0.09***
	(<0.01)	(0.01)	(0.02)	(0.05)	(0.12)	(0.03)
All	<0.01	-0.02**	-0.06***	-0.10***	-0.07	-0.05**
	(<0.01)	(<0.01)	(0.01)	(0.04)	(0.11)	(0.02)

Mean standard errors in parentheses. Significance levels for a t-test of the mean to be different from zero at the 10%, 5%, and 1% level are marked (*), (**), and (***).

Therefore, we find a size effect as well as a trading effect: the mean underperformance for the investors with the smallest portfolio size is 79 basis points, but only 15 for the largest. When fees are excluded from the analysis, there is still a weak size and turnover effect, but only 5 basis points are lost on average when fees are excluded. One reason for this is that investors, on average, pursue strategies that are unprofitable. Barber and Odean (2000) attribute a similar, but daily, effect to costs associated with the bid-ask spread.

It is somewhat puzzling that the largest investors who trade the most lose up to 42 basis points, excluding fees. When comparing Panel A and B, we see that fees only explain 17 basis points of the total trade-adjusted return. On the other hand, this group was also found to be trading more than twice as much as the smallest investors in Table 3. A net cost of 42 basis points may not be so conspicuous considering that almost 90% of the portfolio is traded in one month. Yet, somewhat surprisingly, the investors with the smallest portfolios that trade the most gain 31 basis points by trading, excluding fees. However, the performance in this group is so dispersed that it is insignificant.

4.1.3 Returns: Diversification and technology weights

The natural candidates to analyze the effect of diversification across stock holdings are the market-adjusted industry return and the industry-adjusted passive return. As an extension to Table 4, these returns are investigated across diversification and the technology weight, which here serves as a crude measure of risk.

The market-adjusted industry return measures how the choice of industry has affected investors portfolio return relative to the market. The column on the far right of Panel A in Table 7 reveals that the group of investors who underweighted the technology sector outperformed the value-weighted index. But since over 75% of the investors in this sample did the opposite, the means become negative moving down the column. There is a similar effect across the quintiles sorted by the degree of diversification. The market-adjusted industry return is more negative for investors with few stocks, which is most likely due to the technology weight that was found to be higher among these investors. Therefore, these results simply confirm that investors chose to carry a lot of risk, but faced unfavorable market conditions.

Table 7: Mean industry-adjusted returns

The market-adjusted industry return in Panel A measures the return difference between the market and the chosen industry portfolio for each investor. The industry-adjusted passive return in Panel B measures the difference between the chosen industry portfolio and the actual chosen stocks of the portfolio held at the beginning of the month. There are approximately 673 investors in each sub-quintile corresponding to the partition in the technology weight and diversification dimensions in Table 4.

	Diversification quintiles: Number of stocks held					
	(Few) 1	2	3	4	(Many) 5	All
Panel A: ΔINDM, Market-adjusted industry returns, monthly %						
Technology weight 1 (Low)	2.05***	1.65***	1.33***	1.11***	0.93***	1.41***
	(0.11)	(0.08)	(0.07)	(0.07)	(0.06)	(0.04)
Technology weight 2	-2.38***	-0.60***	-0.49***	-0.27***	0.01	-0.75***
	(0.10)	(0.08)	(0.06)	(0.05)	(0.04)	(0.04)
Technology weight 3	-2.89***	-2.43***	-1.94***	-1.48***	-0.80***	-1.91***
	(0.12)	(0.06)	(0.07)	(0.07)	(0.05)	(0.04)
Technology weight 4	-2.88***	-2.56***	-2.81***	-2.41***	-1.60***	-2.45***
	(0.10)	(0.12)	(0.07)	(0.05)	(0.05)	(0.08)
Technology weight 5 (High)	-2.83***	-2.97***	-2.72***	-2.77***	-2.13***	-2.68***
	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.04)
All	-1.78***	-1.38***	-1.32***	-1.17***	-0.72***	-1.28***
	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.02)
Panel B: ΔPIND, Industry-adjusted passive returns, monthly %						
Technology weight 1 (Low)	-1.27***	-0.16	-0.62***	-0.45***	-0.17**	-0.53***
	(0.41)	(0.28)	(0.17)	(0.14)	(0.09)	(0.11)
Technology weight 2	-0.40	-0.49**	-0.89***	-0.29*	-0.33***	-0.48***
	(0.27)	(0.24)	(0.20)	(0.15)	(0.08)	(0.09)
Technology weight 3	-0.90***	-0.11	-0.40***	-0.27*	-0.36***	-0.41***
	(0.31)	(0.18)	(0.15)	(0.15)	(0.12)	(0.09)
Technology weight 4	-0.22	-0.60***	-0.23*	-0.11	-0.38***	-0.31***
	(0.35)	(0.21)	(0.14)	(0.11)	(0.10)	(0.09)
Technology weight 5 (High)	-0.63**	-0.03	-0.61***	-0.57***	-0.26*	-0.42***
	(0.29)	(0.24)	(0.23)	(0.20)	(0.16)	(0.10)
All	-0.68***	-0.28***	-0.55***	-0.34***	-0.30***	-0.43***
	(0.15)	(0.10)	(0.08)	(0.07)	(0.05)	(0.04)
All, excl. bankrupt investors	-0.55***	-0.22***	-0.54***	-0.34***	-0.30***	-0.43***
	(0.14)	(0.10)	(0.08)	(0.07)	(0.05)	(0.04)

Mean standard errors in parentheses. Significance levels for a t-test of the mean to be different from zero at the 10%, 5%, and 1% level are marked (*), (**), and (***).

Panel B provides more interesting results in this respect. The industry-adjusted passive return controls for the industry choice for each investor at each point in time. Any relative deviation from this benchmark stems from the investor's choice of individual stocks *within* each industry. The risk among firms within industries is likely to be more similar. The overall result, which shows that 43 basis points are lost due to stock selection within the industries, is substantial.

There is little systematic variation across technology quintiles (moving vertically down the rightmost column of Panel B in Table 7). If any, those with lower technology weights appear to underperform their industry benchmark more than those with higher weights. Therefore, there is no evidence that the overall negative return stemming from which stocks to buy in a given industry is related to a preference for technology stocks.

There is a much clearer pattern found horizontally in Panel B of Table 7. Investors with few stocks underperform more relative to those with many stocks in their portfolios. One must bear in mind that the industry-adjusted passive return measures the relative performance of individual stocks and any mix of industries. A random strategy will "average out" investor returns over diversification quintiles if choices were independent. Choosing several stocks within a given industry should reduce the *variance* of such a portfolio, but not change the *mean*. Here, we find that virtually all investor groups with few stocks have inferior mean returns than those who have many. The ability to target individual stocks that perform better increases with the number of stocks held.

The diversification measure could be sensitive to investors going bankrupt. It is more likely that those investors who left the sample due to bankruptcy are to be found in the group holding only one stock. The bottom row in Panel B of Table 7 reports the means when these investors are excluded from the sample. Even if the performance rise for one-stock investors, they still underperform by almost twice the amount compared to those best diversified.

The systematic effect of diversification on performance suggests that this variable could be related to experience or skill, but the relatively high average underperformance could also be an indication that investors choose stocks that are riskier than their respective industry benchmarks. If this is the case,

such risks should also be correlated across investors in the diversification dimension.

4.1.4 Summary of results from the return decomposition

In all, three results are obtained from the return decomposition. First, investors that trade more, lose more. This is found to be almost entirely related to fees, which in turn are related to the size of the portfolio. Large portfolios are less affected by fees due to the fee structure that involves minimum costs. Second, the high gear towards technology stocks in combination with bad market timing means that most of what is lost above the market-adjusted return is related to industry choice. Third and last, the number of stocks held is found to be related to how investors perform when adjusting for industry choice.

These preliminary findings are interesting from a descriptive viewpoint and to understand the data. On the other hand, to be able to make any firm statements about performance, there is a need to make riskadjustments and to control for interdependence among the measured effects.

4.2 Panel estimation

The natural starting point when building a model for portfolio evaluation is the Capital Asset Pricing Model (CAPM). When using the market return as a benchmark to assess the risk of a portfolio, it ignores common variation caused by time-varying expectations. Traditional, unconditional models can ascribe abnormal performance to an investment strategy that only relies on public information as shown, for instance, by Breen, Glosten, and Jagannathan (1989).

Further, given the size of this sample, modelling a separate beta for each investor is not a realistic option. On the other hand, it would be desirable to allow for heterogeneous preferences and investment strategies. The goal, therefore, is to allow beta to vary between investors in some predetermined and structured manner, while allowing for time-variation.

The asset pricing model suggested here is an extension of the conditional CAPM proposed by Ferson and Schadt (1996). Let us assume that investor

returns can be described by

$$R_{i,t} = B_0 R_{M,t} + \sum_{k=1}^{K} B_k \left[y_{k,i} R_{M,t} \right] + \sum_{l=1}^{L} B_{l+K} \left[z_{l,t-1} R_{M,t} \right] + \varepsilon_{i,t}, \qquad \begin{array}{l} i = 1, \ldots, N, \\ t = 1, \ldots, T. \end{array} \tag{1}$$

There are i investors grouped into K investor risk characteristics. The investor characteristics are specific to each individual and hence fixed over time. In addition, there are L information or state variables $z_{l,t-1}$ which describe the investors' opportunity set and is the same for all individuals. The state variables represent information that is common and known to the investors in t. Lower case letters for the characteristics and information variables are deviations from unconditional means, $y_{k,i} = Y_{k,i} - \overline{Y}_{k,\cdot}$ and $z_{l,t-1} = Z_{l,t-1} - \overline{Z}_{l,\cdot}$. The excess return of the market benchmark is denoted by $R_{M,t}$ and $\varepsilon_{i,t}$ is an investor and time-specific disturbance term. The coefficient B_0 can be thought of as the average beta with $B_1, \ldots, B_{K+J}$ as linear response coefficients to investor characteristics and state variables.[17]

In this way, we obtain rich variation in the cross-section, but the individual characteristics are kept fixed over time as to keep the interpretation of the results clear. Similarly, the proxy for the information set across investors is kept constant, but varies over time.

A typical implementation of the model specified by equation (1) is to add intercept terms for each investor and then test the null hypothesis that they are jointly or individually zero. However, the interest here is to relate performance to investor characteristics. We already have reasons to believe that the strong prediction of market efficiency may not be applicable to online investors. Online investors are not well diversified. In addition, they face higher transaction and search costs than, for instance, mutual funds. They are also more likely to be subject to behavioral biases such as overconfidence, and fol-

[17]The average beta is the unconditional mean of the conditional beta with respect to the instruments. The linear response coefficients can be thought of as an approximation of a Taylor expansion around their means, ignoring the higher order terms if the responses are in fact nonlinear.

low naive strategies that may affect their performance.

In essence, it is of interest to model the intercept by controlling for the investor characteristics in various ways. Therefore, the regressions performed is of the form

$$\begin{aligned} R_{i,t} = A_0 + \sum_{j=1}^{J} A_j c_{j,i} + B_0 R_{M,t} + \sum_{k=1}^{K} B_k \left[y_{k,i} R_{M,t} \right] \\ + \sum_{l=1}^{L} B_{l+K} \left[z_{l,t-1} R_{M,t} \right] + \varepsilon_{i,t}, \qquad \begin{array}{l} i = 1, \ldots, N, \\ t = 1, \ldots, T, \end{array} \end{aligned} \tag{2}$$

where there are J controls for investor types $c_{j,i}$, which then vary between individuals. The controls are also demeaned to preserve the interpretation of A_0 as the measured average abnormal return.

We can identify the parameters in (2) with the following moment conditions

$$\begin{aligned} E\left(\varepsilon_{i,t}\right) &= 0, \quad \forall i, \\ E\left(\varepsilon_{i,t} c_{j,i}\right) &= 0, \quad \forall i, j, \\ E\left(\varepsilon_{i,t} R_{M,t}\right) &= 0, \quad \forall i, \\ E(\varepsilon_{i,t} R_{M,t} y_{k,i}) &= 0, \quad \forall i, k, \\ E(\varepsilon_{i,t} R_{M,t} z_{l,t-1}) &= 0, \quad \forall i, l, \end{aligned} \tag{3}$$

such that the error term is uncorrelated with the explanatory variables. The moment conditions in (3) are estimated with GMM, but the point estimates coincide with those obtained by OLS.[18] The main difference is that the variance-covariance matrix allows for both heteroscedasticity and autocorrelation. This is a desirable feature, because standard methods run a clear risk of overstating the precision of the estimates.[19]

The sample moment conditions corresponding to (3) are explicitly considered in Appendix B along with other details regarding the estimation procedure.

[18]This follows directly from the OLS assumption $E(uX) = 0$, by substituting for u and solving for the parameters of the model.

[19]The standard OLS assumption referred to here is that errors are independently distributed. This is clearly too strict an assumption for the data set under consideration.

4.2.1 Selection of variables

The performance analysis is conducted directly in the panel. The previous preliminary analysis found that portfolio size, turnover, and the number of stocks in the portfolio can be important determinants of cross-sectional abnormal performance. These variables are therefore chosen to parameterize the intercept. The same variables are used to control for beta risk across investors. In addition, age and gender are included as controls for heterogeneous risk between investors. The paragraphs below explain these choices.

One of the reasons for the difference in average performance between equally and value-weighted performance may be that risk is related to portfolio size. This can be linked to a relative risk aversion argument: an individual could be prepared to gamble small amounts compared to the level of wealth. Such an investor is likely to take high risk compared to the investor who has more at stake. If this is an important feature of the data, it will be controlled for. Since portfolio size is extremely skewed, the logarithm of the individual size measure is used.

Turnover can be important in two ways. Technically, high turnover could mean that cash is held in the portfolio. This may affect the return measure, since trading capital increases, and ultimately lower our beta estimates.[20] Alternatively, high turnover investors might in fact choose less risky investment strategies. Further, as turnover is included among the intercept terms, it is also a desirable control variable for risk. This is also the case for diversification, defined by the number of stocks. In addition, the degree of diversification could also be correlated with risk, since the allocation to the technology sector varies with the number of stocks held.

Age will matter when old investors have less human capital as a resource for future income; they may prefer to take lower stock market risk. The reason, as shown by Bodie, Merton, and Samuelson (1991), is that such investors have less flexibility than younger investors to adjust their labor supply and consumption if savings were to deteriorate. In this sample, older people may simply find high beta technology stocks less attractive than young people do.

Barber and Odean (2001a) argue that men are more overconfident than

[20]This is only true for investors who liquidate or acquire a *total* net position. Rebalancing a portfolio does not imply a change in trading capital itself.

women; their study confirms that men trade more, and therefore do not perform as well as women. If men are more overconfident, they may also load up on more systematic risk. Also, Levin, Snyder, and Chapman (1997) find, in an experimental setting involving gambles, that women tend to be more risk-averse than men. A gender dummy for women investors is therefore included in the riskadjustment.

When specifying the information or state variables, it is difficult to know what information is relevant. The work of Keim and Stambaugh (1986), and Campbell (1987) shows that lagged stock and money market variables can have significant predictive power for the market risk premium. With the obvious risk of data snooping, the stock index return, the level of the 30-day Treasury bill and the yield spread between a 10-year and 1-year government bond are included in the regressions.

4.2.2 Regression results

The first column of Table 8 marked Model I shows that investor monthly performance is around -1.29% in an unconditional single-index specification. The beta is around 1.4, reflecting that investors in this sample take on considerable market risk.

The second and third regression condition the beta on time variation and heterogeneity in the cross-section. The average performance increases to -0.74%, the average beta increases and its standard deviation falls. This shows that the conditional model indeed controls for important variation in the betas and that the unconditional specification is misleading. In fact, the average underperformance is no longer significant, even though it is still highly negative.

The objective of the panel model is more about seeing how performance varies with investor characteristics than making inferences about risk. The results for the conditional betas are therefore only discussed briefly. The betas vary significantly with the characteristics in the cross-section, but the effect is generally small. For instance, a positive, one-standard deviation change in age above the mean produces about the same effect as when the investor is female: a decrease in beta of around 0.03. The negative effects of turnover and diversification are larger but still small: about two or three times larger than for age. The beta coefficient for portfolio size was never significant, so

it is excluded from all regressions. The relatively low variability in the betas raises some concern as to whether some cross-sectional variation in risk is not controlled for. However, a robustness check at the end of this section confirms all of the main results that follow from the inferences made in Table 8.

The adjusted R^2 is reported in Table 8, even though it is difficult to interpret when we have observations in two dimensions. Nevertheless it gives an indication of how substantial the idiosyncratic component of the returns is for the overall sample. About 30 percent of the total variation is explained by the models under consideration.

The key results regarding investor performance and characteristics are reiterated by the panel regressions. Model IV reports the results of including turnover and portfolio size alone, and Model V when the diversification variable is also included.

The separate effect of turnover is a loss in performance of 1.8 basis points for each percent increase in turnover. This relation is found to be somewhat convex; that is, the marginal effect of turnover diminishes for the majority of investors.[21] These results are quite devastating for most investors. The coefficient estimates imply that around 85 basis points are lost in monthly performance when controlling for portfolio size for the group of most active traders. One should keep in mind that the median portfolio in the sample is small, which is an important explanation for the turnover effect. The results of Model IV imply that investors whose portfolio is twice the size of the mean investor, or around SEK 35,000, gain almost 15 basis points compared to the sample average.

In the final model considered in Table 8—labelled Model V—the diversification variable is included in the regression. The coefficients for turnover are slightly reduced, but the marginal effect of portfolio size is much smaller. This is because the effect of portfolio size is somewhat crowded out by diversification, as the number of stocks and size are positively correlated variables. Performance is unlikely to be a linear function of the number of stocks held over a wider range of stock holdings, but tests for non-linearities did not produce

[21] The break-point where the effect of turnover increases marginally is around 250%, and is overall positive at 500% per month. There are 16 investors that trade more than 500%. Their average monthly total excess return is -0.13% which is clearly above the overall sample average. Such "extreme traders" could be therefore be outperforming in the sample.

Table 8: Panel regression estimates: Main results

There are five regressions measuring performance in the panel. Model I is a simple unconditional, single-index model, and Model II conditions beta risk on the state variables as described in the text. Model III adjusts for risk in the cross-section as well, whereas IV and V characterize the intercept on trading, portfolio size, and the degree of diversification, measured as the number of stocks in the portfolio. The dependent variable is the investors' total excess return, and there are 251,879 observations and 16,831 investors in all cases.

Group of coefficients	Model name	I Unconditional	II Conditional	III Conditional	IV Conditional	V Final model
	Dependent variable	Investor excess return	Investor excess return	Investor excess return	Investor excess return	Investor excess return
		Intercept parameters, %				
A_0	Average intercept	1.292* (0.679)	-0.747 (0.614)	-0.740 (0.607)	-0.740 (0.612)	-0.741 (0.613)
A_j	Turnover$_i$	-	-	-	-1.771*** (0.642)	-1.731*** (0.653)
	Squared turnover$_i$	-	-	-	0.380** (0.162)	0.352** (0.157)
	Log portfolio size$_i$	-	-	-	0.215** (0.105)	0.157* (0.087)
	Diversification$_i$	-	-	-	-	0.071* (0.041)
		Beta parameters				
B_0	Average Beta	1.415*** (0.105)	1.436*** (0.062)	1.444*** (0.061)	1.444*** (0.062)	1.443*** (0.062)
B_k	Log Age$_i$	-	-	-0.103*** (0.032)	-0.101*** (0.031)	-0.101*** (0.031)
	Female$_i$	-	-	-0.027* (0.015)	-0.028* (0.015)	-0.028* (0.015)
	Turnover$_i$	-	-	-0.154*** (0.040)	-0.182*** (0.037)	-0.185*** (0.037)
	Diversification$_i$	-	-	-0.036*** (0.006)	-0.035*** (0.006)	-0.033*** (0.007)
B_l	Lagged index return$_{t-1}$	-	2.115*** (0.690)	2.203*** (0.680)	2.206*** (0.678)	2.201*** (0.677)
	Long m. short bond$_{t-1}$	-	0.247** (0.110)	0.248** (0.111)	0.248** (0.112)	0.248** (0.112)
	Short rate$_{t-1}$	-	5.377*** (1.870)	5.117*** (1.904)	5.118*** (1.907)	5.132*** (1.902)
	Adjusted R^2	0.296	0.307	0.309	0.310	0.310

Newey and West (1987) standard errors, robust with respect to autocorrelation and heteroscedasticity, are given in parentheses. Significant parameter estimates at the 10%, 5%, and 1% level are marked (*), (**), and (***). The null hypothesis for the average beta is $B_0=1$.

any significant results. Investors who hold one more stock than the average investor gain an additional 7 basis points in performance. This means that those in the top quintile of diversified holdings gain some 30 basis points over the average.

The negative intercept of 74 basis points implies an annualized underperformance of about 8.5%. Barber and Odean (2000) find that a portfolio consisting of the top quintile of the most active investors loses around 7% annually compared to those who do not trade. The two results are related in that Barber and Odean's most active investors trade about as much as the *average* investor considered here.

To put the model to additional tests, the regressions of Table 9 use the specified final model with alternative assumptions. Model VI and VII substitute for the dependent variable, and instead use the investor return excluding fees and the passive return. The first return includes trading, but at zero cost; the second measures the return on the fixed portfolio held at the beginning of the month. When fees are excluded, the mean performance increases by roughly 21 basis points. When trading is disregarded altogether, it improves by 26 basis points. None of the intercepts is significant, but the means reiterate the evidence reported earlier that investors would have been better off not trading even if it was costless. The coefficients for turnover and portfolio size diminish, and are now insignificant. However, the coefficient for diversification is virtually unchanged. This is the case for both Model VI and VII, which consolidates the evidence that the parameter for diversification picks up performance that is unrelated to trading and portfolio size. There is no support for a more general negative effect of portfolio size that was found in Panel B of Table 3 when fees are excluded. The size-coefficient is positive but insignificant in both specifications that exclude fees.

As discussed previously, investors who on average trade more may hold a larger proportion of cash in their portfolio, which in turn may affect the measured risk. The coefficient for turnover in Model VII does not support this hypothesis. It is smaller, but still significantly negative, which indicates that high turnover investors also hold passive portfolios that are less risky on average.

The survivorship bias in the sample is likely to be large due to the high

Table 9: Panel regression estimates: Additional results

There are five regressions measuring performance in the panel all based on Model V in Table 8. Model VI and VII substitute for the dependent variable with the total return excluding fees and the passive return. Model VIII is specified for the subset of investors active at sample-end. Model IX excludes the investors who deposited stocks as they entered the sample, and Model X are the investors who entered the sample in February 2000 or earlier.

	Model name	VI Costless	VII Passive	VIII Survivors	IX New	X Early
Group of coefficients	Dependent variable	Excluding fees	Passive return	Investor excess return	Investor excess return	Investor excess return
	No. of investors	16,831	16,831	13,917	11,416	2,218
	No. of obs.	251,879	251,879	228,702	175,240	49,583
		Intercept parameters, %				
A_0	Average intercept	-0.533 (0.613)	-0.481 (0.617)	-0.729 (0.605)	-0.799* (0.445)	-0.929 (0.588)
A_j	Turnover$_i$	-0.761 (0.580)	-0.174 (0.180)	-2.181*** (0.782)	-1.902 (1.280)	-1.261** (0.635)
	Squared turnover$_i$	0.149 (0.142)	0.058 (0.126)	0.511** (0.247)	0.544 (0.417)	0.264** (0.118)
	Log portfolio size$_i$	0.049 (0.086)	0.030 (0.086)	0.159* (0.088)	0.037 (0.147)	-0.005 (0.096)
	Diversification$_i$	0.085** (0.041)	0.082** (0.041)	0.083* (0.044)	0.066** (0.032)	0.080*** (0.021)
		Beta parameters				
B_0	Average Beta	1.444*** (0.063)	1.449*** (0.062)	1.444*** (0.060)	1.287*** (0.043)	1.329*** (0.064)
B_k	Log Age$_i$	-0.099** (0.031)	-0.100*** (0.035)	-0.101*** (0.025)	-0.165*** (0.051)	-0.245** (0.096)
	Female$_i$	-0.028* (0.015)	-0.029* (0.015)	-0.027 (0.017)	-0.058** (0.023)	-0.035 (0.031)
	Turnover$_i$	-0.179*** (0.039)	-0.093*** (0.034)	-0.178*** (0.054)	0.068 (0.106)	-0.170*** (0.053)
	Diversification$_i$	-0.033*** (0.007)	-0.038*** (0.007)	-0.035*** (0.007)	-0.011*** (0.004)	-0.014*** (0.005)
B_l	Lagged index return$_{t-1}$	2.205*** (0.682)	2.299*** (0.676)	2.190*** (0.626)	1.643*** (0.589)	1.875** (0.911)
	Long m. short bond$_{t-1}$	0.247** (0.111)	0.241** (0.112)	0.254** (0.112)	0.090 (0.111)	0.093 (0.149)
	Short rate$_{t-1}$	5.160*** (1.889)	4.839** (1.900)	5.169*** (1.881)	1.794 (1.666)	3.439 (2.222)
	Adjusted R^2	0.310	0.311	0.327	0.303	0.275

Newey and West (1987) standard errors, robust with respect to autocorrelation and heteroscedasticity, are given in parentheses. Significant parameter estimates at the 10%, 5%, and 1% level are marked (*), (**), and (***). The null hypothesis for the average beta is $B_0=1$.

attrition rate. Only investors active at sample-end are included in Model VIII reported in Table 9, and the intercept shows that the average performance increases by 11 basis points. On a yearly basis, this means that the survivorship bias in the sample is in the vicinity of 1.3%, which is about double the size usually found for mutual funds. Further, the effect of diversification is virtually unchanged, indicating that this effect is not driven by investors leaving the sample.

The sample does not enable us to distinguish between individuals who are new to the stock market and those who have owned stocks before. A very crude way of defining new or inexperienced investors is to remove those investors who deposited their first portfolio. These individuals could not have been new to the stock market when they became investors at this brokerage firm. Model IX in Table 9 marked "New" reports the performance for those 11,416 investors who bought their first portfolio. The mean performance for this group is about 80 basis points, which is 6 basis points lower than the sample average. This is a small difference, which is also insignificant when modelled as a fixed effect in the total sample.

It would be interesting to discover whether those who entered the market early performed better than those who came in late. It is difficult to partition the sample into a "bull" and a "bear" market, because there are too few observations during the first part in order to enable any reasonable estimates. In addition, it may not be of much interest to find that some investors experienced high gains during the sharp upturn. There is considerable idiosyncratic noise, making it difficult to conclude if investors were market timers or simply lucky. But if these investors were clever enough to time the market in the upturn, one might also claim that they should have been able to perform better in the downturn. Model X takes the 2,218 "Early" investors who were active in the sample before March 2000 and measure the performance of this group alone. The mean performance of this group is actually much lower than for the whole sample. Since these investors lose 93 basis points on average, compared to 74 for the whole sample, there is no evidence that early investors perform better on average.

4.2.3 Robustness

As an additional test, the same regression model is applied to the 3,367 investors sorted into the highest and lowest quintiles by portfolio size, turnover and diversification. This specification is more demanding, as the regression coefficients now describe the variation within groups rather than across quintiles as in the full sample case. A crude measure of the effect between quintiles is now found in the overall means of the regressions. The results are reported in Table 10.

The average intercepts and betas all confirm the effects that were measured in the overall sample. The investors in the largest portfolio size quintile outperform the smallest by 26 basis points. Similarly, those with the lowest turnover gain 30 basis points more than those who trade the most on average, and those with many stocks in their portfolio gain 36 basis points more than the least diversified investors. The average beta for the investors with the largest portfolios is lower than for for those with the smallest. This suggests that there is a difference in average beta risk between these groups, even though it was not significant for the whole sample.

The parameter estimates for the intercept terms broadly confirm that the previous conclusions hold for the larger portfolios. This is important, because it confirms that the previously reported results are not driven by the many small-sized accounts in data, but are also a valid characterization of those with large portfolios.

The regression for the small portfolios is much noisier, and therefore many of the parameters are insignificant. This is also true for turnover and diversification, as investors are, on average, small in these quintiles as well. In these two last cases, parameters are excluded due to the problem of collinearity. There is little or no variation in turnover and diversification for the lowest quintiles, making these variables impossible to distinguish from their average intercept and beta coefficients.

Turnover has generally a negative effect on performance, except for investors who are least diversified. The coefficients here switch signs, and indicate a strong positive effect. This finding supports a learning behavior where some investors choose to diversify as they become aware of their unprofitable strategy. It could also be that some of these investors simply benefited from

Table 10: Panel regression estimates: Investors sorted into top and bottom quintiles

The six regressions are conducted on the first and fifth quintile for portfolio size, turnover and diversification. The dependent variable is total return, and each quintile contains around 3,366 investors. The parameters for turnover and number of stocks are excluded for quintile 1 in the regressions when they are sorted by turnover and number of stocks due to near collinearity.

Group of coeffi-cients	Model name	Portf. size, Quintile 1	Portf. size, Quintile 5	Turnover, Quintile 1	Turnover, Quintile 5	Diversif., Quintile 1	Diversif., Quintile 5
	No. of obs.	43,160	54,372	36,373	37,041	41,523	54,787
		Intercept parameters, %					
A_0	Average intercept	-0.830 (0.800)	-0.570 (0.515)	-0.706 (0.731)	-1.074* (0.641)	-0.890 (0.847)	-0.528 (0.460)
A_j	Turnover$_i$	-1.934 (1.441)	-1.113** (0.497)	n/a	-0.757** (0.343)	2.588 (1.895)	-1.876*** (0.575)
	Squared turnover$_i$	1.049 (1.196)	0.205* (0.110)	n/a	0.192** (0.097)	-0.691 (0.621)	0.349*** (0.124)
	Log port-folio size$_i$	0.101 (0.417)	-0.072 (0.124)	0.180 (0.207)	0.195* (0.102)	0.135 (0.206)	0.111** (0.055)
	Diversifi-cation$_i$	0.098 (0.192)	0.084*** (0.030)	0.109 (0.091)	0.015 (0.036)	n/a	0.048** (0.020)
		Beta parameters					
B_0	Average Beta	1.584*** (0.084)	1.360*** (0.057)	1.452*** (0.057)	1.353*** (0.071)	1.645*** (0.083)	1.277*** (0.049)
B_k	Log Age$_i$	0.008 (0.046)	-0.172*** (0.061)	-0.061 (0.038)	-0.130 (0.087)	-0.140*** (0.029)	-0.104*** (0.028)
	Female$_i$	0.008 (0.018)	-0.077*** (0.015)	-0.037 (0.025)	-0.012 (0.025)	-0.012 (0.018)	-0.047*** (0.016)
	Turnover$_i$	-0.391*** (0.080)	-0.156*** (0.031)	n/a	-0.251*** (0.021)	-0.106 (0.078)	-0.130*** (0.034)
	Diversifi-cation$_i$	-0.083*** (0.026)	-0.024*** (0.005)	-0.061*** (0.018)	-0.014** (0.006)	n/a	-0.015*** (0.003)
B_l	Lagged index return$_{t-1}$	3.600*** (0.846)	1.564** (0.624)	2.133*** (0.543)	2.163** (0.879)	2.815*** (0.787)	1.892*** (0.539)
	Long m. short bond$_{t-1}$	0.438*** (0.117)	0.150 (0.110)	0.220* (0.133)	0.293** (0.132)	0.366** (0.149)	0.136 (0.091)
	Short rate$_{t-1}$	6.848* (3.604)	4.472*** (1.557)	3.546* (2.067)	7.781*** (2.208)	5.707** (2.513)	3.882*** (1.481)
	Adjusted R^2	0.272	0.378	0.267	0.266	0.237	0.472

Newey and West (1987) standard errors, robust with respect to autocorrelation and heteroscedasticity, are given in parentheses. Significant parameter estimates at the 10%, 5%, and 1% level are marked (*), (**), and (***). The null hypothesis for the average beta is $B_0=1$.

selling their stock. Due to the weak significance of this result, the only conclusive evidence is that trading does not harm the least diversified investors to the same extent as the other investor groups.

In conclusion, the general results broadly hold when partitioning the sample into investor groups, and the regression means reveal important differences between them. The parameters in the top quintiles for each group also indicate significant variation within the studied investor groups.

5 Conclusion

Investor performance can be attributed to several, partly interacting, investor characteristics. The discovered systematic pattern of investor performance deepens our knowledge of the trading behavior of online investors in general, and the relation between performance and characteristics in particular.

Online investors trade aggressively in small portfolios, which means that the commissions they pay are high even if fees are low in absolute terms. The average investor flips her portfolio twice a year, and the 20% who trade the most do so on average seven times a year. The marginal effects of turnover reveal that investors who do not trade gain around 25 basis points more per month than the average investor. But trading is not equally as harmful for those with larger portfolios. Portfolios that are twice the size of the sample average gain 15 basis points per month in performance. The combined effects of turnover and portfolio size are mainly related to fees, as they are insignificant when trading is costless.

The novel finding in this study is that undiversified investors systematically choose underperforming stocks in any given industry, and thus the degree of diversification is also important in explaining cross-sectional differences in performance. The quintile of investors who are best diversified earn 36 basis points per month more than those who are least diversified. The panel regressions confirm that diversification has a separate and distinct effect that is unrelated to portfolio size. Benartzi and Thaler (2001) suggest that mutual fund investors diversify naively over available assets. I find that it is the overall lack of diversification among equity investors that can be linked to performance. Undiversified investors are overconfident in their own stock-

picking ability, because they are shown to take higher risks and underperform more. The choice of stocks could be explained by a naive strategy based on availability in the way proposed by Barber and Odean (2003). Undiversified investors show a clear preference for attention-grabbing technology stocks.

I propose that the explanation for the positive effect of diversification on performance lies in the degree of investor sophistication. Unsophisticated investors are more inclined to follow heuristics than common advice. It is tempting to conclude that individuals investing in one stock rather than a mutual fund are widely unaware of the most basic textbook advice on portfolio diversification. But we need to interpret with care, because they might have other holdings of financial assets than those observed in the sample. Therefore, this explanation is only speculative. On the other hand—if there are other stock holdings—the observed portfolio in this sample must contribute to the investor's overall utility in some way. I argue that this is possible, but unlikely.

First, the observed portfolio could provide necessary negative correlation to some other assets held so as to offset overall risk in the aggregate portfolio. I find this unlikely, considering that the stocks held are primarily high-beta, technology stocks. Second, investors may be constrained by being unable to borrow the funds needed to obtain the desired level of risk. This, I believe, is also unlikely. There are well-diversified mutual funds that track most industries, and that would serve as a low-cost alternative to these individual stocks. Third, investors might simply enjoy gambling, betting on single stocks for the sheer fun of it. Such motives are hard to reject, but they do not explain *why* these investors are less successful than others in selecting stocks.

An interesting question for future research is to understand how stock holdings relate to other investor characteristics, such as total wealth, occupation and education. Such variables are also likely to be useful proxies for investor sophistication, and in turn, the profitability of investment strategies.

In summary, most online investors behave contrary to conventional wisdom: They put all their eggs in one basket and count their chickens before they are hatched. Online investors showed guts in taking risks, but few gloried in it.

Appendix A: Measurement

Let $x_{n,i,t}$ be the number of shares of a stock n held by the individual i at the end of month t. A transaction d during month t is denoted by $x_{n,i,d}$, and superindices B and S indicate whether it is a buy or a sell transaction. Similarly, associated actual purchasing and sales prices net of fees are denoted $p^B_{n,i,d}$ and $p^S_{n,i,d}$ for each of these transactions. In what follows, we also need the closing price for stock n on the last day of month t, which is labelled $p^C_{n,t}$. The stock position for individual i at the end of month t is

$$x_{n,i,t} = x_{n,i,t-1} + \sum_{d \in t} \left(x^B_{n,i,d} - x^S_{n,i,d} \right), \tag{A1}$$

which is the position at the beginning of month t plus the sum of buys and sells during the month, hereafter net purchases for short. In what follows, we will impose the restriction that $x_{n,i,t} \geq 0$, meaning that investors are not allowed to have outstanding negative positions at month-end.

A.1 Payoffs

Trading, position and total payoffs for each stock and individual are as follows. The position payoff is defined as

$$\Pi^P_{n,i,t} = x_{n,i,t-1} \cdot (p^C_{n,t} - p^C_{n,t-1}), \tag{A2}$$

which is simply the position at the beginning of the month times the change in price. The trading payoff in stock n for individual i during month t is given by

$$\Pi^T_{n,i,t} = \sum_{d \in t} p^S_{n,i,d} \cdot x^S_{n,i,d} - \sum_{d \in t} p^B_{n,i,d} \cdot x^B_{n,i,d} + \sum_{d \in t} \left(x^B_{n,i,d} - x^S_{n,i,d} \right) p^C_{n,t}. \tag{A3}$$

The first and second component of (A3) states the net sales revenue of stock n during month t, which is the value of sells minus buys at actual transacted prices. This value needs to be adjusted if the number of stocks sold exceeds sales, or vice versa. The third component of (A3) adjusts payoffs by the value of net purchases. There are two cases. If net purchases is positive, the payoff is

adjusted by multiplying the net increase in the number of shares by the price at the end of the month. If sales exceed buys, there will be stocks included in the trading payoff by (A3) that are already accounted for by (A2). Therefore, the value of these shares at t is deducted from the trading payoff.[22]

Deposits of stocks are assumed to be transacted at the beginning of the month and redemptions at the end. Therefore, $x_{n,i,t-1}$ also includes all deposits of stocks made during the month. This is the most convenient way to include deposits since they cannot be regarded as traded stocks. It would be a mistake not to include redemptions and deposits as there would be at least some individuals who deposit their portfolio, but do not trade.

Investors are allowed to short-sell their stock with these definitions because the summation is invariant to the ordering of purchases and sales. The restriction only means that there must be a positive holding of each stock at the end of the month.[23]

Total payoff for each investor i in stock n is just the sum of trading and position payoff

$$\Pi_{n,i,t} = \Pi^T_{n,i,t} + \Pi^P_{n,i,t}. \tag{A4}$$

To find the payoff for the whole portfolio, we sum over n to obtain total portfolio payoff for individual i in month t

$$\Pi_{i,t} = \sum_n \Pi_{n,i,t} = \sum_n \Pi^T_{n,i,t} + \sum_n \Pi^P_{n,i,t}. \tag{A5}$$

A.2 Capital components

The task is to measure investors' ability to create value in their portfolios over a fixed time frame while accounting for trading. The key issue is to identify the capital tied to the payoff components at the portfolio level. The definition of trading capital is complicated by the fact that investors who trade extensively may turn around their portfolio many times per month. For instance,

[22]The method applied is therefore related to that of Linnainmaa (2003), who investigate the profitability of daytrades. The main difference here is that payoffs for positions are invariant to which stocks are actually sold. Furthermore, the capital components associated with the payoffs that follow are quite differently defined.

[23]In the sample, this proved to be a minor problem as there were only 34 instances where it was needed to cover open short positions at month's end. This was done by dating the corresponding buy transaction at the beginning of the following month, $t + 1$, as belonging to t.

an investor may sell her complete holdings of one stock and invest in another during the month. The capital required for the initial holding and the trading capital needed for the purchase is one and the same.

To facilitate comparisons, we assume here that investors hold unleveraged portfolios. They are unconstrained in that they can borrow cash freely to cover the cost of any net purchases at the portfolio level. In this case, the capital required for trading is the minimum amount of money needed to finance the portfolio.

Similar to payoffs, we distinguish between position and trading capital as follows. Position capital is defined as

$$C_{i,t}^{P} = \sum_{n} \left(x_{n,i,t-1} \cdot p_{n,t-1}^{C} \right), \tag{A6}$$

which is simply the value of all stocks in the portfolio at the beginning of the month.

The amount of capital engaged in trading is determined in two steps. I begin by matching purchases and sales. For each investor, the trades are sorted on a stock by stock basis in calendar time. Buy transactions are assumed to precede sales. This is to ensure that the investor does not borrow any stocks in the portfolio.

In step two, we begin by defining the traded value of any sale or buy as

$$TV_{i,d} = \left\{ \begin{array}{c} p_{i,d} \cdot x_{i,d}^{J} \text{ if } J = S \\ -p_{i,d} \cdot x_{i,d}^{J} \text{ if } J = B \end{array} \right\},$$

such that it represents the revenue of any sales and cost of any purchase independent of the stock that is traded. We then seek the lowest cost that is needed to finance the trading activity during the month. The trade values are ordered during the month from beginning to end for each investor regardless of which stock is traded, and the cash balance is calculated at each point in time. The lowest cumulative cash balance in month t is the minimum amount needed to finance the portfolio without leverage, and is written

$$C_{i,t}^{T} = -\min_{d} \left[\sum_{d \in t} TV_{i,d}, 0 \right], \tag{A7}$$

and is expressed as a positive number since we pick out the largest negative cash balance.

Total capital is the sum of position capital and trading capital,

$$C_{i,t} = C^P_{i,t} + C^T_{i,t}. \tag{A8}$$

Therefore, the capital base is only increased if trading incurs additional funding. But this is exactly what we want, because the investor who reallocates her investment without using additional funds will have the same capital base.

A.3 Simple returns

The simple portfolio return for investor i in month t is

$$r_{i,t} = \frac{\Pi_{i,t}}{C_{i,t}}. \tag{A9}$$

If no trading occurred in month t, it is easy to verify that this expression corresponds to

$$r_{i,t} = \left[\sum_n w_{n,i,t-1} \cdot \frac{p^C_{n,t} - p^C_{n,t-1}}{p^C_{n,t-1}}\right],$$

which is the weighted return of the portfolio held in $t-1$, and where $w_{n,i,t-1}$ is the weight of stock n held by individual i in $t-1$.

A.4 Excess returns

The obvious problem when constructing returns from the definitions above is that no account is taken of any alternative return on funds that is not invested in the market. For example, consider an investor who buys stocks at the end of the month. This portfolio will have a capital base that reflects the value of the additional purchases at the beginning of the month, but a stock return measured over a much shorter horizon.

This effect is mitigated by measuring excess returns, created as follows. It is assumed that the investor borrows at the available 30-day T-bill rate, r^F_{t-1}, in order to finance the portfolio. The interest that is attributable to the position

component, $I^P_{i,t}$, is calculated as the cost of borrowing the value of the portfolio at the beginning of the month, i.e the first part of equation (A8).

If trading occurs, we seek the net interest paid for trading capital during the month. Interest is calculated for each transaction and summed over the month creating the fictitious revenue $I^T_{i,t}$ that corresponds to the interest that is attributable to the actual timing of purchases and sales.[24]

The excess return is therefore

$$R_{i,t} = \frac{\Pi_{i,t} + I^P_{i,t} + I^T_{i,t}}{C_{i,t} - \min\left[I^T_{i,t}, 0\right]}, \tag{A10}$$

where $I^P_{i,t}$ is always 0 or negative and $I^T_{i,t}$ is negative if there is a net cost of financing the monthly transactions. When trading capital is 0 but the investor is net selling, $I^T_{i,t}$ represents the interest earned on investments that is sold out of the portfolio. In this way, timing of the sale is properly accounted for since positive interest is added to the return measure. Both trading capital and $I^T_{i,t}$ can be positive if the investor only draws cash for a short time and for a small amount in comparison to sales revenues in a month.

The interest on trading capital is only added to the capital base if it is negative. This is because it is assumed that interest earned is paid out at the end of the month, but any costs must be covered by capital at the beginning of the month. It therefore ensures that returns are bounded at -1.

In the case of no trading, $I^T_{i,t} = 0$, we obtain the familiar definition of excess returns, which is

$$R_{i,t} = \frac{\Pi_{i,t} + I^P_{i,t}}{C^P_{i,t}} = r_{i,t} - r^F_{t-1}.$$

A.5 Passive returns

The idea of comparing investor performance with their own-benchmark was originally proposed by Grinblatt and Titman (1993). Here, the passive return

[24] Two assumptions apply: the borrowing and lending rates are the same and the effect of compounding is ignored.

captures the same intuition and is defined as

$$R^P_{i,t} = \frac{\Pi^P_{i,t} - I^P_{i,t}}{C_{i,t}}, \tag{A11}$$

which is the position payoff divided by total capital corrected for interest. As the own-benchmark return measures the return of the portfolio since there was no trading during the month, we see that (A10) and (A11) are exactly the same, because then we have that

$$\Pi_{i,t} = \Pi^P_{i,t}.$$

The passive return measure uses total capital as a base. It is therefore assumed that whatever funds are used for net investments during the month are invested at the risk-free rate. The investors can only deviate from the benchmark by trading. During the month, investors can move in and out of the market as a whole or switch allocation between stocks. If these tactical changes in risk and reallocations are profitable, the investors earn a higher excess return on the traded portfolio than on the static own-benchmark.

A.6 Industry returns

The industry weight in industry v for individual i at time $t-1$, $w_{v,i,t-1}$, is obtained by summing the weights of any stocks n the individual holds in each industry v,

$$w_{v,i,t-1} = \sum_{n \in v} w_{n,i,t-1}. \tag{A12}$$

Thus, the investor's industry tracking return is the industry weight multiplied by the respective excess index return,

$$R^{Ind}_{i,t} = \sum_{v} R^{Ind}_{v,t} \cdot w_{v,i,t-1}. \tag{A13}$$

A.7 Turnover

As a measure of turnover, the total traded value is divided by two times total capital,

$$\text{Turnover}_{i,t} = \frac{\sum_{d \in t} |TV_{i,d}|}{2 \cdot C_{i,t}}. \tag{A14}$$

Turnover therefore includes both position and trading capital in the denominator. Total capital is doubled so we can interpret the measure as how often a portfolio is bought and purchased in a month. A turnover measure of one thus implies that the whole portfolio is sold and purchased.

A.8 Concluding example

The calculation of the various returns defined above is illustrated in Table 11 by two simplified examples of two investors holding or trading two different stocks.

Paul initially holds 50 A stocks and 100 B stocks at prices 90 and 50, respectively. He makes one trade during the month, which is an additional purchase of 100 stock A at price 92. At the end of the month, the stock prices are 100 for A and 45 for B. The total payoff for A is 1,300, of which 500 is attributable to the position and 800 to trading. Since there was no trading in B, trading payoff is 0, but there is a position payoff of -500. Total payoff is therefore 800.

The position capital needed to finance this portfolio is 4,500 for A and 5,000 for B, i.e., 9,500 in total. Furthermore, the additional stocks A bought cost 9,200. Since there are no more trades, this is the lowest cash balance during the month. Therefore, trading capital and total capital sums up to 18,700. All in all, this yields a total portfolio return of 4.28%. The passive return, given by the return on the portfolio held in $t-1$, is 0%. Turnover, which is the value of the purchases divided by two times total capital, is almost 25%, indicating that this month Paul bought and sold a quarter of his portfolio.

The other investor—Magnus—starts out with 100 A stocks and makes three trades. The ordering of the trades are marked by super-indices. He begins by buying 50 B stocks to price 45. Later, he sells 140 A stocks (such that in effect he short-sells 40 A stocks) at price 85. Finally, he decides to buy back 100 A stocks at price 95.

Table 11: Two examples of return measure

The return measure is illustrated by two examples reflecting a one-month investment history of two investors. The monthly $t-1$ and t closing prices are 90 and 100 for stock A and 50 and 45 for stock B. The order for which the trades occur are marked by super-indices. Paul holds 50 units of A and 100 of B. He then buys 100 more A at price 92. Magnus holds 100 A stocks. Then 50 units of B are purchased at price 40, followed by 140 A sold at 87. Finally 100 A stocks are bought at price 95. For simplicity, the returns here are simple rather than excess returns used in the actual calculations.

	Paul*		Magnus*	
Assumptions	Stock A	Stock B	Stock A	Stock B
Closing price in t-1, $p^C_{n,t-1}$	90	50	90	50
Closing price in t, $p^C_{n,t}$	100	45	100	45
Initial position, $x_{n,i,d}$	50	100	100	0
Amount bought, $x^B_{n,i,d}$	100[1]	0	100[3]	50[1]
Price bought, $p^B_{n,i,d}$	92	-	95	40
Amount sold, $x^S_{n,i,d}$	0	0	140[2]	0
Price sold, $p^S_{n,i,d}$	-	-	87	-
Payoffs				
Trading payoff, $\Pi^T_{n,i}$	800	0	-1,320	250
Position payoff, $\Pi^P_{n,i}$	500	-500	1,000	0
Total payoff, $\Pi_{n,i}$	1,300	-500	-320	250
Capital requirements				
Trading capital, $C^T_{i,t}$		9,200		2,000
Position capital, $C^P_{i,t}$		9,500		9,000
Total capital, $C_{i,t}$		18,700		11,000
Returns				
Total return, $R_{i,t}$		4.28%		-0.64%
Passive return, $R^P_{i,t}$		0.00%		9.09%
Turnover		24.6%		107.6%

*) Any resemblance to actual persons or events are unintentional and purely coincidental.

Magnus generates a trading payoff of 250 in B as the stocks that were bought at 40 are each worth 45 at month-end. The trading payoff for A is calculated as follows. The value of sales minus purchases is 2,680 and is adjusted by 40 stocks valued at 100, such that the trading payoff is -1,320 in all. A position payoff of 1,000 is recorded for the stocks owned at the beginning of the month and held to the end, such that the total payoff for A is -320.

We can convince ourselves that this is indeed correct by noting that the monthly mean purchasing price of A stocks is 92.50. Magnus owned 100 A shares that were worth 90 at the beginning of the month, and 100 shares was bought at 95. Magnus incurred a loss of 770 when 140 shares were sold at 87,

but gained on the remaining 60 stocks that were kept to month-end. The 7.50 profit on each of these 60 shares amounts to 450. Losses and profits come to -320.

Position capital is defined by the value of the holdings, which in this case is 100 A stocks to the value of 9,000. We retrieve the trading capital by considering the order of the trades. The lowest value we obtain summing over the trades is 2,000, which is needed to finance the first transaction.[25] Trading capital is therefore 2,000. Total capital is 11,000 which corresponds to the initial holding of 100 A stocks at price 90 plus the 50 B stocks bought at price 40.

All in all, dividing payoffs by capital, Magnus total portfolio return is -0.64%. The own-benchmark return is 9.09%, which is the return on the 100 A stocks held at the beginning of the period. The turnover is measured at 108%, which means that this month Magnus bought and sold more than the value of his portfolio.

This is a simplified example where any interest with respect to the timing of the trades are unaccounted for in the return measure. The corresponding excess returns to those here could be created by the adjustments given previously in the text.

[25]The cash balance for the second trade is 10,180, obtained by adding the 12,180 in revenue for the sales to -2,000. For the third trade, the cash balance is 680.

Appendix B: GMM estimation

The regressions of the portfolio excess return for each investor i at time t can generally be specified as follows:

$$\begin{aligned} R_{i,t} &= A_0 + B_0 R_t^M + \sum_{j=1}^{J} A_j c_{i,t,j} \\ &\quad + \sum_{k=1}^{K} B_k z_{i,t,k} R_t^M + \varepsilon_{i,t}, \qquad \begin{array}{l} i = 1, \ldots, N, \\ t = 1, \ldots, T, \end{array} \end{aligned} \tag{B1}$$

where the A:s and B:s are true regression parameters, c denotes J investor characteristics, z denotes K conditional risk attributes, and ε denotes the error term. In this general form, both the characteristics and attributes can vary over time and between individuals. In all, we have $2 + J + K$ parameters and $i = 1, \ldots, N$ individual portfolio observations over time $t = 1, \ldots, T$.

Consider the following sample moment conditions:

$$\mathbf{g}_T(\boldsymbol{\theta}) = \frac{1}{T} \sum_{t=1}^{T} \begin{bmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{N,t} \\ \varepsilon_{1,t} R_t^M \\ \vdots \\ \varepsilon_{N,t} R_t^M \\ \varepsilon_{1,t} c_{1,t,j} \\ \vdots \\ \varepsilon_{N,t} c_{N,t,J} \\ \varepsilon_{1,t} z_{1,t,k} R_t^M \\ \vdots \\ \varepsilon_{N,t} z_{N,t,K} R_t^M \end{bmatrix} = \frac{1}{T} \sum_{t=1}^{T} f\left(\mathbf{X}_t, \boldsymbol{\theta}\right), \tag{B2}$$

where $\mathbf{X}_t$ summarizes the data and $\boldsymbol{\theta}$ contains all parameters. There are $2 + J + K$ parameters and $(2 + J + K)N$ moment conditions, so the system is over-identified. We recover the parameters by forming $2 + J + K$ linear com-

binations of $\mathbf{g}_T(\boldsymbol{\theta})$, that is,

$$\mathbf{A}\mathbf{g}_T(\boldsymbol{\theta}) = \mathbf{0},$$

where $\mathbf{A}$ is a matrix of constants. More specifically, we let $\mathbf{A}$ be of the following form

$$\mathbf{A} = \begin{bmatrix} \mathbf{1}_{1\times N} & \mathbf{0}_{1\times N} & \mathbf{0}_{1\times JN} & \mathbf{0}_{1\times KN} \\ \mathbf{0}_{1\times N} & \mathbf{1}_{1\times N} & \mathbf{0}_{1\times JN} & \mathbf{0}_{1\times KN} \\ \mathbf{0}_{J\times N} & \mathbf{0}_{J\times N} & \mathbf{I}_{J\times J}\otimes\mathbf{1}_{1\times N} & \mathbf{0}_{J\times KN} \\ \mathbf{0}_{K\times N} & \mathbf{0}_{K\times N} & \mathbf{0}_{K\times JN} & \mathbf{I}_{K\times K}\otimes\mathbf{1}_{1\times N} \end{bmatrix},$$

where $\mathbf{1}$ denotes a vector of ones and $\mathbf{I}$ is the identity matrix. We then ensure that

$$\mathbf{A}\mathbf{g}_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\begin{bmatrix} \sum_{i=1}^{N}\varepsilon_{i,t} \\ \sum_{i=1}^{N}\varepsilon_{i,t}R_t^M \\ \sum_{i=1}^{N}\varepsilon_{i,t}c_{i,t,1} \\ \vdots \\ \sum_{i=1}^{N}\varepsilon_{i,t}c_{i,t,J} \\ \sum_{i=1}^{N}\varepsilon_{i,t}z_{i,t,1}R_t^M \\ \vdots \\ \sum_{i=1}^{N}\varepsilon_{i,t}z_{i,t,K}R_t^M \end{bmatrix} = \mathbf{0}_{1\times(2+J+K)}. \tag{B3}$$

Hence, the system of moment conditions in (B3) is exactly identified. It is straightforward to show that these moment conditions correspond exactly to a least square estimator of (B1).

Hansen (1982) shows that the asymptotic distribution of the parameter estimates $\boldsymbol{\theta}_T$ of the true parameter vector $\boldsymbol{\theta}_0$ is given by

$$\sqrt{T}\,(\boldsymbol{\theta}_T - \boldsymbol{\theta}_0) \xrightarrow{d} N(\mathbf{0}, (\mathbf{A}\mathbf{D}_0)^{-1}\left(\mathbf{A}\mathbf{S}_0'\mathbf{A}\right)(\mathbf{A}\mathbf{D}_0)^{-1'}), \tag{B4}$$

where

$$\mathbf{S}_0 = \sum_{m=-\infty}^{\infty} E\left[f(\mathbf{X}_t, \boldsymbol{\theta}_0)\, f(\mathbf{X}_{t-m}, \boldsymbol{\theta}_0)'\right],$$

and $\mathbf{D}_0$ is the gradient of the moment conditions for the true parameters. The gradient is estimated from its sample counterpart and the sample variance-

covariance matrix is estimated in the manner described by Newey and West (1987). It can be shown that

$$(\mathbf{AD}_0)^{-1}\left(\mathbf{AS}_0'\mathbf{A}\right)(\mathbf{AD}_0)^{-1'} \geq \left(\mathbf{D}_0'\mathbf{S}_0^{-1}\mathbf{D}_0\right)^{-1},$$

implying loss of efficiency when the matrix $\mathbf{A}$ is constructed arbitrarily, as is the case here. However, the standard errors in (B4) are robust to heteroscedasticity and serial correlation.

When investors enter the sample at different points in time, there are missing observations for the months in which they are not observable. Bansal and Dahlquist (2000) derive results that are used to estimate pooled models with missing data, i.e., constructing a balanced panel from an unbalanced one. They define indicator variables based on data availability according to

$$I_{i,t} = \begin{cases} 1 \text{ if data are observed at } t \text{ for individual } i \\ 0 \text{ if data are not observed at } t \text{ for individual } i \end{cases}$$

The critical assumption they make is that the indicator variable is independent of $\varepsilon_{i,t}$ which implies that the data are missing randomly. When this is the case, we can form moment conditions based on the product of the previously modelled errors and the indicator variable. This implies that, for all practical purposes, we can use the same estimation approach proposed earlier on the full sample by treating missing observations in the moment conditions as zeros. See Bansal and Dahlquist (2000) for an example.

References

Bansal, Ravi, and Magnus Dahlquist, 2000, The forward premium puzzle: Different tales from developed and emerging markets, *Journal of International Economics* 51, 115–144.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 60, 773–806.

———, 2001a, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–292.

———, 2001b, The Internet and the investor, *Journal of Economic Perspectives* 15, 41–54.

———, 2002, Online investors: Do the slow die first?, *Review of Financial Studies* 15, 455–487.

———, 2003, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, Working Paper, University of California, Berkeley.

Benartzi, Shlomo, and Richard H. Thaler, 2001, Naive diversification strategies in defined contribution savings plans, *American Economic Review* 91, 427–465.

Bodie, Zvi, Robert C. Merton, and William F. Samuelson, 1991, Labor supply flexibility and portfolio choice in a life-cycle model, *Journal of Economics, Dynamics and Control* 16, 427–449.

Breen, William, Lawrence R. Glosten, and Ravi Jagannathan, 1989, Economic significance of predictable variations in stock index returns, *Journal of Finance* 44, 1177–1190.

Brown, Stephen J., William N. Goetzmann, Roger G. Ibbotson, and Stephen A. Ross, 1992, Survivorship bias in performance studies, *Review of Financial Studies* 5, 553–580.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373–399.

Coval, Joshua D., David A. Hirshleifer, and Tyler G. Shumway, 2003, Can individual investors beat the market?, Working Paper, Harvard University.

Daniel, Kent, David A. Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security under- and overreactions, *Journal of Finance* 53, 1839–1885.

De Long, J. Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Ferson, Wayne E., and Rudi W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425–461.

Glaser, Markus, and Martin Weber, 2003, Overconfidence and trading volume, Working Paper, University of Mannheim.

Grinblatt, Mark, and Matti Keloharju, 2000, The investment behavior and performance of various investor types: A study of Finland's unique data set, *Journal of Financial Economics* 55, 43–67.

Grinblatt, Mark, and Sheridan Titman, 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* 66, 47–68.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Hansen, Lars P., 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 50, 1029–1054.

Heaton, John, and Deborah J. Lucas, 1996, Evaluating the effects of incomplete markets on risk sharing and asset pricing, *Journal of Political Economy* 104, 443–487.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond market, *Journal of Financial Economics* 17, 357–390.

Kyle, Albert S., and Albert Wang, 1997, Speculation duopoly with agreement to disagree: Can overconfidence survive the market test?, *Journal of Finance* 52, 2073–2090.

Langer, Ellen J., and Jane Roth, 1975, Heads I win, tails its chance: The illusion of control as a function of the sequence of outcomes in a purely chance task, *Journal of Personality and Social Psychology* 32, 951–955.

Levin, Irwin P., M. A. Snyder, and D.P. Chapman, 1997, The interaction of experimental and situational factors and gender in a simulated risky decision-making task, *Journal of Psychology* 122, 173–181.

Linnainmaa, Juhani, 2003, Essays on the interface of market microstructure and behavioral finance, Doctoral dissertation, Helsinki School of Economics.

McClelland, Alastair G. R., and Fergus Bolger, 1994, The calibration of subjective probabilities: Theories and models 1980-94, in George Wright, and Peter Ayton, ed.: *Subjective Probability*. pp. 453–482 (John Wiley & Sons Ltd.: New York, N.Y.).

Newey, Whitney K., and Kenneth D. West, 1987, A simple semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Odean, Terrance, 1998, Are investors reluctant to realize their losses?, *Journal of Finance* 53, 1775–1797.

——— , 1999, Do investors trade too much?, *American Economic Review* 89, 1279–1298.

Schlarbaum, Gary G., Wilbur G. Lewellen, and Ronald G. Lease, 1978, Realized returns on common stock investments: The experience of individual investors, *Journal of Business* 51, 299–325.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777–790.

Slovic, Paul, Baruch Fischhoff, and Sarah Lichtenstein, 1982, Facts versus fears: Understanding perceived risk, in Daniel Kahneman, Paul Slovic, and Amos Tversky, ed.: *Judgement under Uncertainty: Heuristics and Biases* . pp. 463–489 (Cambridge University Press: Cambridge, M.A.).

Svensson, Ola, 1981, Are we all less risky and more skillful than our fellow drivers?, *Acta Psychologia* 47, 143–148.

Varian, Hal R., 1989, Differences of opinion in financial markets, in Courtenay C. Stone, ed.: *Financial Risk: Theory, Evidence, and Implications* . pp. 3–37 (Kluwer Academic Publishers: Boston).

Weber, Martin, and Colin F. Camerer, 1998, The disposition effect in securities trading: an experimental analysis, *Journal of Economic Behavior and Organization* 33, 167–184.

Chapter III

Equity Mutual Fund Flows and Stock Returns in Sweden

Behavior is the mirror in which everyone shows their image.
—Johann Wolfgang von Goethe

1 Introduction

The market for mutual funds has experienced remarkable growth in Sweden over the last few decades. At the beginning of the 1970s, Swedes had around 300 million Swedish kronor (SEK) invested in mutual funds, and by 1993 this had increased to SEK 202 billion. By the end of 2000, total holdings were SEK 898 billion, of which 595 billion were equity funds.[1] This development has seen the mutual fund share of financial savings rise from 0.4% to 30%, and Swedish equity fund holders become the largest group of investors in the Stockholm Stock Exchange. The only countries that have comparable developments are the U.K. and the U.S., but the fact that 60% of the population invests in privately managed funds still makes Sweden exceptional. Moreover, Swedes allocate around 70% to stocks and 30% to bonds and bills, while

[0] I would like to thank Magnus Dahlquist, Peter Englund, Matti Keloharju, and Paul Söderlind for helpful comments and suggestions.

[1] One USD fluctuated between SEK 6.60 and SEK 10.10 during the sample period.

the reverse is true for most other Europeans. Over the sample period between 1993 and 2000, aggregate net flows to equity funds alone contributed a substantial SEK 183 billion to asset holdings measured in 2000 prices. At the same time, the Swedish stock market outperformed a value-weighted world portfolio by more than 100% and reached levels of valuation unprecedented by most financial yardsticks.

A common explanation for this development is that equity mutual funds may exert price pressures on stock markets. If this is true, the demand for stocks is downward sloping, which from a financial economic view means that many fundamental market efficiency characteristics fail to hold. Sweden may be a good place to look for price pressure effects, as the stock market is small and mutual fund investment high, by international standards. On the other hand, the causality may go in the other direction: returns cause flows. If investors in the aggregate chase returns, flows may follow returns with a lag.

The purpose of this paper is, however, not only to look for causal relations. A concurrent effect is documented and measured in an attempt to track down the possible source of this finding. The approach is to use two derived time series models for unexpected shocks to mutual fund flow. There have been three distinct institutional changes during the sample period which can be associated with corresponding extreme observations. The two models derived relate to these events by regarding them as either expected or unexpected.

Price pressure effects may be detected by finding price reversals, but there is little evidence of this. There is no support for the feedback trading hypothesis, as it is discovered that the feedback pattern found can be attributed to the expected part of flows only. There is firm evidence of a concurrent relation between unexpected flows and returns also in Sweden, but the extreme flow observations are not associated with corresponding returns.

The concurrent effect can have three sources. First, flows may just pick up variation in systematic risk, which would make the flow and return causality suspect. The concurrent relation remains in a CAPM specification with a world index as a proxy for the market portfolio, and also remains when other potential risk factors are added, such as term premium, growth in retail sales and industrial production. Second, there may be intra-month feedback trading or price pressure effects that are not picked up in monthly data. Monthly

flows are found to be associated with excess returns in the first and second week, which could be due to intra-month positive feedback trading. Third, mutual fund flows may represent the sentiment of noise traders. If this hypothesis is true, flows can be regarded as a measure of this sentiment, and in turn, be an additional source of risk. Although difficult to test, there is no evidence of flows representing noise trading, when proxied by returns on a stock index composed of smaller stocks.

The pattern for weekly returns, the lack of price reversals, and weak impact on prices of the extreme flow observations do not support the price pressure hypothesis. Rather, it is more likely that the concurrent monthly relation stems from intra-month positive feedback trading or informed trading. However, if measured unexpected flows do represent information, it is found that they are small in comparison to total flows. This, in turn, indicates that the general information content in aggregate flows is low. Consequently, it is also found that flows do not predict returns.

The outline of the paper is as follows. Section 2 gives the theoretical background of possible flow and return relations and discusses the previous research as well as the most important institutional changes in the Swedish mutual fund industry. Section 3 presents the time series of aggregate flow data and returns. Section 4 presents the results, and Section 5 concludes.

2 Returns and flows

This section begins by presenting the theories that can be related to the lag structure between flows and returns. The previous literature is subsequently described by separating research on individual funds from industry level studies. Finally, this section contains a brief overview of the most important institutional changes that have taken place in Sweden.

2.1 Returns lead flows

There are two competing and mutually exclusive theories of how individuals react to returns: the "positive feedback" hypothesis and the "contrarian" hypothesis.

The *positive feedback* hypothesis states that returns lead flows because individuals purchase assets that have previously gained in value, and correspondingly, sell assets that have previously declined in value. A rational reason for an investor to follow such a rule is that returns follow a similar pattern. Jegadeesh and Titman (1993) find a *momentum* effect, in that buying winners and selling losers is profitable for individual stocks when the time horizon is between three months and a year. For managed assets, such as mutual funds, Gruber (1996) points out that returns can also work as a signal of future superior performance. But the relation could have other rational explanations. Brennan and Cao (1996) explore a dynamic rational expectations model in which market participants trade in response to new information. They argue that observed lags between returns and flows may be the result of a transition phase when trading takes place between agents with heterogenous information. Some psychological factors may also produce positive flows from past returns. Gervais and Odean (2001) argue that investors learn to be overconfident in bull markets due to the difficulty of distinguishing their own investment ability from market-wide movements. If this is the case, one is likely to see an increase in both sales and purchases, but new money flows may increase in response to increasing confidence. Statman, Thorley, and Vorkink (2003) link evidence of individual security trading activity to overconfidence, as trading increases when prices rise.

The *contrarian* hypothesis on the other hand states that individuals choose to sell assets that previously gained in value, and thus positive returns are followed by outflows. Shefrin and Statman (1985) find a *disposition effect*, which is a combination of *mental accounting* (Kahneman and Tversky, 1983), and *prospect theory* (Kahneman and Tversky, 1979), in mutual fund trading.[2] The disposition effect occurs when the psychological cost of selling a loser stock is greater than that of selling a winner. Even if this effect relates only to individual portfolio holdings, Shefrin and Statman argue that it is reasonable that aggregate prices should correlate with overall volume if this effect is important.

[2]This effect have also later been documented experimentally by Weber and Camerer (1998), and among individual investors' stock portfolios by Odean (1998).

2.2 Returns and flows are instantaneous

There can be two reasons why returns and flows react instantaneously. First, there might be a common factor—for instance information or common expectations—that drives both flows and returns. Second, there might be shocks to the demand for stocks that are not fully absorbed by perfect capital markets. In this case, price pressures could originate from unexpected flows.

In the *information* hypothesis, flows are merely an effect of the release of new, specific information or a common change in the expectation of market conditions. Traders will act upon this information, which will be measured by flows. A common assumption is that capital markets are perfect. An important implication of this assumption is that an investor has the opportunity to sell unlimited amounts of traded assets at the given market price. The force of arbitrage will ensure that volume in itself will not affect prices in any given direction.

Price pressures can occur when assets are in fixed supply in the short run, but the demand curve for equity is downward sloping. This means that investors have different views about fundamental values. A shock to demand, by for instance new money coming into equity funds, will force stock market prices to rise. Shleifer (1986), Harris and Gurel (1986), and Lynch and Mendenhall (1997) find significant positive concurrent returns associated with the inclusion of new stocks in the S&P 500 index. The price reaction suggests that the stock market is driven by liquidity shocks, since inclusions in an index should be irrelevant from a normative pricing viewpoint.

If the demand curve for stocks is downward sloping, flows that originate from irrational behavior will also have a price effect. De Long, Shleifer, Summers, and Waldmann (1990) show that the existence of *noise traders* in the economy, who are not trading on information but on some correlated sentiment, implies that risk is higher than warranted by fundamentals.[3] Lee, Shleifer, and Thaler (1991) hypothesize that closed-end mutual funds have a larger share of noise traders among their owners than the stock market average, because the number of small investors is larger. This may explain why these mutual funds

[3]The term "Noise trading" was originally introduced by Black (1986).

are underpriced. Rational investors avoid closed-end mutual funds because they are subject to higher noise trading risk. They also infer that noise trading risk is likely to be more prominent among small firms, as they are found to have a more dispersed investor base.

It is difficult to distinguish between the two hypotheses in the data, but finding price reversals may be an indication of shocks to demand. Further, if some assets are more exposed to noise trading risk than others, these should react more to a given change in sentiment.

2.3 Returns lag flows

Positive flow and lagged, negative returns are consistent with the price pressure hypothesis if a positive concurrent relation also exists between returns and flows. Such a pattern may suggest that prices adjust to a shock to unanticipated demand.

The other alternative, when a positive flow is associated with a lagged and positive return, is commonly referred to as the *smart money* hypothesis, which is more relevant to individual funds. Gruber (1996) finds evidence of new cash flows acting upon the predictability of individual mutual fund returns, which is "smart" in that it is indicative of investors earning superior abnormal returns.

2.4 Fund level studies

Performance persistence suggests that one should buy previous winning mutual funds and sell losing funds. The evidence for persistence is quite conclusive regarding the worst performing funds in the U.S. (Hendricks, Patel and Zeckhauser (1993), Carhart (1997), Brown and Goetzmann (1995)). Evidence for persistence among the highest performing funds is somewhat weaker. Hendricks, Patel, and Zeckhauser (1993), and Malkiel (1995) find evidence for repeated winners on the U.S. fund market, but Brown, Goetzmann, Ibbotson, and Ross (1992) argue that this can be due to survivorship bias. Furthermore, profitable strategies for exploiting these results are sensitive to the specific time period under study, which in turn may indicate the existence of sources of risk not accounted for in the performance measures used (Brown

and Goetzmann, 1995). Ferson and Schadt (1996) condition individual fund betas on public macro information variables and conclude that the average underperformance found in unconditional models can be attributed to common time-variation in the conditional betas and the expected market return. Dahlquist, Engström, and Söderlind (2000) find no evidence in favor of persistence in fund performance for Swedish equity funds in a sample representing two-thirds of the total net assets of equity funds between 1993 and 1997. They also use lagged flows to investigate the smart money hypothesis, but find only weak evidence as the lagged flow coefficients in many cases were negative.

Other fund level studies seek to determine flows into and out of individual funds. Here, returns are treated as one attribute among numerous others, such as marketing, risk and size. Chevalier and Ellison (1997), and Sirri and Tufano (1998) find that lagged flows and concurrent returns are significantly positively correlated, but not proportionally so. Individual fund flows are found to be more sensitive to deviations from the benchmark return when the deviation is large. This implies that flows follow market-adjusted fund returns in a non-linear fashion. Gruber (1996) finds evidence of smart money in new cash flows to mutual funds, as they are found acting upon the predictability of individual mutual fund returns. Zheng (1999) confirms Gruber's evidence and tests to see if there is any information in the flows that can used to form profitable trading strategies. He finds no overall evidence of this, except that it may be profitable to follow flows associated with small funds.

2.5 Industry level studies

Industry level studies are primarily concerned with finding evidence of causality between flows and returns on the aggregate level. Warther (1995) measures the concurrent relation between flows and returns to determine if mutual fund investors are feedback traders. Using time series methods, he decomposes flows from a near complete sample of U.S. mutual funds between 1984 and 1993 into expected and unexpected flows. The main finding is that monthly concurrent unexpected flows and returns are strongly positively correlated, which is in line with both the information and the downward sloping demand hypothesis. A two-standard deviation shock to unexpected flows is associated

with a concurrent 5.7% increase in returns, and flows alone explain up to 55% of the variation in returns. Further, he finds a positive relation between flows and subsequent returns, and a negative relation between returns and subsequent flows. Thus, there is no evidence of either positive feedback trading or price reversals. Regressions of weekly data reveal that most of the concurrent monthly effects can be attributed to the first three weeks.

Santini and Aber (1998) characterize new net flows to the mutual fund industry using a multivariate specification of fund flows and quarterly data between 1973 and 1985, a total of 50 observations. Coefficients for the lagged long-term interest rate is negatively related to fund flows, while contemporaneous stock market performance and personal disposable income, is positively related to fund flows. The additional variables also added some explanatory power to the flow regression. Coefficients for lagged returns were all insignificant, giving no support for feedback trading.

Edelen and Warner (2001) undertake a similar study using daily flow data, but for a limited sample representing funds worth 20% of total mutual fund net assets. Their main finding is that the flow and return relation is largely concurrent. The relation between flows and market returns is similar in magnitude to the price effect documented in the literature of institutional trades.[4] The strong correlation between flow and lagged daily returns can either be due to partial adjustment to new information or short lagged feedback trading. The authors establish that the strong monthly correlation is not necessarily due to flow driving returns. Rather, it reflects the strong correlation between flow and lagged daily returns.

Goetzmann and Massa (2003) follow flows from investors in three U.S. index funds, and find a strong contemporaneous relation between daily inflows and returns to the S&P 500 index. They find no evidence of positive feedback trading. When inflows and outflows are measured separately, they find some evidence that investors react asymmetrically to past returns; they seem to be more willing to sell shares the day after market declines than to buy after market increases. A somewhat puzzling positive relation is also found between implied market volatility and flows. The authors hypothesize that this effect could be due to changes in the investor base: a larger share of speculators

[4] As found by, e.g., Chan and Lakonishok (1995).

possibly enter the market at periods of high volatility.

Thus, the general result for the U.S. suggests a strong concurrent relation between returns and flows, and that if feedback trading behavior exists, the lag is surprisingly short.

2.6 Institutional changes in the Swedish mutual fund market

The Swedish government initiated the first public savings program in 1978. This program allowed Swedes to save initially SEK 400 and later SEK 600 monthly in funds investing in Swedish equity only. The incentive was zero tax on capital gains, which could be contrasted with a 20% to 40% tax on equity. In 1984, these funds were more precisely defined as *Allemansfonder* (hereafter referred to as A funds), and the investment opportunity set for such mutual funds was widened to include the money market. The tax advantage is likely to be an important reason for the rapid growth and wide distribution of individuals' saving into A funds. In January 1989, Sweden deregulated its capital market, and mutual funds were allowed to invest in foreign equity. Increased savings in mutual funds demanded more precise regulations. Under the Swedish Mutual Funds Act, funds were to have a maximum weight of 10% of the asset value in the equity of a single company. This was an attempt on the part of the government to guarantee diversification.

An important change for the sample period under study was the 1991 tax reform, whose purpose was to simplify the fiscal structure and stimulate savings. This was achieved by introducing a flat tax rate of 30% on capital gains, while removing some of the tax deductibility for lending rates.[5] Owners of A fund shares were still favored in that they were generally taxed at 20% tax on capital gains, except in 1994 when the tax incentives that made these funds more attractive than others disappeared. This fiscal change was a result of an election outcome in September 1994, that brought a change of government.[6] The second notable change is that in January 1997 investors in A funds lost all their tax benefits. Since then, realized gains from A funds are taxed at 30% in the same manner as individual equity. In 1998, the Swedish government de-

[5]The previous tax regulation distinguished between long- and short-term holdings. See Green and Rydqvist (1999) for a more comprehensive discussion of marginal effects of Swedish taxes.

[6]The winning Social Democratic Party had increased capital gains taxes on its agenda.

cided to revise the public pension plan which was previously managed under a pay-as-you-go scheme. Under the new plan, 2.5% of annual wage income goes to a funded system, where the individual can choose freely among mutual funds authorized by a government controlled institution named the Premium Pension Authority (PPM). PPM also has the huge task of managing pension accounts for some 4.4 million Swedes that are covered by the plan, with savings distributed over 450 mutual funds. PPM manages the contribution to individual pension accounts and investments in funds on a monthly basis, when also individual portfolio rebalancing can be done. When the scheme came into effect in November 2000, the initial choice also included retroactive pension contributions paid for the years 1995 to 1998. Therefore, this initial fund choice injected some SEK 56 billion into mutual funds in the year 2000.

3 Data

The data on aggregate equity mutual fund flows were collected from *Fondbolagen*, an association of virtually all mutual fund companies operating on the Swedish market, similar to the Investment Company Institute in the U.S. Flows are defined here as net sales and purchases of equity mutual fund shares, which are reported on a monthly basis from January 1994, but only available in aggregate form. The fund flows recorded thus consist of foreign as well as Swedish equity fund investments.[7] Measured flows represent 90% to 95% of the total flows during the whole sample period from January 1994 to December 2000, a total of 84 observations. The data on returns and interest rates were collected from *Findata*, except for the small firm return series provided by Stefan Engström. The macro series data for retail sales, consumer price index and industrial production were collected from Statistics Sweden.

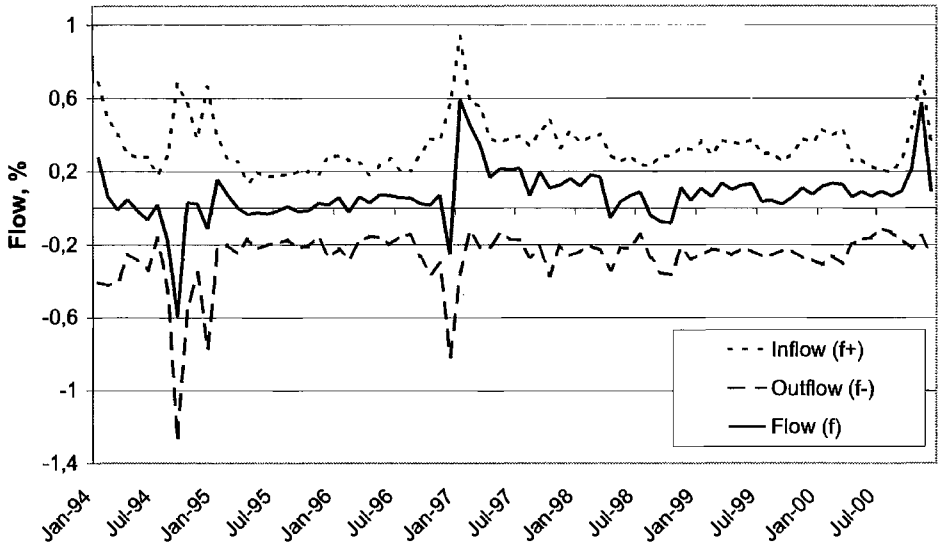
3.1 Flows

The time series of net mutual fund sales is normalized for stationarity reasons. The increased demand for mutual funds over time reflects not only increased

[7]Details of aggregate mutual fund investment styles are available on a yearly basis from 1996, when mutual funds investing in foreign stocks represented 31% of total equity mutual fund wealth. At the end of 2000, this figure had grown to 42%, indicating decreasing home bias.

Figure 1: Monthly aggregate mutual fund flows

The time series flow (f), inflows ($f+$) and outflows ($f-$) depict percent flows to and from equity mutual funds in Sweden in relation to total market capitalization.



popularity, but a more general wealth effect. The net sales series is therefore divided by total stock market capitalization, although the use of total market value of all equity funds or total market turnover do not change the general results.[8] In what follows, the normalized flow variable is labelled f and formally defined as

$$f_t = \frac{\text{Net sales}_t}{\text{Total market capitalization}_t},$$

and is plotted along with corresponding normalized outflows ($f-$) and inflows ($f+$) in Figure 1.

There are four specific observations during the sample period that originate from the institutional changes in the market. The first observation is the massive outflow in September 1994, when -1.27 of the stock market value at that time represented about SEK 11.1 billion. Although inflows were high, the

[8]Warther (1995), and Goetzmann and Massa (2003) also use stock market value when normalizing flows.

net effect was a flow of -0.59% of market capitalization—or SEK 5.15 billion—which is almost four standard deviations from the net sales series mean. These flows can be linked to a change of government: mutual fund investors feared increased taxes. The large flows suggests that some investors chose to realize gains (to avoid increased taxation) and reinvest, while the overall reaction was negative.

The second observation to note is the large outflow in December 1996, with a net withdrawal measuring almost two standard deviations: -0.25% of the stock market value or SEK 4.09 billion. This money seems not to have been withdrawn for good, given a record inflow of SEK 10.24 billion in January of 1997, which is the third notable observation. It is likely that the change in taxes applicable to A funds played an important role here. Dahlquist, Engström, and Söderlind (2000) show that the extreme flows in 1994 and 1996 can be attributed to large outflows from A funds in yearly data, where the accumulated outflows were SEK 10.65 for 1994 and 15.34 billion for 1996. The authors also conclude that these funds did not perform as well as regular equity funds over this period. One may thus expect a large shift from A funds to other mutual funds or individual equities when the tax benefit disappeared. What is more surprising is that outflows and inflows occurred in different months. One may argue that people could choose to wait until the end of 1996 to rebalance, but it is more difficult to see why they would wait until the following year to reinvest. A speculative explanation for this behavior has its origins in the fiscal regulations: investors could have made withdrawals at the turn of the year to avoid wealth tax.[9]

The fourth and final extreme observation is the large net inflow in November 2000 due to the revised pension scheme. The observed net inflow of 0.58% of market capitalization here represents SEK 21 billion.

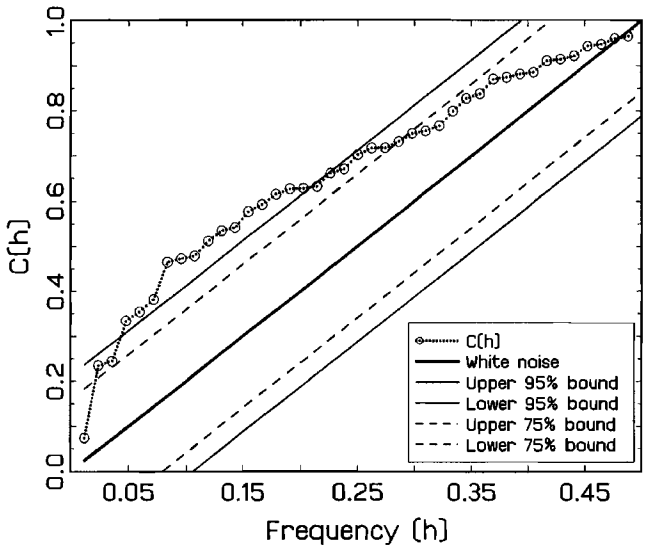
The cumulative sample periodogram in Figure 2 shows the series flow plotted in the frequency domain.[10] Even if the time series shows some evidence of persistence, there is little concern for non-stationarity. But Figure 2 clearly shows the presence of autocorrelation at the lowest frequencies, suggesting an underlying autoregressive process. Seasonalities appear as small

[9]Wealth tax has been 1.5% on total assets over a defined break point (SEK 900,000 as of 1999) according to Swedish tax regulations.

[10]The formal derivation of the sample periodogram is given in Appendix A.

Figure 2: Sample cumulative periodogram

The circled line displays the sample cumulative periodogram of the series flow (f). The thin solid and dashed lines display Komolgorov-Smirnov 75% and 95% probability bounds centered around a theoretical white noise diagonal (thick solid line).



jolts around frequencies of 0.04 and 0.08 (which correspond to 25 and 12.5 months), and could therefore potentially be significant in explaining the series as an ARMA process.

3.2 Returns

Three continuously compounded excess stock returns are used: a value-weighted return of the total Swedish stock market adjusted for dividends (r_{SIX}); the Carnegie Small Cap return of small firms (r_{CSC}); and the Morgan Stanley world index, (r_{MSW}). The returns have been adjusted with the return of a Swedish 30-day Treasury bill.[11] The return of the world index is used as a proxy for a broader stock market portfolio when comparing Swedish

[11]Details of the CSC series can be found in Dahlquist, Engström, and Söderlind (2000). The original series for MSW is denoted in USD and has been recalculated to SEK. The weight for Swedish stocks in this index has been roughly 1% over the sample period.

Table 1: Summary of data

Spearman non-parametric correlations and moments for time-series flow and three returns. Subindexes "SIX", "CSC", and "MSW" refer to a value-weighted Swedish stock index, a value-weighted Swedish small firm index and the Morgan Stanley world index. Correlations that are significantly different from zero at the 10%, 5%, and 1% levels are marked (*), (**), and (***). The sample period is January 1994 to December 2000, in which there are 84 monthly observations.

	Correlation						Moments	
	f_{t-1}	f_t	f_{t+1}	$r_{SIX,t}$	$r_{CSC,t}$	$r_{MSW,t}$	Mean, %	Std. dev.
f_{t-1}	1.00	-	-	-	-	-	-	-
f_t	0.56***	1.00	-	-	-	-	0.070	0.148
f_{t+1}	0.47***	0.56***	1.00	-	-	-	-	-
$r_{SIX,t}$	-0.12	0.27**	0.12	1.00	-	-	1.202	5.639
$r_{CSC,t}$	-0.10	0.26**	0.13	0.72***	1.00	-	0.703	5.961
$r_{MSW,t}$	0.04	0.32***	0.18*	0.55***	0.32***	1.00	0.557	4.158

risk-adjusted returns and flows. The small cap return is included for control. If the noise trading hypothesis is true, that is, if flows represent the sentiment of small and uninformed investors, it can be useful to compare the impact of flows on different groups of assets, although it is unclear from this theory where one should expect noise traders to be over-represented. The correlation matrix and sample moments for the monthly series of returns and leaded and lagged flows are presented in Table 1.

The correlation between Swedish returns and lagged flows is negative; strongly positive for concurrent flows; and positive, but weaker so, for leading flows. This lag structure broadly supports the expected relation for positive feedback trading. The flow variable itself is, however, positively autocorrelated and declining in the lags, which may also be the reason for this result. The contemporaneous correlation between returns and flows is strongest for the world index, which reveals that there is a broad relation between flows in Sweden and stock markets in general. The sample means suggest that the time period is characterized by heavily increasing stock prices, where the value-weighted Swedish excess return is about double the size of the world excess stock return.

4 Results

The results are presented in the following sequence. In section 4.1, preliminary regressions document the broad flow and return relation and establish the order of autocorrelation of the flow variable. Two time series models are then derived by the use of standard Box and Jenkins (1976) diagnostics to separate the unexpected component from the expected flows. The set of variables used for predicting flows excludes stock returns, which is investigated in detail as follows. The models are used in Section 4.2 to explore if returns predict flows, and in Section 4.3 if flows predict returns. Finally, Section 4.4 investigates the concurrent effect in two ways: to see whether returns and unexpected flows are related when incorporating risk factors commonly used in explaining returns, and what the associated weekly return pattern is when holding monthly unexpected flows fixed. All coefficients are estimated using GMM where the point estimates coincide with OLS, but allowing errors to be heteroscedastic and serially correlated.[12] A Ljung-Box (Q) and Breusch-Godfrey LM tests are conducted to reveal the presence of autocorrelation.[13]

4.1 Expected and unexpected flows

The direct relation between flows and returns is investigated using a preliminary regression in Table 2, denoted by P. The coefficient for concurrent flows is positive and significant, and the first lag negative and strongly significant, which is in line with a price pressure effect. A coefficient value of 9.47 implies that a positive one-standard deviation shock to flows is associated with a 1.4% excess return over the mean return of 1.05% in the concurrent month. The negative coefficient of the lags can also be due to the predictable component of the flow variable as indicated in the correlation matrix and periodogram. Lagged flows would then work as an instrument by removing this component, and mistakenly be taken for price reversals. The second regression P′ then omits

[12]The moment conditions are of the form $\frac{1}{T}\sum_{t=1}^{T}[x_t'(y_t - x_t\theta)] = 0$, where θ is a parameter. See Appendix B in chapter II for details regarding this procedure.

[13]See, e.g., Greene (1997) for a derivation of these tests. Even if standard errors of the point estimates are asymptotically robust to autocorrelation, the tests are important tools for analyzing the predictability of flows.

concurrent flows, with the result that the lags are insignificant and the regression loses its explanatory power.

First and second order autocorrelations are formally investigated in regression models A and A' in Table 2. The results suggest that adding an additional lag to the flow variable improves the fit only marginally, and the higher order coefficients are not significant. In unreported work, there were specifications including moving average coefficients and stochastic seasonality, but with only weak improvements. A deterministic, linear trend is strongly significant and also adds considerably to the explanatory power. Regression Model I specifies the predictable component of flows, while regarding all four liquidity shocks as unexpected.

To enable a comparison of the differences in the extreme flow observations, an additional model is derived to control for these events. The purpose of this is twofold. First, excluding these observations shows that the autoregressive specification is robust. Second, they represent significant liquidity shocks to the mutual fund market that may be important for detecting price pressure effects. The results can then be compared when including or excluding these observations. The significance of the indicator variables for these events is strong in Model II, and the fit improves dramatically with an adjusted R^2 of 0.72. LM and Q tests show no joint significance of autocorrelation of the two and six first lags.

The models do not take any exogenous information into account in determining expected flows. Santini and Aber (1998) find that both the contemporaneous and lagged level of long and short interest rates where significant in determining equity fund flows, and Goetzmann and Massa (2003) also incorporate analysts' recommendations. In unreported work, I added four lagged information variables: long and short interest rates, change in real hourly wage and real industrial production growth.[14] The coefficient for the level of interest rates was negative and significant in a specification leaving out the deterministic trend. As interest rates during the sample period generally trend downwards, this should be interpreted with care. Interests rates were not significant when the trend was included.

[14]The long and short interest rates are defined as the yield on a 10-year bond and 1-month inter-bank borrowing rate. Industrial production is seasonally adjusted.

Table 2: Regressions of expected flow

The dependent variable is the value-weighted excess return (r_{SIX}) and flow (f). The first two regressions named P describe index return as a function of flow. The four last regression models forecast flows using lagged values, deterministic dummy variables, and a linear trend. In Model I, the four liquidity shocks in the sample are regarded as unexpected, whereas in Model II they are expected. There are two tests for autocorrelation in the residuals from which p-values are reported. The LM test is conducted with two lags, and the Ljung-Box Q test with six lags.

Model	P	P'	A	A'	I	II
Dependant variable	Return (r_{SIX})	Return (r_{SIX})	Flow (f)	Flow (f)	Flow (f)	Flow (f)
Constant	1.05	1.41**	0.04**	0.04**	-0.18**	-0.07
	(0.66)	(0.66)	(0.02)	(0.02)	(0.08)	(0.05)
f_t	9.47*	-	-	-	-	-
	(5.06)					
f_{t-1}	-6.01***	-2.87	0.36***	0.33**	0.28**	0.32**
	(2.47)	(2.96)	(0.12)	(0.13)	(0.13)	(0.15)
f_{t-2}	-2.41	-1.36	-	0.11	-	-
	(2.84)	(2.96)		(0.08)		
Dummy Sep-94	-	-	-	-	-	-0.55***
						(0.03)
Dummy Dec-96	-	-	-	-	-	-0.31***
						(0.01)
Dummy Jan-97	-	-	-	-	-	0.63***
						(0.05)
Dummy Nov-00	-	-	-	-	-	0.43***
						(0.02)
Linear trend	-	-	-	-	0.16***	0.08**
					(0.06)	(0.04)
No. of obs.	82	82	83	82	83	83
Adjusted R^2	0.03	-0.02	0.12	0.13	0.18	0.72
LM, p-value	0.07	0.08	0.25	0.42	0.47	0.69
Q, p-value	0.36	0.44	0.71	0.91	0.94	0.15

Newey and West (1987) standard errors, robust with respect to autocorrelation and heteroscedasticity, are given in parentheses. Significant parameter estimates at the 10%, 5%, and 1% level are marked (*), (**), and (***).

Model I and II are chosen for the analysis and are decomposed into an expected, f^E, and unexpected, f^U, part from the variable f such that

$$f = f_i^E + f_i^U,$$

where subscript i denotes I and II with reference to corresponding models.

4.2 Flows and value-weighted index returns

The relation between flows and the value-weighted stock market excess return is examined by the regression

$$f_{i,t}^* = a_0 + a_1 r_{SIX,t} + a_2 r_{SIX,t-1} + a_3 r_{SIX,t-2} + u_t, \tag{1}$$

where u is an error term, and f_i^* is the combined name for the decomposed time series flow where subindex i indicates if the flows under consideration are from model I or II. Evidence of positive feedback trading would be significant positive estimates of a_2 and a_3, and concurrent effects are measured by a_1. The results of the five regressions specified by equation (1) are presented in Table 3.

The direct relation between flows and returns can be studied in the first regression (1a) in Table 3. Concurrent and lagged returns are positive, but not significant, and the explanatory power is merely non-existent. This may partly be due to the extreme observations introducing considerable noise, and the autoregressive component blurring the causal relation. By taking the latter into account in regression (1c), concurrent returns become highly significant for unexpected flows, but the fit is still virtually zero. The associated expected flow in (1b) has insignificant coefficients for concurrent and lagged returns.

Unexpected flows of Model II in regression (1e) in Table 3 treat all four liquidity shocks as expected. The coefficient value for the concurrent effect drops somewhat, the significance rises and R^2 improves to 10%. In other words, the concurrent effect is modelled much better when we assume the liquidity shocks were expected. The economic interpretation of the coefficient for unexpected flows is that a one percent return in the concurrent month is associated with an additional inflow of 0.48 basis points into equity funds compared to

Table 3: Flows and the value-weighted index return

Monthly flows are partitioned into an expected (f_i^E), and unexpected part (f_i^U), and explained by two lags of the value-weighted index excess return, r_{SIX}. The LM test for autocorrelation is specified with two lags, from which the p-value is reported. There are 82 observations in all regressions.

Model	1a	1b	1c	1d	1e
Dependent variable	Flow (f)	Exp. flow (f_I^E)	Unexp. flow (f_I^U)	Exp. flow (f_{II}^E)	Unexp. flow (f_{II}^U)
Constant	6.02***	6.52***	-0.51	6.64***	-0.62
	(2.34)	(1.26)	(1.55)	(2.06)	(0.85)
Concurrent return	0.46	-0.08	0.54**	-0.02	0.48***
	(0.28)	(0.10)	(0.26)	(0.26)	(0.13)
Return, lag 1	0.14	0.18	-0.04	0.13	0.01
	(0.22)	(0.13)	(0.19)	(0.18)	(0.20)
Return, lag 2	0.03	0.08	-0.05	-0.06	0.09
	(0.30)	(0.11)	(0.26)	(0.29)	(0.14)
Adjusted R^2	0.00	0.00	0.01	0.00	0.10
LM, p-value	0.00	0.00	0.85	0.02	0.98

Newey and West (1987) standard errors, robust with respect to autocorrelation and heteroscedasticity, are given in parentheses. Significant parameter estimates at the 10%, 5%, and 1% level are marked (*), (**), and (***).

market capitalization. Calculated at the stock market value of December 2000, this represents an additional inflow of approximately SEK 178 million.

Table 3 shows no evidence of lagged returns explaining unpredicted flows in any specification. It can also be noted that the autoregressive component of flows is picked up by the predicted flow regressions in the first lag, as this coefficient is similar in magnitude to the one found in regression (1a).

4.3 Returns and unexpected flows

To further investigate the relation between unexpected flows and returns, the regression is reversed, with the excess return of the value-weighted market index (SIX) and small firms index (CSC) as the dependent variable (collectively labelled r_s) in

$$r_{s,t} = b_0 + b_1 f_{i,t}^U + b_2 f_{i,t-1}^U + b_3 f_{i,t-2}^U + u_t, \tag{2}$$

where u is an error term. A positive b_1, with the addition of negative b_2 and b_3, is indicative of price reversals. The results of regression (2) are found in Table 4.

The most striking result is the general significance of concurrent flows in models (2c) and (2d). In addition, the regression coefficients for the lags are negative in all specifications, although not significant. In models (2a) and (2b), the parameter values for the concurrent return are low, and the regression has poor explanatory power. This suggests that the liquidity shocks did not cause corresponding price movements, but it may be too extreme an assumption to regard all of them as unexpected. To investigate price pressures in more detail, unexpected flows are constructed identically to the specification in (2c), but the dummy for September 1994 is left out. In other words, we can view this as a model in which the election outcome was unexpected. Unexpected flows in regression models (2e) and (2f) are denoted f^U_{II*}, and reveal that this specification makes little difference. The concurrent and lagged flow coefficients, as well as the fit of the model, is lower. Even if the general pattern in the data supports the price pressure hypothesis, it cannot be confirmed due to lack of significance of the lagged coefficients.

The explanatory power in the small cap return specification is low compared to the equation with the value-weighted return as the dependent variable. Hence, there is no evidence of a closer relation between unexpected flows and returns for small companies, as suggested by Lee, Shleifer, and Thaler (1991).

The economic interpretation of the concurrent effect of 26.05 between f^U_{II} and the value-weighted excess return is that a one-standard deviation increase in unexpected flow translates into a 1.8% additional excess return above the mean of 1.28%.[15]

In unreported work, I find evidence that the concurrent effect stems mainly from outflows rather than inflows. None of the coefficients in the inflow regression was significant, but concurrent outflows were negative and highly significant, which is also found by Goetzmann and Massa (2003). This result could be due to substitution between equity funds due to fiscal reasons during

[15]The corresponding interpretation of the relation for f^U_I and the market return is 1.21% for a one-standard deviation shock to flows.

Table 4: Monthly excess returns and flows

Dependent variables are excess returns (r_s) from a value-weighted index (SIX) and small firm index (CSC). The LM test for autocorrelation is specified with two lags, from which the p-value is reported. There are 81 observations in all regressions.

Model	2a	2b	2c	2d	2e	2f	2g
Dependent variable	r_{SIX}	r_{CSC}	r_{SIX}	r_{CSC}	r_{SIX}	r_{CSC}	r_{SIX}
Independent variable	Unexp. flow (f_I^U)	Unexp. flow (f_I^U)	Unexp. flow (f_{II}^U)	Unexp. flow (f_{II}^U)	Unexp. flow ($f_{II^*}^U$)	Unexp. flow ($f_{II^*}^U$)	Exp. flow (f_{II}^B)
Constant	1.27* (0.69)	0.71 (0.73)	1.28** (0.66)	0.73 (0.72)	1.28* (0.66)	0.73 (0.72)	1.09* (0.65)
Concurrent flow	9.19* (4.84)	7.21 (4.74)	26.05*** (7.89)	23.88*** (8.56)	18.87*** (6.35)	14.79** (6.91)	-0.36 (5.14)
Flow, lag 1	-3.50 (2.59)	-2.72 (2.06)	-6.41 (7.04)	-7.08 (5.40)	-4.55 (7.95)	-4.88 (3.72)	-
Flow, lag 2	-2.25 (2.59)	-4.88 (3.07)	-7.22 (6.02)	-6.31 (6.86)	-3.47 (3.90)	-4.43 (4.47)	-
Adjusted R^2	0.03	0.01	0.11	0.09	0.10	0.05	0.00
LM, p-value	0.14	0.16	0.15	0.16	0.08	0.15	0.27

Newey and West (1987) standard errors, robust with respect to autocorrelation and heteroscedasticity, are given in parentheses. Significant parameter estimates at the 10%, 5%, and 1% level are marked (*), (**), and (***).

the sample period.[16]

The last column of Table 4 investigates return predictability. The predicted value of the concurrent expected flows is a function of past flows and trend, which is common information to investors.[17] The coefficient for predicted flows is weakly and negatively related to returns, but it has virtually no explanatory power at all. Therefore, there is no support for return predictability with respect to equity fund flows in the models under study.

4.4 Concurrent unexpected flows, risk factors and weekly excess returns

To investigate the concurrent flow-return relation in more detail, we consider a multi-factor model where the value-weighted return, ($r_{SIX,t}$), is regressed

[16]Evidence of rebalancing is supported by the fact that all dummies in both the inflow and outflow regressions were highly significant.

[17]The flow information is available on *www.fondbolagen.se* about ten days into a new month.

onto a set of factors and unexpected flows

$$r_{SIX,t} = c_0 + \sum_{j=1}^{J} c_j F_{j,t} + c_{J+1} f_{i,t}^U + u_t, \tag{3}$$

where F_j is a risk factor associated with the index return, f_i^U collectively denotes the unexpected flows I and II, and the pricing error is denoted u. Although this specification may be regarded as a joint test of the particular specification of risk and the flow-return relation, it may give some indication as to how important unexpected flows are in explaining Swedish stock returns while controlling for various macro factors. In particular, if unexpected flows are found to be perfectly correlated with innovations to other risk factors, both the information and the price pressure interpretations for the concurrent relation are suspect. Unexpected flows are then measuring innovations to some other, common risk factor.

The results are presented in Table 5, where the first regression denoted model (3a) is an unconditional CAPM specification where the world market return is used as a factor. The effects of adding the two proxies for unexpected flows are documented by regressions (3b) and (3c).

The beta estimate of the Swedish stock portfolio is 0.86 during the period, and the constant—or Jensen's alpha—is 0.59, but not significant. When the unexpected flows are included in regressions (3a) and (3b), they are strongly significant. This suggests that the measured flows are a separate effect, unrelated to overall world stock market risk. The explanatory power also improves marginally, from an adjusted R^2 of 0.42 to 0.45.

Models (3d) and (3e) consider a multi-factor model specified with prediction errors in the Swedish yield curve (PEY), real retail sales growth (RSG), and real industrial production (IPR) in addition to the world index.[18] The yield curve prediction error was obtained from a time series model, using a linear proxy for the yield curve as the difference between a 10-year bond and a 30-day T-Bill.[19] The coefficients of regression (3d) are then interpreted as fac-

[18] Retail sales is a proxy for consumption, as this series was unavailable on a monthly basis in Sweden.

[19] With the timing convention used here, the prediction error is the difference in the observed and the estimated term premium at time t, considering the known information available at $t-1$.

Table 5: Risk factors and unexpected flows

The excess return of the value-weighted index (SIX) is regressed on the world index return (r_{MSW}), unexpected flows, and various risk factors: PEY is the one step ahead prediction error of the yield curve approximated by a Swedish 10-year bond rate and 30 day T-bill; RSG is seasonally adjusted real retail sales growth, and IPR is seasonally adjusted real industrial production growth. There are 82 observations in all regressions.

Model	3a	3b	3c	3d	3e
Dependent variable	r_{SIX}	r_{SIX}	r_{SIX}	r_{SIX}	r_{SIX}
Constant	0.59 (0.50)	0.63 (0.54)	0.63 (0.53)	0.32 (0.53)	0.38 (0.52)
r_{MSW}	0.86*** (0.11)	0.80*** (0.11)	0.78*** (0.11)	0.91*** (0.10)	0.84*** (0.10)
Unexp. flow (f_I^U)	-	8.15** (4.05)	-	-	-
Unexp. flow (f_{II}^U)	-	-	13.77** (6.01)	-	12.15* (6.33)
PEY	-	-	-	-2.18* (1.17)	-1.96* (1.14)
RSG	-	-	-	0.46 (0.31)	0.42 (0.30)
IPR	-	-	-	0.31** (0.15)	0.24* (0.14)
Adjusted R^2	0.42	0.43	0.45	0.43	0.45

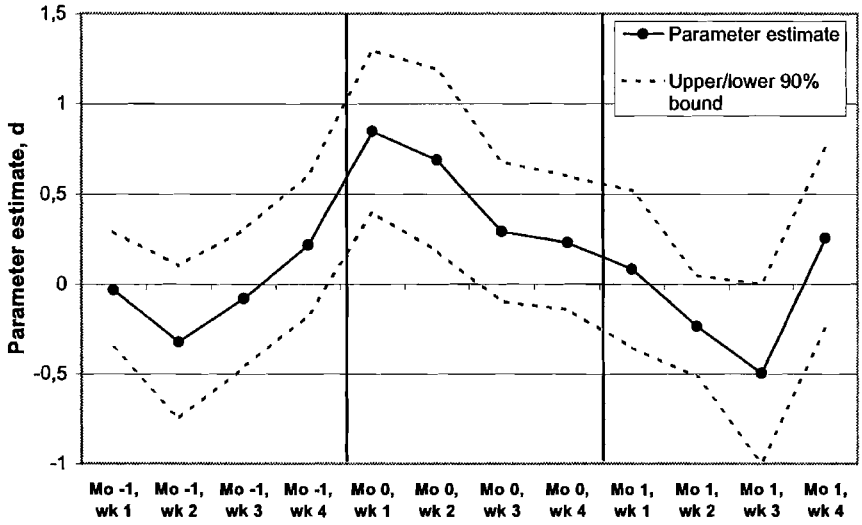
Newey and West (1987) standard errors, robust with respect to autocorrelation and heteroscedasticity, are given in parentheses. Significant parameter estimates at the 10%, 5%, and 1% level are marked (*), (**), and (***).

tor exposures, and are significant for the yield curve variable and industrial production but not for retail sales growth. Regression (3e) then confirms that unexpected flows are still strongly related to Swedish stock returns, and are independent of the specified macro factors, since they have a distinct influence by their own.

The results presented in Table 5 are open to three different interpretations. First, the behavioral view would acknowledge that unexpected flows originate from correlated investor sentiment and, independently from fundamental values, drive stock returns. Second, for the information hypothesis to be true, at least some mutual fund traders must be quite informed—or trade in the same direction as informed traders. The third possibility is that monthly

Figure 3: Monthly flows and weekly returns

The solid line represents values of regression coefficients in the regression of weekly excess returns and monthly unexpected flows derived from Model II along with 90% confidence bounds (dashed lines).



data may not represent the true relation between returns and flows. There may be feedback trading within the month, and thus the concurrent effect may be overestimated.

Another attempt to better understand the concurrent relation between unexpected flows and returns is to look at the intra-month composition of returns in more detail. A regression of unexpected flows on the value-weighted weekly returns is specified by

$$\begin{aligned} f_{i,t}^{U} &= d_0 + d_{m,w1} r_{SIX,t+m,w1} + d_{m,w2} r_{SIX,t+m,w2} \\ &\quad + d_{m,w3} r_{SIX,t+m,w3} + d_{m,w4} r_{SIX,t+m,w4} + u_t \end{aligned} \tag{4}$$

for $m \in [-1, 0, 1]$, indicating lagged and led months for each of the four weeks, $w1$ to $w4$. There are therefore thirteen estimated coefficients including the constant d_0, that measures the relation for each week over the three month period. The coefficient values along with 90% probability bounds are presented graphically in Figure 3.

Most of the return during the concurrent month is attributable to the first two weeks, as these coefficients are highly positive and strongly significant. Rather weak evidence of price reversals in monthly data here appear as a barely significant reversal in the third week of the subsequent month. A Wald test of coefficient restrictions does not reject that the four subsequent month weekly returns are all zero at sensible levels of significance.

Warther (1995) also finds similar evidence in U.S. data, i.e. that the major part of the monthly return occurs at the beginning of the concurrent month. The common belief is that most flows enter funds at the end of the month, which is also confirmed for the U.S. by Edelen and Warner (2001). It may well be that the expected flows at the end of the month are already accounted for, so that the only remaining unexpected flow is money coming in early in the concurrent month. This explanation assumes that fund managers react swiftly to new deposits that unexpectedly come at the beginning of the month. Price pressure effects would a priori mean reversals following immediately after the excess return. If Figure 3 represented the true pattern for flows and returns, the adjustment process is quite slow.

5 Conclusion

The main finding of this paper is a concurrent relation between flows and returns in data. A one-standard deviation shock to returns is associated with approximately SEK 178 million in flows calculated at year-end 2000 prices. The mean net flow to equity funds during the sample period is SEK 1,192 million. If unexpected flows represent informed trading, this is then a relatively small part of total fund flows. On the other hand, a one-standard deviation shock to unexpected flows corresponds to a 1.8% excess return, which is very large. The Swedish stock market must therefore be quite sensitive to unexpected liquidity shocks if the concurrent effect is due to price pressures.

The explanatory power is lower than found for the flow and return relation in the U.S. Only about 11% of the variation in unexpected flows can be associated with the value-weighted index excess return, while the corresponding figure for the U.S. is up to 55%. This additional noise can have several sources. The most important source is probably tax changes that lead to portfolio re-

balancing. Also, the present sample does not only contain funds investing exclusively in Sweden.

There is no evidence of market return predictability with respect to flows. This may be an interesting finding for practitioners, who sometimes refer to fund flows when making stock market forecasts.

The concurrent effect is not likely to stem from price pressures for the following reasons. First, price reversals are weak and insignificant. Second, four liquidity shocks did not affect market returns in any significant way. Third, most of the concurrent effect is found to stem from the first two weeks of monthly returns, which I find more supportive of intra-month feedback trading. The relation between volatility and flows (not reported) suggests a negative relation between risk and flows. Ruling out that mutual fund flows have a stabilizing effect on the stock market, this relation is consistent with mutual fund investors fleeing the stock market in times of uncertainty. However, future research of the volatility—flow relation should also acknowledge the potential causality between returns and volatility in order to provide stronger evidence for this hypothesis. In addition, it would be beneficial to study the relation between flows and returns during the recent period of falling stock market prices.

Appendix A: Cumulative periodogram

The periodogram, $c(h_i)$, of a mean zero time series y_t is defined as

$$c(h_i) = \frac{2}{T}\left[\left(\sum_{t=1}^{T} y_t \cos 2\pi h_i t\right)^2 + \left(\sum_{t=1}^{T} y_t \sin 2\pi h_i t\right)^2\right],$$
$$t = 1, \ldots, T, \quad i = 1, \ldots, q, \tag{A1}$$

where $q = (T-2)/2$ for T an even integer, and $h_i = i/T$ is the frequency. The periodogram is a device for correlating the realizations y_t with the sine and cosine waves of different frequencies. The power spectrum $p(h_i)$ for white noise has a constant value of $2\sigma_y^2$ over the frequency domain 0-0.5 cycles. Define the cumulative power spectrum $P(h_i)$ to be the integration of $p(h_i)$ over all frequencies. Thus, $P(h_i)/\sigma_y^2$ for a white noise process plotted against the frequency h_i is a straight line running from (0,0) to (0.5,1). It can be shown that (A1) provides an unbiased estimate of $p(h_i)$ and therefore the normalized cumulative periodogram,

$$C(h_j) = \frac{\sum_{i=1}^{j} c(h_i)}{T s_y^2}, \quad i = 1, \ldots, q, \tag{A2}$$

is an unbiased estimate of $P(h_i)/\sigma_y^2$ where s_y^2 is the sample counterpart of the true variance σ_y^2. Deviations from the white noise line traced out by $P(h)/\sigma_y^2$ can be assessed by a Kolmogorov-Smirnov test which puts approximate probability limit bounds around this line. The distance for the bounds is

$$\pm\frac{K_\varepsilon}{\sqrt{q}},$$

where $(1-\varepsilon)$ denotes the confidence limit.

References

Black, Fischer, 1986, Noise, *Journal of Finance* 41, 529–543.

Box, George E. P., and Gwilym M. Jenkins, 1976, *Time Series Analysis* (Holden-Day: San Fransisco, C.A.).

Brennan, Michael J., and H. Henry Cao, 1996, Information, trade and derivative securities, *Review of Financial Studies* 9, 163–208.

Brown, Stephen J., and William N. Goetzmann, 1995, Performance persistence, *Journal of Finance* 50, 679–698.

———, Roger G. Ibbotson, and Stephen A. Ross, 1992, Survivorship bias in performance studies, *Review of Financial Studies* 5, 553–580.

Carhart, Mark M., 1997, On persistance in mutual fund performance, *Journal of Finance* 52, 57–82.

Chan, Louis K. C., and Josef Lakonishok, 1995, The behavior of stock prices around institutional trades, *Journal of Finance* 50, 1147–1174.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Dahlquist, Magnus, Stefan Engström, and Paul Söderlind, 2000, Performance and characteristics of Swedish mutual funds, *Journal of Financial and Quantitative Analysis* 35, 409–423.

De Long, J. Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.

Edelen, Roger M., and Jerold B. Warner, 2001, Aggregate price effects of institutional trading: a study of mutual fund flow and market returns, *Journal of Financial Economics* 59, 195–220.

Ferson, Wayne E., and Rudi W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425–461.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1–27.

Goetzmann, William N., and Massimo Massa, 2003, Index funds and stock market growth, *Journal of Business* 76, 1–28.

Green, Richard C., and Kristian Rydqvist, 1999, Ex-day behavior with dividend preference and limitations to short-term arbitrage: The case of Swedish lottery bonds, *Journal of Financial Economics* 53, 145–187.

Greene, William H., 1997, *Econometric Analysis, 3rd ed.* (Prentice-Hall: Upper Saddle River, N.J.).

Gruber, Martin J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783–810.

Hansen, Lars P., 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 50, 1029–1054.

Harris, Lawrence, and Eitan Gurel, 1986, Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures, *Journal of Finance* 41, 815–829.

Hendricks, Darryl, Jayendu Patel, and Richard Zeckhauser, 1993, Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988, *Journal of Finance* 48, 93–130.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–292.

———, 1983, Choices, values and frames, *American Psychologist* 39, 341–350.

Lee, Charles M. C., Andrei Shleifer, and Richard H. Thaler, 1991, Investor sentiment and the closed-end fund puzzle, *Journal of Finance* 46, 75–109.

Lynch, Anthony W., and Richard R. Mendenhall, 1997, New evidence on stock price effects associated with changes in the S&P 500 index, *Journal of Business* 70, 351–383.

Malkiel, Burton G., 1995, Returns from investing in equity mutual funds, *Journal of Finance* 50, 549–572.

Newey, Whitney K., and Kenneth D. West, 1987, A simple semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Odean, Terrance, 1998, Are investors reluctant to realize their losses?, *Journal of Finance* 53, 1775–1797.

Santini, Donald, and Jack Aber, 1998, Determinants of net new money flows to the equity mutual fund industry, *Journal of Economics and Business* 50, 419–429.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777–790.

Shleifer, Andrei, 1986, Do demand curves for stocks slope down?, *Journal of Finance* 41, 579–590.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Statman, Meir, Steven Thorley, and Keith Vorkink, 2003, Investor overconfidence and trading volume, Working paper, University of Santa Clara, C.A.

Warther, Vincent, 1995, Aggregate mutual fund flows and security returns, *Journal of Financial Economics* 39, 209–235.

Weber, Martin, and Colin F. Camerer, 1998, The disposition effect in securities trading: an experimental analysis, *Journal of Economic Behavior and Organization* 33, 167–184.

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Center for Management and Organization 50 (1951-2001).
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