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Modeling Behavioral Biases of Stock Investors

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Modeling Behavioral Biases of Stock Investors

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Abstract

Modeling Behavioral Biases of Stock Investors

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For psychological and emotional reasons, human beings do not always make decisions rationally. The vagarious nature of human behavior has been studied in psychology, economics and even finance. In the stock market, behavioral biases interrupt the price equilibrium process and cause price momentum.

In my thesis, I concentrate on three behavioral biase; naïve reinforcement learning, overconfidence and risk aversion. Naïve reinforcement learning is a simple probable principle for learning behavior in decision problems. The investors who follow the naïve reinforcement heuristics, 'Naïve Learners', pay more attention to their experiences of actions and payoffs than other factors that are considered by rational investors. Naïve learners are pleased to repeat the actions that was successful and avoid to repeat the investment decision which was painful. I also focuse on two psychological phenomena, overconfidence and risk aversion, to examine the emotional process of evaluating gains and losses. Overconfidence is one of the most documented biases (Daniel and Titman 2000). Investors who are overconfident in their investing abilities are more willing to make risky decisions. Conversely, risk aversion is the tendency of investors to avoid risky choices. To address these

two conflicting concepts, overconfidence and risk aversion, I use the reference price as the pivot position for psychological recognition by investors.

I propose three proxies; PNLR (Proxy of Naïve Reinforcement Learning), DOC (Degree of Overconfidence) and DRA (Degree of Risk Aversion). These proxies are estimating the behavioral biases of irrational investors. Furthermore, they can predict future stock returns. The empirical results are economically and statistically significant even after controlling various risk factors such as size, value, profitability, investment pattern, turnover ratio, short-term return, and long-term return.

Keywords: Behavioral Finance, Disposition Effect, Naïve Reinforcement Learning, Stock Market
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Chapter 1. Introduction

1.1 Behavioral Biases

Behavioral finance argues that some financial phenomena can plausibly be understood using models in which some agents are not fully rational. Traditional finance uses models in which the economic agents are assumed to be rational, which means they are efficient and unbiased processors of relevant information and that their decisions are consistent with utility maximization. Barberis and Thaler (2003) note that the benefit of this framework is that it is "appealingly simple." They also note that "unfortunately, after years of effort, it has become clear that basic facts about the aggregate stock market, the cross-section of average returns, and individual trading behavior are not easily understood in this framework."

Behavioral finance is based on the alternative notion that investors, or at least a significant minority of them, are subject to behavioral biases that mean their financial decisions can be less than fully rational. Evidence of these biases has typically come from cognitive psychology literature and has then been applied in a financial context.

For example, Kahneman and Tversky (1979) propose prospect theory as a descriptive theory of decision making in risky situations. Outcomes are evaluated against a subjective reference point (e.g., the purchase price of a stock) and investors are loss averse, exhibiting risk-seeking behavior in the face of losses and risk-averse behavior in the face of gains.

One aspect of the discussion about rational and irrational investors that is important to consider is the extent to which professional traders and money managers are subject to the same behavioral biases that are more commonly discussed in the context of individual (typically assumed uninformed) investors. A number of articles—discussed here—consider this issue directly and find that professionals are far from immune to the biases. A full description of these biases and the evidence for them is beyond the scope of this review. Readers who would like a more detailed discussion should refer to Barberis and Thaler (2003) and Shefrin (2000).

Although the existence of behavioral biases among some investors is an essential component of behavioral finance, a second essential strand relates to the limits to arbitrage. Traditional finance holds that if some (irrational) investors misprice assets, the mispricing will be corrected by the trading actions of rational investors (arbitrageurs) who spot the resulting profit opportunity, buy cheap assets, and sell expensive ones. Behavioral finance theory counters that mispricing may persist because arbitrage is risky and costly, which has the result of limiting the arbitrageurs' demand for the fair-value restoring trades (Shleifer and Vishny 1997).

The existing academic literature has tended to develop behavioral finance against the "foil" of traditional rational finance. But a number of authors (e.g., Statman 1999a; Thaler 1999) make the case for the "end of behavioral finance," arguing that because all financial theory requires some assumptions about investor behavior, researchers should strive to make the best assumptions about behavior in all models rather than invent a subclass

of models featuring empirically observed behavior.

Whereas academics talk about asset pricing and about explaining the cross-section of stock returns, for practitioners, the same issues fall under the simpler heading of "stock picking." If behavioral biases among investors cause mispricing of stocks in a predictable fashion, then active managers may have the scope to beat the market by using strategies based on these smy ces of mispricing.

1.1.1 Investor Sentiment

One important issue is whether investor sentiment has the potential to affect stock returns, which is considered self-evident by most practitioners. But traditional finance theory has little role for sentiment in asset pricing.

Recent behavioral literature (Baker and Wurgler 2006; Kumar and Lee 2006; Tetlock 2007) suggests evidence of investor sentiment affecting stock returns. The effect is most pronounced for stocks that are difficult to value and/or hard to arbitrage. This category includes small stocks, young stocks, unprofitable stocks, and extreme growth stocks. When investor sentiment is high, subsequent returns for these types of stocks tend to be relatively low, and vice versa.

Causes of swings in investor sentiment vary and, in some cases, can be quite trivial. Hirshleifer and Shumway (2003) present evidence that daily returns across the world's markets are affected by the weather in the city of the

country's leading stock exchange. Unfortunately, a strategy to exploit this predictability in returns involves quite frequent trading, and trading costs may well eliminate any available gains for most investors. Kamstra, Kramer, and Levi (2003) provide similar evidence, showing that returns in various countries through the year are related to hmy s of daylight—a result possibly driven by the occurrence of seasonal affective disorder.

The effect of sentiment is evident in various arenas. For example, Gemmill and Thomas (2002) show that noise trader sentiment, as proxied by retail investor fund flows, leads to fluctuations in the discount of closed-end funds. Of note, one measure of sentiment that does not predict returns is the current sentiment—bullish or bearish—of investment newsletter writers. Rather, recent past returns predict the sentiment of the writers, which, in turn, has no correlation with future returns (Clarke and Statman 1998).

1.1.2 Underreaction and Overreaction

Another key area of behavioral research relates to the extent to which investors under- or overreact to information in pricing securities. The available empirical evidence appears to suggest short-term (up to 12 months) return continuations, or momentum (e.g., Jegadeesh and Titman 1993), but longer term (three- to five-year) reversals (e.g., De Bondt and Thaler 1985; Lakonishok, Shleifer, and Vishny 1994). This evidence poses something of a challenge for behavioral researchers to come up with a theory that explains initial underreaction but longer term overreaction and rebuts Fama's (1998)

contention that a market that overreacts about as much as it underreacts can be regarded as broadly efficient.Various behavioral models have been developed to explain the empirical findings. In Barberis, Shleifer, and Vishny (1998), investors suffer conservatism bias and use the representativeness heuristic. Conservatism means that individuals are slow to change their beliefs in the face of new evidence and can explain why investors would fail to take full account of the implications of an earnings surprise. The representativeness heuristic means that individuals assess the probability of an event or situation based on superficial characteristics and similar experiences they have had rather than on the underlying probabilities. This approach can mean that investors, seeing patterns in random data, could extrapolate a company's recent positive earnings announcements further into the future than is warranted, creating overreaction. Daniel, Hirshleifer, and Subrahmanyam (1998) present a related model based on overconfidence and biased self-attribution. Overconfidence leads investors to overweight their private information in assessing the value of securities, causing the stock price to overreact. When public information arrives, mispricing is only partially corrected, giving rise to underreaction. Furthermore, biased self-attribution means that when public information confirms the initial private signal, investor confidence in the private signal rises, leading to the potential for overreaction.

1.1.3 Rational Managers and Irrational Investors

The rational managers/irrational investors school of thought has its main implications in terms of corporate financial structure and the timing of securities issues.

For example, Baker and Wurgler (2000) find that the share of equity issues relative to total equity and debt issues is high before periods of low equity market returns, suggesting that companies time their equity issues to take advantage of positive investor sentiment and market mispricing. These results suggest also that corporate capital structure often reflects the cumulative outcome of past attempts to time the equity market rather than some target capital structure (Baker and Wurgler 2002).

Baker and Wurgler (2004) argue that dividend policy may be influenced by managers "catering" to the demands of investors. According to the authors, managers rationally cater to investor demand by paying dividends when investors put higher prices on payers and not paying when investors prefer nonpayers. The authors show that the lagged dividend premium—the difference between the average market-to-book ratio for dividend payers relative to the average for nonpayers—is positively related to dividend initiations. The authors argue also that investors' time-varying demand for dividends is related to sentiment. When the dividend premium is high, investors are seeking companies that exhibit characteristics of safety, and when it is low, investors are seeking maximum capital growth.

Shleifer and Vishny (2003) present a model that seeks to explain merger and acquisition (M&A) deals in behavioral terms. In the model, stocks are mispriced and management perceives and responds to the mispricing.

The authors argue that M&A decisions and decisions about methods of financing deals are driven by misvaluations of the participating companies; for example, acquisitions will involve payment in stock when valuations are high. The model suggests that acquisitions for stock are made by overvalued companies and target companies tend to be less overvalued. The model is able to explain many of the observed characteristics of the M&A market.

Behavioral finance also has implications for the market for IPOs. These offerings are widely documented as showing high first-day returns, usually taken to imply that the issues are underpriced at the offering price. One puzzle is why issuers and pre-IPO shareholders are prepared to tolerate this "money left on the table" phenomenon.

Loughran and Ritter (2002) propose a model based on prospect theory in which issuers are likely to net the amount of money left on the table by an underpriced offering together with the "gain" in their wealth that comes from the rise in the price of the shares that they retain in the company. The net amount will often be a positive sum with the increase in value of the retained holdings exceeding the difference between the offer price and the market price for the shares sold in the offering. Furthermore, the most underpriced offerings tend to be those in which the offer price has been revised up in the face of strong demand from the price set out in the prospectus. Therefore, the original pre-IPO shareholders can offset the loss of the underpricing with the good news that their total wealth is higher than was previously expected. Ljungqvist and Wilhelm (2005) provide some support for this hypothesis in that issuers of underpriced offerings often use the IPO underwriter for

subsequent equity issues, suggesting they are not unhappy with the service received.

1.1.4 The Psychology of Risk

Risk management is an important aspect of investment, and perceptions of risk are likely to be influenced by psychology. Shiller (2003) looks explicitly at applications of psychology in risk management. Perhaps the most obvious implication of the behavioral biases that underpin behavioral finance is that overconfidence and overoptimism can lead individuals to underestimate risk. The complexity of risk may also create problems in risk perception.

Framing is relevant in that perceptions of risk may be affected by aspects of the presentation of the situation. Shiller notes that risk management may be regarded as more attractive when described as "insurance." Framing outcomes in terms of gains and losses may also affect risk-taking behavior, with evidence that individuals become risk seeking in the domain of losses (as in prospect theory).

Shiller also discusses the notion of "risk as feelings." He notes that intellectual recognition of a risk may not be enough to provoke action without an emotional (or affective) response to the risk. Conversely, some risks that are quite trivial when considered on an intellectual level may provoke action if they somehow manage to create an affective response. An example might be extremely low probability events that have a "dread" element to them, such as a disaster at a nuclear power station.

In terms of levels of risk, changes in investor beliefs can be a smy ce of risk. Kurz (1997) introduces the concept of endogenous uncertainty. Exogenous uncertainty relates to changes in asset prices caused by changes in fundamentals, but asset prices also fluctuate because of changes in investors' beliefs, or endogenous uncertainty. Kurz assumes that economic agents cannot know the true value of an asset and have scope to disagree over the implications of news for future market performance.

1.2 Return Predictability

It hardly needs reiterating that one of the central lines of research in finance is understanding the cross-section of equity market returns. Why one stock's expected return might vary from that of another has preoccupied scholars for decades. The CAPM-APT paradigms (Sharpe, 1964, Lintner, 1965, Mossin, 1966, Merton, 1973, Ross, 1976) based on the risk-expected return tradeoff (henceforth, termed the RR paradigms) brought rigor into the field and have served as null hypotheses against which to test a number of alternatives in the literature. Indeed, the number of publications in the top journals avowing deviations from the standard asset pricing models has mushroomed over the years. What have we learnt from this empirical literature and what research issues does this body of work raise? That is the topic of this review article.

I was able to document at least fifty variables that the literature has used to

predict stock returns in the cross-section, where the cross-section essentially is the same familiar universe of NYSE-Amex-Nasdaq stocks. The predictive variables are motivated principally in one of four ways. These are:

- Informal Wall Street wisdom (such as 'value-investing');
- Theoretical motivation based on risk-return (RR) model variants;
- Behavioural biases or misreaction by cognitively challenged investors;
- Frictions such as illiquidity or arbitrage constraints.

A different issue is the methodologies used to document the significance of the variables of interest. These methodologies fall into two categories:

A regression approach, controlling for risk either by including the factor loadings as controls, or using risk-adjusted returns on the left-hand side. The factors used for risk controls in the above methods vary:

- The Fama and French factors (1993), possibly augmented by a momentum factor and a liquidity factor;
- Factors rooted in macroeconomic influences (Chen et al., 1986);
- Factors extracted from the data using factor analysis or principal components (Connor and Korajczyk, 1988, 1993);
- The alternative to regression analysis is a portfolio approach, where securities are sorted on the criterion of interest and then portfolios returns (usually adjusted for risk) documented across the ranked portfolios.

The tendency of scholars to use one methodology or the other raises the question of whether the results are robust to different methodologies. As I

point out in a later section, however, disparate methodologies are used by different researchers and there usually is little attempt to demonstrate robustness across methods. This is another reason why the picture remains murky and suggests a need for clarifying studies. Basically, it appears to me that the profession is segmented into groups of like-thinking scholars, and perhaps there is inadequate cross-talk across these groups.

1.2.1 Simple Arguments Based on Informal Wall Street Wisdom

I first consider those predictors that are not based on any a priori theoretical reasoning, but are motivated largely by informally appealing to the wisdom of scholars or finance professionals, or are just chance discoveries. Based partially on the notion that recommending stocks based on price/earnings ratios and the like is common on Wall Street, Basu (1977) documents a P/E effect (that low P/E stocks appeared to earn higher abnormal returns than high P/E stocks). Similarly, Banz (1981) documents a size effect in stock returns. The classical version of this effect is that stocks of firms with low market capitalisation outperform those with high market capitalisation. Miller and Scholes (1982) find that low priced stocks earn higher expected returns. In informal reasoning combined with some theory, Brennan (1970) argues that high dividend yield stocks command a differential premium because dividends are taxed at a different rate than capital gains.

The literature on predictors obtained from intuitive reasoning was given a tremendous fillip by Fama and French (1992), who convincingly document

the role of size and book/market in the cross-section of expected stock returns, and show that standard risk/return models are not supported by the data. Fama and French (1993) provide evidence that a three-factor model based on factors formed on the size and book-market characteristics, and the market explains average returns, and argue that the characteristics compensate for 'distress risk'. But Daniel and Titman (1997) argue that, after controlling for size and book/market ratios, returns are not strongly related to betas calculated based on the Fama and French (1993) factors. Zhang (2006) argues that stocks with greater information uncertainty (e.g., those which are small and have low analyst following) exhibit stronger statistical evidence of mispricing in terms of return predictability from book/market and momentum within cross-sectional regressions.

Jegadeesh (1990) documents the negative impact of one lag of the return on future returns. This finding is subsequently confirmed in Cooper (1999), Subrahmanyam (2005), and Avramov et al. (2006). However, the source of the effect is subject to debate. While Cooper (1999) and Subrahmanyam (2005) suggest that overreaction is the cause of this phenomenon, Avramov et al. (2006) indicate that part of the phenomenon may be caused by illiquidity-related price reversals.

Jegadeesh and Titman (1993) demonstrate a momentum effect (prediction from three to twelve months of past returns). Grinblatt and Moskowitz (2004) demonstrate the effects of return consistency, that is, they claim that momentum profits depend on whether returns were achieved in a steady way, or due to a few unusual months.

Hong et al. (2000) (HLM) refine the momentum effect by documenting that momentum profits decrease with size and analyst coverage (i.e., the evidence supports their argument that neglected stocks have less information flows and greater market inefficiencies). Doukas and McKnight (2005) provide out of sample confirmation to HLM by demonstrating that their results carry over to Europe. Cooper et al. (2004) show that momentum profits are much larger after positive market returns than after negative ones. Avramov et al. (2007) argue that momentum profits derive primarily from low credit quality stocks. This is broadly supportive of the HLM notion under the assumption that distressed stocks are not attractive investments and are thus neglected by the investing public.

Chordia and Shivakumar (2002) argue that momentum profits in the U.S. can be explained by business cycles. Specifically, they show that profits to momentum strategies drop significantly once returns are adjusted for predictability based on macroeconomic variables. Griffin et al. (2003), however, do not find support for the

Chordia and Shivakumar (2002) findings in the context of international markets, and find pervasive momentum across many countries. Rouwenhorst (1998) also finds out of-sample evidence of a momentum effect in many European countries. Asness et al. (2009) find that momentum as well as book/market effects are pervasive not only in international equities but also in markets for other assets such as government bonds and foreign currencies. Hvidkjaer (2006) considers how momentum at six- to twelvemonth horizons is related to order flows. He finds that momentum may be caused by the

underreaction of small traders. For example, he uncovers that small traders continue to buy loser stocks for up to a year, and then start selling these stocks. Large traders show no such pattern. In a twist on the momentum literature, Heston and Sadka (2008) document that winner stocks in a given month outperform loser stocks in that same month for up to 20 annual lags, which is an intriguing result destined to receive a lot of attention in future research.

In addition to momentum over six to twelve month horizons, evidence of long-term reversal (negative autocorrelation of returns over three- to five-year horizons) is found by DeBondt and Thaler (1985, 1987) (DT). While Conrad and Kaul (1993) (CK) take issue with the findings of DT partially on the basis of the notion that the reversals are largely due to low-price stocks, Loughran and Ritter (1996) counter this by arguing that low prices simply proxy for low past returns; they also raise the issue that CK's requirement that stocks be present throughout the three-year portfolio pre-formation period introduces a survivorship bias that diminishes the DT effect. In addition to being supported by Loughran and Ritter (1996), DT's finding is confirmed by Chopra et al. (1992).

In a comprehensive study of stock return predictors in the cross-section (obtained from informal reasoning), Haugen and Baker (1996) find that the strongest determinants of expected returns are past returns, trading volume, and accounting ratios such as return on equity and price/earnings. They find no evidence that risk measures such as systematic or total volatility are material for the cross-section of equity returns.

1.2.2 Behavioral Biases or Cognitively Challenged Investors

Many predictors derive from informal arguments about investor overreaction/underreaction. Lakonishok et al. (1994) (LSV) find a negative relation between long horizon returns and past financial performance measures such as earnings or sales growth. They attribute this to the notion that investors extrapolate historical growth too far in the future. However, Doukas et al. (2002) find that analysts are more optimistic about the earnings of value stocks than of growth stocks, thus shedding doubt on the notion that agents excessively extrapolate the earnings of growth stocks. In a vein similar to LSV, La Porta (1996) finds that analysts' long-run earnings growth forecasts are negatively related to future returns, suggesting that analysts also excessively extrapolate future growth from past growth.

On the premise that investors do not properly separate accounting income and cash flows, Sloan (1996) documents that accounting accruals are negatively related to returns. Frankel and Lee (1998) document the positive predictive power of value-price ratios where value is derived from accounting models. The notion here is that investors overreact to information in the value. Cooper et al. (2008) indicate that growth in book assets is cross-sectionally related to future returns and the implication is that investors underreact to information in the time-series of balance sheets.

If managers issue equity when stocks are overvalued, then stock issuance will negatively predict returns. Evidence supportive of this conjecture is provided by Daniel and Titman (2006). In addition, Titman et al. (2004) suggest that

managers often undertake bad investments for reasons of power or empire building and investors do not fully understand this motive for investment. They provide support for this hypothesis by documenting that capital investment negatively predicts returns.

Hvidkjaer (2008) and Barber et al. (2009) show that small trade order flows negatively predict future returns, in the sense that stocks sold by small investors outperform stocks purchased by these investors over horizons of between six months to two years. This indicates that small investors' irrational beliefs cause deviations of prices from fundamental values, and correction of these divergences manifests itself in future returns.

Dichev (1998) and Campbell et al. (2008) show that the risk of bankruptcy is negatively related to expected returns. One would expect these distressed firms to have high book/market, based on the Fama and French (1993) notion that book/market proxies for distress risk. However, Griffin and Lemmon (2002) show that distressed firms often have low book/market ratios and that Dichev's (1998) results are driven by distressed firms with low book-market ratios that earn very low returns. All of this evidence, taken together, contradicts the Fama and French (1993) notion that book/market is positively related to expected returns because book/market ratios capture financial distress. They are instead supportive of the hypothesis that investors underreact to information in the balance sheet about impending distress Cohen and Frazzini (2008) show predictability in returns across economically linked firms. They argue that stock prices of firms upstream from customer firms underreact, based on their finding that investment strategies involving buying

firms whose customer firms have performed well in the past and vice versa earn positive returns. Baker and Wurgler (2006) show that young, risky firms underperform significantly after periods of high sentiment, as measured by proxies such as IPO/SEO activity and trading volume.

The notion is that periods of high sentiment reflect overvaluation for hard to value firms (i.e.., young firms with high return volatility).

Research has also focused on the stock price reactions to recommendations of stock market analysts. Womack (1996) shows that stock prices drift in the direction of analysts' revisions, suggesting that investors underreact to these revisions. Sorescu and Subrahmanyam (2006) indicate that the drift is only for experienced analysts; revisions by inexperienced analysts actually experience price reversals. Bernard and Thomas (1989, 1990) show that stock returns, on average, drift in the direction of earnings surprises for up to three months after earnings announcements, and the implied notion is that investors underreact to information contained in earnings surprises.

Gompers et al. (2003) (GIM) develop a measure of corporate governance and show that better governed firms have greater average returns in the future than others, suggesting an underreaction to governance quality. However, Johnson et al. (2009) (JMS) indicate that the GIM results are sensitive to the methods used in the study; specifically, JMS take issue with the industry controls in GIM. Chen et al. (2009) show that stocks in industries with organized labor unions have a higher cost of equity. This can be interpreted either as underreaction to information contained in unionization or an increased risk premium due to organized labor.

1.2.3 Frictions such as Illiquidity or Arbitrage Constraints

There is a vast literature on market frictions as predictors of stock returns. The basic notion is that greater trading frictions cause investors to require a higher return. In a landmark paper, Amihud and Mendelson (1986) find evidence that asset returns include a significant premium for the quoted bid-ask spread. Since that study, several papers have elaborated upon the role of liquidity as a determinant of expected returns.

An important issue in studies that relate illiquidity to asset prices is the measurement of illiquidity. Other than direct empirical measurements of illiquidity by the bid-ask spread, the approach taken in the literature has been to employ empirical arguments in order to measure illiquidity. For example, Amihud (2002) proposes the ratio of absolute return to dollar trading volume as a measure of illiquidity. Brennan and Subrahmanyam (1996), based on the analysis of Glosten and Harris (1988), suggest measuring illiquidity by the relation between price changes and order flows. Both of these studies find that their measures are positively related to average stock returns Datar et al. (1998), and Brennan Glosten and Harris, Chordia et al. (1998) suggest measuring liquidity by share turnover and find that this measure is negatively related to average returns.

In recent work, Chordia et al. (2008) (CHS) use an illiquidity measure derived from Kyle's (1985) theory and show that it is positively related to future expected returns (CHS's measure incorporates parameters such as return

volatility and volume into the illiquidity measure in a manner indicated by Kyle's expression for illiquidity in equilibrium). Brennan et al. (2008) show that the pricing of illiquidity emanates principally from the sell-side. Allowing for differential price impacts on the buy- and sell-sides, they show that it is the sell-side price impact that is related to future expected returns. The basic notion is that demands for immediacy are likely to be greater on the sell-side (it is unlikely that agents will face needs to buy stock urgently, whereas it is quite plausible that unanticipated liquidity needs may force them to sell stock), thus strengthening the premium for sell-side illiquidity. Some recent studies have focused on whether the second moment of liquidity is priced. The premise is that the variability of prospective future trading costs may command a premium in the stock market in addition to the level of such costs. Chordia et al. (2001) use share turnover as a measure of liquidity and find that the second moment of liquidity actually bears a negative relation to future returns, countering the pricing of liquidity risk. However, Pastor and Stambaugh (2003) measure illiquidity by the extent to which returns reverse upon high volume, an approach based on the notion that such a reversal captures inventory-based price pressures. They do indeed find that stock sensitivities to aggregate liquidity risk are related to expected returns. Acharya and Pedersen (2005) use Amihud's (2002) measure to also conclude that liquidity risk is priced.

There also have been attempts to document the pricing of information risk, or the risk of trading with agents who have superior information. Easley et al. (2002) indicate that their theory-based measure of information asymmetry,

PIN, is priced in the cross-section of returns. However, Duarte and Young (2009) decompose the PIN into components due to information-based and liquidity trading and find that it is the latter component that is priced, thus raising questions about whether PIN is a valid measure of information asymmetry. Sadka (2006) argues that time-variations in an empirical estimate of the illiquidity parameter in a Kyle (1985)-type model of information asymmetry are priced in the cross-section of stock returns. Coval and Moskowitz (2001) proxy for informed agents by 'local' investors, i.e., funds that are located close to the headquarters of a firm. They find that stocks with greater holdings by local investors command higher average returns.

Hou and Moskowitz (2005) develop an alternative measure, nonsynchronicity, which is one minus the R2 of the regression of stock returns on the market. The notion is that this measure captures information asymmetries under the premise that much private information flows through the idiosyncratic component of returns. They show that their measure predicts future average returns in the cross-section.

There also is a small literature on how proxies for short-selling constraints act as frictions and are predictors of returns the stock market. Jones and Lamont (2002) show that stocks with high costs of borrowing have current high valuations and low future returns. Asquith et al. (2005) show that stocks with high short interest and low institutional ownership (and, in turn, less availability of stock for borrowing) earn low returns. Au et al. (2009) find that high short interest is negatively related to returns, but only for stocks with high idiosyncratic risk. These findings indicate that shortsale constraints and

idiosyncratic risk act as a barrier to arbitrage and cause persistent overvaluation.

Chapter 2. Literature Survey

2.1 Naïve Reinforcement Learning

Naïve reinforcement learning is a simple probable principle for learning behavior in decision problems. The investors who follow the naïve reinforcement heuristics, 'Naïve Learners', pay more attention to their experiences of actions and payoffs than other factors that are considered by rational investors. Naïve learners are pleased to repeat the actions that was successful and avoid to repeat the investment decision which was painful.

In recent years, a number of researchers have presented the evidence of naïve learners and the characteristic of their investment decisions. Based on the findings of these works, we propose a proxy to estimate the influence of naïve reinforcement learning on the future stock return. I build long/short portfolio using the distinction between the proxy values of assets and find the average monthly return is more than 1.5% over 20 years in US Stock market. Our empirical results are economically and statistically significant even after controlling various risk factors such as size, value, profitability,

investment pattern, turnover ratio, short-term return, and long-term return.

I find charateristics of naïve learner from related literatures and make assumptions based on them. Naïve reinforcement learning can be found in various asset markets. Choi et al. (2009) provide evidence of naïve reinforcement learning in 401(k) savings decisions. Strahilevitz et al. (2011) find the behavior in the decision of repurchasing individual stocks. Huang (2012) studies the subsequent purchase of stocks in industry sector level. The behavior is also observed in IPO market by Kaustia and Knupfer (2008). Malmendier and Nagel (2011) shows that naïve reinforcement learning influences the investment decision not only in the stock market but also in the bond market. Naive learners are widespread in the financial market. According to above findings, we assume that there are two types of agents in the stock market, sophisticated investors who have rational expectations and naive learners who are subjected to naïve reinforcement learning .

Change of the decision of investment in the same asset means that the experience alters the risk preference of the investor or changes the expectation of the asset. Risk-taking behavior can be changed by negative experiences in early life (Malmendier and Nagel, 2011) and financial crises (Guiso et al., 2013). However, there is no concrete evidence of change of risk preference caused by regular realization of stocks. It is proper to use standard economic model which assume that individual risk preference are stable across time (Stigler and Becker, 1977) in our assumption. Therefore, we assume that the naïve reinforcement learning change the expectation of

the investor in previously realized stock and alter their tendency to repurchase it.

Additional experiences continue to change the expectation of the investor. Erev and Roth (1995, 1998) describes the reinforcement learning model which stands for the incremental learning of cumulative experience. Their model well explain how economic agent evolves their propensity in a broad range of economics experiments. According to the basic concepts of their model, we assume that naïve learners cumulate their realizations (or payoffs) and weigh more on recent realizations than previous payoffs. Malmendier and Nagel (2011) also mentioned that more recent experiences the stronger effects. Intuitively, one-month-ago realization of a stock is probably more impact than ten-years-ago realization of the stock.

Camerer and Ho (1999) suggest experience-weighted attraction learning that treats both actual payoffs and forgone payoffs. For the simplicity, we assume that only actual and directly experienced outcomes affect future decisions.

Positive reinforcement: the adding of an appetitive stimulus to increase a certain behavior or response. In example, father gives candy to his daughter when she picks up her toys. If the frequency of picking up the toys increases or stays the same, the candy is a positive reinforcer.

Positive punishment: the adding of an aversive stimulus to decrease a certain behavior or response. For example, mother yells at a child when running into the street. If the child stops running into the street, the yelling is positive punishment.

Negative reinforcement: the taking away of an aversive stimulus to increase certain behavior or response. In example, turning off distracting music when trying to work. If the work increases when the music is turned off, turning off the music is a negative reinforcer.

Negative punishment (omission training): the taking away of an appetitive stimulus to decrease a certain behavior. For example, a teenager comes home an hour after curfew and the parents take away the teen's cell phone for two days. If the frequency of coming home after curfew decreases, the removal of the phone is negative punishment.

2.2 Overconfidence

Overconfidence is a psychological phenomenon in which humans believe that their abilities are greater than those of average people. Overconfident individuals also overestimate the precision of their knowledge and their degree of experience. This phenomenon is visible among individuals who participate in the financial markets.

Glaser and Weber (2009) note that investors tend to purchase high-risk stocks after experiencing high profits. The researchers show that the prior returns from holding stocks are highly correlated with the stockholders' subsequent trading activity. Based on the records of option traders at Taiwan Futures Exchange, Liu et al. (2010) find a strong positive relationship between prior trading outcomes and stockholders' subsequent tendency toward risk-taking. Option traders who make positive gains in the morning session will take more

risks in the afternoon trading session than will option traders who lose money. Locke and Mann (2005) also report that the tendency to assume less risk is severe after prior losses.

Odean (1998a) examined the overconfident behavior of traders and market makers in the financial market. According to the findings of Odean (1998), overconfident traders tend to believe that their investing abilities, such as their ability to pick stocks and time buying and selling, are superior to those of other traders. The performance of overconfident traders is significantly lower than the benchmark yields of the particular financial market.

Törngren and Montgomery (2004) demonstrate the overconfidence of stock market professionals by comparing the ability of stock market professionals and non-professionals to forecast the future returns of twenty stocks. The professional investors believe that their prediction errors are half those of laypeople. However, the extent of the professionals' prediction errors is not substantially different from that of non-professionals. Even in the simpler forms of prediction, such as guessing the better performing of two stocks, the professionals are only successful 40% of the time. These results indicate that professionals are highly overconfident with regard to their prediction ability.

Barber and Odean (2001) demonstrate that men are more overconfident than women and that men trade stocks more aggressively and actively. As a result, the average return of men's net profit is almost one percent less than that of women's net profit.

Investor overconfidence affects financial markets. Statman at al. (2006), Odean (1998a), and Glaser and Weber (2007) demonstrate that high share

turnover and volatility are positively correlated with investor overconfidence. The overconfidence of players in the financial market increases trading volume and market depth. Odean (1998a) also shows that overconfident traders can cause markets to underreact to information from neutral traders.

2.3 Risk Aversion

Normative theory suggests that rational people should make decisions in a specific and coherent manner. Expected utility theory (Neumann and Morgenstern, 2007) is a normative model of economic behavior that is based on a rigorous axiomatic treatment. The axioms of the expected utility determine decisions under risk and uncertainty. These are based on the assumption that individuals are of reasonable mind and have definite preferences. Although this theory has been useful in helping researchers to understand people's decisions, there are conflicts between the theoretical predictions and the actual behavior of individuals. Individuals do not always make decisions that are consistent with the axioms of expected utility theory, and the order of their preferences is also inconsistent. Kahneman and Tversky (1979) provide an alternative theory, called "prospect theory." Prospect theory describes how people make choices under uncertainty.

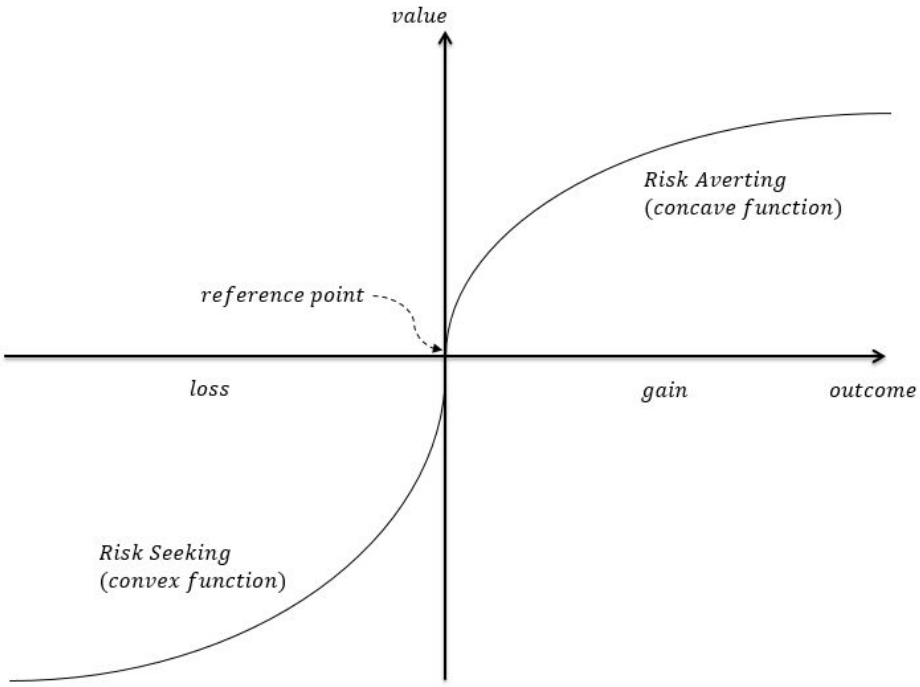
In prospect theory, the utility of decision makers is represented by a function of gains and losses relative to the reference point rather than by a function of absolute wealth. Furthermore, the utility functions of gains and losses are not identical. The function of gains is concave for outcomes, while that of losses

is convex for outcomes. Prospect theory implies, more precisely, that an individual in the domain of gains will be reluctant to take risks (i.e. s/he will exhibit risk aversion) and that an individual in the domain of losses will be willing to accept risk (i.e., sh/e will be risk-seeking).

According to prospect theory (Kahneman and Tversky, 1979), the value function of the decision maker is given by the following formula:

$$v(X) = X^{\gamma} \qquad , X \geq 0$$
$$v(X) = -\lambda(-X)^{\gamma} \qquad , X < 0 \tag{2.1}$$

As illustrated in Figure 2.1, the value function, v(X), passes through the reference point and exhibits an asymmetrical S-shape. X is the gain or loss from the reference point. The reference point is usually the purchase price of an asset or the cost of an investment. γ in the value function equation stands for the marginally decreasing tendency of the function. The coefficient λ indicates the difference between the slope of the gain and the slope of the loss. In Hastie and Dawes (2009) and Tversky and Kahneman (1992), γ is approximately equal to 0.88 and is always less than 1.00, and λ is usually 2.25. The size of λ suggests that the pain prompted by losses is more than twice as great as the happiness inspired by gains.



[Figure 2.1]

The disposition effect is one of the well-documented irrational behaviors of investors that can be explained by risk aversion behavior. The disposition effect is visible in the behavior of investors who hold their losing stocks too long and sell their winning stocks too soon. Investors who have unrealized gains hesitate to accept the risk of price variation and sell their stocks. By contrast, shareholders with losing shares dare to take the risk of keeping their shares. The disposition effect mainly generates the difference between the probability that an investor will sell his/her winning stocks and the probability that s/he will sell his/her losing stocks. Since Shefrin and Statman (1985)

defined this psychological phenomenon as the "Disposition Effect", it has been studied using various financial instruments for different types of investors and different stock markets.

Shefrin and Statman (1985) attracted substantial attention to the impact of the disposition effect on investors and traders in capital markets. Odean (1998) finds strong evidence of the disposition effect: 14.8 percent of paper gains are realized, whereas only 9.8 percent of paper losses are realized. Thus, investors are 50 percent more likely to realize gains than losses. In a laboratory-based study of the disposition effect, Weber and Camerer (1998) find that subjects are approximately 50 percent more likely to dispose of gains than losses. Grinblatt and Keloharju (2001) find evidence of the disposition effect by analyzing the stock transaction history of households and institutions in the Finnish stock market. For all investor types, the odds of selling stocks with losses are roughly half the odds of selling stocks with gains. Relative to other types of investors, financial institutions appear somewhat more willing to liquidate larger losses. Barber et al. (2009) examine the trading records of the Taiwan Stock Exchange (TSE) between 1994 and 1999. Investors in the TSE are approximately twice as likely to realize gains as they are to experience losses. Individual and corporate investors and dealers are influenced by the disposition effect, whereas managers of mutual funds and foreign investors are not significantly subject to the disposition effect. Frazzini (2006) collect the stock transaction data for U.S. mutual funds between 1980 and 2003. These funds are approximately 20 percent more likely to sell gains than they are to sell losses. Locke and Mann (2005) examine the trading behavior of

professional traders in futures markets. They find that most traders have a propensity for the disposition effect. The longer the holding period for the losing stocks, the less profit traders record.

Chapter 3. Naïve Reinforcement Learning and Stock Return Predictability

3.1 Proxy for Naïve Reinforcement Learning

In this section, we propose a proxy to estimate the influence of naïve reinforcement learning on the future stock return based on the findings of section 2.1.

First, we shows how demand of naïve learners skew the equilibrium price path of a stock. I assume the followings;

My basic model is a stripped-down overlapping generation model with two-period-lived agents (De Long et al. 1990; Samuelson 1958). Agents invest all the money to maximize the expected utility of total wealth in the second period. The only decision of agents is to choose a portfolio in the first period.

■ Two types of assets

The economy contains two assets, a risk-free bond and a stock. The risk-free bond pays a fixed rate interest, r_f, after one period. The risk-free bond is in perfectly elastic supply. The price of a risk-free bond is always fixed at one. On the other hand, the stock is not inelastic supply: its supply is unchangeable and normalized to one unit at any period. The price of the stock in period t is denoted P_t.

■ Two types of agents

In the market, there are two types of agents, sophisticated investors (denoted s) who have rational expectations and naive learners (denoted n) who are subjected to naïve reinforcement learning. I assume that the proportion of naive learners is ω and that all agents of a given type are identical. Both types of agents choose their portfolios in the first period (t) to maximize perceived expected utility with their own anticipation of the stock price in the second period (t+1). Public information about the stock arrives just prior to period-t round of trading. The fundamental value of the stock at period t is the fully rational price which reflect available public information and follows a random walk as Equation. (3.1).

$$F_{t+1} = F_t + \varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim N(0, \sigma_\varepsilon^2) \tag{3.1}$$

Each agent's utility is a constant absolute risk aversion (CARA) function of wealth at period t+1:

$$U(W) = \frac{1}{\gamma}(1 - e^{-\gamma W}), \qquad \gamma > 0 \tag{3.2}$$

where γ is the coefficient of absolute risk aversion (γ > 0).

If wealth is normally distributed, maximizing the expected utility of wealth is equivalent to maximizing

$$E(W) - \frac{1}{2}\gamma Var(W) \tag{3.3}$$

■ Expected Utility of Sophisticated Investors

The representative sophisticated investor in period t estimates the distribution of the stock price with the fundamental value of the stock, and so maximizes expected utility given that distribution. Expected value of stock price of the sophisticated investor at period t+1 is

$$E(P_{t+1}) = P_s \tag{3.4}$$

and the variance of that

$$Var(P_{t+1}) = \sigma_s^2 \tag{3.5}$$

The sophisticated investor chooses the amount λ_t^s of the stock held to maximize the expected utility. The wealth at period t+1 is

$$W_{t+1} = (1 + r)(W_t - \lambda_t^s P_t) + \lambda_t^s P_{t+1} \tag{3.6}$$

Expected wealth of the sophisticated investor at period t+1 is

$$E(W_{t+1}) = (1+r)W_t + \lambda_t^s(P_e - (1+r)P_t) \tag{3.7}$$

and the variance of the sophisticated investor is

$$Var(W_{t+1}) = (\lambda_t^s)^2\sigma_e^2 \tag{3.8}$$

From Equation (7), (9), and (10), the optimal amount of investment in the stock is

$$\lambda_t^s = \frac{P_e - (1+r)P_t}{\gamma\sigma_e^2} \tag{3.9}$$

■ Expected Utility of Naïve Learners

The representative naive learner in period t estimates the distribution of the stock with the misperception of naïve learner and the fundamental value of the stock. Same as the sophisticated agents, naive learners thus maximize their expectation of utility given based on their belief of that distribution. The expected value of stock price of the naïve learner at period t+1 is

$$E(P_{t+1}) = E(F_{t+1} + \theta L_t) = F_t + \theta L_t \tag{3.10}$$

and the variance of that is

$$Var(P_{t+1}) = \sigma_{\bar{e}}^2 \tag{3.11}$$

L_t denotes the misperception of naïve learner. The misperception is learned by the cumulative experiences of previous investments until the beginning of period t. θ is a positive constant that measures the influence of the

misperception, L_t, on price.

When the naive learners experienced positive outcomes more than negative outcomes, L_t is a positive value and the expected price of naïve learner higher than that of sophisticated agents. It means that naïve learners are more bullish than the sophisticated agents. On the other hands, L_t is a negative value and the expected price of naïve learner lower than that of sophisticated agents. It means that naïve learners are more bearish than the sophisticated agents.

The naive learner chooses the amount λ_t^n of the stock to maximize expected utility. The wealth at period t+1 is

$$W_{t+1} = (1+r)(W_t - \lambda_t^n P_t) + \lambda_t^n P_{t+1} \tag{3.12}$$

Expected wealth of the sophisticated investor at period t+1 is

$$E(W_{t+1}) = (1+r)W_t + \lambda_t^n(F_t + \theta L_t - (1+r)P_t) \tag{3.13}$$

and the variance of the sophisticated investor is

$$Var(W_{t+1}) = (\lambda_t^n)^2 \sigma_\varepsilon^2 \tag{3.14}$$

Similar to the derivation of Equation (12), the optimal amount of investment in the stock is

$$\lambda_t^n = \frac{F_t + \theta L_t - (1+r)P_t}{\gamma \sigma_\varepsilon^2} \tag{3.15}$$

■ Equilibrium Price

Since the supply of the stock is unchangeable and normalized to one unit at any period, the demand of the sophisticated agents and the demand of the noise agents must sum to one in equilibrium. At the equilibrium of supply and demand, the equilibrium price is

$$P_t^* = \frac{1}{1+r}\left(F_t + \omega\theta L_{t-1} - \gamma\sigma_\varepsilon^2\right) \tag{3.16}$$

where the proportion of naive learners is ω.

Above equation expresses the equilibrium price of the stock at period t as a function of the fundamental value and the misperception of naïve learner. The equilibrium price is higher than the fundamental value only when there exist naïve learners and the naive learners have sufficient positive experience of previous investments. The higher the proportion of the naive learners (ω), the equilibrium price will be further from the expected stock price of sophisticated agents. M_t has the influence on the investment decisions of naive learners in period t.

■ Prediction of Future Return

Finally, we propose the proxy for the return predictability. I can predict the expected change in the stock's price from t to t+1with the equilibrium price in Equation. (3.16). The expected return of the stock is

$$E\left(\frac{P_{t+1} - P_t}{P_t}\right) = \alpha\,\frac{E(L_t - L_{t-1})}{P_t} \tag{3.17}$$

where α is $\frac{\omega\theta}{1+r_f}$, n is the number of outstanding shares. Since the constants

terms, ω, θ, δ, and r_f, are positive, α is positive.

I describe how to estimate the misperception of naïve learners. Naïve learners weigh more the directly experienced outcomes than the outcomes that are merely observed even if experience logically does not predict future success. If investors sell the stock for a loss, they feel pain and regret the past decision of purchasing the stock. This negative experience deters investors from later repurchasing the stock that they sold for a loss. On the other hand, if investors sell the stock for a gain, they are delighted to the past decision of purchasing the stock. This positive experience encourages investors from later repurchasing the stock that they sell for a gain. As a result, the more positive (negative) realized profits investors experienced, the more gain (loss) investors expect in the next investment of the same stock.

To estimate the misperception of naïve learner, L_t, we assume the followings

· Risk preference of each agent is stable across time.

· Naïve reinforcement learning changes the propensity of agents to repurchase the stock.

· Only direct experience affect the propensity of agents to repurchase the stock.

· Positive experiences increase the propensity of repurchase, and negative payoffs decrease it.

· In the formation of misperception, naïve learners cumulate their

realizations of past investment and weigh more on recent realizations than previous payoffs.

Naïve learner cumulates the experience of past realizations and put more weight on recent realized profits than on more distant realizations. L_t is interpreted as

$$L_t = M_{t-1} + (1-\delta)L_{t-1} \tag{3.18}$$

where δ is the depression rate which stands for the recency weighting scheme, ω is the proportion of naive learners, M_t is recency weighted aggregated realizations of all the shares which are sold at time t.

I estimate the realization of all naïve learners as ωM_t. L_t is the aggregated misperception of all naïve learners in the stock.

$$M_t = \sum_{k=1}^{\infty}(P_t - P_{t-k})V_{t-k}\left[\prod_{i=1}^{k-1}(1 - O_{t-k+i})\right]O_t \tag{3.19}$$

P_t is the stock price at end of period t, V_t is the trading volume in period t and O_t is the turnover ratio[1].

According to Equation (3.17), the expected return decreases (increases) as the misperception of naive learners increases (decreases). The price moves in the opposite direction of the misperception of naive learners because the

[1] Turnover ratio in period t is calculated by dividing the trading volume traded in period t by the number of outstanding shares.

depreciation (δ) of misperception. I name this proxy 'PNLR (Proxy of Naïve Reinforcement Learning)'.

$$PNLR(t) = \frac{L_t - L_{t-1}}{P_t} \tag{3.19}$$

It is reasonable to build a long/short portfolio which offsets a long position in stocks with low PNLR by a short position in stocks with high PNLR s. Because of the return predictability of PNLR, we find that the average monthly returns of that long/short portfolio are positive and statistically significant in our empirical results.

3.2 Empirical Result

3.3.1 Data Description

I test the relation between the influence of naïve learner and the cross-section of expected returns in US Stock Market. I obtain stock data for the NYSE, AMEX, and NASDAQ from the CRSP (The Center for Research in Security Prices). The data set include the close price, the trading volume, and the number of outstanding shares for every month between December 1958 and December 2013. Price, dividend, shares, and volume data are historically adjusted for split events to make data directly comparable at different times

during the history of a security.[2]

Based on the CRSP classification of the stocks, we exclude ADRs, REITs, and units of beneficial interest and use only ordinary firms. Following Jegadeesh and Titman (2001), we exclude all stocks priced below $5 at the beginning of the holding period. I exclude these stocks to ensure that the results are not driven primarily by small and illiquid stocks or by bid-ask bounce.

At the beginning of each month t, we estimate PNRL of each stock with its price history of the last past five years.

Table 1 shows the statistics for the selected stocks. Each column describes the following; the average number of ordinary firms listed in the CRSP database, the average total capitalization of ordinary firms listed in the CRSP database, the average number of the stocks with valid PNRLs, the average total capitalization of the stocks with valid PNRLs, the percentage of the stocks which have valid PNRLs, and the percentage of the total market value which have valid PNRLs.

[Table. 3.1]

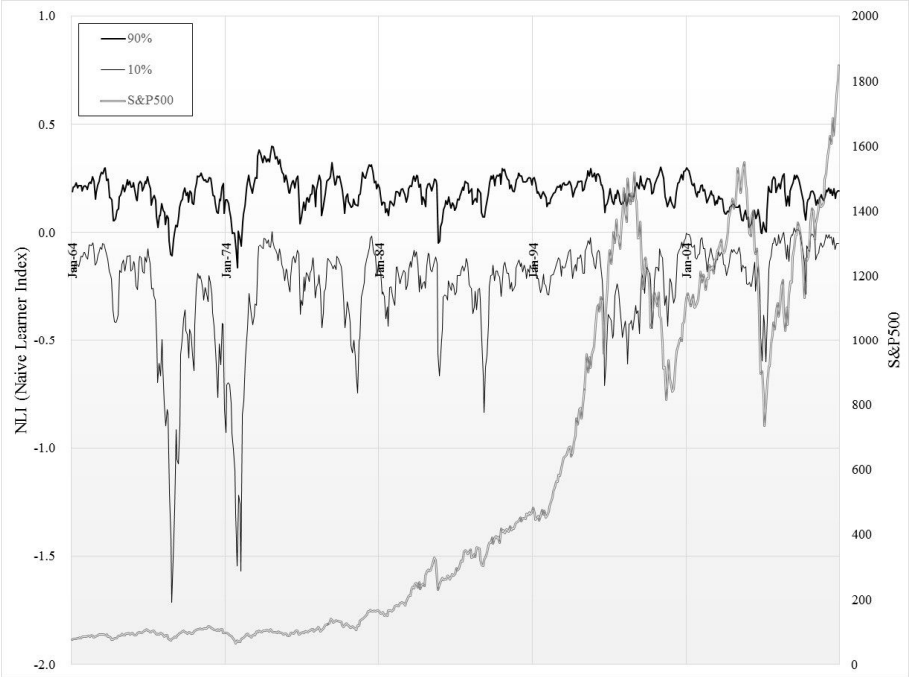
	CAP	N	Cap	N	Cap	N

[2] Split events always include stock splits, stock dividends, and other distributions with price factors such as spin-offs, stock distributions, and rights. Shares and volumes are only adjusted using stock splits and stock dividends. Split events are applied on the ex-distribution date.

Dec-13	14,540	4,071	12,528	1,925	86.2%	47.5%
Dec-03	10,136	6,125	8,045	2,230	79.0%	36.7%
Dec-93	2,833	5,358	2,055	1,503	70.8%	28.0%
Dec-83	1,007	4,055	653	1,093	65.1%	27.1%
Dec-73	619	1,809	370	645	58.8%	37.4%
All	5,827	4,284	4,730	1,479	72.0%	35.3%

According to Table 1, on average, 35.3% of stocks have valid PNRLs in the overall period. Since we use past five years of prior data to estimate PNRL of each stock, about 65% of stocks does not participate in our empirical test. However, the stocks with valid PNRLs cover more than 72% of market capitalization of all ordinary firms in CRSP database. This means that the excluded stocks are very small stocks and does not contribute much to the stock market. I judge that the included stocks are sufficient to test our proposed methodology.

At the beginning of each month t, we sort all stocks with their data of past five years into deciles based on PNRL of each stock and create value weighted portfolios from each decile. Top-decile contains the stocks that have higher PNRL s than other deciles, and bottom-decile contains the stocks that have lower PNRLs than other deciles. The split point was based on NYSE stocks because most NASDAQ stocks are small-cap stocks. Because PNRL varies with the forgetting ratio in Equation (3.18), we estimate PNRL at each forgetting, 0.01, 0.05, 0.1, 0.2 and 0.5.



[Figure. 3.1]

Fig. 3.1 plots the monthly time series of the 10th, 50th, and 90th percentile of the cross-section of the PNRLs of stocks traded on the NYSE with 0.1 of the forgetting ratio. It indicates that there exists wide cross-sectional dispersion in the values of PNRL s at same month. On average, the difference between the 90th percentile and 10th percentile of the cross-section of PNRL These three time series show co-movement with the S&P 500 index only at the period of financial crisis. Since we use past five years of data of each stock to estimate PNRL, those three time series cannot show direct relationship with the market index.

3.3.2 Empirical Result

The empirical tests mainly utilize the k-month rolling strategy. At the beginning of each month t, we sort all stocks based on PNRL and create value weighted portfolios from each decile. PNRL of each stock is estimated with its historical data of past five years. If the stock market is efficient, the stock portfolio from each decile should not earn any abnormal returns.

I compute abnormal returns based on a time-series regression of the portfolio excess returns using the five factor model of Fama and French (2014). If the returns of a portfolio are well explained by their five factors, alpha should not have statistical significance. Otherwise, we can argue that the returns of a portfolio have unexplained factors without their factors in Equation. (3.20).

Fama and French (2014) find that five factors[3], market excess returns, capitalization and book-to-market equity, adequately explain the cross-section of returns on US stocks for the period 1963-2013.

The regression is

$$r(t) - r_f(t) = \alpha + \beta_1 \left(MKT(t) - r_f(t)\right) + \beta_2 SMB(t) + \beta_3 HML(t) + \beta_4 RMW(t) + \beta_5 CMA(t) \quad (3.20)$$

RET is a series of portfolio returns, RF is the return on the one-month

[3] The monthly values of the five factors of the Fama-French Model and the risk-free rate are from Ken French's website. (http://mba.tuck.dartmouth.edu/ pages/faculty/ken.french/data library.html)

Treasury bill, and MKT is the value-weight return on all stocks. SMB (Small Minus Big) mimics the underlying risk factors in monthly returns related to size, HML (High Minus Low) mimics the underlying risk factors in monthly returns related to book-to-market equity, RMW (Robust Minus Weak) mimics the underlying risk factors in monthly returns related to firm profitability, and CMA (Conservative Minus Aggressive) mimics the underlying risk factors in monthly returns related to firm investment.

I, then, analyzed the profitability of rolling investment strategies. For this purpose, we used a rolling portfolio approach, following Jegadeesh and Titman (1993) and Fama and French (1993). The resulting overlapping returns can be interpreted as the returns of a trading strategy that in any given month t holds a series of portfolios selected in the current month as well as in the previous k months, where k-1 is the holding period. All stocks are value weighted within a given portfolio, and the overlapping portfolios are rebalanced at the beginning of each month to maintain equal weights.
This approach makes it possible to estimate how long the profitability of the investment strategy will last. I examine one-, two-, three-, six-, and twelve-month rolling strategies. The time series of returns of the rolling portfolios track the monthly performance of each trading strategy.

The empirical tests focus on short-term effects since every price change alters the degree of overconfidence and risk aversion of the stock. I use a 1-month rolling strategy as our benchmark portfolio when presenting the

results.

[Table. 3.2]

	δ	1	2	3	6	12
Return	0.01	**0.681%**	**0.759%**	**0.703%**	**0.707%**	**0.462%**
	0.05	**0.708%**	**0.733%**	**0.691%**	**0.740%**	**0.534%**
	0.10	**0.683%**	**0.676%**	**0.677%**	**0.749%**	**0.620%**
	0.20	**0.561%**	**0.522%**	**0.499%**	**0.580%**	**0.593%**
	0.50	0.171%	0.224%	0.164%	0.221%	0.382%
5FA	0.01	**0.826%**	**0.913%**	**0.853%**	**0.885%**	**0.689%**
	0.05	**0.815%**	**0.863%**	**0.808%**	**0.881%**	**0.718%**
	0.10	**0.755%**	**0.774%**	**0.761%**	**0.862%**	**0.765%**
	0.20	**0.638%**	**0.635%**	**0.560%**	**0.667%**	**0.694%**
	0.50	0.298%	0.375%	0.265%	0.323%	0.469%

I analyze the average returns of portfolios obtained by double sorting based on PNLRs. Table 3.2 reports the average return in excess of the risk-free rate for long/short portfolios. The long/short portfolio that takes long positions in stocks with the top 10% PNLR and short positions in stocks with the bottom 10% PNLR. Excess returns are presented as monthly percentages, statistical significance at the 5% level is indicated in bold. The excess returns of most of Long/short portfolios have positive excess returns with a statistical significance level of 5%.

[Table. 3.3]

Term	Measure	L1	L10	L/S
TERM2	Return	-0.321%	0.621%	**0.942%**
TERM1		0.333%	**0.888%**	**0.555%**
TERMA		0.006%	**0.755%**	**0.749%**
TERM2	5FA	**-0.860%**	0.229%	**1.089%**
TERM1		**-0.563%**	0.158%	**0.721%**
TERMA		**-0.693%**	0.169%	**0.862%**

In Table 3.3, stocks are first sorted based on their 1-month turnover ratio and then divided into five portfolios labeled 1 (Low), 2, 3, 4, and 5 (High). I examined the average rates of excess returns and the alphas of the long/short portfolios based on the synergies between the two psychological effects at each level of turnover ratio. Excess returns and alphas are presented as monthly percentages, t-statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. At all levels of capitalization, the average excess returns and alphas have positive values. However, the results for the stocks with the top 20% turnover ratios are not statistically significant.

3.3 Summary

One of the assumptions of our model is that for given payoff and aspiration

level, the size of behavior adjustments made by the decision maker is the same over time. One might argue that at later periods the decision maker will be more reluctant to change his or her behavior. This feature is present, for example, in the Erev and Roth (1998) model of reinforcement learning. A formal analysis of Erev and Roth's model, or related models, is beyond the scope of this article. One feature of their model that complicates its analysis is that the decrease in the step size of the decision maker's behavior adjustments is endogenous. The step size depends on the decision maker's experiences, which, in turn, depend on his or her choices. It becomes much easier to extend the results of this article if the decrease in the step size is made exogenous. The simplest way of doing this is to postulate that at iteration n the change in the decision maker's choice probabilities is exactly 1/n of what it is in the model introduced in Section 2. It is well known from the stochastic approximation literature (Benveniste et al., 1990) that the asymptotic behavior of the resulting learning process is closely linked to that of the deterministic differential equation that we constructed as a continuous time approximation. In particular, if the differential equation has a unique, globally stable rest point, then the stochastic learning process will converge to this rest point with probability.

Our simulations suggest that the learning process with endogenous aspiration level typically has a unique globally stable rest point that is interior. If this is correct, then the analysis of this article applies to the asymptotic behavior of the modified learning process as well. For the case that the aspiration level is exogenous and sufficiently low, the analysis is complicated by the fact that the

approximating differential equation, the replicator equation, has multiple fixed points, namely, all pure strategies.

However, since all fixed points except the optimal one have no basin of attraction, it should be easy to extend stochastic approximation results and to show convergence to the optimal action with probability.

Another important extension of our work would be to consider the case in which the decision maker has more than two actions. This extension raises technical problems.

In the most natural extension of our model to the case of more than two actions, probability that is taken away from some action is distributed among the remaining actions in proportion to their current probabilities. Such a proportional rule, however, implies that expected motion is not a continuous function of the current state.

This makes it impossible to appeal to standard theorems when taking continuous time limits. Moreover, if there are more than two actions, an even more sophisticated definition of probability matching will be needed. I expect that these problems can be resolved, but we have not yet done so. I expect the broad picture to remain the same as in the case of two actions.

Finally, it seems highly desirable to extend our work to the case that the decision maker faces a game rather than a single-person decision problem. The results of this article suggest that we should expect that learning rules with either an exogenous but relatively high aspiration level or an endogenously moving aspiration level have in many games interior rest points in which all players' behavior involves some combination of optimization and

probability matching. In such rest points, one would expect randomization to be self-enforcing: Each decision maker's payoff is stochastic because the other players randomize. Moreover, as a result of the probability-matching effect, this randomness in payoffs induces each decision maker to randomize himself or herself.

I conjecture that the only learning rules for which no such rest points exist are those for which the aspiration levels are exogenous and lower than all conceivable payoffs. The learning dynamics in this case become analogous to the replicator dynamics of evolutionary game theory. The details of this case are in Bargers and Sarin (1997).

Chapter 4. Beyond Actual Gain: Overconfidence and Risk Aversion

4.1 Psychological Confliction

Psychological effects complicate simple facts such as gains or losses. Consider two investors, A and B. Investor A bought a share of stock CoA at a share price of $100, whereas Investor B bought a share of stock CoB at a share price of $100. Two months later, both investors still hold their shares, and the stock prices of CoA and CoB both reach $150. What is the psychological value of this event to investors A and B? Obviously, both

investors experience a 50% rate of gain, and there is no reason to think that their emotions about their investments will differ.

However, the price paths of CoA and CoB are different. A month after the purchases, the stock price of CoA is $50, and the stock price of CoB is $200. Do both investors still feel the same emotion? There is room for doubt. The price changes that the two investors experience may set one apart from the other even though there is no difference in their final wealth.

Actual (unrealized) gain/loss is solely based on the shareholder's purchase price. When the current stock price is more than the purchase price, shareholders experience a gain. In the opposite case, shareholders suffer a loss. From a psychological perspective, however, the gain or loss does not depend exclusively on the purchase price because shareholders have their own reference prices for their holding shares. Shareholders evaluate their paper gains or losses based not only on their purchase prices but also on their psychological reference prices. This psychological process of profit evaluation influences the emotional status of the shareholder. As a result, shareholders make irrational decisions in the disposition of holding shares.

In this study, we focused on two psychological phenomena, overconfidence and risk aversion, to examine the emotional process of evaluating gains and losses. Overconfidence is one of the most documented biases (Daniel and Titman 2000). Investors who are overconfident in their investing abilities are more willing to make risky decisions. Conversely, risk aversion is the tendency of investors to avoid risky choices.

To address these two conflicting concepts, overconfidence and risk aversion,

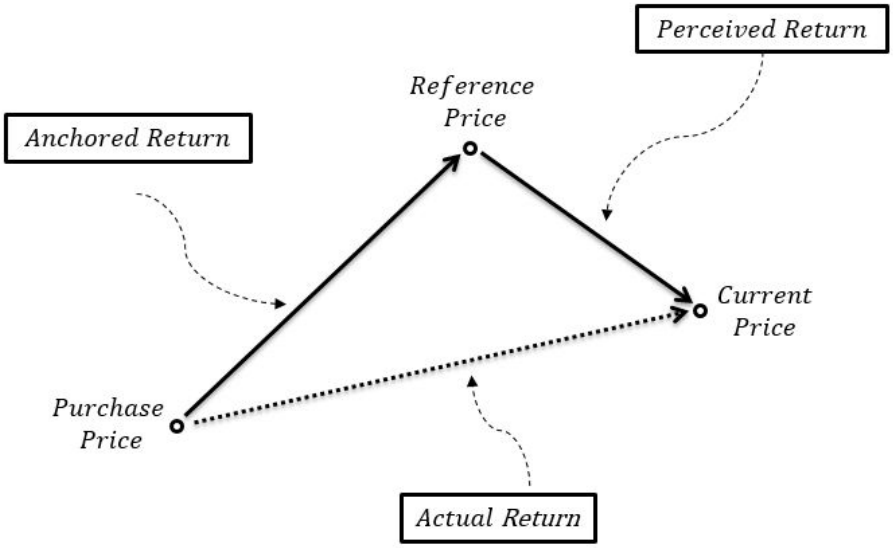
we use the reference price as the anchoring (pivot) position for psychological recognition by investors. Overconfidence is usually related to a shareholder's prior investment results (Glaser and Weber 2009). Investors are overconfident in their investing abilities when they obtain positive returns from prior investment decisions. This overconfidence increases investors' willingness to take more risks in subsequent investments. I assume that the return from the purchase price to the reference price is prior investing performance. I define 'Anchored Return' as the yield from the purchase price to the reference price. Under this assumption, shareholders recognize anchored returns as the results of prior trading.

$$Anchored\ Return = \frac{Reference\ Price}{Purchase\ Price} - 1 \tag{4.1}$$

Risk aversion is associated with unrealized profit from holding shares (Weber and Zuchel 2005). According to prospect theory (Kahneman and Tversky 1979), the likelihood of risk-taking depends on the reference price. If the current stock price is higher than the reference price, shareholders will attempt to avoid risk. Conversely, if the current stock price is lower than the reference price, investors will be willing to take risks to break even. I define 'Perceived Return' as the return from the reference price to the current price of the share. Perceived return is recognized as the psychological paper gain or loss from holding shares by shareholders.

$$Perceived\ Return = \frac{Current\ Price}{Reference\ Price} - 1 \quad (2)$$

Usually, the reference price is the psychological price adjusted from the purchase price. In the empirical experiments, we assume that the reference price is one of the prices experienced between the purchase day and the last business day. Figure 1 shows the relationship between the actual return, anchored return, and perceived return.



[Figure. 4.1]

As we mentioned previously, overconfidence is linked to prior investing outcomes. The return from the purchase price to the reference price, the

anchored return, triggers overconfidence. When the anchored return is positive, shareholders have confidence in their chosen stocks and consequently continue to hold their shares. Conversely, shareholders lose confidence when the anchored return is negative and thus will have misgivings about keeping their shares.

This phenomenon can be applied to all the shareholders of a stock. The more confidence shareholders have, the more willing they are to hold their shares. The less confidence shareholders have, the more willing they are to dispose of their shares.

Prospect theory, which describes the risk tendency of shareholders, is suitable for one-shot decision-making under conditions of risk (Weber and Zuchel 2005). Risk aversion by investors is related to the paper gains or losses from holding positions. The return from the reference price to the current price, the perceived return, changes the psychological statuses of the shareholders. When the perceived return is positive, shareholders tend to avoid risk. Consequently, these shareholders will be more likely to dispose of their shares. By contrast, shareholders will be willing to take risks under negative perceived returns. These shareholders usually hold their shares in the hope of breaking even.

This psychological effect applies to all shareholders of a stock. The more shareholders are afraid to take risks, the more willing they will be to sell their shares. The more shareholders seek risk, the more willing they will be to hold their shares.

These two psychological statuses of shareholders influence future stock returns according to one of the basic concepts of economics, supply and demand (Nelson et al. 2008). If the supply of shares increases and demand remains unchanged, a surplus of shares will become available in the stock market, and the equilibrium price of the stock will decrease. If the supply of shares decreases and demand remains unchanged, a shortage of shares will occur, and the equilibrium price of the stock will increase.

Our conjecture implies the following:

- If most shareholders of a stock feel confident, the stock will be overvalued in the market.
- If most shareholders of a stock lose confidence, the stock will be undervalued in the market.
- If most shareholders of a stock avoid risk, the stock will be undervalued in the market.
- If most shareholders of a stock take risks, the stock will be overvalued in the market.

Our study aims to demonstrate the influence of two psychological phenomena, overconfidence and risk aversion, on future stock returns. Toward this end, we examine the relationship between psychological effects and future stock returns in the US stock market from 1986 to 2010. I propose two measures to estimate the degree of overconfidence and the degree of risk

aversion of all shareholders for each stock. I find a strong link between future stock returns and the proposed estimators. The degree of overconfidence is positively related to future stock returns, and the degree of risk aversion is negatively related to future stock returns.

4.2 Methodology

I propose the use of two estimation measures to conduct empirical tests of abnormal returns induced by the psychological effects of overconfidence and risk aversion. These measures make it possible to summarize the emotional conditions of all shareholders for every stock on a given day and, thus, they are central to my empirical analysis in this paper.

4.2.1 Purchase Price and the Estimation of Holding Shares

To introduce my estimation procedures, we define the purchase price and estimate holding shares. The closing price on business day t, P_t, can be used as a proxy for the price of all transactions that occurred on that day, even though the actual transactions occurred during trading hours. There is no reason to expect the closing price to bias the results one way or the other. In my estimation procedures, the closing price on day t is considered the purchase price of all shares traded on day t.

In the real world, investors can purchase several times and sell portions of their shares on different days. I assume that shareholders are subjected to cost-based mental accounting (Frazzini 2006), which means that they

consider each share in their portfolios separately based on the corresponding purchase price. Based on this supposition, each share can be handled independently.

Next, it is necessary to estimate the proportion of shares that are still held by the original purchasers. Grinblatt and Han (2005) and Frazzini (2006) use a clear and concise method for this purpose. They assume that the turnover ratio, $TO_{t,}$ is the leaving rate of each share and that $1 - TO_t$ is the holding rate. TO_t is a measure of stock liquidity that is calculated by dividing the trading volume traded on day t by the number of outstanding shares. V(t,t-k) is the proportion of shares purchased on day t-k that are still held by the original purchasers on day t.

$$V(t,t-k) = TO_{t-k}\prod_{i=0}^{k-1}(1-TO_{t-i}) \tag{4.2}$$

The first term indicates the proportion of shares that are newly purchased on day t-k, and the second term is the probability that a share was last purchased on day t-k and has not been traded since then.

4.2.2 Reference Price

Anchored returns and perceived returns are evaluated based on the subjective reference prices. The reference price is a topic of debate. Reference dependence is a long-standing tradition in psychology. It was applied to behavioral economics by Kahneman and Tversky (1979) in the context of prospect theory. Kahneman and Tversky (1979) suggest that the reference price is important to investors' attitudes toward risk. One intuitive

reference point is the price at which the share was purchased. Odean (1998b) and Shefrin and Statman (1985) provide evidence of the disposition effect among stock investors based on the purchase price. Taking the purchase price as the reference price, however, ignores the changes that occur in the reference price as the stock price moves away from the purchase price. Chen and Rao (2002) suggest that the reference point shifts as the level of wealth changes. They show that the changes in the reference point follow the direction of the intermediate price. Gneezy (2005) infers that the reference point changes when subjects want to sell their stocks. The empirical results of Gneezy (2005) indicate that subjects are most likely to anchor at historical peaks. Baucells et al. (2011) simulate a financial situation to analyze reference point formation over time. In their experiment, reference points are given in a sequence of information. The researchers argue that the reference price is highly related to the first and last price in the information sequences and is slightly associated with intermediate prices. Based on the literature, we conclude that the reference price lies on the price path that the shareholder experiences after purchase.

Kahneman (1992) discusses two possible mechanisms, integrated and segregated, for multiple reference prices. In using the integrated mechanism, individuals transform multiple reference points into a single reference point. The integrated approach is often adopted in marketing because consumers make decisions by aggregating past prices (Winer 1986). By contrast, in using the segregated mechanism, individuals perform multiple comparisons based on reference prices. Sullivan and Kida (1995) demonstrate that

corporate managers consider multiple reference points when making investment decisions. Ordóñez et al. (2000) also examine multiple reference points in the context of salary decisions. The survey by Redelmeier and Tversky (1992) indicates that the subjects do not spontaneously aggregate multiple prospects.

I consider all of the prices experienced by the shareholder as a set of reference prices because there is no specific way to choose a single reference price.

I make the use of the segregated approach to estimate the emotional status of a shareholder with multiple reference prices. The set of reference prices consists of all of the prices that a shareholder experiences during the holding period.

4.2.3 Degree of Overconfidence

Shareholder overconfidence is positively correlated with prior investing performance. As previously mentioned, we assume that anchored return is prior investing performance. I estimate the degree of overconfidence of all shareholders in a stock with anchored returns of shareholders. If a share is purchased on day t-k and is not sold until day t, the anchored return of each reference price is calculated as follows:

$$AR(t-i, t-k) = \frac{P_{t-i}}{P_{t-k}} - 1, \quad 0 \leq i \leq k \tag{4.3}$$

where t-i is the time between the purchase day t-k and the last day t. P_{t-i} is the reference price, and also stock price on day t-i. P_{t-k} is the purchase price

and, is the stock prices on day t.

There are k+1 values of AR(t-i,t-k) within the range of the shareholder's holding period. I use a recency-weighted average of k+1 values of AR(t-i,t-k) as the proxy for the overconfidence of the shareholder who purchased a share on day t-k and still holds the share:

$$wAR(t,t-k) = \frac{1}{\sum_{i=0}^{k} w(i)} \sum_{i=0}^{k} w(i)AR(t-i,t-k) \tag{4.4}$$

The weight, w(i), is a time-decaying function that represents what is referred to as exponential decay in mathematics and physics (Miller et al. 2010).

$$w(i) = \exp(-\frac{i}{\mu}) \tag{4.5}$$

In the formula for the time-decaying function, μ is the mean lifetime of the influence of the reference prices. The weight decreases as i increases, and the degree of weight decline is inversely proportional to μ. In the empirical test, we use four values of μ: 252 business days (one year), 126 business days (one half-year), 63 business days (one quarter), and 21 business days (one month).

Finally, the overall degree of overconfidence of all shareholders of a stock is estimated as the average of wAR(t,t-k):

$$DOC(t) = \frac{1}{\sum_{k=0}^{\infty} V(t,t-k)} \sum_{k=0}^{\infty} V(t,t-k)wAR(t,t-k) \tag{4.6}$$

where V(t,t-k) is the proportion of shares that are purchased on day t-k and

that are still held by the original purchasers on day t as described in section 3.1. A highly positive value for DOC(t) indicates that most of shareholders experience highly positive anchored returns and feel full of confidence. By contrast, a highly negative value for DOC(t) implies that most of the shareholders suffer highly negative anchored returns, which decreases their confidence.

4.2.4 Degree of Risk Aversion

The return from the reference price to the current price, the perceived return, changes the psychological statuses of the shareholders. When the perceived return is positive, shareholders tend to avoid risk. Consequently, these shareholders will be more likely to dispose of their shares. By contrast, shareholders will be willing to take risks under negative perceived returns. These shareholders usually hold their shares in the hope of breaking even.

Shareholders' tendency toward risk aversion can be represented with their perceived returns. If a share is purchased on day t-k and is not sold until the last day t, the perceived return of each reference price is calculated as

$$PR(t, t-i) = \frac{P_t}{P_{t-i}} - 1, \quad 0 \leq i \leq k \tag{4.7}$$

where t-i is the interval between the purchase day t-k and day t. P_{t-i} is the reference price, and also stock price on day t-i. P_t is the current price and, is

the stock prices on day t. As in the estimation of wAR(t,t-k), we use a recency-weighted average of k+1 values of PR(t,t-i) as a proxy for the risk aversion of the shareholder who purchased stock on day t-k and still holds that stock.

$$wPR(t,t-k) = \frac{1}{\sum_{i=0}^{k} w(i)} \sum_{i=0}^{k} w(i) PR(t,t-i) \tag{4.8}$$

The weight, w(i), is a time-decaying function. Finally, the overall degree of risk aversion of all shareholders of a stock is estimated as the average of wPR(t,t-k):

$$DRA(t) = \frac{1}{\sum_{k=0}^{\infty} V(t,t-k)} \sum_{k=0}^{\infty} V(t,t-k) wPR(t,t-k) \tag{4.9}$$

where V(t,t-k) is the proportion of shares that are purchased at day t-k and are still held by the original purchasers at day t. A highly positive value of DRA(t) indicates that the majority of the shareholders experience highly positive perceived returns and tend to avoid risk. By contrast, a highly negative value of DRA(t) implies that the majority of the shareholders suffer highly negative perceived returns and are willing to take risks to break even. Our aim is to ensure that the proposed degrees of overconfidence and risk aversion are not substantially different from the actual emotions of shareholders.

$$DOC(t) = \frac{1}{\sum_{k=0}^{756} V(t,t-k)} \sum_{k=0}^{756} V(t,t-k) wAR(t,t-k) \tag{4.10}$$

$$DRA(t) = \frac{1}{\sum_{k=0}^{756} V(t,t-k)} \sum_{k=0}^{756} V(t,t-k) wPR(t,t-k) \tag{4.11}$$

I estimate the degree of overconfidence and risk aversion based on Equations 11 and 12. I truncate the estimation at 756 business days (three years) because it is impossible to use an infinite sum. This technique allows us to estimate the reference price of every stock in a consistent manner.

4.3 Empirical Results

4.3.1 Data Description

I obtained stock data for the NYSE, AMEX, and NASDAQ from the CRSP (The Center for Research in Security Prices). Based on the CRSP classification of the stocks, we excluded ADRs, REITs, and units of beneficial interest and included only ordinary firms in my empirical test. The data included the closing price, the trading volume, and the number of outstanding shares for every business day between November 1982[4] and

[4] Because daily prices for NASDAQ securities were first reported on November 1, 1982 in the CRSP, our empirical test must analyze data

December 2010. If the closing price was not available for any given period, the number in the price field was replaced with a bid/ask average[5]. I adjusted the closing price, trading volume, and number of outstanding shares with the factor to adjust price in period and the factor to adjust shares outstanding, which we obtained from the CRSP. These adjustments allowed us to make equivalent comparisons between prices before and after the distribution.

I chose stocks that satisfied three conditions on the last business day of every month. The selected stocks were traded during at least the past three years and over a period that lasted longer than one month. In addition, if a stock had no transaction history in the corresponding month, the stock was excluded from the empirical test for that month.

Table 1 shows the statistics for the selected stocks based on the empirical tests. Each column describes the following. All Stocks are ordinary firms listed in the CRSP database during the given period. The selected stocks are ordinary firms which satisfies my three conditions. Number of Stocks and Total Cap. indicates the average number of ordinary firm stocks and the average total market value of stocks in the given period, respectively.

Proportion (% Stocks) is the percentage of stocks about which there is sufficient historical information, and Proportion (% Cap) is the percentage of the total market value represented by the selected stocks. The table reports the average values and standard deviations of the stock market index returns

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from November 1982 onward.

[5] Daily prices for the NASDAQ small-cap market were first reported on June 15, 1992. The price or bid/ask average for NASDAQ securities is always a bid/ask average before June 15, 1992.

and risk-free rates.

[Table. 4.1]

Period	All Stocks		Selected Stocks		Proportion		Market Return		Risk Free Rate	
	Number of Stocks	Total Cap. ($1M)	Number of Stocks	Total Cap. ($1M)	% Stocks	% MV	Mean	S.D.	Mean	S.D.
1986-1990	5,569	2,591,777	4,188	2,475,970	75.3%	95.6%	1.025%	5.423%	0.553%	0.108%
1991-1995	5,775	4,180,942	4,529	4,029,235	78.8%	96.6%	1.398%	2.936%	0.351%	0.099%
1996-2000	6,557	10,650,333	4,920	10,177,047	75.2%	95.8%	1.434%	4.877%	0.421%	0.049%
2001-2005	4,984	12,283,057	4,413	11,909,458	88.9%	97.0%	0.247%	4.428%	0.176%	0.106%
2006-2010	4,222	13,852,460	3,672	13,165,492	87.0%	95.3%	0.392%	5.238%	0.186%	0.176%
1986-2010	5,421	8,711,714	4,344	8,351,440	81.1%	96.1%	0.899%	4.661%	0.337%	0.184%

According to Table 4.1, on average, 81.1% of stocks satisfied my stock selection rules in the overall period. However, the chosen stocks covered more than 96% of market capitalization of all ordinary firms. This means that the excluded stocks did not contribute much to the stock market.

4.3.2 Empirical Test

I proposed the main hypotheses and designed a trading rule to examine the empirical results. The purpose of the test was to validate the hypothesis regarding shareholder behavior by analyzing the relationship between the proposed estimators, the degree of overconfidence, and the degree of risk aversion and future stock returns.

Hypothesis - Overconfidence: When most of the current shareholders are overconfident (diffident), the supply of shares in the market decreases (increases). According to the law of supply and demand, overconfident (diffident) shareholders put upside (downside) pressure on the equilibrium

price of a stock. As a result, the future returns of stocks held by sanguine investors will be relatively higher than those of stocks held by shareholders whose confidence is shaken.

According to the overconfidence hypothesis, a long position in stocks with a higher degree of overconfidence will perform better than a long position in stocks with a lower degree of overconfidence. Therefore, it is reasonable to build a long/short strategy in which the investor offsets a long position in stocks with a higher degree of overconfidence by a short position in stocks with a lower degree of overconfidence. If the difference between the degree of confidence associated with the long and short sides is positively large, the long/short strategy will yield higher returns.

Hypothesis - Risk Aversion: When most current shareholders are avoiding risk (seeking risk), the supply of shares in the market will increase (decrease). By the law of supply and demand, risk-averting (risk-taking) shareholders put downside (upside) pressure on the equilibrium price of a stock. As a result, the future returns of stocks held by more risk takers will be relatively higher than those of stocks held by fewer risk takers.

According to the risk aversion hypothesis, the return from taking long positions in stocks with a lower degree of risk aversion will be higher than the return from taking short positions in stocks with a higher degree of risk aversion. Consequently, it will be profitable to build a long/short strategy in

which long positions in stocks with a lower degree of risk aversion are offset by short positions in stocks with a higher degree of risk aversion. If the difference in the degree of risk aversion between the long and short sides is negatively large, the long/short strategy will yield higher returns.

Based on the two hypotheses, the future returns of stocks with a higher degree of overconfidence and a lower degree of risk aversion will be greater than those of stocks with a lower degree of overconfidence and a higher degree of risk aversion. This strategy can also be used to compose a long/short stock portfolio that is long in stocks with a higher degree of overconfidence and a lower degree of risk aversion and short in stocks with a lower degree of overconfidence and a higher degree of risk aversion. This long/short portfolio is referred to as 'psychological synergy portfolio' in the later section.

To analyze the impact of the two psychological phenomena, we divided all of the stocks into nine portfolios on the last business day of each month. The split point was based on NYSE stocks because most AMEX and NASDAQ stocks are small-cap stocks. Double sorting was used to rank the NYSE stocks based on the degree of overconfidence and the degree of risk aversion. I divided the NYSE, AMEX, and NASDAQ stocks into three groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) ranked values for the degree of overconfidence for NYSE stocks. I also divided all of the traded stocks into three groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) ranked values for the degree of risk aversion for NYSE stocks. Based

on the split points for the two grouping schemes, the grouped stocks were double sorted and assigned to one of the nine portfolios. Table. 4.2 shows the proportion of stocks that belong to the corresponding portfolios. Because the degree of overconfidence and the degree of risk aversion vary with the mean lifetime of the time decay, we present the proportion of stocks at each mean lifetime, 252, 126, 63, and 21 business days. Labels 1, 2, and 3 represent the bottom 30%, middle 40%, and top 30%, respectively.

[Table 4.2]

a) Mean lifetime of time-decaying function is 252 business days (one year)

		Degree of Risk Aversion		
		1	2	3
Degree of Overconfidence	1	29.3%	9.4%	4.9%
	2	7.7%	14.3%	8.1%
	3	2.7%	8.0%	15.5%

b) Mean lifetime of time-decaying function is 126 business days (one half-year)

		Degree of Risk Aversion		
		1	2	3
Degree of Overconfidence	1	27.6%	9.8%	6.0%
	2	8.1%	13.7%	8.5%

	3	3.3%	8.5%	14.5%

c) Mean lifetime of time-decaying function is 63 business days (one quarter)

		Degree of Risk Aversion		
		1	2	3
Degree of Overconfidence	1	25.3%	10.4%	7.5%
	2	8.5%	13.1%	8.8%
	3	4.1%	9.0%	13.2%

d) Mean lifetime of time-decaying function is 21 business days (one month)

		Degree of Risk Aversion		
		1	2	3
Degree of Overconfidence	1	21.8%	11.1%	9.9%
	2	9.0%	12.5%	9.2%
	3	5.5%	9.6%	11.5%

We, then, analyzed the profitability of rolling investment strategies. For this purpose, we used a rolling portfolio approach, following Jegadeesh and Titman (1993) and Fama and French (1993). The resulting overlapping returns can be interpreted as the returns of a trading strategy that in any given month t holds a series of portfolios selected in the current month as well as in the previous k months, where k is the holding period. All stocks are value weighted within a given portfolio, and the overlapping portfolios are rebalanced at the end of each month to maintain equal weights. This approach makes it possible to estimate how long the profitability of the investment strategy will last. The empirical tests mainly utilize the 1-month rolling strategy. In the section on robustness, we also examine one-, two-, three-, six-, and twelve-month rolling strategies.

The time series of returns of the rolling portfolios track the monthly performance of each trading strategy. If the stock market is efficient, the trading strategy should not earn any abnormal returns. I compute abnormal returns based on a time-series regression of the portfolio excess returns using the three factors of the Fama and French (1993) model. Fama and French (1993) find that three factors[6], market excess returns, capitalization and book-to-market equity, adequately explain the cross-section of returns on US stocks for the period 1963-1990.

$$RET(t) - RF(t) = \alpha + \beta_1\big(MKT(t) - RF(t)\big) + \beta_2 SMB(t) + \beta_3 HML(t) \qquad (4.12)$$

[6] The monthly values of the three factors of the Fama-French Model and the risk-free rate are from Ken French's website. (http://mba.tuck.dartmouth.edu/ pages/faculty/ken.french/data library.html)

Fama and French use six portfolios formed by sorting stocks based on capitalization and book-to-equity. RET is a series of portfolio returns, and MKT is the value-weight return on all stocks. RF is the return on the one-month Treasury bill. SMB (Small Minus Big) mimics the underlying risk factors in monthly returns related to size, and HML (High Minus Low) mimics the underlying risk factors in monthly returns related to book-to-market equity. Under the proposed hypotheses, the investment rules can earn both positive returns and positive alphas.

Our empirical tests focus on short-term effects since every price change alters the degree of overconfidence and risk aversion of the stock. I use a 1-month rolling strategy as my benchmark portfolio when presenting the results.

[Table 4.3]

a) Mean lifetime of time-decaying function is 252 business days (one year)

		Degree of Risk Aversion			
		1	2	3	1-3
Degree of Overconfidence	1	0.370% (0.90)	0.151% (0.47)	-0.338% (-0.92)	**0.708%** **(2.27)**
	2	**0.674%** **(2.12)**	0.307% (1.21)	0.105% (0.40)	**0.569%** **(2.72)**
	3	**1.252%** **(3.49)**	**0.745%** **(2.75)**	0.461% (1.69)	**0.791%** **(3.06)**

	3-1	**0.883%**	**0.594%**	**0.799%**	
		(2.83)	**(2.58)**	**(2.75)**	

b) Mean lifetime of time-decaying function is 126 business days (one half-year)

		Degree of Risk Aversion			
		1	2	3	1-3
Degree of Overconfidence	1	0.457%	0.129%	-0.320%	**0.777%**
		(1.12)	(0.40)	(-0.89)	**(2.47)**
	2	**0.680%**	0.333%	0.117%	**0.564%**
		(2.09)	(1.30)	(0.44)	**(2.75)**
	3	**1.165%**	**0.712%**	0.433%	**0.732%**
		(3.36)	**(2.65)**	(1.58)	**(2.89)**
	3-1	**0.708%**	**0.583%**	**0.753%**	
		(2.27)	**(2.46)**	**(2.72)**	

c) Mean lifetime of time-decaying function is 63 business days (one quarter)

		Degree of Risk Aversion			
		1	2	3	1-3
Degree of Overconfidence	1	0.512%	0.187%	-0.601%	**1.113%**
		(1.22)	(0.57)	(-1.86)	**(3.60)**
	2	**0.697%**	0.342%	0.078%	**0.619%**
		(2.19)	(1.34)	(0.29)	**(3.03)**
	3	**1.270%**	**0.677%**	0.405%	**0.865%**
		(3.68)	**(2.53)**	(1.46)	**(3.37)**
	3-1	**0.758%**	**0.490%**	**1.006%**	

		(2.29)	**(1.99)**	**(3.89)**	

d) Mean lifetime of time-decaying function is 21 business days (one month)

		Degree of Risk Aversion			
		1	2	3	1-3
Degree of Overconfidence	1	0.765% (1.79)	0.296% (0.88)	-0.647% (-1.90)	**1.412%** **(5.12)**
	2	**0.591%** **(1.97)**	0.425% (1.65)	-0.099% (-0.37)	**0.690%** **(3.67)**
	3	**1.121%** **(3.50)**	**0.756%** **(2.85)**	0.278% (0.98)	**0.843%** **(3.97)**
	3-1	0.356% (1.11)	0.460% (1.77)	**0.924%** **(3.41)**	

I analyze the average returns of portfolios obtained by double sorting based on the degree of overconfidence and the degree of risk aversion.

Table 4.3 reports the average return in excess of the risk-free rate for nine value-weighted portfolios formed on the double sorts. In Table 4.3, a), b), c), and d) are the average excess returns of stocks at each mean lifetime: 252, 126, 63, and 21 business days. Labels 1, 2, and 3 represent the bottom 30%, middle 40%, and top 30%, respectively. For each degree of overconfidence, the column labeled '1-3' presents the average rate of excess returns of the long/short portfolio that takes long positions in stocks with the bottom 30% degree of risk aversion and short positions in stocks with the top 30% degree of risk aversion. For each degree of risk aversion, the row labeled '3-1'

shows the average rate of excess returns of the long/short portfolio that takes long positions in stocks with the top 30% degree of overconfidence and short positions in stocks with the bottom 30% degree of overconfidence. Excess returns are presented as monthly percentages, t-statistics are listed below the coefficient estimates in brackets, and statistical significance at the 5% level is indicated in bold.

Consistent with hypothesis-overconfidence, Table 4.3 shows that the average returns of portfolios decrease monotonically with their degree of risk aversion for each given level of overconfidence. As a result, the long/short portfolios in the last column have positive excess returns with a statistical significance level of 5%. Table 4.3 also reports that the average portfolio returns increase monotonically with the degree of overconfidence for each given level of risk aversion. This finding is consistent with hypothesis-risk aversion. Therefore, the long/short portfolios in the last row have positive excess returns with a statistical significance level of 5% except for d) in Table 3. A mean lifetime of one month (21 business days) seems too short to capture the degree of overconfidence.

The results in Table 4.3 demonstrate that a portfolio with stocks with the bottom 30% degree of risk aversion and the top 30% degree of overconfidence generates the highest average excess return of the nine portfolios. The positive synergy between the higher degree of overconfidence and lower degree of risk aversion increases the portfolio's average excess return.

By contrast, the portfolio with stocks with the top 30% degree of risk

aversion and the bottom 30% degree of overconfidence produces the lowest average excess return of the nine portfolios. The negative synergy between the lower degree of overconfidence and the higher degree of risk aversion decreases the average excess return of the portfolio relative to that of the other portfolios.

I also examine alphas of Fama-French three factor model for each stock portfolios. If a portfolio's return are well explained by the factors in the Fama-French three-factor model, alpha should not have statistical significance in Equation. 4.12. Otherwise, the return of a portfolio has unexplained factors without three factors in the regression. I report alphas and their t-Statistics in Table 4.3. The dependent variable is the monthly excess return over the Treasury Bill rate. The explanatory variables are the monthly returns from the Fama-French model. Alphas are in monthly percentages, t-statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. With the exception of the replacement of excess returns with alphas, the configuration of Table 4.4 is the same as that of Table 4.3.

[Table 4.4]

a) Mean lifetime of time-decaying function is 252 business days (one year)

		Degree of Risk Aversion			
		1	2	3	1-3
Overco	1	-0.438% (-1.87)	**-0.549%** **(-3.09)**	**-1.170%** **(-5.21)**	**0.732%** **(2.42)**

	2	0.037% (0.24)	**-0.279%** **(-3.74)**	**-0.480%** **(-4.12)**	**0.517%** **(2.50)**
	3	**0.579%** **(2.64)**	0.207% (1.87)	-0.073% (-0.60)	**0.653%** **(2.53)**
	3-1	**1.017%** **(3.24)**	**0.756%** **(3.32)**	**1.097%** **(4.05)**	

b) Mean lifetime of time-decaying function is 126 business days (one half-year)

		Degree of Risk Aversion			
		1	2	3	1-3
Degree of Overconfidence	1	-0.311% (-1.29)	**-0.575%** **(-3.21)**	**-1.125%** **(-5.17)**	**0.814%** **(2.66)**
	2	0.005% (0.03)	**-0.245%** **(-3.12)**	**-0.471%** **(-4.08)**	**0.476%** **(2.38)**
	3	**0.487%** **(2.37)**	0.166% (1.50)	-0.099% (-0.79)	**0.586%** **(2.31)**
	3-1	**0.798%** **(2.55)**	**0.741%** **(3.13)**	**1.026%** **(3.94)**	

c) Mean lifetime of time-decaying function is 63 business days (one quarter)

		Degree of Risk Aversion			
		1	2	3	1-3
Overconfiden	1	-0.281% (-1.15)	**-0.519%** **(-2.75)**	**-1.286%** **(-6.30)**	**1.005%** **(3.40)**
	2	0.038%	**-0.233%**	**-0.513%**	**0.551%**

		(0.27)	**(-2.89)**	**(-4.29)**	**(2.76)**
	3	**0.594%** **(2.85)**	0.136% (1.28)	-0.127% (-0.96)	**0.721%** **(2.79)**
	3-1	**0.876%** **(2.65)**	**0.655%** **(2.67)**	**1.159%** **(4.57)**	

d) Mean lifetime of time-decaying function is 21 business days (one month)

		Degree of Risk Aversion			
		1	2	3	1-3
Degree of Overconfidence	1	-0.036% (-0.15)	**-0.411%** **(-2.09)**	**-1.378%** **(-6.75)**	**1.342%** **(5.13)**
	2	-0.061% (-0.49)	-0.145% (-1.74)	**-0.682%** **(-5.72)**	**0.621%** **(3.31)**
	3	**0.515%** **(3.00)**	0.225% (2.09)	-0.260% (-1.91)	**0.775%** **(3.59)**
	3-1	**0.551%** **(1.99)**	**0.636%** **(2.45)**	**1.118%** **(4.19)**	

Consistent with hypothesis-overconfidence, Table 4.4 shows that the alphas of the portfolios decrease monotonically with their level of risk aversion for each given degree of overconfidence. As a result, the long/short portfolios in the last column have positive alphas with a statistical significance of 5%. Table 4.4 also reports that the alphas of the portfolios increase monotonically with their level of overconfidence for each given degree of risk aversion. This relationship is consistent with hypothesis-risk aversion. Therefore, the long/short portfolios in the last row have positive alphas with a statistical

significance at 5%. In contrast to the results for d) in Table 4.3, the long/short portfolios based on the degree of overconfidence yield a statistically significant result for d) in Table 4.4.

[Table 4.5]

Mean Lifetime	μ = 256	μ = 126	μ = 63	μ = 21
Excess Return	**1.590%**	**1.485%**	**1.871%**	**1.768%**
	(4.85)	**(4.77)**	**(5.90)**	**(6.02)**
Alpha	**1.750%**	**1.612%**	**1.880%**	**1.893%**
	(5.41)	**(5.20)**	**(5.89)**	**(6.44)**

The positive and negative synergies between the degree of overconfidence and the degree of risk aversion can be used to compose a long/short stock portfolio that holds stocks with the top 30% (3) degree of overconfidence and the bottom 30% (1) degree of risk aversion and offsets this position by shorting in stocks with the bottom 30% (1) degree of overconfidence and the top 30% (3) degree of risk aversion. Table 4.5 shows the average rates of excess returns and alphas of the long/short portfolios based on synergies between the two psychological effects. Excess returns and alphas are presented as monthly percentages, t-statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. The average rate of excess returns and alphas are statistically significant for all mean lifetimes.

In the following sections, we examine long/short portfolios based on the

synergies between the two psychological effects to simplify the empirical descriptions. I also use 252 business days as the mean lifetime of the time-decaying function.[7]

4.3.3 Cross-sectional Determinant

Table 4.6 reports the coefficients from the Fama-MacBeth regressions of the degree of overconfidence and the degree of risk aversion of the five regressors (Fama and MacBeth, 1973). The results in Table 6 are based on the proposed estimators with a mean lifetime of 252 business days.

Ret(1M) is the stock return for the prior one month, Ret(2M-12M) is the return for the previous 2-12 months, Ret(13M-36M) is the return for the previous 13-36 months, and log(Cap.) is the natural logarithm of the market capitalization. Turnover(1M) is the turnover ratio in the last month. Cross-sectional regressions were performed every month, and the standard errors were adjusted for heteroscedasticity and autocorrelation using the Newey-West adjustment (Newey and West 1987). t-Statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. The R^2 is the average R^2 from the Fama-Macbeth cross-sectional regressions.

[Table 4.6]

Dependent Variable	Degree of Overconfidence	Degree of Risk Aversion

[7] Nearly identical results were obtained using the other mean lifetimes of the time-decaying function.

Constant	**-0.1942**	**-0.1735**
	(-10.34)	**(-9.21)**
Ret(1M)	**0.0517**	**0.4077**
	(13.03)	**(14.01)**
Ret(2M-12M)	**0.0579**	**0.0534**
	(5.63)	**(5.40)**
Ret(13M-36M)	**0.0175**	**0.0026**
	(4.11)	**(2.35)**
log(CAP)	**0.0347**	**0.0287**
	(16.49)	**(12.87)**
Turnover(1M)	**-0.0838**	**-0.0773**
	(-5.35)	**(-6.46)**
R^2	0.3123	0.3605

Both the degree of overconfidence and the degree of risk aversion are positively influenced by Ret(1M), Ret(2M-12M), Ret(13M-36M), and the capitalization. The turnover ratio has negative effects on both degrees. The regression coefficients are similar with the exception of the coefficient of the short-term return, Ret(1M). The effect of the short-term return on the degree of risk aversion is much greater than that of the degree of overconfidence. The reason is that the last price in a stock price path is compared to every possible reference price in the formula for estimating degree of overconfidence Therefore, short-term returns greatly influence the degree of risk aversion.

4.3.4 Rolling Periods

I use the rolling strategy suggested by Jegadeesh and Titman (1993) to examine how long these emotional effects influence stock prices. In any given month t, the strategies determine a series of portfolios that are selected in the current month as well as in the previous h-1 months, where h is the holding period.

I use long/short portfolios based on synergies between the two psychological effects. Positive and negative synergies between the degree of overconfidence and the degree of risk aversion can be used to compose a long/short stock portfolio that is long in stocks with the top 30% degree of overconfidence and the bottom 30% degree of risk aversion and that is short in stocks with the bottom 30% degree of overconfidence and the top 30% degree of risk aversion. The profits of the above strategies were calculated for a series of portfolios that were rebalanced monthly to maintain value weights. I consider holding periods of 1, 2, 3, 6 and 12 months.

[Table. 4.7]

Rolling Period	Excess Return	Alpha
+1	**1.590%**	**1.750%**
	(4.85)	**(5.41)**
+2	**0.754%**	**0.872%**
	(2.85)	**(3.35)**
+3	**0.556%**	**0.685%**
	(2.34)	**(2.98)**

+6	0.152%	0.326%
	(0.72)	(1.66)
+12	-0.240%	-0.079%
	(-1.33)	(-0.48)

Table 4.7 shows the average excess returns and alphas of psychological synergy portfolio, which is the long/short portfolios based on the synergies between the two psychological effects. Excess returns and alphas are presented as monthly percentages, t-statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. The results are based on the proposed estimators with a mean lifetime of 252 business days. The average rates of returns and the alphas are statistically significant when the holding period is less than or equal to 3 months. If the rolling period is longer than 3 months, the effect of overconfidence and risk aversion disappears. Even though the average excess returns and alphas for rolling periods of 2 and 3 months are statistically significant, the corresponding figures for a rolling period of 1 month are considerably higher. The results in Table 4.7 indicate that the effect of the two psychological phenomena diminishes rapidly with time due to price changes and the disposition of shares.

4.3.5 Robustness

To validate my empirical findings, we confirmed robustness in various ways.

First, we checked that these psychological phenomena revealed different stock sizes as well as the influence of the turnover ratio.

[Table 4.8]

Quintile	Excess Return	Alpha
1-Low	**2.222%**	**2.177%**
	(6.02)	**(5.81)**
2	**1.093%**	**1.125%**
	(2.77)	**(2.81)**
3	**1.999%**	**2.119%**
	(4.97)	**(5.26)**
4	**1.010%**	**1.028%**
	(2.60)	**(2.68)**
5-High	**1.924%**	**1.957%**
	(4.97)	**(5.08)**

In Table 4.8, stocks are sorted by their market capitalization and then divided into five portfolios labeled 1 (Low), 2, 3, 4, and 5 (High). I examined the average excess returns and the alphas of the long/short portfolios based on the synergies between the two psychological effects at each level of capitalization. Excess returns and alphas are presented as monthly percentages, t-statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. At all levels of capitalization, the average excess returns and alphas are statistically significant. The effects of overconfidence and risk aversion can be found for a stock of any size.

[Table 4.9]

Quintile	Excess Return	Alpha
1-Low	**1.081%**	**1.215%**
	(2.89)	**(3.33)**
2	**1.392%**	**1.532%**
	(3.46)	**(3.77)**
3	**1.076%**	**1.217%**
	(2.37)	**(2.69)**
4	**1.177%**	**1.384%**
	(2.44)	**(2.93)**
5-High	0.738%	1.103%
	(1.06)	(1.58)

In Table 4.9, stocks are first sorted based on their 1-month turnover ratio and then divided into five portfolios labeled 1 (Low), 2, 3, 4, and 5 (High). I examined the average rates of excess returns and the alphas of the long/short portfolios based on the synergies between the two psychological effects at each level of turnover ratio. Excess returns and alphas are presented as monthly percentages, t-statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. At all levels of capitalization, the average excess returns and alphas have positive values. However, the results for the stocks with the top 20% turnover ratios are not statistically significant. A high turnover ratio indicates that shareholders dispose of their shares easily. As a result, the emotional effect on shareholders of the stocks with high turnover ratios disappears rapidly.

The first fifteen years and last ten years of my sample period present

different portraits of the stock market. From 1986 to 2000, the average market returns were above one percent and the risk-free rate was quite high. In addition, liquidity was low, and trading costs, including commissions, were high. In the second half of my sample period, 2001 to 2010, the market returns and risk-free rate were lower, and the tick size was decimalized.

[Table 4.10]

Period	Excess Return	Alpha
1986-2000	**1.449%**	**1.430%**
	(3.49)	**(3.53)**
2001-2010	**1.803%**	**2.049%**
	(3.37)	**(3.76)**
1986-2010	**1.590%**	**1.750%**
	(4.85)	**(5.41)**

Table 4.10 shows the average excess returns and the alphas of the long/short portfolios based on the synergies between the two psychological effects. Excess returns and alphas are presented as monthly percentages, t-statistics are listed below the coefficient estimates, and 5% statistical significance is indicated in bold. Despite these differences, the average excess returns and alphas were highly significant and positive in both subperiods.

Illiquidity can lead to the misinterpretation of stock returns. Less-frequently traded stocks exhibit improper price fluctuation, which results in misleading return behavior. It is not realistic to include low price stocks, which

obviously have intolerably large bid-ask spreads, in portfolio formation. I chose stocks that satisfied two conditions on the last business day of every month to reduce the potential for misleading effects of illiquidity. The selected stocks are traded on more than 99% of the business days during the previous one year, and their tick sizes[8] are less than 0.5% of their stock prices. I built a long/short portfolio based on the synergies between two psychological effects without illiquid stocks. I used 252 business days as the mean lifetime of the time-decaying function. The average rate of excess returns was 1.675% with a t-Statistic of 5.24, and alpha was 1.772% with a t-Statistic of 5.88. Although illiquid stocks were excluded, the long/short portfolio still yielded statistically significant positive returns.

[Table 4.11]

a) Tick size of NYSE

Tick Size	$0.125	$0.0625	$0.03125
Before	≥ $1.00	< $1.00	< $0.25
Jun-97	▪	> $0.50	< $0.50
Jan-01	Decimalization (Tick Size = $0.01)		

b) Tick size of NASDAQ

Tick Size	$0.125	$0.0625	$0.03125
Before	≥ $10.00	< $10.00	< $5.00
Jun-97	▪	≥ $10.00	< $10.00

[8] Table 4.11 shows the history of the minimum tick size in NYSE, NASDAQ, and AMEX. (Wu, Y. et al. 2011, Chung and Chuwonganant 2004, U.S. Securities and Exchange Commission 2012)

Apr-01	Decimalization (Tick Size = $0.01)

c) Tick size of AMEX

Tick Size	$0.125	$0.0625	$0.03125
Before	≥ $1.00	< $1.00	< $0.25
Sep-92	≥ $5.00	< $5.00	< $0.25
Feb-95	≥ $10.00	< $10.00	< $0.25
May-97	▪	≥ $0.25	< $0.25
Jan-01	Decimalization (Tick Size = $0.01)		

4.4 Summary

I suggests that overconfidence and risk aversion can induce changes in the supply of shares, leading to return predictability. A future stock return depends on both the degree of confidence and the degree of risk aversion. If most of the current shareholders are overconfident (diffident), the supply of shares in the market will decrease (increase). As a result, the future returns of stocks held by sanguine investors will be higher than those of stocks held by shareholders whose confidence is shaken; conversely, if most of the current shareholders avoid risk (seek risk), the supply of shares in the market will increase (decrease). Therefore, the future returns of stocks held by more risk takers will be relatively higher than those of stocks held by fewer risk takers. This paper provides empirical tests of these hypotheses.

I propose the use of two new measures to estimate the degree of overconfidence and the degree of risk aversion for individual stocks that rely

on historical stock prices and trading volumes. The two new concepts ‘anchored return’ and ‘perceived return’ are used to isolate the influence of two competing psychological effects. The anchored return is the yield from the purchase price to the reference price, and the perceived return is the return from the reference price to the current price. The anchored return and perceived return are linked to the effect of overconfidence and the influence of risk aversion, respectively.

The empirical tests of my estimator strongly indicate the influence of these factors. Using double sorts based on the degree of overconfidence and the degree of risk aversion, we find that the average portfolio returns increase monotonically as the degree of overconfidence increases. Conversely, the average portfolio returns decrease monotonically as the degree of risk aversion decreases. Using the Fama-French three-factor model, we find that the abnormal portfolio returns are separate from capitalization, book-to-equity, and market returns.

The largest positive abnormal returns are achieved with a higher degree of overconfidence and a lower degree of risk aversion, and the stocks with a lower degree of overconfidence and a higher degree of risk aversion have negative returns and strong negative alphas. Based on the positive and negative synergies between the degree of overconfidence and the degree of risk aversion, we can build a long/short stock portfolio that is long in stocks with a higher degree of overconfidence and a lower degree of risk aversion and that is short in stocks with a lower degree of overconfidence and a higher degree of risk aversion. This portfolio has strong positive returns and

alphas under various conditions: different sizes of capitalization, different levels of turnover ratio, two subperiods of sample data, and illiquidity limitations. However, the stocks with a high turnover ratio have no statistically significant returns. The high turnover indicates frequent changes on the part of the shareholders for a stock, which makes it difficult to interpret the overall emotional status of these shareholders.

The extant literature has presented extensive evidence of the relationship between trading activity and prior returns. Both overconfidence and risk aversion are positively correlated with prior returns. As mentioned in Chou and Wang (2011), the risk attitudes of overconfident investors and risk-averting investors are directly opposed to each other. Our aim is, using the proposed estimators of overconfidence and risk aversion, to provide a reasonable explanation for investor risk attitudes. Our findings indicate that overconfidence is related to the purchase price and the reference price anchored in the investor's mind and that risk aversion is linked to the yield from the reference price to the current price.

Chapter 5. Conclusion

For psychological and emotional reasons, human beings do not always make decisions rationally. The vagarious nature of human behavior has been studied in psychology, economics and even finance.

A number of papers in the finance literature have proposed behavioral theories

to account for asset pricing anomalies. To provide support for their models' assumptions about investor behavior, these papers draw heavily on the experimental psychology literature, in which evidence of cognitive biases is abundant.

On the one hand, behavioralists contend that this evidence has been important in prompting researchers to consider heterodox explanations of market anomalies. On the other hand, skeptics argue that there exists so much of such evidence that behavioralists can "psycho-mine" the experimental psychology literature to find support for the particular set of assumptions that allow their models to match otherwise anomalous data. Contributing to the skeptics' argument, many of the behavioral theories rely on biases that are quite different from each other and often produce opposite conclusions about investor behavior. Not surprisingly, strong demand has emerged for empirical work that identifies which of the biases, if any, influences investor decisions. Even stronger is the demand to determine whether these biases are merely a curious aspect of certain market participants' behavior or whether they have important consequences for prices. This paper supplies evidence about both of these issues.

Empirical tests of behavioral models face a number of challenges. First, the models cannot be easily tested with aggregate data. As noted by Campbell (2000), "[Behavioral models] cannot be tested using aggregate consumption or the market portfolio because rational utility-maximizing investors neither consume aggregate consumption (some is accounted for by nonstandard investors) nor hold the market portfolio (instead they shift in and out of the

stock market)". As a result, testing behavioral models is quite difficult without detailed information on the trading behavior of market participants. Unfortunately, given the issues of confidentiality associated with such data, availability of such information is generally quite low. An additional difficulty is that an investor's horizon, while highly ambiguous in most empirical settings, represents a key dimension in behavioral models. For instance, when fund managers are averse to losses, it is not clear whether their aversion relates to returns at the monthly, quarterly, or annual horizons, or even whether they view losses on positions taken recently as equivalent to losses on positions entered into years ago. Finally, even if biases can be identified in investor behavior, to demonstrate that this is more than just instances of noise trading, empirical tests must be positioned to identify a link between biases in individual trader behavior and overall prices.

Naïve reinforcement learning is a simple probable principle for learning behavior in decision problems. The investors who follow the naïve reinforcement heuristics, 'Naïve Learners', pay more attention to their experiences of actions and payoffs than other factors that are considered by rational investors. Naïve learners are pleased to repeat the actions that was successful and avoid to repeat the investment decision which was painful.

In recent years, a number of researchers have presented the evidence of naïve learners and the characteristic of their investment decisions. Based on the findings of these works, we propose a proxy to estimate the influence of naïve reinforcement learning on the future stock return. We build long/short

portfolio using the distinction between the proxy values of assets and find the average monthly return is more than 1.5% over 20 years in US Stock market. Our empirical results are economically and statistically significant even after controlling various risk factors such as size, value, profitability, investment pattern, turnover ratio, short-term return, and long-term return.

The risk attitudes of overconfident investors and risk-averting investors are directly opposed to each other. To isolate these two conflicting concepts, we use the reference price as the psychological anchoring position. Overconfidence is related to the purchase price and the reference price, and risk aversion is linked to the reference price and the current price. We propose two measures to estimate overconfidence and risk aversion of all shareholders for each stock in the US stock market. The degree of overconfidence is positively related to future stock returns, and the degree of risk aversion is negatively related to them.

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Abstract

Modeling Behavioral Biases of Stock Investors

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For psychological and emotional reasons, human beings do not always make decisions rationally. The vagarious nature of human behavior has been studied in psychology, economics and even finance. In the stock market, behavioral biases interrupt the price equilibrium process and cause price momentum.

In my thesis, I concentrate on three behavioral biase; naïve reinforcement learning, overconfidence and risk aversion. Naïve reinforcement learning is a simple probable principle for learning behavior in decision problems. The investors who follow the naïve reinforcement heuristics, 'Naïve Learners',

pay more attention to their experiences of actions and payoffs than other factors that are considered by rational investors. Naïve learners are pleased to repeat the actions that was successful and avoid to repeat the investment decision which was painful. I also focuse on two psychological phenomena, overconfidence and risk aversion, to examine the emotional process of evaluating gains and losses. Overconfidence is one of the most documented biases (Daniel and Titman 2000). Investors who are overconfident in their investing abilities are more willing to make risky decisions. Conversely, risk aversion is the tendency of investors to avoid risky choices. To address these two conflicting concepts, overconfidence and risk aversion, I use the reference price as the pivot position for psychological recognition by investors.

I propose three proxies; PNLR (Proxy of Naïve Reinforcement Learning), DOC (Degree of Overconfidence) and DRA (Degree of Risk Aversion). These proxies are estimating the behavioral biases of irrational investors. Furthermore, they can predict future stock returns. The empirical results are economically and statistically significant even after controlling various risk factors such as size, value, profitability, investment pattern, turnover ratio, short-term return, and long-term return.

Keywords: Behavioral Finance, Disposition Effect, Naïve Reinforcement Learning, Stock Market

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