ESSAYS ON STOCK ANOMALIES AND EQUITY FUND PERFORMANCE

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Dedication

Dedicated to my family - for their unconditional support, love and sacrifice.

Abstract

My dissertation focuses on understanding the behavior of participants in financial markets and the cross-sectional variation in the returns of financial assets. In particular, I examine: a) how the interaction between managers and investors in the equity fund industry affects fund performance, b) how the behavioral biases of investors in the equity market are associated with stock returns that are not well captured by standard risk factor models.

Chapter one investigates the role of diseconomies of scale in mutual fund performance. I argue that there are two crucial aspects that are related to subsequent performance. In addition to the well-known metrics based on past returns (i.e., α and tracking errors), I demonstrate that managerial ability to overcome diseconomies of scale is also a key factor. I propose two new proxies for the degree of diseconomies of scale by contrasting two types of past success, namely, accumulated success in industry exploration (i.e., buying stocks from unknown industries) and accumulated success in industry exploitation (i.e., buying stocks from familiar industries). Accumulated success in industry exploration, representing low degree of diseconomies of scale, plays a significant positive role in absorbing fund inflows, leading to good and persistent benchmark-adjusted performance in the subsequent period. By sharp contrast, accumulated success in industry exploitation, representing high degree of diseconomies of scale, does exactly the opposite. Although these results suggest the importance of different degrees of diseconomies of scale in fund performance, I find that only investors in good performing funds realize their distinction.

Chapter two, coauthored with Jianfeng Yu, examines the profitability premium. Previous studies show that the profitability-based factor can explain almost all asset pricing anomalies, highlighting the importance of firm profitability. This paper investigates both risk-based and behavioral-based explanations of the profitability premium itself. First, we show that there is moderate support for risk-based structural models with shareholder advantage and investment flexibility. Second, the profitability premium exists primarily among firms with high arbitrage costs or high information uncertainty. Third, the majority of the profitability premium is derived from the negative alpha of low profitability firms, consistent with the notion that overpricing is more prevalent than underpricing due to greater impediments to short. Finally, portfolio return behavior around earnings announcements suggests that investor underreaction and limits-to-arbitrage are partially responsible for the profitability premium.

Chapter three, coauthored with Jinghua Yan and Jianfeng Yu, studies the cross-sectional risk-return tradeoff in the stock market. The fundamental principle in finance posits a positive relation between risk and expected return, whereas recent empirical evidence suggests that low-risk firms tend to earn higher average returns. We apply prospect theory to shed light on this violation of this fundamental principle. Prospect theory posits that when facing prior loss relative to a reference point, individuals tend to be risk-seeking, rather than risk-averse. Consequently, among stocks where investors face prior losses, there should be a negative risk-return relation. By contrast, among the stocks where investors face capital gains, the traditional positive risk-return relation

should emerge since investors of these stocks are risk averse. Using several intuitive measures of risk, we provide empirical support for our hypotheses. The role of prospect theory in the idiosyncratic volatility puzzle is also discussed.

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Chapter 1

The Role of Exploration and Exploitation in Diseconomies of Scale in the Mutual Fund Industry

1.1 Introduction

It is widely believed that the mutual fund industry is subject to capacity constraints.[1] When fund assets exceed the maximum size that a manager can efficiently run, the failure to quickly identify new undervalued stocks to absorb additional money inflows can induce

[1] In this paper, "capacity," "economies of scale," and "scalability" are equivalent terms. In particular, large "capacity" has the same meaning as high degree of "diseconomies of scale',' and better "scalability".

costs that disproportionately increase in scale. Typical examples of such costs include high bid-ask spreads from scaling up existing holdings and unwanted opportunity costs from holding too much cash.

Although this phenomenon is disappointing to fund investors, Berk and Green (2004) explain it as precisely the driving force that leads the competitive capital market to reach its efficient equilibrium. In their model, fund managers have different skills, *defined* as the ability to generate benchmark-adjusted returns (i.e., α) *before* incurring additional costs from asset growth. These costs are further assumed to be beyond managers' control. Assume that fund investors provide capital competitively with an infinite elasticity, the expected return (i.e., the benchmark-adjusted return *after* deducting all expenses) has to be zero across all funds in equilibrium. Rational fund flows flock into more skilled managers, who then end up with larger assets under management and pay higher costs to scale, compared to their less skilled peers.

By introducing an exogenous wedge between true managerial skills and expected returns to investors, this parsimonious framework successfully reconciles many regularities, such as the existence of superior managerial ability, the rationality of fund flows, and the lack of persistence in fund performance. However, instead of this ideally efficient scenario in which money instantly flows into good-performing funds to the point where the induced costs from asset growth just offset any positive expected returns, in reality flow adjustment often takes much longer and is far more complicated. Given that costs to scale decrease the payout to investors in all cases, the dynamics of gradual flow adjustment implies that different degrees of diseconomies of scale would matter as well. In other words, if funds are also different in their ability to absorb money inflows and to overcome negative scale effect, then a careful examination of this wedge is worthwhile.

In light of the previous analysis, this paper investigates the impacts of diseconomies of scale on fund performance and flow-performance sensitivity.[2] To accomplish this goal, the first and most important step is to construct empirical proxies for different costs to scale. In particular, I contrast two types of investment activities and argue that they reflect different degrees of diseconomies of scale. Imagine an investment process that typically involves a decision among three options: the first to increase existing ownership shares in the portfolio (i.e., expansion in familiar industries); the second to buy new stocks from industries in which the portfolio previously held some positions in the past (i.e., *exploitation* of familiar industries); and the third to buy new stocks, but from industries in which the portfolio never held a position (i.e., *exploration* of new industries). Although all of these options might have contributed to good performance in the past, their successes have different implications for scalability and subsequent performance. While the option of a simple scale-up of existing ownership shares is most likely to induce high costs to scale because of price impact or liquidity constraints, the other two options, although both involving the purchase of new stocks, turn out to have different effects as well, due to their different industry preferences. Compared to successful industry exploitation, successful industry exploration is more likely to help

[2]To be succinct, the term"fund performance" in this paper refers to "expected return to fund investors," which is the benchmark-adjusted return deducting all expenses, unless explicitly specified otherwise.

keep good performance momentum for at least four reasons.

First of all, funds with more success in industry exploration are expected to have larger capacity to absorb money inflows than funds with more success in industry exploitation. More success in industry exploration suggests that there are more good investment ideas from a broader range of industries, indicating more flexibility to allocate new money inflows. By sharp contrast, though the investment in undervalued stocks at the top of the investment list might bring in past success in industry exploitation, this success couldn't be sustained, given that additional money inflows require the execution of suboptimal ideas further down the list.

In addition to this better scalability, more success in industry exploration also reflects superior intrinsic managerial ability. Achieving success in industry exploration is presumably more difficult and requires additional skills than doing the same in industry exploitation. Since different industries have specific characteristics, so existing models are usually not reliable enough in valuations of new industries. That is, successful exploration of a new industry indicates the accomplishment of several demanding tasks, such as collecting relevant information on industry fundamentals, doing thorough data analysis, developing accurate prediction models, and so on. Thus, this success shows the evidence of superior skills to some extent.

Moreover, successful industry exploration also helps to improve scalability over time. The experience of successfully exploring a new industry itself is a good opportunity to further learn and polish skills in how to efficiently explore unknown areas and generalize valuation models. In the spirit of learning-by-doing, the accumulation of such experience helps to increase the maximum capacity of funds as well. However, past success in industry exploitation is less likely to fulfill this function of climbing the steep learning curve of exploring unknown areas.

Lastly, the advantage of success in industry exploration over success in industry exploitation will be even more significant if fund investors fail to fully understand their distinction. Suppose some (not necessarily all) investors only rely on past performance to infer managerial ability. Then on average, funds with more success in industry exploration will have too few inflows relative to their true ability, implying that their good performance is likely to continue, whereas funds with more success in industry exploitation will have too many inflows relative to their true ability, inducing even higher costs to scale.

According to this conjecture, I construct two measures from fund trading history, namely, accumulated success in industry exploration and accumulated success in industry exploitation, to proxy for low and high costs to scale, respectively. My initial tests confirm their different implications for scalability. Although the choice between industry exploration and industry exploitation is highly predictable in response to money inflows, only the success in industry exploration is persistent.

Based on this initial analysis, I proceed to examine the impact of fund scalability on performance. The results are intriguing. In response to money inflows, accumulated success in industry exploration positively predicts subsequent performance, whereas accumulated success in industry exploitation has the opposite effect. Given 1% additional fund inflows, one standard deviation of accumulated success in industry exploration increases returns in the subsequent quarter by roughly 40 basis points, whereas one standard deviation of accumulated success in industry exploitation reduces returns in the subsequent quarter by around 50 basis points. This contrast indicates the importance of managerial skill in overcoming diseconomies of scale in determining investment outcome.

Furthermore, the distinction between these two types of past success suggests a way to test investor rationality by examining flow-performance sensitivity. Intuitively, sophisticated investors should be aware of their difference and react accordingly. Confirming previous studies on investor rationality, my results also show a significant variation: investors in good-performing funds appear to be more responsive to accumulated success in industry exploration than to accumulated success in industry exploitation. By sharp contrast, those investors in poorly performing funds treat these successes as the same and are reluctant to withdraw capital regardless.

In sum, my empirical results show strong support for the heterogeneity of diseconomies of scale among mutual funds. A lower degree of diseconomies of scale, represented by more accumulated success in industry exploration, leads to better performance and attracts more money inflows from rational investors.

The rest of the paper is organized as follows. Section 1.2 reviews the literature. Section 1.3 describes the data and defines key variables. Section 1.4 presents the empirical results. Section 1.5 reports several robustness checks, and Section 1.6 concludes.

1.2 Literature Review

This paper is related to three strands of mutual fund literature. The first set is primarily interested in the question of the existence of superior managerial skills. Unfortunately, this question doesn't yet have a universally accepted answer. On the one hand, studies as early as Jensen (1968) and Gruber (1996), and more recently Fama and French (2010), all fail to find persistence in fund performance. As a result, they suggest that good performance is attributable to luck. On the other hand, several factors have been proposed to predict performance, such as the industry concentration index in Kacperczyk et al. (2005) and active share in Cremers and Petajisto (2009), which shed light on both the existence and source of managerial talents. Despite considerable debate on the empirical side, the picture is less ambiguous on the theory side. Based on the assumption that the mutual fund industry features diseconomies of scale, Berk and Green (2004) reconcile the existence of managerial talents and the lack of persistence in performance in a rational and competitive framework.

The Berk and Green model sparked another host of empirical studies on the relation between fund scale and performance, and the underlying sources of diseconomies of scale if it exists. For example, Chen et al. (2004) find that small funds tend to outperform large ones after controlling for other observable characteristics. Their tests further suggest liquidity and organizational diseconomies as two potential reasons that explain diseconomies of scale. More recently, Edelen et. (2007), after a careful analysis on fund trades along with brokerage commissions and transaction costs on a stock-level basis, infer that diseconomies of scale are caused by the detrimental effect from high agency-motivated trading costs induced by soft dollar relations.

Besides the previous two streams of studies on fund performance, there is also a huge literature on the behavior of fund investors. The general finding is that a large variation exists in investor rationality. At one extreme, Elton et al. (2004) and Berk and Tonks (2007) notice the pattern of return persistence in inferior index funds and the worst-performing actively managed equity funds, suggesting the unwillingness of investors to withdraw capital even from funds in losses. At the other extreme, there is also substantial evidence for the "smart" money effect among well-performing funds. Gruber (1996), Zheng (1999), and Wermers (2003) all document that the benchmark-adjusted short-term performance of funds with money inflows is significantly better than the performance of funds with money outflows.

Complementary to existing literature, this paper emphasizes another aspect of managerial ability, that is, the ability to overcome diseconomies of scale. To the extent that fund investors are subject to the negative externality from asset growth, diseconomies of scale is essentially a meaningful topic to pursue. Unlike studies aiming to track down the sources of diseconomies of scale, this paper focuses on certain behavior that might help to mitigate it. Moreover, the proposed empirical measures are both intuitive and straightforward as well. In fact, the contrast of exploration versus exploitation has received significant attention from scholars interested in organizational behavior for decades. Successful exploration is generally believed to connect to "flexibility and innovation" and generate routines that facilitate future exploration, whereas successful exploitation is blamed for creating inertia and building over-confidence.[3] Finally, this paper adds a new factor to the set of factors that fund investors should take into account when selecting funds. Besides popular indicators such as past performance and tracking errors, more subtle but critical elements (e.g., funds' capacity to absorb money inflows) deserve attention as well.

1.3 Data

1.3.1 Fund Characteristics

The data used in this study comes from four sources. Thomson/CDA holdings database includes information on fund equity holdings.[4] CRSP Survivorship Bias Free Mutual Fund Database contains information on fund assets under management (TNA), net returns (RET), expense ratio (EXP), turnover ratio (TURNOVER), and investment objectives. Fund flow is defined as the growth rate of fund assets adjusting for appreciation based on the assumption that all cash flows are invested at the end of the period:

$$Flow_t = \frac{TNA_t - TNA_{t-1} \times (1 + RET_t)}{TNA_{t-1}}.$$

[3] For example, King and Tucci (2002), Winter (2003), March (1991), Levinthal and March (1993), Benner and Tushman (2002), Eggers and Jung-Hyun (2011), and Eggers (2012).

[4] Before 1985, all funds were required to report their holdings quarterly. Although funds were required to report their holdings only semiannually after 1985, Wermers (1999) points out that the majority of funds choose to continue to report holdings to Thomson/CDA on a quarterly basis.

These two datasets are merged using WRDS MFLinks table. I also match each reported stock holding to CRSP stock database in order to find its price, return, and industry classification code. The industry classification follows Fama-French 48 industry definition.

The sample spans the period from January 1980 to December 2010. My empirical analysis primarily focuses on actively managed diversified equity funds in the United States, so I first eliminate balanced, bond, index, international, commodity, and sector funds. Next, I exclude all fund observations where fund size in the previous quarter does not exceed \$5 million or where fewer than 11 different stock holdings are identified.[5] Finally, I eliminate the duplicated funds and compute the fund-level variables by aggregating across the different share classes for funds with multiple share classes.[6] After all of these exclusions, my final sample includes 3,001 funds over a 30-year sample period.

The top part of Panel A in Table 1.1 reports the summary statistics of basic fund characteristics. Largely consistent with prior studies, the mutual fund industry exhibits significant cross-sectional variation. Fund flow shows an asymmetric pattern that good-performing funds have heavy inflows, whereas poorly performing funds suffer less severe outflow. Also note that compared to fund asset growth, funds appear to be reluctant to increase the number of both stocks and industries in portfolio holdings, with the median

[5] The Investment Company Act, 1940, section 5(b)1 defines a fund as diversified if no more than 5% of its assets are invested in any one company's securities and it holds no more than 10% of the voting shares in any one company. Thus, funds with fewer than 10 equity holdings, if diversified, must have less than half of assets under management allocated to equities.

[6] For most variables, I use a value-weighted average for the fund-level observations. For fund age, I use the oldest of all share classes. This method for aggregating different class shares is a common treatment in previous studies; See Kacperczyk, Sialm and Zheng (2008).

being only 64 and 24, respectively.

1.3.2 Performance Measures

I use both factor-based and holding-based measures to evaluate fund performance.

Fama-French-Carhart α: This measure is based on factors identified by Fama and French (1995) and Carhart (1997) (hereafter, the Fama-French-Carhart model), which include market, value, size, and momentum factors.[7] Since investors can relatively costlessly mimic the strategy on which this model is based, returns adjusted by this benchmark reflect managerial ability. Monthly α is monthly fund net return minus each fund factor loading multiplied by its respective factor return. Fund factor loadings are estimated from regressions of monthly portfolio returns of the stocks held in the fund (using the most recently available data on portfolio holdings from Thomson/CDA) on the Fama-French-Carhart model for the previous 36 months. The cumulative monthly α within each quarter is the quarterly α of each fund.

DGTW Characteristic-adjusted Measures: I also construct two holding-based measures, CS and CT, following Daniel, Grinblatt, Titman, and Wermers (1997) (hereafter, DGTW).

CS (characteristic selectivity) denotes the stock selection ability, that is, whether stocks in fund portfolios earn higher returns than benchmark portfolios of stocks that are matched to each of the fund's stock holdings every quarter along the dimensions of size,

[7] All data on factors were taken from Kenneth French's website: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library`.

book-to-market ratio, and momentum:

$$CS_t = \sum_j w_{j,t-1}[R_{j,t} - BR_t(j, t-1)],$$

where $R_{j,t}$ is the return of stock j during period t; $BR_t(j, t-k)$ is the return of the benchmark portfolio during period t to which stock j was allocated during the period $t-k$ according to its size, value, and momentum characteristics; and $w_{j,t-k}$ is the relative weight of stock j at the end of period $t-k$ in fund portfolio holdings.

CT (characteristic timing) denotes the style-timing ability, that is, whether fund managers can generate additional performance by exploiting time-varying expected returns of the size, book-to-market, or momentum benchmark portfolios:

$$CT_t = \sum_j [w_{j,t-1} BR_{j,t-1} - w_{j,t-5} BR_t(j, t-5)].$$

The middle section of Panel A in Table 1.1 presents the summary statistics of time-series averages of fund net returns, Fama-French-Carhart α, CS, and CT, all in percentage and quarterly frequency. The mutual fund industry obviously shows a striking variation in performance. For example, in the case of net returns, investors of the best-performing funds earn roughly 20% per quarter, that is, more than 80% per year, whereas investors of the worst-performing funds lose almost 15% per quarter. In addition, both the mean and the median Fama-French-Carhart α are negative, suggesting that on average, actively managed funds fail to beat the standard four-factor model.

Finally, confirming DGTW, the ability of managers appears to be better when they are evaluated by their holdings-based performance.

1.3.3 Experience Measures

This subsection describes the procedure for constructing my empirical proxies for different costs to scale. As argued in the introduction, depending on the driving force, past success includes varying information about the scalability of funds. In particular, I contrast two activities, industry exploration vs. industry exploitation, which represent low and high costs to scale, respectively. To avoid redundancy, whenever there is no confusion, "industry exploration" and "industry exploitation" are correspondingly abbreviated as "exploration" and "exploitation" in the future, unless explicitly specified otherwise.

The measures of experience is constructed following a three-step process (see the timeline in Figure 1).

Step 1. Define exploration and exploitation (identification quarter): First, I compare fund holdings in two subsequent quarters to identify all newly purchased stocks. For each of these newly purchased stocks, the stock is categorized as exploration if it belongs to a new industry (i.e., an industry in which the fund had never held a position since its establishment). Otherwise, it is categorized as exploitation.[8] As an example, consider the JP Morgan small-cap value fund. Comparing its portfolio holdings in 1996Q4 and

[8]The first quarter that a fund appears in the sample is excluded to avoid the potential bias from categorizing all of its holdings to be exploration, but all results still carry through even if I include it.

1997Q1, I notice 15 newly added stocks, 3 of which are in industries that had never existed in its portfolio since it launched in September 1995. Therefore, these 3 stocks are considered as 3 counts of exploration in 1997Q1; similarly, the other 12 purchases are 12 counts of exploitation.

Step 2. Define the quarterly success of exploration and exploitation (evaluation quarter): A newly-purchased stock is counted as a success if its return is higher than the return of a pre-specified benchmark in the subsequent quarter. Otherwise, it is counted as a failure. In the main tests, this benchmark is chosen to be the gross return (i.e., net return adding back expense) of the median fund within the same investment objective category. The CRSP Survivorship Bias Free Mutual Fund Database provides information on fund investment objectives. Depending on data availability, I use the Wiesenberger style codes before 1992, the Strategic Insight objective codes from 1993 to 1999, and the Lipper objective codes from 1999 onward.

Choosing this benchmark has at least three advantages: First, from a risk perspective, funds within the same investment objective category are more likely to be exposed to the same underlying risks. As a result, the median fund is a good candidate to control for potentially unobservable risks. In addition, a typical fund selection process often starts with choosing a broad category such as large-cap value, mid-cap growth, and so on. Many popular fund consulting providers like Morningstar also use a similar classification system to categorize funds and give advice. Thus, in order to attract potential investors, it is especially important for a fund to beat the median and stay on the right side of the performance distribution of funds within its investment objective category. Finally, adding back expense ensures that the net outcome of this new stock purchase is above the median, which is essentially what fund investors earn.

After applying this procedure to all newly purchased stocks in each quarter, the quarterly success in exploration is computed as the fraction of successful stocks in exploration, and similarly for the quarterly success in exploitation. To continue with the JP Morgan small-cap value fund example, the benchmark in this case would be the median gross return of small-cap value funds. Comparing it to the quarterly return of each of the 15 newly purchased stocks in 1997Q2, I find 6 outperformers: 1 out of the 3 stocks in exploration and 5 out of the 12 stocks in exploitation. Therefore, the quarterly success measures in exploration and exploitation are 1/3 and 5/12, respectively.

Step 3. Calculate accumulated success in exploration and exploitation. For each fund in each quarter, accumulated success in exploration is the sum of all past quarterly success in exploration up to the previous quarter, and similarly for accumulated success in exploitation.[9] This pair of success measures then represent low and high costs to scale.

The bottom part of Panel A in Table 1.1 summarizes the time-series averages of the total number of newly purchased stocks, the number of newly purchased stocks in exploration and exploitation, and the accumulated success in each category. It is clear that, although the number of newly purchased stocks in exploration is far less than that in exploitation for the average fund, with only one-quarter of observations involved in the

[9]To be conservative, only the success until the previous quarter is taken into account because one additional quarter is needed to evaluate success.

whole sample, the difference of accumulated success between exploration and exploitation is much smaller.

1.4 Empirical Results

This section presents the main empirical results. I start with some preliminary analysis on how the two success measures from the pervious section are associated with different costs to scale. Then I proceed to investigate their implications for subsequent performance and flow-performance sensitivity.[10]

As mentioned in the introduction, success in exploration differs from that in exploitation in at least two aspects. First, successful exploration of a new industry is arguably more challenging than successful exploitation of familiar industries. Hence, the achievement of success in exploration signals managerial talent to some degree. More remarkably, the repetition of the exact experience in successful exploration has great potential to create a mutually reinforcing cycle in the spirit of learning-by-doing. This reinforced efficiency in flexibly identifying undervalued stocks from all industries, both new and familiar, would play a remarkable role, especially when there is a large influx of capital. By contrast, accumulated success in exploitation is more likely to result in involuntary investment in suboptimal ideas from the bottom of an investment list based on a few familiar industries. Taken together, these results suggest that compared to accumulated success in exploitation, accumulated success in exploration implies lower

[10] In Appendix, I derive a simple variation of the Berk and Green model to show that my empirical results are consistent with their model's predictions as well.

costs to scale.

To formally test this conjecture, I propose the following hypothesis.

Hypothesis 1: In response to money inflows, accumulated success in industry exploration encourages future participation in the same activity and this success tends to continue, whereas accumulated success in industry exploitation only predicts future participation in industry exploitation, not future success in it.

The basic idea behind this hypothesis is as follows. Whereas the likelihood to engage in certain activity is relatively constant and predictable, only success in exploration is persistent. This distinction is particularly striking when interacted with money inflows. In order to test this preliminary hypothesis, I run two sets of regressions. The first set is the logistic regression of a general form to estimate the probability of participation in exploration or exploitation:

$$
\begin{aligned}
Prob_{i,t+1} = f(&\beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Flow^{+}_{i,t} \times EXPLORE_{i,t} \\
&+ \beta_4 \times Flow^{+}_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Flow^{-}_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Flow^{-}_{i,t} \times EXPLOIT_{i,t} \\
&+ \beta_7 \times Flow^{+}_{i,t} + \beta_8 \times Flow^{-}_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} \\
&+ \beta_{12} \times TURNOVER_{i,t} + \beta_{13} \times N(INDUSTRY)_{i,t} + \beta_{14} \times N(STOCK)_{i,t} + \varepsilon_{i,t+1}),
\end{aligned}
$$

where the subscript i and t represent the fund and the time, respectively. The regressor $Prob$ denotes the probability of exploration $Prob(EXPLORE)$ or exploration $Prob(EXPLOIT)$ in the two regressions. $Flow^{+}$ and $Flow^{-}$ represent positive and negative fund flows, and $EXPLORE$ and $EXPLOIT$ correspond to accumulated success in exploration and exploitation. A number of fund characteristics and quarter time fixed effects are also included in the regression as control variables.[11]

The second set is the panel regression of a general form to estimate quarterly success in exploration or exploitation:

$$\Delta SUCCESS_{i,t+1} = \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Flow^+_{i,t} \times EXPLORE_{i,t}$$

$$+ \beta_4 \times Flow^+_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Flow^-_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Flow^-_{i,t} \times EXPLOIT_{i,t} + \beta_7 \times Flow^+_{i,t}$$

$$+ \beta_8 \times Flow^-_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} + \beta_{12} \times TURNOVER_{i,t} + \varepsilon_{i,t+1},$$

where the regressor $\Delta SUCCESS$ denotes the quarterly success of exploration $\Delta EXPLORE$ or that of exploitation $\Delta EXPLOIT$ in the two regressions. A number of fund characteristics and quarter time fixed effects are included. Standard errors are clustered at the fund level. These regressions are implemented in both the whole sample and a subsample that only includes observations engaged in exploration or exploitation in the current quarter.

Tables 1.2 and 1.3 present the regression results. It is clear from the first column of Table 1.2 that unconditionally, accumulated success in exploration encourages future exploration, whereas accumulated success in exploitation strongly discourages it. Conditionally, the positive coefficients on the two interaction terms including $Flow^+$ indicate that this tendency is more obvious in response to money inflows when it is more urgent that funds come up with new investment ideas. The significant coefficients on the two interaction terms including $Flow^-$ show similar exploratory momentum even in response to money outflows. Moreover, the opposite pattern is revealed in the second

[11] Continuous variables are winsorized at 1% and 99% in case of outliers.

column of the exploitation regression. Finally, coefficients on other control variables are largely consistent with the intuition. For example, smaller and younger funds tend to be more active in exploring new industries, probably because they have more unexplored industries and are generally more flexible. Viewed as a whole, this table lends strong support to the possibility that the decision on exploration or exploitation is linked to some intrinsic trait of funds.

Regarding the second set of regressions, the results in Table 1.3 confirm the hypothesis as well. In both the whole sample and the subsample, accumulated success in exploration strongly predicts its subsequent success, especially in response to inflows, whereas accumulated success in exploitation does the opposite. These results are consistent with a scenario in which success in exploration itself signals prior managerial ability or the accumulation of such success helps improve managerial ability, or both. On the contrary, none of these patterns show up in the predictive regression of success in exploitation, suggesting that for funds focusing on exploitation, though they may have been successful in the past, this success is not a lasting phenomenon, especially when a large influx of capital forces them to invest in suboptimal ideas from the bottom of their investment lists.

Overall, the evidence above indicates the link between two measures of accumulated successes and different costs to scale. Using these empirical proxies, I next investigate the impacts of different scalability on subsequent performance. Lower costs to scale is expected to absorb fund inflows more efficiently and lead to better subsequent performance. Formally, I test the following hypothesis:

Hypothesis 2 (Performance Prediction): In response to money inflows, accumulated success in industry exploration positively predicts subsequent performance, but accumulated success in industry exploitation does not.

To test this hypothesis, I estimate panel regressions of a general form:

$$
\begin{aligned}
& PERF_{i,t+1} = \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Flow^{+}_{i,t} \times EXPLORE_{i,t} \\
& + \beta_4 \times Flow^{+}_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Flow^{-}_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Flow^{-}_{i,t} \times EXPLOIT_{i,t} \\
& + \beta_7 \times Flow^{+}_{i,t} + \beta_8 \times Flow^{-}_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} \\
& + \beta_{12} \times TURNOVER_{i,t} + \beta_{13} \times N(STOCK)_{i,t} + \beta_{14} \times N(INDUSTRY)_{i,t} + \beta_{15} \times ICI_{i,t} + \varepsilon_{i,t+1},
\end{aligned}
$$

where the regressor $PERF$ denotes each of three alternative performance measures, Fama-French-Carhart α, CS, and CT, as described in Section 1.3.2. ICI is the Industry Concentration Index in Kacperczyk et al. (2005), computed as the sum of the square of the difference between the industry weights of a mutual fund holding and the total market portfolio. A number of fund characteristics and quarter time fixed effects are included. Standard errors are clustered at the fund level.

Table 1.4 presents the performance prediction regression results. Several interesting patterns can be observed: first, if two experiences are treated as the same, baseline regressions without success measures confirm the finding from previous studies that fund flow is barely related to future performance. After adding two measures of accumulated success along with their interaction terms with flows, accumulated success in exploration turns out to facilitate an efficient use of these money inflows. The coefficient on the interaction term of positive flows and accumulated success in exploration is positive and significant across all three specifications of performance. Nevertheless, accumulated success in exploitation jeopardizes fund performance when interacted with money inflows. Not only is this result statistically significant, but also the magnitude is economically meaningful. Consider for example, the regression of Fama-French-Carhart α. Given 1% additional fund inflows, one standard deviation of accumulated success in industry exploration increases returns in the subsequent quarter by roughly 40 basis points, whereas one standard deviation of accumulated success in industry exploitation reduces returns in the subsequent quarter by around 50 basis points. Moreover, the overall predictive power of the model also improves. Compared to the baseline predictive regression of CS, the adjusted R-square is increased by around 30% after including the success measures. This result makes sense, given that CS separates the stock selection ability from other abilities related to market or characteristic timing. In addition, the positive impact of accumulated success in exploration is weakest on CT among the three performance measures. This result is not surprising, given the failure to identify characteristic timing ability in previous studies. Finally, coefficients on other control variables are also reasonable. Although fund age, size, and expense ratio are negatively associated with future performance, the number of stocks, the number of industries, and the concentration of industries in fund holdings all play a positive role in generating returns.

Related to this test on the interaction of past successes with asset growth, another nature implication of cross-sectional variation in diseconomies of scale is in its impact on performance persistence. In particular, funds incurring lower costs to scale should have more persistent performance. To rephrase it in my empirical framework, this means that accumulated success in exploration is expected to play a positive role to help funds deliver persistent performance. Therefore, I have the following hypothesis:

Hypothesis 3 (Performance Persistence Prediction): Accumulated success in industry exploration leads to more persistent performance, but accumulated success in industry exploitation does not.

To test this hypothesis, one difficulty is to measure performance. As suggested by many existing studies, the answer to the question that whether fund performance is persistent or not is sensitive to the definitions of performance. To ensure my tests are general, I adopt two popular specifications: net returns (RET) and Fama-French-Carhart α, and allow both dependent variable (subsequent performance $PERF$) and independent variable (lag performance $Lagperf$) to take these values.[12] This treatment therefore leads to four possible sets of regressions. I estimate panel regressions of a general form:

$$
\begin{aligned}
PERF_{i,t+1} &= \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Lagperf^{+}_{i,t} \times EXPLORE_{i,t} \\
&+ \beta_4 \times Lagperf^{+}_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Lagperf^{-}_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Lagperf^{-}_{i,t} \times EXPLOIT_{i,t} \\
&+ \beta_7 \times Lagperf^{+}_{i,t} + \beta_8 \times Lagperf^{-}_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} \\
&+ \beta_{12} \times TURNOVER_{i,t} + \beta_{13} \times N(STOCK)_{i,t} + \beta_{14} \times N(INDUSTRY)_{i,t} + \beta_{15} \times ICI_{i,t} + \varepsilon_{i,t+1},
\end{aligned}
$$

quarter time fixed effects are included and standard errors are clustered at the fund level.

[12] In unreported tables, I also tried raw returns and found that results were very similar to the case of net returns.

Table 1.5 reports the regression results. Block (I) and (II) correspond to cases when the subsequent performance is measured by net returns and α, respectively. Within each block, the dependent variable is past performance defined by net returns in the first two columns and by α in the other two columns. A couple of intriguing points deserve some attention. First, if two experiences are treated as the same, baseline regressions without experience measures are consistent with existing studies: future net return is more predictable than future benchmark adjusted α, while past α has slightly higher predictive power than past net return. Moreover, the distinction between two experiences appears after including experience measures and their interaction terms with past performance. Accumulated success in exploration strongly contributes to keep fund performance momentum regardless, while accumulated success in exploitation plays a significantly negative role, especially among good performing funds.

Altogether, the results from previous two hypothesis highlight the central idea of this paper: not all success is the same; even though many funds might appear to be equally good investment opportunities in terms of past performance, they can have fundamental difference in the driving force and relevant experience behind the past success. Moreover, this difference turns out to be a crucial determinant for subsequent performance, especially in the case of large money inflows. Past success that is related to exploration is particularly valuable in helping funds to overcome negative impacts from asset growth and to deliver persistent performance.

Given the sharp distinction between the two accumulated success, this in turn provides a natural framework to examine investor rationality. Rational investors should be aware of the existence of different scalability and exhibit different flow-performance sensitivity. In other words, I have the following hypothesis:

Hypothesis 4 (Flow-Performance Sensitivity): Rational fund investors show higher flow-performance sensitivity to accumulated success in industry exploration than to accumulated success in industry exploitation.

I employ panel regressions of a general form:

$$Flow_{i,t+1} = \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times PERF^{+}_{i,t} \times EXPLORE_{i,t} + \beta_4 \times PERF^{+}_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times PERF^{-}_{i,t} \times EXPLORE_{i,t} + \beta_6 \times PERF^{-}_{i,t} \times EXPLOIT_{i,t} + \beta_7 \times PERF^{+}_{i,t} + \beta_8 \times PERF^{-}_{i,t} + \beta_9 \times LOGAGE_{i,t} + \beta_{10} \times EXP_{i,t} + \beta_{11} \times LOGTNA_{i,t} + \beta_{12} \times TURNOVER_{i,t} + \varepsilon_{i,t+1},$$

where $PERF$ represents lagged performance and takes each of two alternative measures: net returns (RET) and Fama-French-Carhart α. $PERF^{+}_{i,t}$ and $PERF^{-}_{i,t}$ represent positive and negative performance, respectively. The purpose of this specification is twofold: first, the distinction between positive and negative performance allows an asymmetric reaction of fund flows to good and poor performance, as widely documented in prior works (e.g., Sirri and Tufano (1998)). Second, investors might react to either benchmark-adjusted or unadjusted performance depending on how sophisticated they are, so it is better to test both measures of performance.

Table 1.6 reports the flow-performance sensitivity regression results. As expected, fund flow exhibits a strong reaction to recent performance unconditionally, regardless of the performance specifications. More interestingly, investors in good-performing funds appear to be aware of the distinction between two accumulated successes: although the coefficient on the interaction term of performance and accumulated success in exploration is positive and significant, the coefficient on the corresponding term of exploitation is significant with the opposite sign. This result makes sense, given that they are likely to be rational investors. In terms of magnitude, one standard deviation of accumulated success in exploration attracts almost another 2% of money inflows, given a 1% increase in fund performance, whereas one standard deviation of accumulated success in exploitation deters about 2.5%. However, a different pattern is observed among poorly performing funds, whose investors display a reluctance to withdraw money regardless. Altogether, these results confirm the conclusion from prior studies about the large variation in investor sophistication.

In sum, the empirical results in this section confirm the existence of heterogeneous diseconomies of scale and its different implications for fund performance. In particular, accumulated success in exploration corresponds to lower costs to scale than accumulated success in exploitation. Although on average fund flow is barely related to subsequent performance, accumulated success in exploration effectively helps to absorb money inflows, which in turn leads to better performance. On the contrary, accumulated success in exploitation, the signal of high costs to scale, has a significantly negative effect on future performance, especially when interacted with fund inflows. Under this framework, I look further into the question of investor rationality and notice some evidence of "smart money," but only among good-performing funds.

1.5 Additional Robustness Checks

This section conducts a series of additional tests to assess the robustness of the main results under different empirical specifications.[13]

The first variation is to use alternative benchmarks to define the success of a newly purchased stock as discussed in Section 1.3.3. Recall that Step 2 compares the return of every newly purchased stock to the benchmark of the gross return of the median fund within the same investment objective category. Instead of this benchmark, I adopt two alternative reference points here: one is the matching portfolio return from 125 DGTW (1997) passive portfolios (DGTW), and the other is the "hypothetic" gross return of the fund itself, assuming the same portfolio as in the current quarter (self). Although the former reference point is supposed to capture most of the underlying market wide risk exposure of stocks sharing similar characteristics, the latter is more analogous to the scenario in which a fund would be forced to invest in suboptimal stocks from the bottom of its investment list when its assets exceed the maximum capacity. Adopting this benchmark indicates that any new investment idea has to beat the old ones in order to be counted as success, which is less likely if the new idea is simply next on the investment list.

Tables 1.7 and 1.8 present the regression results for the two main hypotheses of per-

[13] Performance persistence robustness checks are not reported in this section for two reasons. First, there is less consensus on the performance measures to use in the tests of performance persistence hypothesis. Therefore, this set of less well-defined tests are omitted to save space. Second, the driving force behind performance persistence is funds' capability to absorb money inflows, which is essentially Hypothesis 2.

formance prediction and flow-performance sensitivity.[14] As can be seen, the significance and magnitude of regression coefficients are largely the same as shown in Tables 1.4 and 1.6, and confirm my main conclusions.

The second variation changes the definitions of exploration and exploitation activities and the length of history over which past success is accumulated. Section 1.3.3 utilizes the whole trading history since the launching of the fund to categorize exploration and exploitation and accumulate past success within each category. This procedure implicitly ignores the difference between mutual funds and mutual fund managers. One argument is that it is often the whole management team that makes investment decisions, rather than an individual manager, so the accumulation of any experience is still expected to be valuable and to have an impact on future investment, even though a manager might leave the fund.

To make sure that my results still hold even after taking this concern into account, I shorten the length of history that is used to label new industries and accumulate past success. In particular, rather than tracking the entire history of fund holdings since a fund's establishment, I look only at the past 10 years.[15] Under this new definition, a newly purchased stock is categorized as exploration activity if it is in an industry that did not exist in fund portfolio holdings in the past 10 years and is classified as an exploitation activity otherwise. After labeling each new stock as either exploration or exploitation, I proceed to compare their subsequent returns to each of three benchmark

[14]In unreported tables, I first repeat the preliminary tests and find that they still hold under these variations.

[15]I also tried 5 and 7 years, and my results were not sensitive to this choice.

returns (i.e., median, DGTW, and self) as in Step 2, and decide whether the stock is successful or not under the corresponding criterion. Finally, accumulated success in exploration with respect to each of three distinct benchmarks of success is calculated as the sum of quarterly success in exploration during the past 10 years. By repeating a similar procedure for exploitation, I also obtain measures of accumulated success in exploitation.

Tables 1.9 and 1.10 display the results of the two main tests under each specification.[16] Consistent with the main results in Tables 1.4 and 1.6, all coefficients on interaction terms with positive fund flows show correct signs with significance.

The last set of robustness check applies to the subsample of large funds. One possible concern for my conclusion is the role of fund size. Given that small funds have more unexplored industries and are generally more flexible in absorbing money inflows, the advantage of accumulated success in exploration might be simply a coarse reflection of small size effect. To rule out this possibility, I repeat the main performance prediction regression to a subsample of observations with total net assets at least $500 million dollars. Considering the median fund in the whole sample has less than $200 million assets under management, this threshold is expected to be large enough.

Table 1.11 reports the results of this subsample analysis. As expected, the positive effect of accumulated success in exploration is not as significant as before, but the contrast between two types of success still exist and the results are qualitatively the same as those in Table 1.4.

[16] In unreported tables, I also repeat the preliminary hypothesis, and confirm that all results still hold.

Altogether, the documented effects of fund scalability on performance prediction and on flow-performance sensitivity are robust across different specifications and in the subsample. Accumulated success in exploration and accumulated success in exploitation correspond to low and high costs to scale in the universe of mutual funds, and have opposite implications for fund capacity to absorb money inflows. This in turn leads to their contrary impacts on subsequent performance. In addition, although investors of good-performing funds seem to be sophisticated enough to realize this distinction and react accordingly, investors of poorly performing funds are found to be less rational in making investment decisions.

1.6 Conclusion

This paper studies the impact of different scalability among actively managed U.S. equity funds and highlights the importance to take into account this dimension when evaluating funds. Given that costs to scale make up a large portion of expenses, if scalability is under the funds' control to some degree, ceteris paribus, better scalability would always be preferable and deserves attention.

To measure different scalability, I contrast two types of accumulated success, one in industry exploration and the other in industry exploitation, and show that they represent low and high costs to scale, respectively. My empirical tests confirm their different degrees of efficiency in absorbing fund inflows: accumulated success in industry exploration significantly alleviates diseconomies of scale, but accumulated success in industry exploitation does the opposite. Under this framework, I further test investor rationality by conducting flow-performance sensitivity analysis. Confirming previous studies, not all investors show the same sophistication; only those in good-performing funds are wise enough to differentiate accumulated success in industry exploration from that in industry exploitation.

As an early salient attempt to directly compare different scalability of funds, this paper remains silent on how accumulated success in industry exploration is really associated with better scalability. As mentioned, success in exploration might reflect managerial talent, might be the outcome of learning-by-doing, or might be both. Closer scrutiny of this more fundamental question would be an interesting and desirable study. In particular, if learning-by-doing plays a role, then it would be a potentially fruitful area to link to the relevant literature. Along this line, any effort to uncover additional channels through which funds can improve scalability would be highly rewarding and beneficial to underlying investors.

Table 1.1: Summary Statistics

Panel A reports the time-series averages of quarterly cross-sectional characteristics of actively managed U.S. equity funds from 1980 to 2010. AGE is fund age. TNA is total net assets under management. EXP is the expense ratio. TURNOVER is turnover ratio. N(stock) and N(industry) are the number of stocks and the number of industries in fund portfolios respectively. RET is the return net of expense. Flow is fund flow defined as the difference between the growth rate of TNA and RET between two quarters. α is the risk-adjusted return net of expense from Fama-French-Carhart four-factor models. CS (characteristic selection) and CT (characteristic timing) are holding-based performance measures according to DGTW (1997). N(BUY) is the number of newly purchased stocks. N(EXPLORE) and N(EXPLOIT) are the number of newly purchased stocks categorized as industry exploration and industry exploitation activity, respectively. Industries are based on the Fama-French 48 industries classification. A newly purchased stock is an industry exploration activity if it is in an industry that had never existed in fund holdings since its establishment. Otherwise, it is an industry exploitation activity. EXPLORE and EXPLOIT are accumulated success in industry exploration and accumulated success in industry exploitation, respectively. A newly purchased stock is one success if its return is higher than the median fund return before expenses with the same investment objective in the subsequent quarter. Accumulated success in industry exploration is the sum of quarterly success in industry exploration over the fund history, and quarterly success in industry exploration is the successful rate of stocks belonging to industry exploration in the current quarter. Accumulated success in industry exploitation is defined similarly. Panel B reports the contemporaneous correlations between the main variables.

Panel A: Fund Characteristics

	MEAN	STD	MIN	Q25	MEDIAN	Q75	MAX
Total number of funds	3001						
AGE (years)	17	14	2	8	12	22	72
EXP (%)	1.231	0.470	0.240	0.918	1.173	1.498	2.731
FLOW (%)	2.219	14.319	-28.392	-3.743	-0.612	4.453	81.259
TNA (millions)	913.152	3058.114	5.702	60.531	193.058	646.069	53465.307
TURNOVER (%)	90.009	91.444	4.737	37.537	72.408	125.374	551.262
N(INDUSTRY)	24	9	2	19	24	30	47
N(STOCK)	107	171	12	44	64	101	2112
RET (%)	3.108	6.654	-13.587	-0.807	2.997	6.931	20.837
α (%)	-0.149	3.846	-10.993	-2.266	-0.167	1.909	11.470
CS (%)	0.284	3.387	-9.140	-1.394	0.281	2.099	11.323
CT (%)	0.058	2.066	-5.682	-0.970	0.099	1.200	6.969
N(BUY)	19	24	0	5	12	24	149
N(EXPLORE)	1	2	0	0	0	1	12
N(EXPLOIT)	19	24	0	5	11	23	145
EXPLORE	3.270	2.555	0.004	1.273	2.841	4.751	12.807
EXPLOIT	8.327	6.930	0.000	3.338	6.772	11.617	30.211

Panel B: Correlation Structure

Variables	EXPLORE	EXPLOIT	AGE	EXP	FLOW	TNA	α	TURNOVER
EXPLORE	1.000							
EXPLOIT	0.697	1.000						
AGE	0.332	0.481	1.000					
EXP	-0.054	-0.199	-0.238	1.000				
FLOW	-0.069	-0.095	-0.124	0.029	1.000			
TNA	0.100	0.232	0.288	-0.281	0.000	1.000		
α	0.097	-0.006	-0.058	0.236	-0.005	-0.108	1.000	
TURNOVER	0.003	-0.006	-0.018	-0.028	0.020	-0.001	0.009	1.000

Table 1.2: Logistic Regressions of Future Probability

This table reports the coefficients of quarterly panel logistic regressions of the general form

$$Prob_{i,t+1} = f(\beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Flow^{+}_{i,t} \times EXPLORE_{i,t} + \beta_4 \times Flow^{+}_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Flow^{-}_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Flow^{-}_{i,t} \times EXPLOIT_{i,t} + \beta_7 \times Flow^{+}_{i,t} + \beta_8 \times Flow^{-}_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} + \beta_{12} \times TURNOVER_{i,t} + \beta_{13} \times N(INDUSTRY)_{i,t} + \beta_{14} \times N(STOCK)_{i,t} + \varepsilon_{i,t+1})$$

$Flow^{+}$ and $Flow^{-}$ represent positive and negative fund flows, respectively. See the caption of Table 1 for a description of other variables. Quarter fixed effects are included. The sample includes U.S. actively managed equity funds from 1980 to 2010. Standard errors of the regressions are in parentheses.

	Dependent Variable: Probability	
	Prob(EXPLORE)	Prob(EXPLOIT)
EXPLORE	0.057***	−0.028***
	(0.006)	(0.006)
EXPLOIT	−0.085***	0.069***
	(0.003)	(0.002)
$FLOW^{+} \times EXPLORE$	0.388***	−0.271***
	(0.060)	(0.051)
$FLOW^{+} \times EXPLOIT$	−0.313***	0.258***
	(0.029)	(0.025)
$FLOW^{-} \times EXPLORE$	−0.468***	0.329***
	(0.123)	(0.110)
$FLOW^{-} \times EXPLOIT$	0.131**	−0.116**
	(0.050)	(0.043)
$FLOW^{+}$	0.770***	0.810***
	(0.076)	(0.070)
$FLOW^{-}$	1.012***	0.661***
	(0.257)	(0.233)
EXP	8.211***	−1.865
	(1.698)	(1.630)
LOGAGE	−0.397***	0.330***
	(0.012)	(0.011)
LOGTNA	−0.079***	0.091***
	(0.005)	(0.005)
TURNOVER	0.055***	0.013**
	(0.008)	(0.007)
N(INDUSTRY)	0.023***	−0.011***
	(0.001)	(0.001)
N(STOCK)	−0.004***	0.004***
	(0.000)	(0.000)
Qtr FE	YES	YES
Number of Events	27668	85480
Number of Observations	116322	116322

***1% significance, **5% significance, *10% significance.

Table 1.3: Persistence of Success

This table reports the coefficients of quarterly panel regressions of the general form

$$\Delta SUCCESS_{i,t+1} = \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Flow^+_{i,t} \times EXPLORE_{i,t} + \beta_4 \times Flow^+_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Flow^-_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Flow^-_{i,t} \times EXPLOIT_{i,t} + \beta_7 \times Flow^+_{i,t} + \beta_8 \times Flow^-_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} + \beta_{12} \times TURNOVER_{i,t} + \varepsilon_{i,t+1}$$

$Flow^+$ and $Flow^-$ represent positive and negative fund flows, respectively. The dependent variable $\Delta SUCCESS$ denotes the success in industry exploration and the success in industry exploitation, respectively. Within each category, regressions are run in both the whole sample (left) and the subsample of funds involved in the corresponding activity in the current quarter (right). See the caption of Table 1 for a description of other variables. All regressions include quarter fixed effects. Standard errors are clustered at the fund level and given in parentheses.

	Dependent Variable: $\Delta SUCCESS$			
	$\Delta EXPLORE$		$\Delta EXPLOIT$	
	ALL	SUBSAMPLE	ALL	SUBSAMPLE
EXPLORE	0.007***	0.038***	0.010***	0.008***
	(0.001)	(0.003)	(0.002)	(0.002)
EXPLOIT	−0.002***	0.001	0.007	0.008
	(0.000)	(0.001)	(0.006)	(0.006)
$FLOW^+ \times EXPLORE$	0.086***	0.100***	0.025**	0.020*
	(0.008)	(0.020)	(0.010)	(0.012)
$FLOW^+ \times EXPLOIT$	−0.038***	−0.034***	0.020	0.026
	(0.003)	(0.010)	(0.014)	(0.111)
$FLOW^- \times EXPLORE$	−0.073***	−0.094*	−0.036*	-0.025
	(0.013)	(0.049)	(0.021)	(0.024)
$FLOW^- \times EXPLOIT$	0.016***	0.030	-0.029	-0.035
	(0.004)	(0.020)	(0.040)	(0.023)
$FLOW^+$	0.130***	0.117***	−0.150***	−0.146***
	(0.011)	(0.023)	(0.013)	(0.018)
$FLOW^-$	0.199***	0.320***	0.455***	0.526***
	(0.031)	(0.087)	(0.048)	(0.056)
EXP	−3.900***	−4.400***	−3.090***	−2.434***
	(0.302)	(0.758)	(0.566)	(0.665)
LOGAGE	−0.041***	−0.069***	−0.071***	−0.069***
	(0.002)	(0.006)	(0.004)	(0.005)
LOGTNA	−0.009***	−0.011***	−0.009***	−0.012***
	(0.001)	(0.003)	(0.002)	(0.002)
TURNOVER	0.002**	-0.004	0.002	−0.005**
	(0.001)	(0.004)	(0.003)	(0.003)
Qtr FE	YES	YES	YES	YES
Number of Observations	116322	27668	116322	85480
Adjusted-R^2	0.176	0.526	0.724	0.742

***1% significance, **5% significance, *10% significance.

Table 1.4: Performance Prediction Regressions

This table reports the coefficients of quarterly panel regressions of the general form

$$PERF_{i,t+1} = \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Flow^+_{i,t} \times EXPLORE_{i,t} + \beta_4 \times Flow^+_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Flow^-_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Flow^-_{i,t} \times EXPLOIT_{i,t} + \beta_7 \times Flow^+_{i,t} + \beta_8 \times Flow^-_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} + \beta_{12} \times TURNOVER_{i,t} + \beta_{13} \times N(STOCK)_{i,t} + \beta_{14} \times N(INDUSTRY)_{i,t} + \beta_{15} \times ICI_{i,t} + \varepsilon_{i,t+1}$$

$Flow^+$ and $Flow^-$ represent positive and negative fund flows respectively. ICI is the Industry Concentration Index in Kacperczyk et al. (2005), defined as the sum of the square of the difference between the industry weights of a mutual fund and the total market portfolio. The dependent variable PERF denotes quarterly performance using Fama-French-Carhart four-factor α and DGTW (1997) holdings-based performance, CS and CT. See the caption of Table 1 for a description of other variables. All regressions include quarter fixed effects. Standard errors are clustered at the fund level and given in parentheses.

	Dependent Variable: Quarterly Performance (bp)					
	α	α	CS	CS	CT	CT
EXPLORE		0.009		0.017*		0.007*
		(0.010)		(0.009)		(0.004)
EXPLOIT		0.000		-0.001		-0.003
		(0.003)		(0.003)		(0.002)
$FLOW^+ \times EXPLORE$		0.154**		0.197**		0.105*
		(0.061)		(0.095)		(0.056)
$FLOW^+ \times EXPLOIT$		−0.070***		−0.067**		−0.031**
		(0.026)		(0.029)		(0.015)
$FLOW^- \times EXPLORE$		-0.186		−0.342*		0.096
		(0.202)		(0.187)		(0.097)
$FLOW^- \times EXPLOIT$		0.050		0.092*		-0.006
		(0.065)		(0.058)		(0.031)
$FLOW^+$	0.437	0.444**	0.634	0.244	0.218	0.206*
	(0.275)	(0.181)	(0.717)	(0.157)	(0.185)	(0.112)
$FLOW^-$	-0.321	-0.186	0.829	0.190	0.269*	-0.116
	(0.307)	(0.536)	(0.784)	(0.495)	(0.143)	(0.294)
EXP	−23.930***	−24.249***	−22.983***	−17.294***	−3.360*	−3.336*
	(3.684)	(3.700)	(3.837)	(3.616)	(1.905)	(1.775)
LOGAGE	−0.038**	−0.047**	-0.004	-0.022	0.004	0.016
	(0.019)	(0.022)	(0.018)	(0.021)	(0.010)	(0.011)
LOGTNA	−0.026***	−0.028***	-0.011	−0.018**	-0.006	0.001
	(0.009)	(0.009)	(0.010)	(0.009)	(0.005)	(0.005)
TURNOVER	0.006	0.003	0.053***	0.046**	-0.004	-0.006
	(0.021)	(0.021)	(0.017)	(0.018)	(0.011)	(0.011)
N(STOCK)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N(INDUSTRY)	0.007***	0.007***	0.007***	0.009***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
ICI	1.415***	1.469***	0.449**	0.835***	0.659***	0.651***
	(0.181)	(0.186)	(0.234)	(0.211)	(0.147)	(0.140)
Qtr FE	YES	YES	YES	YES	YES	YES
Number of Observations	121822	121822	121416	121416	118418	118418
Adjusted-R^2	0.094	0.107	0.114	0.142	0.079	0.103

***1% significance, **5% significance, *10% significance.

Table 1.5: Performance Persistence Regressions

This table reports the coefficients of quarterly panel regressions of the general form:

$$PERF_{i,t+1} = \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times Lagperf^{+}_{i,t} \times EXPLORE_{i,t} + \beta_4 \times Lagperf^{+}_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times Lagperf^{-}_{i,t} \times EXPLORE_{i,t} + \beta_6 \times Lagperf^{-}_{i,t} \times EXPLOIT_{i,t} + \beta_7 \times Lagperf^{+}_{i,t} + \beta_8 \times Lagperf^{-}_{i,t} + \beta_9 \times EXP_{i,t} + \beta_{10} \times LOGAGE_{i,t} + \beta_{11} \times LOGTNA_{i,t} + \beta_{12} \times TURNOVER_{i,t} + \beta_{13} \times N(STOCK)_{i,t} + \beta_{14} \times N(INDUSTRY)_{i,t} + \beta_{15} \times ICI_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable PERF is quarterly performance using net return (I) and Four-factor α (II). Under each specification, $Lagperf^{+}$ and $Lagperf^{-}$ represent positive and negative past performance defined as net return (RET) and α, respectively. See the caption of Table 1 for a description of other variables. All regressions include quarter fixed effects. Standard errors in parentheses are clustered at the fund level.

	Dependent Variable: Quarterly Performance (bp)							
	(I) RET				(II) α			
$Lagperf$	RET	RET	α	α	RET	RET	α	α
EXPLORE		0.027^{**}		0.005		0.034^{***}		0.001
		(0.011)		(0.013)		(0.010)		(0.009)
EXPLOIT		0.009		-0.009^{***}		-0.010^{***}		0.003
		(0.010)		(0.003)		(0.003)		(0.003)
$Lagperf^{+} \times EXPLORE$		0.151^{**}		3.888^{***}		0.333^{***}		0.645^{***}
		(0.069)		(0.723)		(0.109)		(0.163)
$Lagperf^{+} \times EXPLOIT$		-0.204^{***}		-0.024^{***}		-0.072^{**}		-0.312^{*}
		(0.042)		(0.009)		(0.031)		(0.160)
$Lagperf^{-} \times EXPLORE$		-0.449^{***}		-2.422^{***}		0.065		-0.692^{*}
		(0.198)		(0.448)		(0.154)		(0.384)
$Lagperf^{-} \times EXPLOIT$		0.174^{***}		0.579^{***}		-0.174^{*}		0.236^{*}
		(0.059)		(0.132)		(0.100)		(0.124)
$Lagperf^{+}$	6.023	6.997^{*}	6.848^{**}	5.899	2.982	3.301	6.778	6.954
	(5.837)	(3.533)	(2.395)	(4.476)	(4.352)	(2.196)	(6.052)	(5.271)
$Lagperf^{-}$	7.079^{*}	3.129^{***}	7.550^{***}	7.693	5.555	6.557^{**}	3.152^{*}	3.382^{***}
	(4.388)	(0.752)	(2.778)	(5.569)	(6.434)	(3.184)	(1.866)	(0.992)
EXP	-15.359^{***}	-21.577^{***}	2.600	2.170	-22.002^{***}	-22.365^{***}	-23.351^{***}	-23.513^{***}
	(3.741)	(3.767)	(2.993)	(2.978)	(3.714)	(3.725)	(3.478)	(3.484)
LOGAGE	0.022	0.015	0.043^{***}	0.025	-0.047^{***}	-0.058^{**}	-0.046^{**}	-0.055^{**}
	(0.020)	(0.025)	(0.015)	(0.019)	(0.018)	(0.021)	(0.018)	(0.021)
LOGTNA	-0.109^{***}	-0.113^{***}	-0.069^{***}	-0.072^{***}	-0.037^{***}	-0.039^{***}	-0.026^{***}	-0.028^{***}
	(0.010)	(0.010)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)
TURNOVER	0.005	-0.032	0.041^{**}	0.037^{**}	0.009	0.008	0.004	0.000
	(0.019)	(0.023)	(0.017)	(0.017)	(0.018)	(0.018)	(0.019)	(0.020)
N(STOCK)	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N(INDUSTRY)	0.032^{***}	0.036^{***}	0.027^{***}	0.027^{***}	0.006^{***}	0.006^{***}	0.008^{***}	0.008^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ICI	2.630^{***}	2.912^{***}	2.062^{***}	2.173^{***}	1.333^{***}	1.402^{***}	1.305^{***}	1.356^{***}
	(0.173)	(0.183)	(0.145)	(0.156)	(0.184)	(0.189)	(0.172)	(0.176)
Fund/Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES
Number of Observations	121822	121822	121822	121822	121822	121822	121822	121822
Adjusted-R^2	0.702	0.781	0.747	0.879	0.098	0.112	0.097	0.112

***1% significance, **5% significance, *10% significance.

Table 1.6: Flow-Performance Sensitivity Regressions

This table reports the coefficients of the quarterly panel regressions of the general form

$Flow_{i,t+1} = \beta_0 + \beta_1 \times EXPLORE_{i,t} + \beta_2 \times EXPLOIT_{i,t} + \beta_3 \times PERF^+_{i,t} \times EXPLORE_{i,t} +$
$\beta_4 \times PERF^+_{i,t} \times EXPLOIT_{i,t} + \beta_5 \times PERF^-_{i,t} \times EXPLORE_{i,t} + \beta_6 \times PERF^-_{i,t} \times EXPLOIT_{i,t} + \beta_7 \times PERF^+_{i,t} +$
$\beta_8 \times PERF^-_{i,t} + \beta_9 \times LOGAGE_{i,t}$
$+ \beta_{10} \times EXP_{i,t} + \beta_{11} \times LOGTNA_{i,t} + \beta_{12} \times TURNOVER_{i,t} + \varepsilon_{i,t+1}$

$PERF$ is fund past performance defined as net return (left) and the Fama-French-Carhart four-factor α (right). $PERF^+$ and $PERF^-$ represent positive and negative performance, respectively. See the caption of Table 1 for a description of other variables. All regressions include quarter fixed effects. Standard errors are clustered at the fund level and given in parentheses.

	Dependent Variable: Quarterly Flow	
PERF	RET	α
EXPLORE	0.004	-0.024
	(0.005)	(0.044)
EXPLOIT	-0.007	-0.009
	(0.015)	(0.015)
$PERF^+ \times EXPLORE$	0.728**	0.526**
	(0.371)	(0.220)
$PERF^+ \times EXPLOIT$	−0.352**	−2.619***
	(0.149)	(0.673)
$PERF^- \times EXPLORE$	0.138	−0.558***
	(0.112)	(0.172)
$PERF^- \times EXPLOIT$	−0.092*	−1.377***
	(0.054)	(0.389)
$PERF^+$	0.586***	0.849***
	(0.023)	(0.053)
$PERF^-$	0.356***	0.338***
	(0.024)	(0.032)
EXP	-27.414	−31.269*
	(17.687)	(17.951)
LOGAGE	−2.067***	−2.146***
	(0.108)	(0.110)
LOGTNA	−0.147***	−0.094**
	(0.043)	(0.043)
TURNOVER	0.292***	0.290***
	(0.095)	(0.095)
Qtr FE	YES	YES
Number of Observations	116322	116322
Adjusted-R^2	0.092	0.085

***1% significance, **5% significance, *10% significance.

Table 1.7: Performance Regressions: Alternative Success Benchmark

This table repeats the performance regressions in Table 1.4 using two alternative definitions of success: for every newly purchased stock, DGTW benchmark records one success if its return is higher than the return of DGTW (1997) matching portfolios. SELF benchmark records one success if its return is higher than the hypothetic return of the fund portfolio, assuming the same weight as in the current quarter. The dependent variable PERF denotes quarterly performance using the Fama-French-Carhart four-factor α and DGTW (1997) holdings-based performance, CS and CT. See the caption of Table 1 for a description of other variables. All regressions include quarter fixed effects. Standard errors are clustered at the fund level and given in parentheses.

	Benchmark in Definitions of Success					
	DGTW			SELF		
	Dependent Variable: Quarterly Performance (bp)					
	α	CS	CT	α	CS	CT
EXPLORE	0.002	-0.005	0.007	0.003	0.000	-0.001
	(0.009)	(0.010)	(0.005)	(0.008)	(0.009)	(0.004)
EXPLOIT	0.005*	-0.002	0.000	0.006	-0.001	0.000
	(0.003)	(0.003)	(0.002)	(0.011)	(0.003)	(0.001)
$FLOW^+ \times EXPLORE$	0.201**	0.143***	0.033**	0.040***	0.180**	0.016*
	(0.091)	(0.030)	(0.013)	(0.014)	(0.086)	(0.009)
$FLOW^+ \times EXPLOIT$	−0.115***	−0.028*	−0.013**	−0.051***	−0.044**	−0.001***
	(0.031)	(0.016)	(0.006)	(0.011)	(0.016)	(0.000)
$FLOW^- \times EXPLORE$	0.087	-0.096	-0.028	-0.154	-0.235	0.001
	(0.165)	(0.212)	(0.087)	(0.160)	(0.176)	(0.074)
$FLOW^- \times EXPLOIT$	0.023	0.056	0.039	-0.010	0.081*	0.021
	(0.054)	(0.061)	(0.029)	(0.049)	(0.049)	(0.024)
$FLOW^+$	0.667***	0.121	0.118	0.736*	0.073	0.098
	(0.204)	(0.198)	(0.106)	(0.396)	(0.190)	(0.116)
$FLOW^-$	-0.751	-0.346	-0.075	0.237	-0.129	-0.060
	(0.583)	(0.567)	(0.332)	(0.555)	(0.562)	(0.307)
EXP	−22.369***	−17.853***	-2.960	−23.949***	−17.581***	-2.706
	(3.830)	(3.644)	(1.860)	(3.824)	(3.662)	(1.872)
LOGAGE	−0.048**	0.011	0.009	−0.078***	0.005	0.013
	(0.023)	(0.022)	(0.012)	(0.024)	(0.022)	(0.012)
LOGMTNA	−0.033***	-0.013	-0.003	−0.040***	-0.014	-0.003
	(0.009)	(0.009)	(0.005)	(0.010)	(0.009)	(0.005)
TURNOVER	-0.020	0.051***	-0.006	-0.002	0.049**	-0.005
	(0.019)	(0.019)	(0.011)	(0.019)	(0.019)	(0.011)
N(STOCK)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N(INDUSTRY)	0.007***	0.008***	0.007***	0.007***	0.009***	0.007***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
ICI	1.463***	0.729***	0.603***	1.445***	0.773***	0.582***
	(0.195)	(0.208)	(0.132)	(0.190)	(0.209)	(0.132)
Fund/Qtr FE	YES	YES	YES	YES	YES	YES
Number of Observations	121822	121416	118418	121822	121416	118418
Adjusted-R^2	0.108	0.147	0.100	0.108	0.142	0.100

***1% significance, **5% significance, *10% significance.

Table 1.8: Flow-Performance Sensitivity: Alternative Success Benchmark

This table repeats the flow-performance sensitivity regressions in Table 1.6 using two alternative definitions of success: for every newly purchased stock, DGTW benchmark records one success if its return is higher than the return of DGTW (1997) matching portfolios. SELF benchmark records one success if its return is higher than the hypothetic return of the fund portfolio, assuming the same weight as in the current quarter. All regressions include quarter fixed effects. Standard errors are clustered at the fund level and given in parentheses.

	Benchmark in Definitions of Success			
	DGTW		SELF	
	Dependent Variable: Quarterly FLOW			
PERF	RET	α	RET	α
EXPLORE	-0.012	0.020	0.028	-0.022
	(0.048)	(0.049)	(0.046)	(0.043)
EXPLOIT	-0.032^{*}	-0.050^{***}	-0.037^{**}	-0.053^{***}
	(0.017)	(0.017)	(0.014)	(0.014)
$PERF^{+} \times EXPLORE$	0.677^{**}	0.653^{***}	1.136^{**}	0.427^{**}
	(0.274)	(0.246)	(0.511)	(0.206)
$PERF^{+} \times EXPLOIT$	-0.550^{***}	-2.002^{***}	-0.399^{***}	-2.277^{***}
	(0.157)	(0.763)	(0.130)	(0.554)
$PERF^{-} \times EXPLORE$	-0.144^{**}	-0.249^{**}	-0.791^{**}	1.077
	(0.051)	(0.124)	(0.360)	(1.086)
$PERF^{-} \times EXPLOIT$	-0.305^{*}	-1.715^{***}	-0.351^{***}	-1.372^{***}
	(0.163)	(0.380)	(0.097)	(0.314)
$PERF^{+}$	0.561^{***}	0.825^{***}	0.617^{***}	0.907^{***}
	(0.024)	(0.062)	(0.031)	(0.066)
$PERF^{-}$	0.382^{***}	0.383^{***}	0.348^{***}	0.350^{***}
	(0.025)	(0.038)	(0.023)	(0.042)
EXP	-28.859^{*}	-32.718^{*}	-19.615	-27.549
	(17.664)	(17.927)	(18.228)	(17.955)
LOGAGE	-1.993^{***}	-2.057^{***}	-1.842^{***}	-1.834^{***}
	(0.116)	(0.117)	(0.117)	(0.116)
LOGTNA	-0.141^{**}	-0.083^{*}	-0.143^{***}	-0.059
	(0.044)	(0.043)	(0.045)	(0.043)
TURNOVER	0.288^{***}	0.285^{***}	0.367^{***}	0.280^{***}
	(0.095)	(0.095)	(0.091)	(0.095)
Qtr FE	YES	YES	YES	YES
Number of Observations	116322	116322	116322	116322
Adjusted-R^2	0.090	0.085	0.093	0.086

***1% significance, **5% significance, *10% significance.

Table 1.9: Performance Regressions: Alternative Experience Length

This table repeats the performance regressions in Table 1.4 using an alternative length of fund holding history to categorize industry exploration and industry exploitation activity, and to accumulate past success. A newly purchased stock is classified as industry exploration activity if it is in an industry that did not exist in fund holdings in the past 10 years, according to the Fama-French 48 industries classification. Otherwise, it is classified as industry exploitation activity. Accumulated success in industry exploration is the sum of quarterly success in industry exploration in the past 10 years. Accumulated success in industry exploitation is defined similarly. See the caption of Table 1 for a description of other variables. All regressions include quarter fixed effects. Standard errors are clustered at the fund level and given in parentheses.

	Benchmark in Definitions of Success								
	MEDIAN			DGTW			SELF		
	Dependent Variable: Quarterly Performance (bp)								
	α	CS	CT	α	CS	CT	α	CS	CT
EXPLORE	0.004	0.009	0.007	-0.004	-0.010	0.009^{*}	-0.007	-0.011	-0.001
	(0.010)	(0.009)	(0.005)	(0.010)	(0.009)	(0.005)	(0.009)	(0.009)	(0.004)
EXPLOIT	-0.003	0.000	-0.004^{**}	-0.006	-0.009	0.000	0.003	-0.008	0.000
	(0.005)	(0.004)	(0.002)	(0.006)	(0.006)	(0.003)	(0.005)	(0.005)	(0.002)
$FLOW^{+} \times EXPLORE$	0.139^{***}	0.088^{***}	0.096^{**}	0.065^{***}	0.060^{**}	0.037	0.068^{***}	0.138^{**}	0.054^{**}
	(0.041)	(0.029)	(0.044)	(0.015)	(0.030)	(0.025)	(0.022)	(0.050)	(0.019)
$FLOW^{+} \times EXPLOIT$	-0.094^{**}	-0.072^{**}	-0.025^{**}	-0.063^{***}	-0.017^{***}	-0.024^{*}	-0.051^{***}	-0.018^{***}	-0.012^{***}
	(0.040)	(0.033)	(0.011)	(0.018)	(0.005)	(0.013)	(0.014)	(0.005)	(0.004)
$FLOW^{-} \times EXPLORE$	-0.149	-0.513^{***}	0.078	0.149	-0.332^{*}	0.004	0.020	-0.352^{**}	-0.032
	(0.204)	(0.155)	(0.102)	(0.216)	(0.179)	(0.097)	(0.180)	(0.169)	(0.078)
$FLOW^{-} \times EXPLOIT$	0.065	0.059	0.004	0.034	0.035	0.039	-0.092	0.058	0.016
	(0.085)	(0.065)	(0.042)	(0.091)	(0.075)	(0.047)	(0.075)	(0.064)	(0.037)
$FLOW^{+}$	0.499^{*}	0.468	0.210	0.504	0.312	0.155	0.487	0.051	0.056
	(0.309)	(0.359)	(0.116)	(0.859)	(0.213)	(0.125)	(0.531)	(0.203)	(0.125)
$FLOW^{-}$	-0.333	0.641	-0.083	-0.834	0.505	-0.093	0.309	0.367	0.122
	(0.609)	(0.529)	(0.322)	(0.712)	(0.662)	(0.419)	(0.702)	(0.659)	(0.380)
EXP	-23.694^{***}	-20.129^{***}	-3.286^{*}	-23.674^{***}	-20.565^{***}	-2.872	-24.043^{***}	-18.210^{***}	-2.805
	(3.709)	(3.857)	(1.774)	(3.704)	(3.875)	(1.855)	(3.714)	(3.636)	(1.865)
LOGAGE	-0.024	0.000	0.012	-0.017	0.020	0.014	-0.048^{**}	0.021	0.012
	(0.021)	(0.021)	(0.010)	(0.022)	(0.022)	(0.011)	(0.023)	(0.020)	(0.011)
LOGMTNA	-0.023^{**}	-0.017	0.000	-0.023^{**}	-0.014	-0.002	-0.028^{***}	-0.011	-0.003
	(0.009)	(0.010)	(0.005)	(0.009)	(0.010)	(0.005)	(0.009)	(0.009)	(0.005)
TURNOVER	0.006	0.051^{***}	-0.005	0.010	0.054^{***}	-0.006	0.007	0.053^{***}	-0.005
	(0.021)	(0.017)	(0.011)	(0.021)	(0.017)	(0.011)	(0.021)	(0.018)	(0.011)
N(STOCK)	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N(INDUSTRY)	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.009^{***}	0.007^{***}
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
ICI	1.394^{***}	0.536^{**}	0.654^{***}	1.370^{***}	0.433^{**}	0.604^{***}	1.413^{***}	0.756^{***}	0.590^{***}
	(0.189)	(0.226)	(0.142)	(0.185)	(0.219)	(0.131)	(0.183)	(0.208)	(0.132)
Fund/Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of Observations	121810	121416	118418	121810	121416	118418	121810	121416	118418
Adjusted-R^2	0.106	0.141	0.100	0.108	0.142	0.100	0.107	0.141	0.100

***1% significance, **5% significance, *10% significance.

Table 1.10: Flow-Performance Sensitivity: Alternative Experience Length

This table repeats the flow-performance sensitivity regressions in Table 1.6 using an alternative length of fund holding history to categorize industry exploration and industry exploitation activity, and to accumulate past success. A newly purchased stock is classified industry exploration activity if it is in an industry that did not exist in fund holdings in the past 10 years, according to the Fama-French 48 industries classification. Otherwise, it is classified as industry exploitation activity. Accumulated success in industry exploration is the sum of quarterly success in industry exploration in the past 10 years. Accumulated success in industry exploitation is defined similarly. All regressions include quarter fixed effects. Standard errors are clustered at the fund level and given in parentheses.

	Benchmark in Definitions of Success					
	MEDIAN		DGTW		SELF	
	Dependent Variable: Quarterly FLOW					
PERF	RET	α	RET	α	RET	α
EXPLORE	0.040	0.011	-0.037	0.009	-0.015	-0.049
	(0.050)	(0.048)	(0.051)	(0.052)	(0.047)	(0.047)
EXPLOIT	-0.091^{***}	-0.104^{***}	-0.243^{***}	-0.246^{***}	-0.230^{***}	-0.269^{***}
	(0.024)	(0.022)	(0.028)	(0.028)	(0.026)	(0.024)
$PERF^+ \times EXPLORE$	1.089^{**}	0.695^{***}	1.022^{*}	0.484^{***}	1.000^{*}	1.395^{***}
	(0.540)	(0.213)	(0.536)	(0.157)	(0.510)	(0.469)
$PERF^+ \times EXPLOIT$	-0.849^{***}	-3.836^{***}	-0.709^{***}	-3.200^{***}	-1.328^{***}	-3.640^{***}
	(0.222)	(0.806)	(0.254)	(0.877)	(0.235)	(0.668)
$PERF^- \times EXPLORE$	-1.040^{**}	-2.637^{**}	0.638	1.551	-1.133^{***}	-2.152^{**}
	(0.425)	(1.221)	(0.532)	(1.113)	(0.376)	(0.973)
$PERF^- \times EXPLOIT$	-0.196^{**}	-2.502^{***}	-0.859^{***}	-3.204^{***}	-0.509^{**}	-2.440^{***}
	(0.084)	(0.505)	(0.265)	(0.502)	(0.203)	(0.411)
$PERF^+$	0.599^{***}	0.829^{***}	0.551^{***}	0.839^{***}	0.653^{***}	0.983^{***}
	(0.028)	(0.054)	(0.027)	(0.073)	(0.035)	(0.082)
$PERF^-$	0.331^{***}	0.338^{***}	0.390^{***}	0.379^{***}	0.345^{***}	0.353^{***}
	(0.022)	(0.034)	(0.028)	(0.041)	(0.028)	(0.047)
EXP	-24.958^{*}	-31.088^{*}	-28.912^{*}	-26.528	-12.865	-14.734
	(18.204)	(17.999)	(17.564)	(18.228)	(18.056)	(18.241)
LOGAGE	-1.946^{***}	-2.039^{***}	-1.671^{***}	-1.762^{***}	-1.404^{***}	-1.468^{***}
	(0.099)	(0.099)	(0.100)	(0.103)	(0.101)	(0.102)
LOGTNA	-0.131^{***}	-0.062	-0.084^{*}	-0.042	-0.063	0.001
	(0.045)	(0.043)	(0.043)	(0.044)	(0.044)	(0.044)
TURNOVER	0.384^{***}	0.317^{***}	0.359^{***}	0.428^{***}	0.412^{***}	0.428^{***}
	(0.089)	(0.094)	(0.094)	(0.089)	(0.088)	(0.088)
Qtr FE	YES	YES	YES	YES	YES	YES
Number of Observations	116322	116322	116322	116322	116322	116322
Adjusted-R^2	0.091	0.083	0.092	0.085	0.095	0.087

***1% significance, **5% significance, *10% significance.

Table 1.11: Performance Prediction: Subsample Analysis of Large Funds

This table repeats Table 4 in the subsample including only observations with total net asset larger than $500 million. See the caption of Table 4 for a description of variables. Standard errors are given in parentheses.

	Dependent Variable: Qtrly Performance (bp)		
	α	CS	CT
EXPLORE	0.034**	0.022	0.016**
	(0.014)	(0.014)	(0.007)
EXPLOIT	-0.001	0.002	−0.006***
	(0.004)	(0.004)	(0.002)
$FLOW^+ \times EXPLORE$	0.235***	0.422**	0.116***
	(0.079)	(0.178)	(0.031)
$FLOW^+ \times EXPLOIT$	−0.135**	−0.112*	−0.025*
	(0.056)	(0.062)	(0.014)
$FLOW^- \times EXPLORE$	-0.068	-0.179	0.608***
	(0.340)	(0.351)	(0.202)
$FLOW^- \times EXPLOIT$	0.186*	0.007	−0.124**
	(0.100)	(0.106)	(0.057)
$FLOW^+$	1.485**	0.137**	0.454
	(0.615)	(0.502)	(0.291)
$FLOW^-$	−4.821***	-0.169	−0.178**
	(1.569)	(1.368)	(0.845)
EXP	−32.344***	−16.278***	−5.043*
	(6.759)	(6.874)	(3.462)
LOGAGE	0.046	-0.028	0.020
	(0.030)	(0.030)	(0.016)
LOGMTNA	−0.060**	−0.058**	-0.004
	(0.023)	(0.022)	(0.012)
TURNOVER	−0.121***	0.045	-0.020
	(0.038)	(0.041)	(0.026)
N(STOCK)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
N(INDUSTRY)	0.017***	0.014***	0.005**
	(0.003)	(0.003)	(0.002)
ICI	1.759***	1.192***	0.174
	(0.379)	(0.360)	(0.199)
Fund/Qtr FE	YES	YES	YES
Number of Observations	39900	39596	39338
Adjusted-R^2	0.145	0.165	0.160

***1% significance, **5% significance, *10% significance.

Table 1.12: Performance Prediction: Subsample Analysis of Small-Cap Funds

This table repeats Table 4 in the subsample including only small-cap funds. See the caption of Table 4 for a description of variables. Standard errors are given in parentheses.

	Dependent Variable: Qtrly Performance (bp)		
	α	CS	CT
EXPLORE	0.004***	0.015	0.017*
	(0.001)	(0.025)	(0.010)
EXPLOIT	0.021	-0.021	-0.004
	(0.036)	(0.004)	(0.004)
$FLOW^{+} \times EXPLORE$	0.328***	0.366**	0.091*
	(0.078)	(0.170)	(0.048)
$FLOW^{+} \times EXPLOIT$	−0.152***	−0.137**	-0.023
	(0.020)	(0.069)	(0.017)
$FLOW^{-} \times EXPLORE$	−0.699***	−1.160***	0.283
	(0.125)	(0.372)	(0.177)
$FLOW^{-} \times EXPLOIT$	0.100	0.369**	-0.012
	(0.142)	(0.123)	(0.062)
$FLOW^{+}$	0.429	0.264	-0.097
	(0.457)	(0.341)	(0.184)
$FLOW^{-}$	2.131*	0.392	-0.464
	(1.218)	(1.020)	(0.599)
EXP	−16.305*	12.647	1.516
	(9.990)	(10.768)	(3.489)
LOGAGE	-0.004	0.101	0.013
	(0.062)	(0.070)	(0.024)
LOGMTNA	−0.094***	−0.075**	-0.004
	(0.029)	(0.030)	(0.011)
TURNOVER	-0.084	-0.075	-0.024
	(0.061)	(0.051)	(0.020)
N(STOCK)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
N(INDUSTRY)	0.024***	0.016**	0.008**
	(0.007)	(0.008)	(0.003)
ICI	5.180***	5.556***	1.325*
	(1.839)	(2.065)	(0.689)
Fund/Qtr FE	YES	YES	YES
Number of Observations	18099	18201	17696
Adjusted-R^2	0.215	0.246	0.078

***1% significance, **5% significance, *10% significance.

Table 1.13: Performance Prediction: Fund Family

This table runs the performance prediction regression taking into account the impacts of fund family. $EXPLORE_{Family}$ and $EXPLOIT_{Family}$ are accumulated success in exploration and exploitation of all other funds in the same family. See the caption of Table 4 for a description of other variables.

	Dependent Variable: Qtrly Performance (bp)		
	α	CS	CT
EXPLORE	0.012	0.016*	0.007*
	(0.010)	(0.009)	(0.004)
EXPLOIT	-0.001	-0.001	-0.003
	(0.003)	(0.003)	(0.002)
$FLOW^+ \times EXPLORE$	0.109***	0.201**	0.117**
	(0.036)	(0.097)	(0.057)
$FLOW^+ \times EXPLOIT$	−0.057**	−0.071**	−0.038*
	(0.024)	(0.036)	(0.023)
$FLOW^- \times EXPLORE$	-0.120	-0.251	0.094
	(0.126)	(0.193)	(0.099)
$FLOW^- \times EXPLOIT$	0.035	0.058	-0.009
	(0.069)	(0.063)	(0.032)
$FLOW^+$	0.351*	0.209	0.218*
	(0.193)	(0.176)	(0.122)
$FLOW^-$	0.175	0.245	-0.260
	(0.545)	(0.499)	(0.323)
$EXPLORE_{Family}$	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)
$EXPLOIT_{Family}$	0.001	0.000	0.000
	(0.001)	(0.000)	(0.000)
$FLOW^+ \times EXPLORE_{Family}$	0.040*	0.003***	0.009
	(0.022)	(0.001)	(0.007)
$FLOW^+ \times EXPLOIT_{Family}$	−0.009*	0.000	-0.003
	(0.005)	(0.004)	(0.002)
$FLOW^- \times EXPLORE_{Family}$	-0.047	−0.081***	0.005
	(0.031)	(0.027)	(0.015)
$FLOW^- \times EXPLOIT_{Family}$	0.011	0.024***	0.001
	(0.009)	(0.008)	(0.004)
EXP	−24.120***	17.190***	−3.328*
	(3.708)	(3.615)	(1.783)
LOGAGE	−0.057***	-0.022	0.017
	(0.022)	(0.021)	(0.011)
LOGMTNA	−0.045***	−0.018**	0.003
	(0.009)	(0.009)	(0.005)
TURNOVER	-0.008	0.045**	-0.003
	(0.021)	(0.018)	(0.011)
N(STOCK)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
N(INDUSTRY)	0.006***	0.009***	0.007***
	(0.002)	(0.002)	(0.001)
ICI	1.260***	0.849***	0.686***
	(0.192)	(0.216)	(0.147)
Fund/Qtr FE	YES	YES	YES
Number of Observations	121822	121822	121822
Adjusted-R^2	0.128	0.147	0.103

***1% significance, **5% significance, *10% significance.

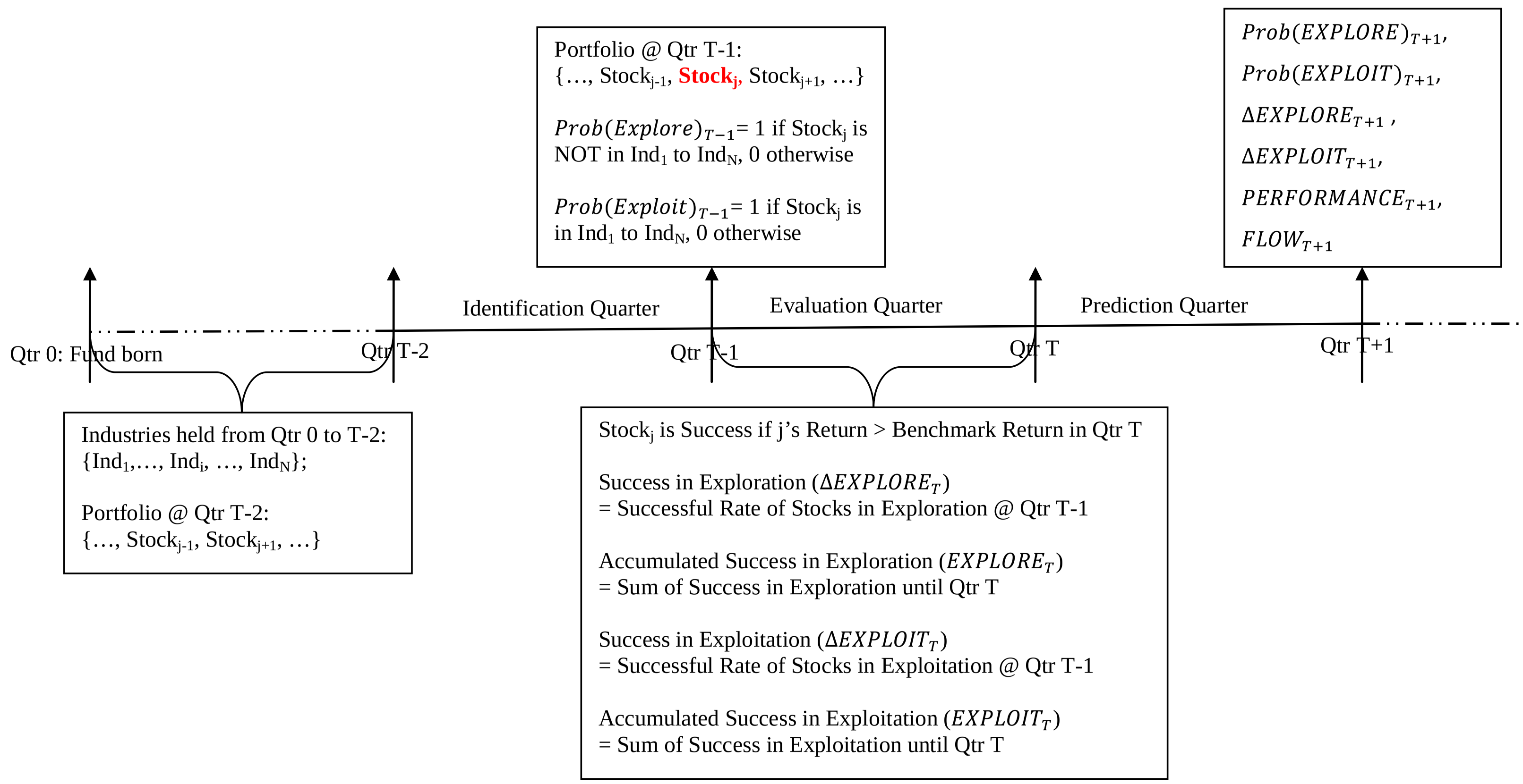


Figure 1: Timeline of Experience Measures

Chapter 2

Dissecting the Profitability Premium

[1]

2.1 Introduction

Motivated by valuation theory, Fama and French (2006, 2008) explore the relation between profitability and expected returns and find that more profitable firms have higher expected returns.[2] More recently, inspired by q-theory, Chen, Novy-Marx, and Zhang (2010) (CNZ hereafter) form portfolios by sorting directly on past return-on-assets (ROA) and find that firms with high ROA earn substantially higher returns during sub-

[1]This part is coauthored with Jianfeng Yu.

[2]Early studies suggesting a positive relation between expected profitability and expected returns include Haugen and Baker (1996), Piotroski (2000), Cohen, Gompers, and Vuolteenaho (2002), and Griffin and Lemmon (2002).

sequent periods. We label this return spread the *profitability premium*. This paper aims to explore the underlying mechanism for the profitability premium by examining how it varies with a variety of firm characteristics and macroeconomic conditions.

Understanding the force behind the profitability premium is important for several reasons. First, like other prominent anomalies, a CAPM alpha of 1.02% per month is abnormally large. More importantly, distinct from other anomalies, CNZ (2010) show that the ROA-based factor can help explain a large set of asset-pricing anomalies. In another intriguing paper, Novy-Marx (2012) uses gross profitability as a measure of profitability and shows that the factor based on gross profitability-to-assets can help account for almost all existing asset pricing anomalies.[3] Thus, the profitability-based factor model can be used as a benchmark model in many potential applications, including the calculation of alpha for a portfolio strategy, the calculation of costs of capital in capital budgeting, mutual/hedge fund performance evaluation, and so on.

Given its extraordinary empirical explanatory power and strong theoretical motivation, understanding the economic mechanism underlying the base factor is worthwhile. If the profitability premium is due to risk, we finally have a theoretically grounded factor model that can explain the cross section of stock returns. Therefore, further exploring the sources of risk is worthwhile. If the profitability premium is due to mispricing, however, it implies that there is a common mispricing component in many seemingly unrelated

[3]Since the ROA factor can account for many other anomalies, it is natural that the ROA factor is related to other anomalies such as momentum and the post earning announcement drift (PEAD). However, the profitability premium is distinct from other individual anomalies since the ROA factor has the unique power in explaining many asset pricing anomalies simultaneously, while other anomaly-based factor has no such power.

anomalies, suggesting that systematical behavioral biases underlie these anomalies. In addition, profitable firms are less prone to distress, have lower operating leverage, and have longer cash flow duration than unprofitable firms. Thus, the observed profitability premium presents a challenge to leading explanations for the value premium, such as the q-theory or the duration theory. Therefore, understanding the source of the profitability premium can also guide us in developing new models or refining existing models of the value premium.

We first explore the sources of systematic risk in the ROA effect. Prominent existing models of the value premium typically cannot produce the ROA premium because firms with low profitability are riskier due to a higher operating leverage or financial leverage. However, the ROA effect is consistent with several recent structural models including Garlappi, Shu, and Yan (2008), Garlappi and Yan (2011), and Hackbarth and Johnson (2011). In these models, firms are allowed to abandon projects by disinvesting or filing for bankruptcy. In these models, the abandonment option is a hedge, and firms with low profitability have a higher abandonment options value. Thus, firms with low ROA could be less risky and earn lower subsequent returns. An important implication is that among firms with high shareholder advantage (and therefore a higher abandonment option value for shareholders during default) or with high investment flexibility, the ROA effect should be stronger. For example, in the model of Hackbarth and Johnson (2011), when firms are very inflexible in adjusting investment, the value premium obtains as in traditional investment-based models of the value premium. However, when firms have a lot of flexibility, the ROA effect emerges since the abandonment option accounts for a large portion of firm value among these firms.

Using various proxies for shareholder advantage and investment flexibility, we investigate the empirical relevance of these risk-based explanations for the ROA premium. We find weak to moderate support for the above two channels. In particular, among firms with high shareholder advantage, we indeed find a slightly stronger ROA effect. Among firms with more flexible investment policies, the ROA effect is also stronger, providing moderate support for the role of both shareholder advantage and investment flexibility in the ROA premium.

The above tests focus on the cross-sectional heterogeneity of the ROA effect. We also investigate the time-series variation of the ROA effect. Previous studies have documented a set of macroeconomic variables that can predict the market risk premium. If the anomalous returns are driven by systematic risk, the natural prediction is that these traditional macro variables have predictive power for the ROA premium. However, we find that macroeconomic variables show little power to predict return spreads. In addition, we find that the ROA spread is mostly positive during recessions, suggesting that exposure to traditional macroeconomic risk is not much greater for high ROA firms than for low ROA firms. Furthermore, Savor and Wilson (2010) document that excess market returns on macro news announcement days are about 10 times larger than those on non-announcement days, suggesting a disproportionately large fraction of risk premium on macro news announcements. Hence, if the profitability premium is due to compensation for macro risk, we would expect the profitability premium to be larger on announcement days than on non-announcement days. However, we find that the profitability premium is similar on both announcement and non-announcement days. This evidence again suggests that traditional macro risk is unlikely to be the source of the observed profitability premium.

The profitability premium may still be driven by a missing factor that is not captured by the traditional macro variables. To investigate this possibility, we follow previous studies (e.g., Fama and French (1993) and Daniel and Titman (1997)) by extracting a mimicking factor from the profitability characteristic itself. This approach provides a way to identify a risk factor that is most closely related to the profitability premium, if it is indeed driven by risk. We then compare the predictive power of the factor loadings on this risk factor with the profitability characteristic itself. We again find that in horse race regressions in which the future stock return is the dependent variable, the profitability characteristic tends to drive out the predictive power of the factor loadings, suggesting that investors might misvalue the profitability characteristic.

The above evidence suggests that risk might not completely explain the ROA premium. Thus, we examine the possibility that the profitability premium is partly driven by mispricing. The profitability premium, to the extent that it reflects mispricing, should be larger among firms that are more difficult to arbitrage and have greater information uncertainty. With higher limits-to-arbitrage, the mispricing is more likely to be sustained. In addition, with greater information uncertainty, psychological biases are increased and information is more asymmetric among investors, leaving more room for mispricing. We employ a large set of standard proxies for limits-to-arbitrage and information uncertainty in the literature. We find that the profitability premium is substantially stronger among firms that are more difficult to arbitrage and have greater information uncertainty.

Specifically, the profitability premium is insignificant or marginally significant among firms that have low information uncertainty and are easy to arbitrage. Our results are also economically significant. For example, the profitability premium is about 1% higher per month among firms with smaller capitalization, younger age, higher return volatility, higher cash flow volatility, less analyst coverage, larger analyst forecast dispersion, fewer institutional holdings, higher idiosyncratic return volatility, lower dollar trading volume, higher bid-ask price spread, lower credit rating, and higher illiquidity. We also find that the majority of the ROA alpha is derived from the subsequent low returns from the low ROA firms. This is consistent with the notion that overpricing is harder for arbitrageurs to correct due to greater shorting impediments.

Given the potential significant role for mispricing in the profitability premium, we further investigate the source of mispricing. One possibility is that investors underreact to the current profitability news, and hence high (low) profitability firms are relatively underpriced (overpriced). To explore this possibility, we follow La Porta et al. (1997) by examining portfolio returns around subsequent earnings announcements. In particular, we test whether earnings surprises after portfolio formation are systematically positive for firms with high past ROA and negative for firms with low past ROA. We also examine whether this return spread on earnings announcements is more pronounced among firms with high arbitrage costs and information uncertainty. Our empirical evidence lends support to the underreaction argument. This finding suggests that investors may underestimate the importance of current fundamentals and hence overestimate (underestimate) the payoffs from future earnings for low (high) ROA firms.

Worth noting is that the rational learning models of Veronesi (2000), Pastor and Veronesi (2003, 2006), and Johnson (2004) can potentially produce a higher ROA effect among firms with higher information uncertainty. Although developing such a learning model to account for the ROA premium and its interaction with information uncertainty is certainly interesting, we think that this task is beyond the scope of our current study. In addition, such a learning model tends to be silent on the relation between the ROA effect and the arbitrage costs and on the asymmetric behavior from the long and short legs of the ROA strategy. Thus, in the current study, we instead focus on testing existing potential mechanisms of the ROA effect (e.g., shareholder advantage, investment flexibility, and limits-to-arbitrage). Moreover, our results do not imply that there is an arbitrage opportunity. The pattern in the ROA premium is consistent with the notion that the market is efficient up to the point where arbitrageurs face transaction costs and risk aversion barriers. However, even if we cannot profit from the ROA premium, we believe that it is still interesting to understand where this predictability comes from, especially given that the ROA factor can account for many seemingly unrelated anomalies.

Our study belongs to a large and growing literature that examines the role of limits-to-arbitrage and information uncertainty in asset-pricing anomalies. Notable recent papers include Ali, Hwang, and Trombley (2003) on book-to-market; Nagel (2005) on book-to-market, analyst forecast dispersion, turnover, and volatility; Zhang (2006) on price continuation anomalies; Mashruwala, Rajgopal, and Shevlin (2006) on total accruals; Li and Zhang (2010) on investment growth, net operating assets, and net stock issues; and Lam and Wei (2011) on asset growth, among others. Our results are also consistent with recent findings in Stambaugh, Yu, and Yuan (2012), who show that many anomalies, including the profitability premium, are due to the extremely low return from the short legs of various long-short strategies following high sentiment periods, suggesting that the short legs are overpriced when investor sentiment is high.

The rest of the paper is organized as follows. We discuss the related literature and develop hypotheses in Section 2.2. Section 2.3 describes the data and the proxies for arbitrage costs and information uncertainty. Section 3.3 presents the empirical findings. Section 3.5 concludes.

2.2 Hypothesis Development

Our first task is to examine two existing risk-based explanations of the ROA effect. In particular, we consider the models of Garlappi, Shu, and Yan (2008), Garlappi and Yan (2011), and Hackbarth and Johnson (2011). Although these original studies do not consider the ROA premium, the mechanisms in these models can actually produce the

ROA effect in the cross section of stock returns. We elaborate their model intuition below and further develop testable hypotheses.

Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) argue that in the event of financial distress or default, shareholders have potential recovery resulting from the renegotiation between claim holders. Shareholder advantage is the ability of shareholders to extract rents from their interactions with other claim holders in the event of financial distress. When shareholder advantage is strong, default options account for a larger portion of the equity value. Since the default option is a hedge, their model can explain the low average return of financially distressed firms.

Since firms with low ROA are closer to financial distress, one can easily generalize their argument to account for the profitability premium. When shareholder advantage is very weak, the value of default options to shareholders is very low. Thus, the traditional force (such as the financial leverage and operating leverage) plays a stronger role, and firms with high ROA, which tend to have lower leverage, are less risky. On the other hand, when shareholder advantage is strong, the abandonment option accounts for a large portion of the equity value, and the hedging effect could dominate. Thus, firms with low ROA are less risky than firms with high ROA, leading to the profitability premium. An important implication of Garlappi, Shu, and Yan (2008) is that among firms with high shareholder advantage, the ROA effect should be stronger, whereas among firms with low shareholder advantage, the ROA spread should be smaller or even negative.

In a similar vein, Hackbarth and Johnson (2011) provide a model of firm expansion and contraction. They show that for firms with lower adjustment costs (i.e., higher investment flexibility), their risk falls on average as operating leverage (or book-to-market) increases, whereas risk rises with operating leverage for firms with less flexibility. Their study focuses on the value premium and operating leverage. One can easily extend their argument to study the ROA effect. Notice that disinvestment is an abandonment option and that firms with low ROA are more likely to disinvest.

In the model of Hackbarth and Johnson (2011), when firms are very inflexible in adjusting investment (especially in adjusting divestiture), firms with low ROA have few abandonment options, and are riskier due to the operating leverage effect, as in traditional investment-based models (see, e.g., Carlson, Fisher, and Giammarino (2004) and Novy-Marx (2011)). However, when firms have a lot of flexibility, the ROA effect emerges since the abandonment option accounts for a large portion of firm value among these firms and its effect dominates the operating leverage effect. Hence, an important implication of their model is that among firms with high flexibility, the ROA effect should be stronger. By contrast, among firms with low flexibility, the ROA premium should be small or even negative.

In sum, the ROA effect could obtain if the average firm has strong shareholder advantage or a very flexible investment policy. More importantly, the ROA effect should be stronger among firms with stronger shareholder advantage and more flexibility. Here, we reach our first hypothesis, which will be tested using various proxies for shareholder advantage and investment flexibility.

Hypothesis 1: Among firms with stronger shareholder advantage or a more flexible investment policy, the ROA effect should be stronger.

Moreover, many previous studies relate the stock market returns to systematic risk compensation. On the empirical side, Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Fama and French (1989), Ferson and Harvey (1991), Lettau and Ludvigson (2001) and Li (2001) find evidence that stock market returns show significant time variation over the business cycle and can be predicted by variables related to the business cycle, such as the relative Treasury bill rate, the term spread, the default spread, and the consumption-to-wealth ratio. On the theory side, Campbell and Cochrane (1999) propose an external habit model in which time-varying risk aversion could produce a countercyclical risk premium.

In addition, Savor and Wilson (2010) document that excess market returns on macro news announcement days are about 10 times larger than those on non-announcement days, suggesting a disproportionately large fraction of risk premium on macro news announcements. Hence, as argued in the introduction, if the profitability premium is due to compensation for macro risk, we would expect the profitability premium to be larger on announcement days than on non-announcement days.

Along this line, our second hypothesis is that, if the profitability premium is driven by systematic risk, then it should vary with the business cycle and be predictable by common risk premium predictors. Also it should be stronger during macro news announcement days.

Hypothesis 2: Following bad macroeconomic conditions, the ROA effect should be stronger. Moreover, the ROA premium should be stronger during macro news announcements than during non-announcements

Our second task is to examine the role of behavioral bias-induced mispricing in the profitability anomaly. Both an uninformed demand and a limit on arbitrage are required for a mispricing. Therefore, mispricing would occur when investors' behavioral biases such as under- or overreaction to new information generate an uninformed demand shock, and at the same time, limits on arbitrage prevent rational investors from fully absorbing this shock.

On the one hand, Hirshleifer (2001) and Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) posit that psychological biases are increased when there is more uncertainty. Therefore, when investors' information on certain firms is more limited, their investment decisions tend to be more biased. For example, in face of high information uncertainty, investors tend to be more overconfident about their private information and underreact more to public information. Motivated by these ideas, Zhang (2006) studies the momentum effect and finds that the momentum strategy works well only among high-uncertainty stocks. On the other hand, Shleifer and Vishny (1997) argue that since arbitrage is costly, systematic mispricing would not be quickly and completely traded away in situations in which there are more limits on arbitrage. Building on this idea and using different proxies for limits on arbitrage, prior studies find that many anomalies are more pronounced among firms with more limits on arbitrage (e.g., Ali, Hwang, and

Trombley (2003), Nagel (2005), Lam and Wei (2011), and Li and Zhang (2010)). We thus reach our third testable hypothesis.

Hypothesis 3: Among firms with higher arbitrage costs or higher information uncertainty, the ROA effect should be stronger.

We test the above hypothesis using six proxies for information uncertainty (size, age, stock volatility, cash flow volatility, analyst coverage, and dispersion in analyst forecast) and seven proxies for limits on arbitrage (number of institutional holders, percentage of outstanding shares held by institutional investors, idiosyncratic stock return volatility, dollar trading volume, bid-ask spreads, firms' credit rating history, and Amihud's (2002) illiquidity from the prior literature). The above argument implies that the ROA effect is not completely eliminated by arbitrageurs due to arbitrage costs. Thus, no free money is left on the table, and the market is still efficient subject to the constraints of arbitrageurs.

2.3 Data and Measurements

The sample data come from five sources. Data on accounting information are from the Compustat Annual and Quarterly Industrial Files. Stock market data are from CRSP. Institutional holdings records are from Thomson Reuters. Information on analyst forecasts is from I/B/E/S. The macro news release data are from Bureau of Labor Statistics (BLS) and the Federal Reserve System. The sample is from January 1972 to December 2011. The starting date is restricted by the availability of quarterly Compustat data. We delete financial firms, firms with negative book equity, firms with less than

10 million in sales (Compustat item REVT), and firms appearing in Compustat for less than 2 years.

2.3.1 Profitability Measure

Following CNZ (2010), we use return-on-assets (ROA) as the profitability measure since it produces a large return spread. We construct the quarterly ROA variable as in CNZ (2010). ROA is quarterly income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged total assets (item ATQ). Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). When we construct portfolios, we sort NYSE, AMEX, and NASDAQ stocks based on the ranked values of ROA with most recent earnings at the beginning of each month, and the portfolios are rebalanced every month. Monthly value-weighted returns on the portfolios are calculated.

2.3.2 Proxies for Shareholder Advantage and Flexibility

Following Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011), we use the firm's asset size (TA), the degree of tangibility of its assets (Tang), the ratio of R&D expenditure to assets (XRD), and the concentration of a firm's industry (IC) as proxies for shareholder advantage. First, firms with large asset size have fewer concentrated debt holders, leading to a disadvantage in monitoring the firm. Thus, higher asset size tends to strengthen the shareholders' bargaining power in the event of financial distress. Second, an increase in asset tangibility is likely to reduce the liquidation cost and hence lower shareholder advantage. Third, firms with high costs of R&D are particularly vulnerable to liquidity shortage in financial distress, putting shareholders in a disadvantaged bargaining position with creditors. Fourth, if a firm's assets are highly specific, then they are likely to suffer from fire-sale discounts during liquidation. The Herfindahl index captures industry concentration, which could be a proxy for asset specificity. Finally, following Hackbarth and Johnson (2011), investment inflexibility (Inflex) is calculated as the s-tandardized industry median firm range of operating costs (i.e., the sum of Compustat's COGSQ and XSGAQ) over sales (i.e., SALEQ). Detailed descriptions of these proxies are available in Garlappi, Shu, and Yan (2008) and Hackbarth and Johnson (2011).

2.3.3 Proxies for Arbitrage Costs

We employ seven commonly used proxies for limits on arbitrage in the previous literature (e.g., Amihud (2002), Ali, Hwang, and Trombley (2003), Nagel (2005), Mashruwala, Rajgopal, and Shevlin (2006), Avramov et al. (2010), Lam and Wei (2011), and Duan, Hu, and McLean (2010)). By examining the profitability premium among firms with more and less severe limits on arbitrage, we can explore the role of arbitrage cost in the profitability premium. Below, we provide a brief discussion of each of the seven proxies.

The first and most important proxy for arbitrage cost is idiosyncratic stock return volatility (IVOL). We measure the standard deviation of the residual values from the following three-factor Fama-French (1993) regression:

$$R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t},$$

where $R_{i,t} - R_{ft}$ is stock i's monthly excess return in month t, MKT_t is the excess return of the market value-weighted portfolio, SMB is the size premium and equals the return differential between portfolios of small and large stocks, and HML represents the value premium and equals the return differential between portfolios with high and low book-to-market ratios.[4] We estimate the above equation for each stock each month in the data set with the previous 36 months of returns.[5] Shleifer and Vishny (1997) argue that professional arbitrage is conducted by a relatively small number of highly specialized investors using other people's capital. Such arbitrage is ineffective when prices diverge further from fundamental values before they converge. Furthermore, arbitrageurs are risk averse and typically poorly diversified, and hence they are concerned about the idiosyncratic risk of their portfolios. Thus, Shleifer and Vishny (1997) predict that idiosyncratic volatility will deter arbitrage activities. Moreover, Pontiff (2006) forcefully argues that idiosyncratic volatility is the single largest cost faced by arbitrageurs.[6]

The second proxy is the number of institutional investors holding a firm's shares at the portfolio formation date (N_I). It is a commonly used proxy for shareholder sophistication (e.g., Chen, Hong, and Stein (2002) and Ali, Hwang, and Trombley (2003)). The more sophisticated the investors are, the less mispricing would take place.

[4] We thank Ken French for providing updated series for these factors.

[5] As a robustness check, we also measure the monthly idiosyncratic volatility with daily stock return data in each month. Our results remain similar. In particular, the profitability premium exists only among firms with high idiosyncratic volatility.

[6] Pontiff (2006) argues that the larger the portfolio weight that an arbitrageur assigns to a stock, the more the stock's idiosyncratic variance affects the portfolio's variance. Hence, all else equal, the risk-averse arbitrageur will take a relatively small position in a high idiosyncratic risk stock (for both short and long positions). This result does not depend on the arbitrageur's level of diversification, and hence idiosyncratic risk will limit arbitrage with equal effectiveness in portfolios containing many and few securities.

The third proxy is the percentage of outstanding shares held by institutional investors at the portfolio formation date (Per_I). Low institutional holdings make it difficult to borrow stocks for short selling (e.g., D'Avolio (2002)). Hence, this proxy is inversely related to short-sale constraints. Higher short-sale constraints imply higher transaction costs and hence more severe limits to arbitrage.

The fourth proxy is dollar trading volume (DVol). We calculate the dollar trading volume as the time-series average of the monthly share trading volume multiplied by the monthly closing price over the 12 months prior to the portfolio formation date. This proxy measures how quickly an investor can trade a large block of shares (e.g., Bhushan (1994)). Higher dollar volume implies less price pressure and hence fewer arbitrage costs.

The fifth proxy is the bid-ask spread (B/A). The bid-ask spread is calculated as the time-series average of $2 * |Price - (Ask + Bid)/2|/Price$ at the end of each month over the 12 months prior to the portfolio formation date, where Price is the closing stock price and Ask (Bid) is the ask (bid) price. It measures the trading cost, so the higher the bid-ask spread is, the higher the arbitrage cost.

The sixth proxy is the credit rating (CR). It is a dummy variable, which is equal to zero if a firm has a Standard & Poor's long-term credit rating in the Compustat database, and one otherwise. Avramov et al. (2010) show that many anomalies exist only among firms with a low credit rating. They argue that low-rated stocks are considerably more difficult to short sell and are substantially more illiquid. Therefore, the lower the credit rating or the higher the credit numeric score, the higher the arbitrage cost.

The last proxy is Amihud's (2002) illiquidity (Illiq). Amihud (2002) defines illiquidity as the annual average of the daily ratio of absolute stock return to its daily dollar trading volume. A higher illiquidity value implies a larger impact on the stock price per order flow, so a larger transaction cost for investors. Thus, the larger the illiquidity measure, the higher the arbitrage cost.

2.3.4 Proxies for Information Uncertainty

Besides the proxies for arbitrage cost, we employ six commonly used proxies for information uncertainty in the previous literature. Our proxies for information uncertainty are the same as in Zhang (2006), which explores the sensitivity of momentum to information uncertainty. By examining the profitability premium among firms with more and less information uncertainty, we can explore the role of information uncertainty in the profitability premium. Following Zhang (2006), we briefly discuss the six proxies below.

The first proxy is firm size. We measure size as the market capitalization at the portfolio formation date. Small firms are less diversified and have less information available for the market than large firms. Therefore, smaller firms are subject to more severe information asymmetry and are more likely to be mispriced.

The second proxy is firm age. We measure age as the number of years since the firm was first covered by CRSP. A longer history implies that more information is available to the market. Therefore, age inversely proxies for information uncertainty, and younger firms are subject to more severe information asymmetry.

The third proxy is individual stock volatility (σ_R). We measure stock volatility as the standard deviation of weekly excess returns over the year ending at the portfolio formation date. Weekly returns are calculated from Thursday to Wednesday to mitigate nonsynchronous trading effects in daily prices. Predicting future returns of a stock with more volatile returns in the past year would be more difficult. Therefore, the more volatile the stock return, the more uncertain its future return, and the more likely it is to be mispriced.

The fourth proxy is cash flow volatility (σ_{CF}). We measure cash flow volatility as the standard deviation of cash flow from operations in the past five years with a minimum of three years of data. Cash flow from operations is measured as earnings before extraordinary items (Compustat annual item IB) minus total accruals, scaled by average total assets (item AT). Here, total accruals equal changes in current assets (item ACT) minus changes in depreciation expense (item DP), cash (item CHE), and changes in current liabilities (item LCT), plus changes in short-term debt (item DLC). The more volatile the past cash flow, the more uncertain the underlying business.

The fifth proxy is analyst coverage (N_A). We measure analyst coverage as the number of analysts following the firm in the previous month. Larger analyst coverage corresponds to more information available about the firm (e.g., Hong, Lim, and Stein (2000)). Therefore, the more analyst coverage, the less information uncertainty.

The last proxy is dispersion in analyst forecast (σ_A). Dispersion in analyst forecast is measured as the standard deviation of analyst one-year earnings forecasts at the portfolio formation date scaled by the prior year-end stock price to mitigate heteroskedasticity. It is a proxy for the uncertainty about future earnings or the degree of consensus among analysts or market participants (e.g., Diether, Malloy, and Scherbina (2002) and Johnson (2004)). Thus, wider analyst disagreement on the next-year earnings implies more information uncertainty.

Finally, we do not view the proxies for information uncertainty and limits on arbitrage as exclusive. Actually, firms with high information uncertainty tend to be those that are difficult to arbitrage. In this sense, information uncertainty and limits on arbitrage are mutually reinforcing.

2.3.5 Macroeconomic Variables

Several macroeconomic variables shown by the literature to predict stock returns are used as control variables in this paper. Specifically, we use the monthly default premium (DEF), the monthly term premium (TERM), the monthly real interest rate (INT), the monthly inflation rate (INFL), and Lettau and Ludvigson's (2001) quarterly consumption wealth ratio, CAY. Previous studies show that each of these variables has predictive power for the market risk premium.

DEF is the yield spread between BAA and AAA bonds obtained from the St. Louis Federal Reserve. TERM is the difference between the 20-year Treasury bond yield and the 1-year Treasury yield, obtained from the St. Louis Fed. CAY is defined as in Lettau and Ludvigson (2001), obtained from Martin Lettau and Sydney Ludvigson's website. The inflation rate is calculated from the monthly consumer price index (CPI), obtained from CRSP. The real interest rate is defined as the difference between the 30-day T-bill rate and the inflation rate. The monthly dividend yield is calculated as the difference between the log of the last 12-month dividend and the log of the current level of the CRSP valued-weighted index. Finally, Campbell and Cochrane's (1999) surplus ratio is approximated by a smoothed average of the past 40 quarters' consumption growth as in Wachter (2006). In monthly regressions, we use the most recent quarterly consumption-wealth ratio as our monthly measure.

2.3.6 Macro News Announcements

Following Savor and Wilson (2010), we obtain dates of prescheduled monthly macroeconomic news announcements about inflation and unemployment from the BLS from 1972 to 2011, and the Federal Open Market Committee (FOMC) interest rate from the Federal Reserve from 1978 to 2011. We use producer price index (PPI) announcements rather than CPI announcements because PPI numbers for a given month are always released a few days earlier, thereby diminishing the news content of CPI numbers. Before February 1994, we assume that the FOMC decision became public one day after its meeting (as in Kuttner (2001)). We exclude any unscheduled announcements and adjust the date to the next trading day if announcements are nontrading days. To calculate excess returns, we obtain the daily risk-free rate from the Fama-French data library.

2.3.7 Summary Statistics

Table 2.1 reports the summary statistics for our firm characteristic variables and their correlation. Panel A shows that the more profitable firms tend to be the large, growth, liquid, and winner firms. Panel B shows that the decile portfolio has a return spread of 0.83% per month, whereas the quintile portfolio has a return spread of 0.56% per month. Both are statistically significant. In particular, the majority of abnormal returns are due to the large negative alpha from the firms with low profitability. In addition, if we skip one month immediately after portfolio formation, the return spread remains very similar, suggesting that the market micro structure is unlikely to account for the observed premium.

Finally, Panel C shows that the correlations between the proxies for investment flexibility and shareholder advantage and the proxies for limits-to-arbitrage and information uncertainty are quite low, typically less than 10%. These low correlations make the tests of the two alternative explanations less confounded. The only exception is the total asset size. Garlappi, Shu, and Yan (2008) use total asset size as a proxy for shareholder advantage. However, the asset size is highly correlated to firm market capitalization, a proxy for information uncertainty and arbitrage costs. Thus, the model with shareholder advantage implies that the ROA effect should be stronger among firms with large asset size, whereas the mispricing hypothesis implies the opposite. Eventually, seeing which effect is stronger in the data is an empirical question.

2.4 Empirical Results

This section presents the main empirical results. We first explore the role of systematic risk in the ROA effect. Then we examine the potential role of limits-to-arbitrage and information uncertainty in the ROA effect.

2.4.1 Profitability Premium and Systematic Risk

2.4.1.1 Implications of Shareholder Advantage and Investment Flexibility

In this subsection, we first use the portfolio approach to study how the profitability premium varies with shareholder advantage and investment flexibility. Each month we first sort NYSE, AMEX, and NASDAQ stocks into five groups based on the quintile of the ranked values of one of the proxies for shareholder advantage or flexibility, and then sort stocks within each group into five groups based on the quintile of the ranked values of ROA. Within each group, we further sort stocks into five groups based on past ROA. We omit firms with sales less than $10 million from our sample to alleviate the impact of small firms.

Panel A of Table 2.2 reports the monthly high-ROA, low-ROA, and the high-minus-low portfolio returns within each proxy group and the corresponding t-statistics. The result based on the total asset proxy is quite weak and is the opposite of Hypothesis 1. This might be because total assets are highly negatively correlated with arbitrage cost-s and information uncertainty. According to Hypothesis 3, the ROA spread should be stronger among firms with low total assets, the opposite of Hypothesis 1. Because of this compounding effect, total assets might not be a good proxy to test the hypothesis related to shareholder advantage. Thus, we focus our attention on the other three proxies, which have a very low correlation with arbitrage costs and information uncertainty proxies, as shown in Table 2.1. For the other three proxies, we observe that the profitability spreads are higher among the group of firms with high shareholder advantage, consistent with Hypothesis 1. However, the differences in ROA spreads across firms with high and low shareholder advantage are generally insignificant. The t-statistics for the differences are 0.53, 0.66, and 1.62, respectively, for tangible assets, R&D, and industrial concentration. These results lend some moderate support to the notion that higher shareholder advantage increases the abandonment option value to equity holders, especially for firms with low ROA. Finally, a similar pattern emerges for the investment flexibility proxy in the last row of Panel A in Table 2.2.

Besides examining the raw excess portfolio returns, we also investigate whether the spreads can be explained by the traditional Fama-French (1993) three-factor model. If this classic model can capture the cross-sectional variation in stock returns, the intercept from the following regressions should be statistically indistinguishable from zero:

$$R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}, \tag{2.1}$$

where $R_{i,t} - R_{ft}$ is the return of portfolio i in excess of the risk-free rate in month t. Panel A of Table 2.2 also reports the intercepts and the t-statistics from the above regression for each proxy. We can see that risk-adjusted alpha provides a similar level of support to Hypothesis 1. In addition, using CAPM or Carhart's (1997) four-factor model renders similar results, which are available upon request.

In sum, our evidence indicates that part of the ROA premium results from the large hedging option value of the low ROA firms. The firms with low ROA are less risky due to the shareholders' ability to renegotiate and the firms' ability to abandon projects in case of adverse productivity shocks.

2.4.1.2 Business Cycle Variation

The previous section studies the cross-sectional heterogeneity of the ROA effect. This section investigates the time-series variation of the ROA premium. Hypothesis 2 states that, if the profitability premium is driven by systematic risk, then it should vary with the business cycle and should be predictable by traditional risk premium predictors. Table 2.3 presents the results of a predictive regression of the profitability spread on lagged macro variables. It turns out that none of these macro variables are significant in our regression. Furthermore, many coefficients have a sign that is opposite to that predicted. For example, the coefficient on the surplus ratio should be negative, since a high surplus ratio implies a lower risk aversion and hence a low profitability premium. Similarly, the sign on the dividend yield should be positive, but it is negative in our predictive regression.[7]

Moreover, if the ROA effect is due to risk, one should expect that firms with high ROA earn lower returns than firms with low ROA during bad times. Figure 1 plots the annual ROA spread from 1972 to 2011 across booms and recessions. As shown, the spread is largely positive during recessions. In addition, compared with the momentum

[7]On the other hand, mispricing hypotheses would suggest that the ROA effect should be stronger following high sentiment periods (Stambaugh, Yu, and Yuan (2012)) and following periods with high dispersion of opinion (Hong and Sraer (2012)). Indeed, in untabulated analysis, which is available upon request, we find supportive evidence.

effect, which usually experiences large crashes following recessions, the ROA effect is relatively stable. Overall, Table 2.3 and Figure 1 indicate that exposure to traditional macro risk factors is not much greater for high ROA firms than for low ROA firms. Thus, to understand the underlying risk dynamics of the ROA portfolios, one might need to search for unconventional risk sources, such as investment-specific shocks.

In sum, we fail to identify time variation in the profitability premium related to any business cycle variable. Given that the predictive ability of business cycle variables for the aggregate risk premium is not particularly strong, one might argue that the test based on our predictive regression is not very powerful. Therefore, in the next subsection, to further identify the role of macroeconomic risk in the profitability premium, we investigate the portfolio returns across prescheduled macro news announcement dates and nonannouncement dates.

2.4.1.3 Macro News Announcement Returns

Recently, Savor and Wilson (2010) document that excess market returns on macro news announcement days are about 10 times larger than those on nonannouncement days. Their finding suggests that macro risk is significantly priced and that the risk premium is much higher on announcement dates. Hence, if the profitability premium is due to compensation for macro risk, we would expect the profitability premium to be larger on announcement days than on nonannouncement days.

Table 2.4 reports the average daily stock returns on announcement days and nonannouncement days and their difference. Panel A confirms Savor and Wilson's (2010) finding that market excess returns are about eight times higher on macro news announcement days than on non-announcement days. Panels B and C report the high-minus-low ROA portfolio excess returns of 10 and 5 ROA portfolios, respectively. We can see that the profitability spreads are actually opposite those in Savor and Wilson's (2010) findings. Although the daily market excess return is 8 basis points on announcement dates versus a significantly lower value of 1 basis point on nonannouncement dates, the decile and the quintile ROA portfolios have an insignificant and negative spread difference between announcement and nonannouncement days.

In sum, we find that the profitability premium is similar on both announcement and nonannouncement days. This evidence suggests that macro risk related to PPI, employment, and interest rates is unlikely to be the source of the observed profitability premium.

2.4.1.4 Mimicking Factor and Characteristics

The findings in the previous three subsections suggest that the profitability premium is unlikely to be completely explained by traditional macro risk factors. However, proposing additional risk factors to explain the profitability premium is still possible. If an important risk factor, which is not captured by the traditional macro variables, is missed, the risk-based hypothesis could be incorrectly rejected.

Previous researchers have developed a systematic approach to identifying the risk factor that is most closely related to an anomaly, if it is indeed driven by risk. We apply this approach to the profitability anomaly. In this approach, a factor-mimicking portfolio is constructed to load heavily on whatever risk factor is driving an anomaly (again, if risk is indeed the driver). This procedure can be used to extract measures of risk even if the researcher does not observe the factor structure underlying the stock returns. This approach is originally developed by Fama and French (1993), and is followed and extended by numerous subsequent studies. In particular, Daniel and Titman (1997) extend the approach to examine whether risk or mispricing explains the size and value premia, and Hirshleifer, Hou, and Teoh (2012) extend the approach to examine the accrual anomaly.

The construction of the mimicking factor is analogous to that of SMB and HML. Following Fama and French (1993) and CNZ (2010), we construct the factor-mimicking portfolio by taking a long position on high ROA firms and a short position on low ROA firms, adjusted for size. Since any underlying factors that are important for the pricing of the profitability premium are likely to be picked up by the factor-mimicking portfolio, our result indicates that the profitability premium is unlikely to be explained by systematic risk factors.

Further, we follow Daniel and Titman (1997) by comparing the loadings on the mimicking factor and the ROA characteristic in predicting future asset returns. In particular, we perform Fama and MacBeth (1973) cross-sectional regressions of individual stock returns and portfolio returns on ROA, mimicking factor loading, and other return predictors. Unlike the portfolio sorting approach, this approach allows us to run a horse race between the ROA characteristic and factor loadings and to conveniently include a number of control variables.[8] Table 2.5 presents these findings. Panel A reports the results of the portfolio-level regressions using returns on the 27 triple-sorted portfolios based on size, ROA, and the pre-formation ROA factor loading. The first regression of Panel A shows that the ROA factor loading is positively associated with future average returns. However, once we include the average ROA characteristic, the coefficient of the ROA factor loading is insignificant. Furthermore, the sign is wrong once we control for the loadings on Carhart's (1997) four-factor model.

To complement the portfolio-level analysis in Panel A, Panel B reports the results from firm-level regressions. The firm-level analysis allows us to control more firm-level characteristics. In general, the firm-level analysis is consistent with the portfolio analysis. For all the specifications, the ROA characteristic dominates the loading on the mimicking factor in predicting future returns. Overall, our evidence suggests that systematic risk is not a complete explanation for the profitability premium.

2.4.2 The Role of Arbitrage Costs and Information Uncertainty in the Profitability Premium

2.4.2.1 Portfolio Analysis

In this section, we use the portfolio approach to study how the profitability premium varies with the severity of limits on arbitrage/information uncertainty. Following Zhang

[8] In unreported results, we form portfolios by triple sorting. We find that controlling for the firm size and ROA characteristic, firms with high ROA-factor loadings have subsequent returns similar to firms with low ROA-factor loadings. On the other hand, firms with high ROA have high subsequent returns, even after controlling for the firm size and ROA-factor loading.

(2006), we use reciprocals of some proxies (i.e., size, age, analyst coverage, number of institutional holdings, percentage of institutional holdings, and dollar trading volume) to make sure that higher-ranked portfolios are stocks with more severe limits on arbitrage or more information uncertainty. We do this only to make the results easier to interpret and compare. Within each group, we further sort stocks into five groups based on past ROA.

Panel B of Table 2.2 reports the monthly high-ROA, low-ROA, and the high-minus-low portfolio returns within each arbitrage costs proxy group and the corresponding t-statistics. Consistent with our hypothesis, for all seven proxies for limits to arbitrage, we observe that the profitability spreads are typically insignificant or marginally significant among the low arbitrage risk group and highly significant among the high arbitrage risk group. The differences across firms with high and low arbitrage costs are also highly significant for each of the proxies. For example, for the IVOL proxy, the mean profitability spread increases from 0.16% in the low IVOL group (low arbitrage cost) to 1.29% in the high IVOL group (high arbitrage cost). The difference between these two groups is 1.13% per month with t-statistics of 3.21. This difference is economically significant as well. The profitability premium is about 1% per month higher among the firms with high arbitrage costs than that among the firms with low arbitrage costs. This result is consistent with the notion that arbitrage costs deter mispricing from being fully corrected.

Similar patterns emerge for the information uncertainty proxies in Panel C of Table

2.2. For each of the six proxies, the profitability premium is insignificant or marginally significant among firms with low information uncertainty and highly significant among firms with greater information uncertainty. This finding supports the hypothesis that, faced with high information uncertainty, investors' investment decisions tend to be more affected by their behavioral biases, leaving more room for mispricing. In untabulated analysis, we form portfolios by independent sorting and by sorting on ROA first, then on the proxies. The results, omitted for brevity, are quantitatively similar.[9]

Moreover, the majority of the long-short abnormal profits are derived from the short leg of the strategy. This pattern is evident for our most important proxy for arbitrage costs, the idiosyncratic volatility. Among low IVOL firms, the Fama-French three-factor alpha from the short leg is -0.26% and the alpha from the long leg is 0.25%. By contrast, among high IVOL firms, the short leg has an alpha of -1.32%, while the long leg has an alpha of only 0.21%. The stronger results for the short leg is consistent with the notion that short-selling faces more impediments than purchasing; thus, overpricing is more prevalent than underpricing due to asymmetric constraints faced by arbitrageurs. Averaged across all of the 13 proxies, among firms with high limits to arbitrage and high information uncertainty, the short leg has an alpha of -1.07%, whereas the long leg has an alpha of 0.53%. Thus, about two-thirds of the alpha is derived from the short leg.

Panels B and C of Table 2.2 examine both the raw excess returns and the Fama-

[9] As mentioned in the introduction, the pattern in Panel C could potentially be consistent with the learning model of Veronesi (2000) and Pastor and Veronesi (2003, 2006). In particular, Pastor and Veronesi (2006) shows that uncertainty regarding long-term profitability can affect risk premium. Although it is beyond the scope of the current paper to develop a fully fledged model based on learning and parameter uncertainty to account for the pattern documented in Panel C, it is certainly interesting to pursue along this avenue in future research.

French three-factor model alpha. We can see that the risk-adjusted alpha is generally more significant. This is because the high-minus-low profitability portfolios have a negative loading on the market and the HML factor. In untabulated analysis, we find that the difference-on-differences are still significant even after we adjust the raw returns with CAPM or Carhart's four-factor model.

In sum, the portfolio analysis provides consistent support to our hypothesis that the profitability premium should be stronger among firms with more severe limits on arbitrage and more information uncertainty if mispricing can partially account for this premium.

2.4.2.2 Fama-MacBeth Regression Tests

The simple double-sorting approach in the previous section provides support to our Hypothesis 2. However, the different ROA spread across firms with different levels of arbitrage costs or information uncertainty could be driven by forces other than those proposed by us. As argued by Grinblatt and Han (2005), double sorting cannot explicitly control for other variables that might influence returns, and sorting on three or more variables is impractical. Thus, to investigate other possible mechanisms, we perform a series of Fama and MacBeth (1973) cross-sectional regressions, which allows us to conveniently control for additional variables.

In particular, if the lagged profitability spread is high among firms with more limits on arbitrage, then the higher profitability premium among this category of firms might simply be due to the higher variation in past profitability characteristics, not to the higher limits on arbitrage per se. The multivariate Fama-MacBeth (1973) type regression is convenient in controlling for this confounding problem. Moreover, Johnson (2004) argues that analyst forecast dispersion can be interpreted as a proxy for idiosyncratic parameter risk. For a levered firm, the negative relation between dispersion and expected returns obtains from a general options-pricing result. Johnson (2004) shows that due to convexity, leverage can affect the relation between idiosyncratic parameter risk and stock returns. If ROA is negatively linked to firm leverage and our proxies for information uncertainty are a proxy for idiosyncratic parameter risk, then it is possible that our results are driven, at least partly, by the leverage effect identified by Johnson (2004). Thus, to control for this leverage effect, we include leverage and its interaction with arbitrage and information uncertainty proxies in our series of Fama-MacBeth regressions. Similar to the portfolio approach, we take reciprocals if necessary to make sure that the larger the proxy, the more severe limits on arbitrage or more information uncertainty is involved.

Specifically, we test our hypothesis using the following multivariate Fama-MacBeth (1973) type regression:

$$R_{i,t} = c_0 + c_1 * ROA_{i,t-1} + c_2 * X_{i,t-1} + c_3 * ROA_{i,t-1} * X_{i,t-1} + Controls_{t-1} + \varepsilon_{i,t}, \quad (2.2)$$

where $R_{i,t}$ is the monthly raw return on stock i, and $X_{i,t-1}$ is one of our proxies for shareholder advantage or flexibility known at the portfolio formation date. Similar to our portfolio approach, $Controls$ are $lnSIZE$ (natural logarithm of market equity in the previous month), $lnBM$ (natural logarithm of book equity according to Fama and French (1993) at the end of fiscal year $t-1$ divided by the market equity value at the end of December of year $t-1$), MOM (the 6-month cumulative stock returns from month $t-7$ to month $t-2$), LEV (leverage, calculated as total assets divided by market equity in last December), and the interaction of leverage and proxies. Variables are winsorized at the 1% and 99% levels. t-statistics are calculated using Newey and West (1987) standard errors. Similar to the portfolio approach, we take reciprocals if necessary to make sure that the larger the proxy, the more severe limits on arbitrage or more information uncertainty is involved.

The coefficients of interest are the coefficients on the interaction terms in Table 2.6. The corresponding t-statistics are calculated with Newey and West (1987) robust standard errors. Our hypothesis predicts that it should be positive, implying a positive relationship between stock returns and the severity of limits on arbitrage or information uncertainty after controlling for the effect of ROA. Table 2.6 confirms this prediction. Panel B reports the regression results for proxies for arbitrage risk, and Panel C reports the results for proxies for information uncertainty. (For completeness, Panel A reports the regression results for proxies for shareholder advantage and investment inflexibility.) We can see that interaction terms are positive and highly significant for all proxies except for dispersion in analyst forecasts.[10]

[10]Because of different sample periods and difference control variables in the regression, the result-s reported in Table 2.6 also differ from those in Johnson (2004). In Johnson (2004), the coefficient for the interaction between analyst forecast dispersion and leverage is negative, whereas we obtain an insignificant and positive coefficient.

To alleviate the effect from small firms, we have already excluded firms with sales less than \$10 million in our sample. To further reduce the effect from small firms, we follow Lam and Wei (2011) by reporting the results based on weighted least squares (WLS) regressions with market capitalization as the weighting. As expected, the WLS t-statistics are typically weaker, but many still remain significant, consistent with the notion that limits-to-arbitrage are stronger among smaller firms. The control variables in WLS regressions, unreported in Table 2.6 to save space, are the same with the corresponding ordinary least squares (OLS) regressions.

In sum, both the portfolio approach and regression tests show that the profitability premium is much stronger among firms with high limits on arbitrage or information uncertainty. Although none of the 13 proxies are perfect for limits on arbitrage or information uncertainty, the consistent evidence across all of the proxies suggests that mispricing is likely to play a prominent role in the profitability premium.

2.4.3 Further Evidence from Earnings Announcement Returns

Given that our evidence suggests a significant role for mispricing in the profitability premium, we further explore the source of this potential mispricing. One possibility is underreaction to profitability news. For example, in face of good (bad) profitability news, investors update the prior too slowly and underestimate (overestimate) the future outcome of the firm. Hence, when past profitability is high (low), prices are too low (high) relative to fundamentals. When mispricing subsequently get corrected, we observe higher (lower) returns on high (low) ROA firms. When there is more information uncertainty, the underreaction (overestimation) can be more severe. As a result, we observe a larger profitability premium among the firms with more information uncertainty. This is consistent with the well-documented conservatism bias (e.g., Edwards (1968)), which posits that individuals are slow to change their beliefs in face of new evidence.[11]

Following La Porta et al. (1997), we examine abnormal stock price movements around earnings announcement dates to assess whether systematic expectational errors can explain the profitability premium. In particular, if the large profitability premium in the group of firms with severe limits on arbitrage and information uncertainty is due to mispricing, and if investors revise their expectations when earnings announcements are made, we would expect high (low) ROA firms to earn high (low) returns around earnings announcement days when investors realize their previous expectation errors. This is because firms with high (low) past profitability tend to have positive (negative) earnings surprises on average. Furthermore, the return spread during announcements should be most pronounced in stocks with severe limits on arbitrage and information uncertainty. We measure quarterly event returns over a three-day window $(-1, +1)$ around the Wall Street Journal publication dates over the next quarter after portfolio formation. Data on Wall Street Journal quarterly earnings announcement days are from Compustat. For each month, the three-day buy-and-hold event return is calculated for each stock, and equally weighted averages across all stocks within each portfolio are calculated as the monthly event return of this portfolio.

[11]See Barberis, Shleifer, and Vishny (1998) for a list of asset-pricing phenomena that are consistent with the conservatism.

The middle and right panels of Table 2.7 report these results. (Again, for completeness, the left panel reports the results for proxies for shareholder advantage and investment inflexibility.) Among stocks with severe limits on arbitrage or high information uncertainty, the equally weighted earnings announcement returns are usually negative for low ROA firms and positive for high ROA firms. The return spreads during earnings announcements among this category of firms are significant. Furthermore, the return spreads during earnings announcements are much weaker and usually insignificant for firms with less information uncertainty and fewer limits on arbitrage. The evidence is consistent with the notion that investors underreact to current earnings news, and arbitrage costs prevent this underreaction-induced mispricing from being fully corrected by arbitrageurs. In terms of magnitude, the profitability premium is about $2.5 - 5\%$ per quarter among firms with high arbitrage costs and high information uncertainty. Table 2.7 shows that about 20% of the profitability premium is realized during earnings announcements in the subsequent quarter.

One might argue that there is a disproportionately high fraction of uncertainty about a stock on earnings announcements. Hence, earnings announcement days might carry a large share of the risk premium. Since the risk premium for high ROA firms is larger, these firms should exhibit higher event returns than low ROA firms, and the profitability premium should be larger during earnings announcements. To rule out this possibility, we follow La Porta et al. (1997) by using cross-sectional regression analysis. We want to see whether there is systematically more positive news for more profitable stocks and negative news for less profitable stocks. In particular, for each month in the sample, we run cross-sectional regressions of the daily return for each stock on the value-weighted market return and a dummy variable for whether the day belongs to the $(-1, +1)$ window around the next quarter's earnings announcement. Regressions are run separately for stocks in the lowest ROA decile and the highest ROA decile, with portfolios rebalanced every month. Table 2.8 reports these regression results. The coefficient on the event dummy is significantly negative for low ROA stocks and significantly positive for high ROA stocks, which implies that, on average, the market receives negative surprises for low ROA stocks and positive surprises for high ROA stocks on earnings announcement days.

In a nutshell, our evidence suggests that investors underestimate the importance of current fundamentals, probably due to conservatism in updating beliefs. The profitability premium emerges partially because the underpricing (overpricing) for the high (low) ROA firms is corrected during subsequent earnings announcements.

2.5 Conclusion

Both the standard valuation theory and the q-theory of investment imply that all else equal, more profitable firms have higher expected returns. Many empirical studies further confirm that more profitable firms earn significantly larger returns. However, these theories are generally agnostic about whether the observed profitability premium is due to rational or irrational pricing. In this paper, we tackle this question by examining how the profitability premium varies systematically with firm characteristics and macroeconomic conditions.

We find that the ROA effect tends to be slightly stronger among firms with higher shareholder advantage and higher investment flexibility, consistent with the view that low ROA firms are closer to bankruptcy and thus the hedge option accounts for a higher portion of the firm value. Apart from the relatively weak support for the role of shareholder advantage and investment flexibility in the ROA premium, we find stronger evidence that investors underreact to current profitability news and that this underreaction is stronger among firms with greater information uncertainty. Because of limits to arbitrage, the overpricing (underpricing) in more (less) profitable firms is not fully countervailed by arbitrageurs, and hence the profitability premium is substantially stronger among firms with higher arbitrage costs or greater information uncertainty. Although our study does not aim to find a complete explanation for the profitability premium, our evidence suggests that temporary mispricing at least partly explains the observed profitability premium, especially among firms that are difficult to arbitrage.

Taking into account the fact that factor models based on profitability could successfully explain a wide range of anomalies, our evidence suggests that a common mispricing component or a systematic behavioral bias underlies many seemingly unrelated anomalies. Our results indicate that incorporating behavioral biases into an otherwise standard q-theory model to account for a range of anomalies could be an interesting area for future research.

Table 2.1: Descriptive Statistics

Each month we sort NYSE, AMEX, and NASDAQ stocks (excluding financial firms, firms with negative book equity, sales less than \$10 million stocks, and appearing in Compustat for less than two years) into five groups based on the quintile of the ranked values of return-on-assets (ROA). ROA is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). MOM is the 6-month cumulative stock return from month $t-7$ to month $t-2$. BM is the book value of equity divided by the market value at the end of the last fiscal year. We consider five rational proxies: Total Asset is the quarterly market value of assets. Tang Asset is based on Berger, Ofek, and Swary (1996) estimation: $Tang = (0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times Capital + Cash)$, and scaled by total book asset. XRD is the ratio of R&D expenditure to the book value of assets. Industry Concentration (IC) is the Herfindahl index on sales based on two-digit SIC code industry classification. Investment Inflexibility (INFLEX) is based on Hackbarth and Johnson (2011), calculated as the industry median firm range of operating costs over sales. We consider seven limits-to-arbitrage proxies: Number of institutional holders (N_I) is the number of institutional investors holding a firm's shares each month. Percentage of outstanding shares held by institutional investors (Per_I) is the percentage of outstanding shares held by institutional investors each month. Idiosyncratic stock return volatility (IVOL) is the standard deviation of the previous 36-month residual values from the Fama-French three-factor regression ($R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$, where $R_{i,t} - R_{ft} =$ is the monthly excess return on stock i). Dollar trading volume (DVol) is the time-series average of the monthly share trading volume multiplied by the monthly closing price over the past 12 months. Bid-ask spreads (B/A) is the time-series average of $2 * |Price - (Ask + Bid)/2|/Price$ at the end of each month over the 12 past months. Credit rating history (CR) is a dummy variable representing firms' credit rating, which is 0 if a firm has an S&P long-term credit rating and 1 otherwise. Amihud's (2002) illiquidity (Illiq) is the annual average of the daily ratio of absolute stock return to its daily dollar trading volume. We consider six uncertainty proxies: SIZE is the market value of equity. AGE is the number of years since the firm was first covered by CRSP. Stock volatility (σ_R) is the standard deviation of weekly excess returns over the past year. Cash flow volatility (σ_{CF}) is the standard deviation of cash flow from operations in the past five years with a minimum of three years. Analyst coverage (N_A) is the number of analysts following the firm each month. Dispersion in analyst forecast (σ_A) is the standard deviation of analyst forecasts scaled by the prior year-end stock price to mitigate heteroskedasticity. Panel A reports the time-series averages of various attributes of the portfolios based on the ROA ranking. Panel B reports the value-weighted excess returns, the intercepts (α^{CAPM}) of the CAPM regression ($R_{i,t} - R_{ft} = \alpha + b_{i,M}(R_{M,t} - R_{ft}) + \varepsilon_{i,t}$), and the intercepts ($\alpha^{FF3}$) of the Fama-French three-factor regression ($R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$), The corresponding t-statistics are reported for the quintile and decile portfolios, respectively. Panel C reports the time-series averages of monthly firm-level cross-sectional correlations between firm attributes, limits-to-average proxies, and uncertainty proxies. The sample period is January 1972 to December 2011, except March 1980 to December 2011 for N_I and Per_I, January 1994 to December 2011 for B/A, and January 1976 to December 2011 for N_A and σ_A. ROA, XRD, IVOL, B/A and σ_A are represented in percentages; SIZE, DVol, and TA are in billions; and Illiq is in the unit of 10^{-6}.

Panel A: ROA Portfolio Characteristics							
	Low	2	3	4	High	H-L	t-stat
Firm Attributes							
ROA	-3.48	0.31	1.12	1.94	3.92	7.40	9.54
BM	1.23	1.19	1.00	0.79	0.56	-0.66	-6.84
LEV	3.55	3.22	2.39	1.65	1.06	-2.49	-5.34
Rational Proxies							
TA	0.90	2.59	3.44	3.32	3.64	2.75	3.25
Tang	0.55	0.52	0.51	0.53	0.57	0.02	1.74
XRD	5.08	1.97	1.76	2.15	3.28	-1.80	-2.13
IC	0.12	0.12	0.11	0.11	0.11	-0.00	-1.29
Inflex	8.01	8.27	8.45	8.14	8.12	0.12	1.79
Limits-to-Arbitrage Proxies							
IVol	14.60	11.02	9.80	9.66	10.57	-4.02	-6.96
N_I	24	43	60	71	77	53	4.12
Per_I	18.17	24.96	28.51	31.06	30.96	12.79	6.03
DVol	0.70	1.15	1.63	2.13	3.05	2.35	2.6
B/A	3.20	2.58	2.02	1.77	1.61	-1.60	-5.06
CR	0.65	0.49	0.45	0.48	0.56	-0.09	-1.03
Illiq	8.46	4.51	2.64	1.92	1.65	-6.81	-4.79
Uncertainty Proxies							
ME	0.31	0.80	1.32	1.65	2.05	1.74	3.88
AGE	11	13	14	14	12	1.69	2.74
σ_R	0.17	0.14	0.12	0.12	0.13	-0.04	-5.36
σ_{CF}	0.11	0.07	0.07	0.07	0.08	-0.03	-4.91
N_A	5	7	8	8	9	3.94	16.94
σ_A	3.81	1.32	0.73	0.52	0.44	-3.36	-7.03

Panel B: ROA Portfolio Excess Returns							
	Low	2	3	4	High	H-L	t-stat
R_5^e	0.03	0.39	0.53	0.54	0.59	0.56	2.25
α_5^{CAPM}	-0.60	-0.11	0.07	0.10	0.13	0.73	2.98
α_5^{FF3}	-0.63	-0.26	-0.01	0.10	0.32	0.94	4.5
	Low	2	5	9	High	H-L	t-stat
R_{10}^e	-0.15	0.13	0.49	0.48	0.68	0.83	2.72
α_{10}^{CAPM}	-0.81	-0.47	0.03	0.03	0.21	1.02	3.46
α_{10}^{FF3}	-0.82	-0.51	-0.08	0.15	0.45	1.27	4.8

Panel C: Correlation Matrix

	ROA	RET	BM	SIZE	MOM	LEV	AGE	σ_R	σ_{CF}	N_A	σ_A	N_I	Per_I	IVOL	DVol	B/A	CR	Illiq	TA	Tang	XRD	IC	Inflex
ROA	1.00																						
RET	0.02	1.00																					
BM	-0.18	0.02	1.00																				
SIZE	0.08	0.00	-0.08	1.00																			
MOM	0.18	0.02	0.05	0.02	1.00																		
LEV	-0.16	0.01	0.69	-0.06	0.03	1.00																	
AGE	0.05	0.01	0.07	0.16	0.03	0.02	1.00																
σ_R	-0.20	-0.01	0.03	-0.19	0.01	0.08	-0.34	1.00															
σ_{CF}	-0.09	-0.01	-0.03	-0.10	-0.02	0.01	-0.15	0.36	1.00														
N_A	0.12	-0.01	-0.16	0.47	-0.01	-0.11	0.24	-0.30	-0.18	1.00													
σ_A	-0.03	-0.01	0.01	-0.01	-0.02	0.02	-0.01	0.02	0.02	-0.01	1.00												
N_I	0.14	0.00	-0.16	0.75	0.03	-0.11	0.31	-0.35	-0.18	0.77	-0.04	1.00											
Per_I	0.16	0.00	-0.18	0.15	0.04	-0.15	0.16	-0.33	-0.18	0.45	-0.04	0.47	1.00										
IVOL	-0.21	-0.01	0.07	-0.20	0.04	0.12	-0.31	0.89	0.33	-0.33	0.03	-0.36	-0.37	1.00									
DVol	0.10	-0.01	-0.12	0.77	0.02	-0.09	0.12	-0.15	-0.07	0.54	-0.01	0.69	0.21	-0.16	1.00								
B/A	-0.15	0.02	0.29	-0.13	-0.03	0.26	-0.09	0.26	0.10	-0.40	0.02	-0.35	-0.54	0.32	-0.15	1.00							
CR	-0.06	-0.01	0.05	-0.21	-0.03	-0.04	-0.21	0.29	0.17	-0.39	0.01	-0.45	-0.38	0.29	-0.23	0.31	1.00						
Illiq	-0.12	0.02	0.21	-0.05	-0.02	0.21	-0.04	0.21	0.10	-0.17	0.01	-0.13	-0.22	0.24	-0.07	0.65	0.16	1.00					
TA	0.03	0.00	-0.04	0.89	0.01	0.02	0.16	-0.19	-0.11	0.42	-0.01	0.69	0.14	-0.20	0.62	-0.12	-0.22	-0.06	1.00				
Tang	0.04	0.00	-0.10	-0.06	0.00	-0.15	-0.13	0.12	0.11	-0.10	0.01	-0.16	-0.09	0.10	-0.02	0.03	0.24	0.00	-0.08	1.00			
XRD	-0.09	0.00	-0.13	0.03	0.00	-0.14	-0.10	0.19	0.13	0.03	0.01	0.00	0.02	0.16	0.09	0.00	0.11	-0.03	-0.01	0.26	1.00		
IC	0.00	0.00	0.00	0.04	0.00	0.06	-0.04	0.06	0.04	-0.04	0.02	-0.02	-0.01	0.06	0.01	0.02	0.02	0.03	0.07	-0.06	-0.11	1.00	
Inflex	0.05	0.01	0.03	0.00	0.03	0.04	0.16	-0.13	-0.06	-0.01	-0.01	0.04	0.04	-0.11	-0.03	0.00	-0.05	0.00	0.02	-0.08	-0.12	0.00	1.00

Table 2.2: Portfolios Sorted by Proxies and ROA

Return-on-assets (ROA) is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). We consider five rational proxies: Total Asset is the quarterly market value of assets. Tang Asset is based on Berger, Ofek, and Swary (1996) estimation: $Tang = (0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times Capital + Cash)$, and scaled by total book asset. XRD is the ratio of R&D expenditure to the book value of assets. Industry Concentration (IC) is the Herfindahl index on sales based on two-digit SIC code industry classification. Investment Inflexibility (INFLEX) is based on Hackbarth and Johnson (2011), calculated as the industry median firm range of operating costs over sales. We consider seven limits-to-arbitrage proxies: Number of institutional holders (N_I) is the number of institutional investors holding a firm's shares each month. Percentage of outstanding shares held by institutional investors (Per_I) is the percentage of outstanding shares held by institutional investors each month. Idiosyncratic stock return volatility (IVOL) is the standard deviation of the previous 36-month residual values from the Fama-French three-factor regression ($R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$, where $R_{i,t} - R_{ft} =$ is the monthly excess return on stock i). Dollar trading volume (DVol) is the time-series average of the monthly share trading volume multiplied by the monthly closing price over the past 12 months. Bid-ask spreads (B/A) is the time-series average of $2 * |Price - (Ask + Bid)/2| / Price$ at the end of each month over the 12 past months. Credit rating history (CR) is a dummy variable representing firms' credit rating, which is 0 if a firm has an S&P long-term credit rating and 1 otherwise. Amihud's (2002) illiquidity (Illiq) is the annual average of the daily ratio of absolute stock return to its daily dollar trading volume. We consider six uncertainty proxies: SIZE is the market value of equity. AGE is the number of years since the firm was first covered by CRSP. Stock volatility (σ_R) is the standard deviation of weekly excess returns over the past year. Cash flow volatility (σ_{CF}) is the standard deviation of cash flow from operations in the past five years with a minimum of three years. Analyst coverage (N_A) is the number of analysts following the firm each month. Dispersion in analyst forecast (σ_A) is the standard deviation of analyst forecasts scaled by the prior year-end stock price to mitigate heteroskedasticity. Each month we first sort NYSE, AMEX, and NASDAQ stocks (excluding financial firms, firms with negative book equity, sales less than $10 million stocks, and appearing in Compustat for less than two years) into five groups based on the quintile of the ranked values of each proxy (except for the case of CR, which is divided into two groups depending on whether the firm has a rating), and then sort stocks within each group into five groups based on the quintile of the ranked values of ROA. Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). We calculate monthly value-weighted portfolio returns for the current month and rebalance the portfolios at the beginning of next month. We report the mean excess returns, the intercepts of the Fama-French three-factor regression ($R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$), and their t-statistics. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. We only report the results of the 1, 5, and 5-minus-1 proxy groups and the 1 (low), 5 (high), and high-minus-low (H-L) ROA portfolios within these groups to save space. The sample period is January 1972 to December 2011, except March 1980 to December 2011 for N_I and Per_I, January 1994 to December 2011 for B/A, and January 1976 to December 2011 for N_A and σ_A. The excess returns and αs are in percentages.

		ROA		R^e_{H-L}		ROA		α_{FF3}	
		Low	High	H-L	$t-stat$	Low	High	H-L	$t-stat$
Panel A: Rational Proxies									
TA	Low	0.40	1.93	1.54	4.51	-0.58	1.00	1.58	5.39
	High	0.35	0.65	0.30	1.41	-0.33	0.31	0.64	3.44
	H-L			-1.24	-4.05			-0.94	-3.43
1/Tang	Low	0.10	0.75	0.64	2.17	-0.34	0.57	0.92	3.59
	High	-0.15	0.67	0.82	2.77	-0.88	0.27	1.16	4.23
	H-L			0.17	0.53			0.24	0.75
1/XRD	Low	0.47	0.94	0.47	1.56	-0.02	0.81	0.84	3.63
	High	-0.06	0.60	0.66	2.60	-0.74	0.18	0.93	4.20
	H-L			0.19	0.66			0.09	0.32
IC	Low	0.13	0.54	0.41	1.48	-0.44	0.30	0.74	3.10
	High	-0.23	0.86	1.10	1.98	-1.19	0.53	1.71	3.49
	H-L			0.69	1.62			0.97	2.28
1/Inflex	Low	0.22	0.68	0.47	1.33	-0.82	0.33	1.15	4.14
	High	-0.21	0.81	1.02	2.83	-0.79	0.63	1.42	4.44
	H-L			0.55	1.48			0.26	0.74
Panel B: Limits-to-Arbitrage Proxies									
IVOL	Low	0.35	0.51	0.16	0.91	-0.26	0.25	0.50	3.30
	High	-0.50	0.79	1.29	3.96	-1.32	0.21	1.53	4.79
	H-L			1.13	3.21			1.03	2.92
$1/N_I$	Low	0.49	0.74	0.25	1.22	-0.10	0.45	0.55	2.58
	High	-0.18	0.77	0.94	2.34	-1.03	0.29	1.33	3.82
	H-L			0.69	2.14			0.77	2.92
$1/Per_I$	Low	0.37	0.82	0.45	2.25	-0.47	0.31	0.78	4.41
	High	-0.48	0.80	1.28	2.77	-1.34	0.35	1.69	4.02
	H-L			0.83	1.98			0.91	2.46
1/DVol	Low	0.08	0.55	0.47	1.94	-0.49	0.34	0.83	3.88
	High	-0.04	1.67	1.71	7.09	-0.85	1.01	1.85	7.95
	H-L			1.23	5.17			1.02	4.11
B/A	Low	0.03	0.76	0.74	1.69	-0.49	0.48	0.97	2.70
	High	-0.21	1.52	1.72	3.45	-0.99	0.99	1.98	5.65
	H-L			0.99	2.10			1.01	2.10
CR	Low	0.24	0.58	0.33	1.54	-0.43	0.32	0.74	4.06
	High	-0.28	0.57	0.85	3.06	-0.93	0.14	1.07	4.76
	H-L			0.52	2.38			0.33	1.75
Illiq	Low	0.19	0.52	0.33	1.56	-0.38	0.31	0.69	3.70
	High	-0.16	1.86	2.02	8.93	-1.04	1.11	2.15	9.45
	H-L			1.69	8.13			1.46	6.67
Panel C: Information Uncertainty Proxies									
1/SIZE	Low	0.21	0.54	0.33	1.76	-0.36	0.32	0.68	3.98
	High	0.39	1.87	1.48	4.30	-0.56	1.07	1.63	5.08
	H-L			1.15	3.44			0.96	2.90
1/AGE	Low	0.35	0.59	0.24	1.23	-0.50	0.24	0.73	4.54
	High	0.02	1.21	1.19	2.75	-0.80	0.58	1.38	3.34
	H-L			0.95	2.41			0.65	1.65
σ_R	Low	0.40	0.55	0.15	0.97	-0.19	0.26	0.45	3.11
	High	-0.65	0.70	1.35	3.89	-1.42	0.09	1.51	4.14
	H-L			1.19	3.14			1.06	2.53
σ_{CF}	Low	0.46	0.58	0.11	0.57	-0.23	0.31	0.53	2.97
	High	-0.17	0.75	0.91	2.89	-0.89	0.44	1.33	4.36
	H-L			0.80	2.43			0.80	2.20
$1/N_A$	Low	0.11	0.59	0.48	1.90	-0.48	0.32	0.80	3.46
	High	-0.25	1.31	1.57	4.28	-1.20	0.59	1.79	5.33
	H-L			1.09	3.90			0.99	3.60
σ_A	Low	0.78	0.76	-0.02	-0.10	0.36	0.54	0.18	1.04
	High	-0.54	0.74	1.28	3.51	-1.52	0.02	1.54	4.68
	H-L			1.30	3.70			1.36	3.82

Table 2.3: Predictive Regression with Macro Variable as Controls

Return-on-assets (ROA) is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). We form 10 monthly value-weighted portfolios based on the decile of the ranked values of ROA. Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). We then regress the high-minus-low portfolio returns on lagged default premium (DEF), term premium (TERM), real interest rate (INT), inflation (INFL), wealth-consumption ratio (CAY), dividend-price ratio (DP) surplus ratio (Splus), and NBER recession indicator ($R_t = c_0 + c * MacroVariables_{t-1} + \varepsilon_t$). We report the coefficients and their t-statistics. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. The sample period is January 1972 to December 2011.

	DEF	TERM	INT	INFL	CAY	DP	Splus	NBER
ROA10-ROA1	-3.5366	-2.5729	1.8975	-0.1441	-0.0070	-0.7039	0.0417	-0.0051
t-stat	-0.36	-0.83	1.00	-0.17	-0.05	-1.20	0.38	-0.62
R-squared								0.02

Table 2.4: Returns on Macro News Announcement Days and Non-announcement Days

This table shows the returns on macro news announcement days, nonannouncement days, and their difference. Announcement days are those trading days when PPI numbers, employment numbers, and FOMC interest rate decisions are scheduled for release. Panel A is the stock market excess returns (difference between the CRSP value-weighted market return and the risk-free rate) from Savor and Wilson (2010). Panel B is monthly value-weighted high-minus-low decile portfolio returns sorted by return-on-assets (ROA). ROA is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). Panel C is monthly value-weighted high-minus-low quintile portfolio returns sorted by return-on-assets (ROA). We report the daily mean returns and their t-statistics. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. The sample period is January 1972 to December 2011. The returns are expressed in percentages.

	ANNOUNCEMENT	NON-ANNOUNCEMENT	Difference
	Panel A: Market Excess Returns		
R^M	0.0803	0.0149	0.0654
	2.44	1.34	1.88
	Panel B: Profitability Spread (ROA-10 portfolios)		
ROA10-ROA1	0.0185	0.0348	-0.0164
	0.60	2.66	-0.49
	Panel C: Profitability Spread (ROA-5 portfolios)		
ROA5-ROA1	0.0114	0.0254	-0.0139
	0.41	2.42	-0.47

Table 2.5: Fama-MacBeth Monthly Cross-Sectional Regressions of Stock Returns on ROA Characteristic and Factor Loadings

Each month all stocks on NYSE, AMEX, and NASDAQ (excluding financial firms, firms with negative book equity, sales less than \$10 million stocks, and appearing in Compustat for less than two years) with at least 24 months of return data in the previous five years are assigned independently into three size groups and three return-on-assets (ROA) groups. The breakpoints for size are the 30th and 70th market value of NYSE stocks, and those for ROA are the 30th and 70th ROA of all stocks on NYSE, AMEX, and NASDAQ. ROA is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). The nine portfolios are then each divided into three portfolios based on individual firm-level preformation ROA factor loadings estimated with monthly returns over the previous 60 months (24 months minimum). Value-weighed monthly returns on these 27 triple-sorted portfolios are calculated. In Panel A, returns on these portfolios are regressed on the portfolio-level value-weighted ROA characteristic and loadings with respect to the market factor, SMB, HML, UMD, and ROA factor. The construction of the ROA factor is analogous to SMB and HML, taking a long position in high ROA firms and a short position in low ROA firms, adjusted for size. The portfolio-level factor loadings are obtained by regressing the monthly excess returns of each portfolio over the last 60 months on those factors. In Panel B, individual stock returns are regressed on LnSize (the log of a firm's market capitalization), LnBM (the log of the book-to-market ratio), MOM (the cumulative return from month -7 to month -2), ROA, and factor loadings. The time-series averages of the monthly regression coefficients are reported with their time-series t-statistics. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. The sample period is January 1972 to December 2011.

	lnBM	lnSIZE	MOM	ROA	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{ROA}
				Panel A: Portfolio-Level Regressions					
Coeff									0.0054
$t-stat$									2.40
Coeff				0.1300					
$t-stat$				3.94					
Coeff				0.1115					0.0020
$t-stat$				2.85					0.78
Coeff				0.2027	-0.0003	0.0038	0.0030	-0.0003	-0.0033
$t-stat$				6.19	-0.10	2.28	1.40	-0.09	-1.99
				Panel B: Firm-Level Regressions					
Coeff	0.0023	-0.0005	0.0067						0.0009
$t-stat$	2.75	-1.28	3.08						1.98
Coeff	0.0036	-0.0010	0.0039	0.1830					
$t-stat$	3.82	-2.49	1.5	6.78					
Coeff	0.0036	-0.0011	0.0036	0.1825					0.0004
$t-stat$	3.81	-2.63	1.33	6.83					0.97
Coeff	0.0035	-0.0011	0.0043	0.1785	0.0009	-0.0003	0.0004	-0.0014	0.0001
$t-stat$	4.61	-2.95	1.74	7.41	0.92	-0.45	0.61	-1.55	0.11

Table 2.6: Fama-MacBeth Regression of Future Returns on Proxies and ROA

Return-on-assets (ROA) is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). We consider five rational proxies: Total Asset is the quarterly market value of assets. Tang Asset is based on Berger, Ofek, and Swary (1996) estimation: $Tang = (0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times Capital + Cash)$, and scaled by total book asset. XRD is the ratio of R&D expenditure to the book value of assets. Industry Concentration (IC) is the Herfindahl index on sales based on two-digit SIC code industry classification. Investment Inflexibility (INFLEX) is based on Hackbarth and Johnson (2011), calculated as the industry median firm range of operating costs over sales. We consider seven limits-to-arbitrage proxies: Number of institutional holders (N_I) is the number of institutional investors holding a firm's shares each month. Percentage of outstanding shares held by institutional investors (Per_I) is the percentage of outstanding shares held by institutional investors each month. Idiosyncratic stock return volatility (IVOL) is the standard deviation of the previous 36-month residual values from the Fama-French three-factor regression ($R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$, where $R_{i,t} - R_{ft} =$ is the monthly excess return on stock i). Dollar trading volume (DVol) is the time-series average of the monthly share trading volume multiplied by the monthly closing price over the past 12 months. Bid-ask spreads (B/A) is the time-series average of $2 * |Price - (Ask + Bid)/2|/Price$ at the end of each month over the 12 past months. Credit rating history (CR) is a dummy variable representing firms' credit rating, which is 0 if a firm has an S&P long-term credit rating and 1 otherwise. Amihud's (2002) illiquidity (Illiq) is the annual average of the daily ratio of absolute stock return to its daily dollar trading volume. We consider six uncertainty proxies: SIZE is market value of equity. AGE is the number of years since the firm was first covered by CRSP. Stock volatility (σ_R) is the standard deviation of weekly excess returns over the past year. Cash flow volatility (σ_{CF}) is the standard deviation of cash flow from operations in the past five years with a minimum of three years. Analyst coverage (N_A) is the number of analysts following the firm each month. Dispersion in analyst forecast (σ_A) is the standard deviation of analyst forecasts scaled by the prior year-end stock price to mitigate heteroskedasticity. MOM is the six-month cumulative stock returns from month $t-7$ to month $t-2$. We run the following multivariate Fama-MacBeth regression on each stock: $R_{i,t} = c_0 + c_1 * ROA_{i,t-1} + c_2 * X_{i,t-1} + c_3 * ROA_{i,t-1} * X_{i,t-1} + Controls + \varepsilon_{i,t}$. Controls are log of B/M, log of SIZE, MOM, LEV, and the interaction of LEV and proxies. Variables are winsorized at the 1% and 99% levels. We report the regression coefficients and their t-statistics. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. The sample period is January 1972 to December 2011, except March 1980 to December 2011 for N_I and Per_I, January 1994 to December 2011 for B/A, and January 1976 to December 2011 for N_A and σ_A. The column $\text{Inter}_{\text{ROA}}^{\text{OLS}}$ reports the coefficient for the interaction between ROA and proxies with OLS regression. The column $\text{Inter}_{\text{LEV}}$ reports the coefficients for the interaction between LEV and proxies. Finally, the column $\text{Inter}_{\text{ROA}}^{\text{WLS}}$ reports the coefficient for the interaction between ROA and proxies with WLS regression. The control variables for WLS regressions are the same as those in OLS regressions. Only the interaction between ROA and proxies are reported for WLS regressions.

PROXY	ROA	PROXY	$\text{Inter}^{\text{OLS}}_{\text{ROA}}$	$\text{Inter}^{\text{WLS}}_{\text{ROA}}$	LEV	$\text{Inter}_{\text{LEV}}$	lnBM	lnSIZE	MOM
Panel A: Rational Proxies									
TA	0.0597	0.0000	0.0000	0.0000	-0.0007	0.0000	0.0043	-0.0010	0.0051
	1.21	-0.06	1.30	-0.48	-2.41	-0.69	4.19	-2.27	1.84
1/Tang	0.0148	-0.0010	0.1023	0.0619	-0.0006	0.0002	0.0041	-0.0008	0.0049
	0.23	-1.04	2.66	1.57	-1.28	1.04	4.68	-2.04	1.88
1/XRD	-0.0412	-0.0369	0.2749	0.4405	0.0091	-0.0092	0.0045	-0.0008	0.0041
	-0.12	-1.83	0.78	1.20	1.79	-1.84	5.30	-1.94	1.62
IC	0.0654	-0.0134	0.8748	0.6452	-0.0005	0.0015	0.0041	-0.0008	0.0055
	3.18	-4.01	6.56	3.87	-1.90	1.90	4.55	-1.84	2.06
1/Inflex	-0.0265	-0.0172	1.4625	0.8333	0.0000	-0.0025	0.0037	-0.0009	0.0049
	-1.89	-0.65	5.06	1.76	0.03	-0.43	4.13	-2.16	1.85
Panel B: Limits-to-Arbitrage Proxies									
IVOL	0.0730	-0.0557	0.9974	1.4287	-0.0003	0.0012	0.0028	-0.0013	0.0060
	2.60	-3.59	3.14	3.06	-1.03	0.50	4.09	-4.11	2.68
$1/N_I$	0.0477	-0.0288	0.9709	0.8411	-0.0010	0.0063	0.0036	-0.0010	0.0069
	2.74	-3.68	6.88	2.74	-2.52	2.37	3.80	-1.78	2.36
$1/Per_I$	0.0761	-0.0001	0.0039	0.0048	-0.0007	0.0000	0.0036	-0.0006	0.0068
	3.70	-3.08	5.58	2.67	-2.07	1.67	3.72	-1.40	2.26
1/DVol	0.1025	2.7301	485.9962	799.9152	-0.0006	1.5472	0.0037	-0.0006	0.0064
	5.49	0.70	3.79	4.15	-1.85	1.08	4.15	-1.14	2.43
B/A	0.0052	-0.0082	4.0110	3.0706	-0.0015	0.0224	0.0029	-0.0010	0.0056
	0.40	-0.17	3.15	1.59	-1.73	1.28	2.91	-1.32	1.21
CR	0.0858	-0.0085	0.1237	0.0448	-0.0008	0.0008	0.0033	-0.0017	0.0063
	4.37	-9.80	6.52	1.83	-3.44	4.04	3.66	-3.83	2.32
Illiq	0.1069	0.0001	0.0168	0.0293	-0.0005	0.0000	0.0037	-0.0005	0.0061
	5.60	0.48	3.68	3.51	-1.87	1.09	4.13	-1.18	2.30
Panel C: Information Uncertainty Proxies									
1/SIZE	0.1210	0.0514	0.9165	1.8139	-0.0005	0.0002	0.0041		0.0074
	5.97	3.93	3.64	2.31	-2.44	0.09	4.85		3.07
1/AGE	-0.0009	-0.0302	1.2141	1.2333	-0.0002	0.0009	0.0037	-0.0009	0.0055
	-0.03	-3.43	5.05	3.38	-0.15	0.24	4.30	-2.07	2.10
σ_R	-0.0221	-0.0587	1.2554	1.6906	-0.0010	0.0060	0.0028	-0.0013	0.0054
	-1.28	-3.40	5.07	4.94	-2.80	2.28	4.47	-4.07	2.12
σ_{CF}	0.0592	-0.0417	1.1524	-0.2660	-0.0007	0.0053	0.0029	-0.0010	0.0038
	3.39	-4.59	4.86	-0.66	-2.76	2.26	3.35	-2.65	1.48
$1/N_A$	0.0474	-0.0083	0.2528	0.2127	-0.0011	0.0014	0.0035	-0.0012	0.0077
	2.67	-5.60	7.39	4.20	-2.39	3.27	3.67	-2.12	2.73
σ_A	0.1371	-0.0189	0.3956	0.4203	-0.0005	0.0012	0.0035	-0.0013	0.0061
	4.10	-1.85	1.41	1.06	-1.08	0.48	3.34	-2.61	1.88

Table 2.7: Event Days Returns on Double-Sorting ROA Portfolios

This table reports average excess returns around a (-1,+1) three-day earnings announcement window in the first quarter after portfolio formation. Each month we form 25 portfolios, first sorted by the quintile of each proxy and then by the quintile of ROA. Excess returns are measured as raw returns minus the value-weighted market return. Portfolio returns are equally weighted. Return-on-assets (ROA) is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). We consider five rational proxies: Total Asset is the quarterly market value of assets. Tang Asset is based on Berger, Ofek, and Swary (1996) estimation: $Tang = (0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times Capital + Cash)$, and scaled by total book asset. XRD is the ratio of R&D expenditure to the book value of assets. Industry Concentration (IC) is the Herfindahl index on sales based on two-digit SIC code industry classification. Investment Inflexibility (INFLEX) is based on Hackbarth and Johnson (2011), calculated as the industry median firm range of operating costs over sales. We consider seven limits-to-arbitrage proxies: Number of institutional holders (N_I) is the number of institutional investors holding a firm's shares each month. Percentage of outstanding shares held by institutional investors (Per_I) is the percentage of outstanding shares held by institutional investors each month. Idiosyncratic stock return volatility (IVOL) is the standard deviation of the previous 36-month residual values from the Fama-French three-factor regression ($R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$, where $R_{i,t} - R_{ft} =$ is the monthly excess return on stock i). Dollar trading volume (DVol) is the time-series average of the monthly share trading volume multiplied by the monthly closing price over the past 12 months. Bid-ask spreads (B/A) is the time-series average of $2 * |Price - (Ask + Bid)/2|/Price$ at the end of each month over the 12 past months. Credit rating history (CR) is a dummy variable representing firms' credit rating, which is 0 if a firm has an S&P long-term credit rating and 1 otherwise. Amihud's (2002) illiquidity (Illiq) is the annual average of the daily ratio of absolute stock return to its daily dollar trading volume. We consider six uncertainty proxies: SIZE is the market value of equity. AGE is the number of years since the firm was first covered by CRSP. Stock volatility (σ_R) is the standard deviation of weekly excess returns over the past year. Cash flow volatility (σ_{CF}) is the standard deviation of cash flow from operations in the past five years with a minimum of three years. Analyst coverage (N_A) is the number of analysts following the firm each month. Dispersion in analyst forecast (σ_A) is the standard deviation of analyst forecasts scaled by the prior year-end stock price to mitigate heteroskedasticity. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. The sample period is January 1972 to December 2011, except March 1980 to December 2011 for N_I and Per_I, January 1994 to December 2011 for B/A, and January 1976 to December 2011 for N_A and σ_A. The (three-day cumulative) returns are in percentages.

		ROA		R^e_{H-L}			ROA		R^e_{H-L}			ROA		R^e_{H-L}	
		Low	High	H-L	$t-stat$		Low	High	H-L	$t-stat$		Low	High	H-L	$t-stat$
		Panel A: Rational Proxies					Panel B: Limits-to-Arbitrage Proxies					Panel C: Information Uncertainty Proxies			
Low	TA	-0.04	0.94	0.98	5.90	IVOL	0.29	0.34	0.05	0.71	1/SIZE	0.20	0.35	0.14	1.44
High		0.25	0.48	0.23	1.44		-0.23	0.16	0.39	2.66		0.15	1.20	1.05	7.66
H-L				-0.74	-3.63				0.34	2.05				0.91	6.59
Low	1/Tang	-0.22	0.13	0.35	2.41	$1/N_I$	0.35	0.34	-0.01	-0.06	1/AGE	0.32	0.34	0.02	0.17
High		-0.06	0.50	0.56	4.31		-0.19	0.39	0.58	4.64		-0.36	0.34	0.69	4.39
H-L				0.21	1.08				0.59	4.28				0.67	3.86
Low	1/XRD	-0.21	0.19	0.39	2.48	$1/Per_I$	0.33	0.41	0.08	0.63	σ_R	0.28	0.32	0.04	0.63
High		0.12	0.44	0.32	3.03		-0.35	0.45	0.80	6.13		-0.26	0.19	0.45	3.59
H-L				-0.07	-0.49				0.72	4.30				0.41	3.41
Low	IC	-0.02	0.28	0.30	4.00	1/DVol	0.08	0.25	0.17	1.25	σ_{CF}	0.32	0.34	0.02	0.24
High		-0.19	0.60	0.79	2.50		0.61	1.36	0.75	4.18		-0.39	0.18	0.57	4.23
H-L				0.49	1.55				0.58	2.93				0.55	3.54
Low	1/Inflex	0.11	0.36	0.25	2.50	B/A	0.27	0.50	0.23	0.98	$1/N_A$	0.05	0.38	0.33	2.72
High		-0.27	0.28	0.56	3.89		0.14	1.17	1.04	5.08		-0.40	0.27	0.66	5.31
H-L				0.30	1.79				0.81	3.01				0.33	2.03
Low						CR	0.17	0.34	0.16	1.43	σ_A	0.53	0.45	-0.09	-0.71
High							-0.04	0.35	0.38	3.01		-0.62	-0.14	0.48	3.76
H-L									0.22	1.76				0.57	3.66
Low						Illiq	0.17	0.28	0.11	0.93					
High							0.46	1.32	0.86	5.49					
H-L									0.75	4.63					

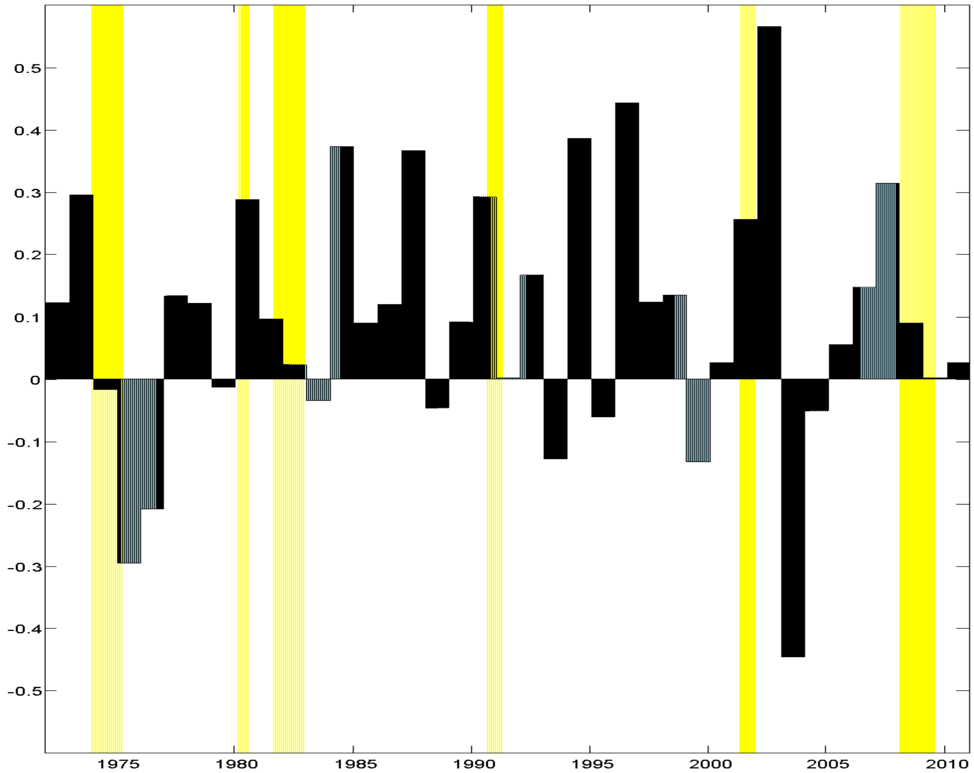
Table 2.8: Cross-Sectional Regression Tests of Difference between Event and Non-event Returns for Low and High ROA Portfolios

Each month we form 10 (5) ROA portfolios based on the decile (quintile) of quarterly return-on-assets (ROA). ROA is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). For each month, we run a cross-sectional regression of the daily return for each stock on the CRSP value-weighted market return and a dummy variable for whether the day belongs to the (-1,+1) window around next quarter's earnings announcement. Regressions are run separately for stocks in the lowest and highest ROA portfolios. The sample period is January 1972 to December 2011.

Portfolio	Intercept	$\text{Dummy}_{\text{Event}}$	R^M
	ROA 10 Portfolios		
1	0.0000	-0.0011	0.7756
	0.18	-4.83	24.51
10	0.0005	0.0006	0.9551
	5.65	3.86	48.54
	ROA 5 Portfolios		
1	-0.0001	-0.0008	0.8193
	-0.53	-4.38	12.96
5	0.0003	0.0008	0.9819
	1.2	7.4	12.72

Figure 2.1: ROA Profits over Business Cycles

The figure plots the annual ROA profits across business cycles from 1972 to 2011. The yellow bars represent the NBER recessions.



Chapter 3

Prospect Theory and the Risk-Return Tradeoff

[1]

3.1 Introduction

This paper studies the basic tenet in finance, the cross-sectional risk-return tradeoff in the stock market. Traditional asset pricing theory (e.g., the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965)) implies a positive relation between risk and expected returns. However, recent empirical studies find that low-risk firms tend to earn higher average returns when risk is measured by CAPM beta or stock return volatility. As forcefully argued by Baker, Bradley, and Wurgler (2011), this empirical

[1] This part is coauthored with Jinghua Yan and Jianfeng Yu.

evidence runs counter to the fundamental principle in finance that risk is compensated with higher expected return. In this study, we apply prospect theory (PT) and mental accounting (MA) to understand this anomalously weak and sometimes negative risk-return association.

One fundamental assumption for the positive risk-return tradeoff is that investors are risk averse, and thus investors demand compensation for bearing risk. However, prospect theory, which describes individuals' risk attitudes in experimental setting very well, posits that when facing prior loss relative to a reference point, individuals tend to be risk-seeking, rather than risk-averse. Thus, for stocks with current prices lower than reference prices, investors of these stocks face capital losses, and thus tend to be risk-seeking. As a result, there should be a negative risk-return tradeoff among these stocks. By contrast, among the stocks where investors face capital gains, the traditional positive risk-return tradeoff should emerge since investors of these stocks are risk averse.

To better understand how PT/MA undermines the traditional positive risk-return tradeoff, let's consider the following example in Figure **??**. There are two stocks A and B. Assume that investors purchased one share of A and B both at price \$20 in the last period and the price is now \$15 for both A and B. Thus, average investors of stocks A and B are facing capital losses and are risk-seeking. PT/MA investors focus on stocks A and B and separate them from the rest of their investments. One period later, the price of stock A can be either \$20 or \$10, with equal probability, and the price of stock B can be either \$18 or \$12, with equal probability as well. Thus, stocks A and B have identical expected payoff, but stock A has higher volatility than stock B. As a result, stock A is more appealing to PA/MA investors due to the convexity as illustrated in Figure ??, and the demand for stock A by PA/MA investors is larger than the demand for stock B. In equilibrium, if the demand by rational investors is not perfectly elastic, the price of stock A is higher than stock B, leading to a lower expected return for stock A. Thus, there is a negative risk-return association in this scenario.

On the other hand, consider stocks C and D in Figure ??. Assume investors purchased one share of C and D both at price \$20 and the price is now \$25 for both C and D. Thus, investors are facing capital gains and hence risk-averse. One period later, stock C has a price of \$38 or \$23 with equal probability, and stock D has a price of \$40 or \$21 with equal probability as well, implying an equal expected value for stocks C and D. However, stock D has higher volatility than stock C, and hence stock C is more appealing due to the concavity as illustrated in Figure ??. Thus, due to inelastic demand function, the price of stock C is higher than stock D, leading to a lower average subsequent return for stock C. As a result, the traditional positive risk-return tradeoff emerges in this scenario.[2]

To test our hypotheses, we first utilize the method in Grinblatt and Han (2005) to calculate the capital-gains-overhang (CGO) for individual stocks, which is essentially the normalized difference between current stock price and the reference price. Larger CGO generally implies larger capital gains. We then sort all individual stocks into portfolios

[2]The above static argument resembles the disposition effect due to S-shaped preferences, as argued in Shefrin and Statman (1985), Odean (1998), Grinblatt and Han (2005), and Frazzini (2006). For recent development on prospect theory in a dynamic setting, see Barberis and Xiong (2009, 2012), Li and Yang (2013), and Ingersoll and Jin (2013). These studies have raised doubts about whether pure prospect theory can produce the disposition effect, and hence they emphasize the importance of the realization utility in addition to the reference-dependent preferences, where investors enjoy realizing profits.

based on lagged CGO and various measures of risk. The central prediction is that high-risk firms should have higher returns among firms with large CGO, and this risk-return association should be weaker and even negative among firms with small CGO. Our empirical evidence shows strong support to these predictions. In particular, among firms with prior capital losses, firms with high return volatility earn 115 basis points (bps) per month lower returns than firms with low return volatility. By sharp contrast, among firms with prior capital gains, firms with high total return volatility earn 45 bps per month higher returns than firms with low return volatility. Similar results hold when risk is measured by CAPM beta. Although prior evidence on negative risk-return association posits a challenge for traditional asset pricing models, our evidence suggests that PT/MA could potentially account for the empirical failure of classical theory. The higher average return for low-risk firms is not a puzzle under the PT/MA framework.

To further explore the role of PT/MA in asset prices, besides CAPM beta and return volatility, we use several alternative intuitive measures of risk: cash flow volatility, firm age, idiosyncratic return volatility, and analyst forecast dispersion. PT/MA investors, for example, could view firm idiosyncratic volatility as risk because they fail to diversify it mentally. Previous studies have used these alternative measures of risk as proxies for information uncertainty, parameter uncertainty, information quality, or divergence of belief under various circumstances. To fix the terminology in this paper, we label these variables as *alternative measures of risk*. Investors might simply view parameter uncertainty as a form of risk. As a result, these alternative measures are correlated with the true risk measure in investors' mind. Thus, prospect theory has the same implication on the relation between expected returns and these alternative risk measures. Indeed, we find that CGO is an important determinant in each of these risk-return relations. Among low-CGO stocks, these relations are negative, whereas among high-CGO stocks, these relations typically become positive, supporting the role of PT/MA in asset prices.

While the above empirical evidence on the risk-return tradeoff is consistent with our hypotheses, an alternative explanation to our findings is underreaction to news. Take the idiosyncratic volatility as an example. Firms with high CGO are likely to have experienced good news in the recent past. If information travels slowly across investors and information travels even slower when idiosyncratic volatility is large, then among firms with recent good news, high idiosyncratic volatility is likely to predict higher future returns due to the current undervaluation. Thus, a positive relation between idiosyncratic volatility and return among firms with high CGO is observed. On the other hand, among the firms with low CGO, these firms probably have experienced negative news, and been overpriced due to underreaction. This overpricing effect is stronger when idiosyncratic volatility is large since the underreaction effect is larger. Thus, there is a negative relation between idiosyncratic volatility and return among firms with low CGO.

To control for the potential effect from underreaction and other possible mechanisms, we perform a series of Fama-MacBeth regressions. First, we show that our results still hold even if we control for the interaction of past returns and risk proxies. In fact, after controlling for the role of CGO, the interaction between past returns and risk proxies is not significant anymore. Second, we control for a battery of additional variables such as shares turnover, leverage and a composite mispricing proxy. The effect of CGO on the risk-return tradeoff remains significant. Moreover, this effect is robust to different subperiods, as well as exclusion of NASDAQ stocks, penny stocks, and illiquid stocks.

In terms of related literature, Barberis and Huang (2001), Barberis, Huang, and Santos (2001), and Barberis and Huang (2008) theoretically explore the role of PT/MA in asset prices in equilibrium settings. These studies suggest that PT/MA can play an important role in explaining asset pricing dynamics and cross-sectional stock returns.[3] Empirically, Grinblatt and Han (2005) find that past stock returns can predict future returns because past returns can proxy for unrealized capital gains. Frazzini (2006) shows that PT/MA induces underreaction to news, leading to return predictability. More recently, Barberis and Xiong (2009, 2012), Ingersoll and Jin (2013) study realization utility with reference-dependent preferences. These theoretical models, in particular Ingersoll and Jin (2013), imply a flatter capital market line and lower expected returns for high volatility stocks since high volatility stocks provide more opportunities for investors to earn realization utility benefits. Moreover, the effect of realization utility on the risk-return relation should be stronger among firms with capital loss than among firms with capital gains. For stocks with capital gains, volatility does not provide more opportunities to earn realization utility benefits due to diminishing sensitivity in the preference.

[3] In a two-period setting with cumulative prospect theory preferences but without mental accounting, Barberis and Huang (2008) show that the CAPM holds under several restrictive assumptions including the same reference point for all agents. When there is a violation of these assumptions, the CAPM typically fails.

In our study, we empirically investigate the fundamental risk-return tradeoff across firms with different levels of capital gains, as implied by PT/MA and realization utility.

Many studies have suggested possible mechanisms responsible for the failure of the risk-return tradeoff implied by the CAPM. These include leverage constraints (Black (1972), Asness, Frazzini, and Pedersen (2012), and Frazzini and Pedersen (2011)), benchmarked institutional investors (Brennan (1993), Baker, Bradley, and Wurger (2011)), money illusion (Cohen, Polk, and Vuolteenaho (2005)), disagreement (Hong and Sraer (2011)), and market wide sentiment-induced mispricing (Shen and Yu (2012)). We propose that prospect theory is another potential mechanism for the failure of CAPM. All mechanisms could work simultaneously. We complement previous studies by showing that the negative risk-return relation only exists among firms with capital losses, whereas the standard positive risk-return relation holds among firms with capital gains. Moreover, most existing studies focus on the time-series variation of the risk-return tradeoff. For example, Cohen, Polk, and Vuolteenaho (2005), Frazzini and Pedersen (2011), Hong and Sraer (2011) and Shen and Yu (2012) document that the slope of the security market line changes with inflation, the TED spread (the difference between LIBOR and T-Bill rates), aggregate disagreement, and investor sentiment, respectively. We complement these existing studies by focusing on the cross-sectional, rather than the time-series, heterogeneity in the risk-return tradeoff.

There is also a huge literature studying the relation between our alternative measures of risk (esp. idiosyncratic return volatility and analyst forecast dispersion) and expected returns. Different theories have different implications for this relationship, and the empirical evidence is quite mixed as well.[4] Existing studies typically focus on the unconditional relation between these alternative risk measures and returns. By contrast, our study focuses on the risk-return tradeoff *conditional* on different levels of CGO. By exploring the heterogeneity of this relation across different types of firms, our study emphasizes the non-monotonicity of this relation.

The rest of the paper is organized as follows. Section 3.2 discusses theoretical background and hypotheses. Section 3.3 describes the definition of risk proxies and presents main empirical findings. Additional robustness tests are covered in Section 3.4. Section 3.5 concludes.

3.2 Theoretical Background and Hypotheses

Most asset pricing pricing models assume expected utility and thus imply a positive risk-return relation. A key assumption of these models is that decision makers have a utility function that is globally concave, and hence investors are uniformly risk averse. This assumption has been a basic premise of most research in finance and economics. However, many researchers, including Friedman and Savage (1948), Markowitz (1952), and Kahneman and Tversky (1979), have questioned the assumption of global risk aversion

[4] Ang, Hodrick, Xing, and Zhang (2006, 2009), for example, find a negative relation between idiosyncratic volatility and expected returns, whereas Tinic and West (1986), Lehmann (1990), Malkiel and Xu (2002), Fu (2009), Huang, Liu, Rhee, and Zhang (2009), and Spiegel and Wang (2010) document a positive relation. In addition, Diether, Malloy and Scherbina (2002), Goetzmann and Massa (2005) document a negative relation between analyst dispersion and stock returns, whereas Qu, Starks, and Yan (2004) and Banerjee (2010) finds the opposite. Boehme, Danielsen, Kumar, and Sorescu (2009) find that this relation depends on short-sale constraints.

on both theoretical and empirical grounds.

In particular, the prospect theory of Kahneman and Tversky (1979) has attracted a lot of attention in finance literature and has been applied to account for many asset pricing phenomena. A critical element in this theory is the reference point. The theory predicts that most individuals have an S-shaped value function that is concave in the gain domain and convex in the loss domain, both measured relative to the reference point. Thus, most individuals exhibit a mixture of risk-seeking and risk-averting behavior, depending on whether the outcome is below or above the reference point, respectively. [5] Mental accounting of Thaler (1980, 1985) provides a theoretical foundation for the way in which decision makers set reference points for each asset they own. The main idea underlying mental accounting is that decision makers tend to mentally frame different assets as belonging to separate accounts, and then apply prospect theory to each account by ignoring possible interaction among these assets.

A natural implication from the prospect theory and mental accounting is that the risk-return tradeoff should be weaker or even negative among stocks where investors have experienced losses and thus are risk-seeking, and that the positive risk-return relation should emerge among stocks where investors have experienced gains and thus are risk-averse. That is, the risk-return tradeoff should crucially depend on individual stocks' CGO. To measure firm risk, one can use the traditional CAPM beta. However, it is

[5] Prospect theory has several other important features such as loss-aversion and probability weighting, which have been studies extensively by Benartzi and Thaler (1995), Barberis, Huang, and Santos (2001), Barberis and Huang (2008), among others. Prospect theory has been used to account for a number of phenomena in finance including, but not limited to, the disposition effect (Shefrin and Statman (1985), Odean (1998), and Barberis and Xiong (2011)) and the equity premium puzzle (Benartzi and Thaler (1995) and Barberis, Huang, and Santos (2001)).

probably more natural for investors to use stock return volatility as an intuitive risk measure.

More recently, Barberis and Xiong (2009, 2012), and Ingersoll and Jin (2013) study realization utility with reference-dependent preferences. Their models, in particular the model by Ingersoll and Jin (2013), implies a flatter capital market line and lower returns for high volatility stocks since high volatility stocks provide more opportunities for investors to earn realization utility benefits. The effect of realization utility on the risk-return relation should be stronger among firms with capital losses than firms with capital gains. Due to diminishing sensitivity in the preference, volatility provides less opportunities for investors to earn realization utility benefits among firms with capital gain than among firms with capital losses. Thus, we arrive at the following hypotheses:

Hypothesis 1: A negative association between expected returns and risk exists among the firms with small and negative CGO.

Hypothesis 2: A positive association between expected returns and risk exists among the firms with large and positive CGO.

We use CAPM beta and stock return volatility as our main measures of risk. However, the alternative measures of risk mentioned in the introduction may also appear to be intuitive to investors. These measures include firm age, cash flow volatility, analysis forecast dispersion, and idiosyncratic stock volatility. These measures have been used as proxies for parameter uncertainty or information uncertainty in previous studies. Investors, however, may simply treat parameter uncertainty or information uncertainty as a measure of risk when making decision under uncertainty. Thus, these alternative measures of risk are positively associated with the true risk measure in investors' mind. As a result, the above two hypotheses should also apply to the relation between alternative measures of risk and expected returns.

Finally, as discussed in the introduction, many studies have suggested possible mechanisms responsible for the low-risk anomaly. Bake, Bradley, and Wurgler (2011), for example, suggest that individuals might have irrational preference for high-volatility s-tocks, probably due to a preference for positive skewness. Due to limits to arbitrage, high-volatility firms tend to be overpriced. It is also possible that high-beta firms are more sensitive to investor disagreement and sentiment (see Hong and Sarer (2011) and Shen and Yu (2012)). Short-sale impediment implies that these high-risk firms tend to be overpriced on average. All of these mechanisms are likely to work simultaneously in the data, which could lead to overpricing for high-risk stocks, even among the firms with capital gains. Thus, the positive association between expected returns and various measures of risk among firms with a positive CGO might be weakened or completely inverted due to the overpricing of high-risk stocks. That is, Hypothesis 2 might not hold well in the data. However, a more robust prediction of our argument is the following:

Hypothesis 3: The return spread between high- and low-risk stocks among the firms with capital gains should be larger than that among the firms with capital losses.

One might be attempted to argue that the return spread between high and low-risk firms should be positively related to the aggregate level of CGO. However, this time-series variation in the risk-return tradeoff is not a very robust prediction of prospect theory due to other potential countervailling effects. Countercyclical risk-aversion, for example, would predict the opposite since high aggregate CGO tends to coincide with economic booms. However, our prediction on the cross-sectional heterogeneity of the risk-return tradeoff is much less subject to these potential aggregate time-series effects. Thus, our current study focuses on the cross-sectional heterogeneity of this risk-return tradeoff.

3.3 Empirical Results

To test our hypotheses, we first define the key variables used in our tests. We then report summary statistics, the double-sorting analysis, and the Fama-MacBeth regression analysis. Finally, we provide a battery of robustness checks.

3.3.1 Definition of Key Variables

Our sample includes all ordinary nonfinancial stocks traded in NYSE, AMEX, and NASDAQ from CRSP, with stock prices at least $5 and nonnegative book equity from January 1962 to December 2011.

To measure CGO, we first use the turnover-based measure from Grinblatt and Han (2005) to calculate reference price. In particular, at each week t, the reference price for each individual stock is defined as

$$RP_t = \sum_{n=1}^{T} \left(V_{t-n} \prod_{\tau=1}^{n-1} (1 - V_{t-n+\tau}) \right) P_{t-n},$$

where V_t is the week t's turnover in the stock and T is 260, the number of weeks in the previous 5 years. Weekly turnover is calculated as weekly trading volume divided by number of shares outstanding. To address the issue of double-counting of volume for NASDAQ stocks, we follow Anderson and Dyl (2005). They propose a rough rule of thumb to scale down the volume of NASDAQ stocks by 38% after 1997 and by 50% before 1997 to make it roughly comparable with the volume on NYSE. Further, to be included in the sample, a stock must have at least 200 weeks of non-missing data in the previous five years. The term in the parentheses is a weight which sums up to one. As argued by Grinblatt and Han (2005), the weight on P_{t-n} reflects the probability that the share purchased at week $t-n$ has not been traded since. The capital-gains-overhang (CGO) at week t is defined as

$$CGO_t = \frac{P_{t-1} - RP_t}{P_{t-1}}.$$

To avoid market microstructure effects, the market price is lagged by one week. Finally, to obtain CGO at a monthly frequency, we simply use the last week CGO within each month. Since we use five year daily data to construct CGO, the CGO variable ranges from January 1966 to December 2011, which is our main sample period.

To measure risk, we use the traditional CAPM beta and return volatility as our main proxies. Specifically, we use 5-year rolling window as in Fama and French (1992) to estimate market beta for individual firms. Following the approach in Baker, Bradley and Wurgler (2011), firm total volatility is calculated as the standard deviation of the previous 5-years of monthly returns. Our results are robust to different measures of total volatility. For example, we can use daily data from the previous month (as in French, Schwert, and Stambaugh (1987)), or we can use monthly returns in the previous year to estimate the volatility as in Baker and Wurgler (2006). The results based on different measures of volatility are available upon request.

As argued before, investors could also use some alternative measures of risk as the proxy for true risk. Thus, the prospect theory can also be applied to understand the relation between these alternative measures of risk and expected returns. We choose four alternative risk measure proxies. The first variable is idiosyncratic stock return volatility (IVOL). Following Ang, Hodrick, Xing, and Zhang (2006), we measure IVOL by the standard deviation of the residual values from the following time-series model:

$$R_{i,d,t} = b_0 + b_1 R_{M,d,t} + b_2 SMB_{M,d,t} + b_3 HML_{M,d,t} + \varepsilon_{i,d,t},$$

where $R_{i,d,t}$ is stock i's daily excess return in month t day d, $R_{M,d,t}$, $SMB_{M,d,t}$, and $HML_{M,d,t}$ are the market factor, the size factor, and the value factor in month t day d, respectively. We estimate the above equation for each stock each month in the data set using the daily return in the previous month. In addition, we can measure idiosyncratic volatility with weekly or monthly data. The results are robust and available upon request.

The other three variables are firm age (AGE), analyst forecast dispersion (DISP), and cash flow volatility (CFVOL). Firm age is measured as the number of years since the firm's first appearance in CRSP till the portfolio formation date; DISP is measured as the standard deviation of analyst forecasts on one-year earnings (obtained from I/B/E/S) at the portfolio formation date scaled by the prior year-end stock price to mitigate heteroscedasticity; and CFVOL is measured as the standard deviation of cash flow over the previous 5 year ending at the portfolio formation date.[6]

These alternative measures of risk can be viewed as, and have been used as, proxies for information uncertainty in Zhang (2006), idiosyncratic parameter uncertainty or information risk in Johnson (2004), divergence of opinion in Diether, Malloy, and Scherbina (2002), parameter uncertainty over firm's profitability in Pastor and Veronesi (2003), Korteweg and Polson (2009) and He, Li, Wei and Yu (2013), and information quality in Veronesi (2000) and Armstrong, Banerjee, and Corona (2012). The existing theories suggest that, unconditionally, parameter/information risk can either be unpriced (Brown (1979)), or positively priced (Merton (1987)), or negatively priced (Miller (1977)). Here, we simply view these variables as proxies for investors' measures of risk and examine how the conditional risk-return tradeoff changes across firms with different levels of CGO.[7]

[6]Following Zhang (2006), cash flows are calculated as follows: CF = (earnings before extraordinary items - total accruals)/average total assets in the past two years; total accruals = change in current assets - change in cash - change in current liabilities - change in depreciation expense + change in short-term debt.

[7]In untabulated analysis, we have considered other proxies for uncertainty such as firm size and analyst coverage. The results, omitted for brevity and available upon request, are largely in line with those based on the proxies we use in the main text.

3.3.2 Summary Statistics and One-Way Sorts

Figure **??** plots the time series of the 10th, 50th, and 90th percentile of the cross-section of the CGO of all individual stocks. Consistent with Grinblatt and Han (2005), there is a fair amount of time-series variation in CGO. More important, there is a wide cross-sectional dispersion in CGO, which is necessary for our analysis on the heterogeneity of the risk-return tradeoff across firms with different levels of CGO.

Table **??** reports the summary statistics for the portfolio returns sorted by lagged CGO. To facilitate the comparison to previous studies on momentum (e.g., Grinblatt and Han (2005)), we focus on the sample period from January 1966 to December 2011, and we report equally weighted portfolio returns based on lagged CGO. However, we report value-weighted returns for the rest of our analysis. Delisting bias in the stock return is adjusted according to Shumway (1997). On average, firms with high CGO earn significantly higher subsequent returns. However, high-CGO firms earn significantly lower returns during January. Consistent with the findings in Table 2 of Grinblatt and Han (2005), this pattern supports the view of price underreaction to information induced by PT/MA, and a December tax-loss selling effect.

Table **??** also reports other firm characteristics across CGO quintiles. Firms with low CGO tend to be smaller in size, higher in book-to-market, less liquid, and have higher CAPM beta. As expected, there is a strong monotonic relation between CGO and lagged returns. In addition, the bottom quintile has 9.7% of the total market value and the top quantile has 24.7% of total market capitalization. Thus, although firms with low

CGO tend to be smaller, they still account for a significant portion of the total market capitalization.

Table **??** reports the summary statistics for single-sorted value-weighted portfolio returns based on various risk proxies. In general, high-risk firms do not earn significantly higher subsequent returns. Instead, firms with high total volatility tend to earn lower returns on average, confirming the findings in Baker, Bradley, and Wurgler (2011). Firms with high idiosyncratic volatility and high analyst forecast dispersion also earn lower subsequent returns. These results are in line with the findings in Diether, Malloy, and Scherbina (2002) and Ang et al. (2006), consistent with the notion in Miller (1977) that stock prices reflect optimistic opinions. Finally, the security market line is almost completely flat in our sample, which is consistent with Fama and French (1992), but contradicts to the traditional CAPM.

As mentioned earlier, existing theories suggest that parameter/information risk can either be unpriced, or positively priced, or negatively priced. The empirical evidence on the unconditional relation between expected returns and the proxies for risk are indeed weak. For all proxies, return spreads are negative and insignificant. In the next section, we explore how the *conditional* risk-return tradeoff changes across firms with different levels of CGO.

3.3.3 Double Sorts

We now turn to the key results of this paper. At the beginning of each month, we first divide all firms in our sample into 5 groups based on lagged CGO, and within each of the

CGO groups, firms are further divided into 5 portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted returns are calculated. Table **??** presents the main results. It is evident that for all risk proxies except for analyst forecast dispersion, among the group with large CGO, the high-risk firms indeed tend to earn higher returns, consistent with Hypothesis 2. However, these results are not statistically significant. This could be due to the forces identified by previous studies such as leverage constraints, sentiment-induced mispricing, or index benchmarking.

Several theories proposed in the literature can generate a capital market line with a slope less steep than that implied by the traditional CAPM. However, these existing theories still typically imply a positive slope, i.e., a positive risk-return tradeoff. For example, both the leverage constraints and the index benchmarking typically imply a positive, albeit weaker, risk-return tradeoff. Our argument, which relies on the PT/MA, can produce a negative risk-return tradeoff among one particular type of firms. It is almost certain that all the forces are at play in reality. Given the empirical evidence on the negative risk-return tradeoff, we view our proposed mechanism as complementary to the economic forces proposed by previous studies. In addition, our focus is on the cross-sectional, rather than the time-series, variation in the risk-return trade-off.

More interestingly, among the group of firms with the lowest CGO, high-risk firms earn significantly lower returns, consistent with Hypothesis 1. For instance, Table **??** shows that among the group with the highest CGO, high-beta firms earn 72 bps per month lower than low-beta firms. Thus, the security market line is completely inverted among firms with low CGO. More dramatically, among the group with the lowest CGO, firms with high total return volatility earn 115 bps per month lower than firms with low total return volatility, whereas among the group with the highest CGO, firms with high total return volatility earn 45 bps per month higher than firms with low total return volatility. Similar results also hold for other risk measures. That is, the risk-return relation is positive among high-CGO firms (except analyst forecast dispersion proxy, and negative among low-CGO firms.

Finally, the differences between the high-minus-low spreads among the highest and the lowest CGO group are always highly significant, confirming Hypothesis 3. For example, for the idiosyncratic return volatility measure, the high-minus-low spread is 221 bps per month (t-stat = 6.14) higher among the highest CGO group than the lowest CGO group. For all other risk measures, this difference is also highly significant both statistically and economically. The difference between the high-minus-low spread among high-CGO firms and among low-CGO firms is 102 bps per month for firm age (t-statistic = 4.13), 79 bps per month for cash flow volatility (t-statistic = 3.10), 54 bps per month for analyst forecast dispersion (t-statistic = 2.07), 160 bps per month for stock total volatility (t-statistic = 4.80), and 101 bps per month for CAPM beta (t-statistic = 3.24). Even though our focus is on the raw excess returns, we also report the results adjusted by the Fama-French three-factor benchmark. In particular, the difference-in-differences remain similar and significant, after adjusting for the Fama-French three-factor benchmark.

It is worth noting that although the unconditional relation between expected returns and various measures of risk is weak across risk proxies (see Table **??**), the heterogeneity of this relation is remarkably strong and consistent across all the risk proxies, lending strong support to our hypotheses. In particular, the risk-return relation changes significantly across firms with different levels of CGO, consistent with Hypothesis 3.

Our findings also shed light on the debate on the relation between idiosyncratic volatility and expected returns. Merton (1987), for example, argues that idiosyncratic volatility may be compensated when each investor knows only about a subset of available securities. On the other hand, if idiosyncratic volatility is a proxy for divergence of opinion, then together with short-sale impediments, Miller (1977) implies that firms with high idiosyncratic volatility tend to be overpriced and these firms should earn lower subsequent returns. We notice that the theory of Merton (1987) assumes global risk aversion. When investors are risk-seeking, firms with high idiosyncratic risk should earn a lower return. Indeed, we find that firms with high idiosyncratic volatility earn much lower returns among firms with low CGO, but the opposite holds among firms with high CGO. This may partially explain the existing mixed evidence on the relation between idiosyncratic volatility and expected returns. Hence, our study complements previous literature by exploring the heterogeneity of this relation across different types of firms, rather than the unconditional relation.

To summarize, we find that among firms with low CGO, high-risk firms indeed earn lower subsequent returns, whereas among firms with high CGO, high-risk firms earn higher returns. However, the negative return spreads between high- and low-risk firms among firms with low CGO typically are much larger in magnitude than the positive return spreads among firms with high CGO. This asymmetry might be due to an unconditional overpricing effect of high-risk firms. Indeed, previous studies (e.g., Baker, Bradely, and Wurgler (2011) and Shen and Yu (2012)) have identified several mechanisms that could lead to an unconditional overpricing for high-risk firms. Together with the PT/MA effect on the risk-return tradeoff studied in this paper, it follows that there are two countervailling forces on the risk-return tradeoff among high-CGO firms, but two reinforcing forces among low-CGO firms. Thus, asymmetric return spreads between high- and low-risk firms among firms with low and high CGO emerge.

The results in Table **??** also indicate that the positive relation between risk and expected returns among the high CGO firms is still not very significant. Previous studies have identified several mechanisms that could lead to a stronger risk-return trade-off during some subperiod of time. Combining our mechanism with the previously identified forces could guide us in finding a strengthened positive risk-return trade-off among a subset of the firms. For example, we should expect a stronger risk return trade-off during low sentiment periods based on Shen and Yu (2012). Indeed, Table **??** repeats the previous double-sorting portfolio analysis in the low-sentiment subperiods based on Baker and Wurgler (2006) sentiment index. As it shows, there is typically a significant positive return spread between high- and low-risk firms among high-CGO firms during low sentiment periods.

3.3.4 Fama-MacBeth Regressions

The simple double-sorting approach in the previous section provides support to our hypotheses. However, the different risk-return tradeoff behavior across firms with different CGO could be driven by forces other than those proposed by us. Double sorting cannot explicitly control for other variables that might influence returns, and it is impractical to sort on three or more variables. Thus, to investigate other possible mechanisms, we perform a series of Fama and MacBeth (1973) cross-sectional regressions, which allows us to conveniently control for additional variables.

Table **??** reports the results. The benchmark regression shows that the coefficient on GCO is significant and positive, confirming the Fama-MacBeth regression results of Grinblatt and Han (2005). Regression (1) includes the interaction term between CGO and risk proxies, the results confirm double-sorting analysis in the previous section that the interaction term is always significant and positive for all the risk measures.[8] Moreover, the interaction between CGO and risk proxies remains significant after controlling for a battery of other variables, such as firm size, book-to-market, past returns, and shares turnover.

However, it is possible that some other forces could account for this empirical pattern. Zhang (2006), for example, argues that information may travel slowly, which can lead to underreaction to news. This underreaction effect might be stronger among firms with

[8]The t-statistics are based on Newey-West (1987) with lag = 12 to account for possible autocorrelation and heteroscedasticity. Since there is no overlapping observations in dependent variables, it is also reasonable to use lag = 0 (i.e. White (1980) t-statistiics. The results based on lag = 0, omitted for brevity, are typically stronger.

high risk (or information uncertainty in Zhang's (2006) terminology). Thus, among the firms with recent good news, high risk is likely to forecast high future returns due to the current undervaluation. Since high-CGO firms tend to have good news in the past, a positive relation between risk and return among firms with high CGO is likely to be observed. On the other hand, among the firms with low CGO, these firms are likely to have experienced negative news, and been overpriced due to underreaction. This overpricing effect is stronger when risk is larger since the underreaction effect is larger. Thus, there is a negative relation between risk and return among the firms with low CGO.

To make sure that our empirical results are not purely driven by this underreaction-to-news effect, we perform Fama-MacBeth regression by controlling for the interaction between past news and CGO.[9] Following Zhang (2006), we use past realized return as the proxy for news. Regression (2) in Table **??** indicates that the interactions of CGO and risk proxies remain highly significant even after controlling for the interaction of past return and risk proxies. Indeed, the t-statistic for the interaction between CGO and risk proxies is 3.31 for CAPM beta, 6.74 for total return volatility, 9.51 for idiosyncratic return volatility, 4.36 for cash flow volatility, 2.15 for firm age, and 2.08 for analyst forecast dispersion.

Interestingly, after controlling for the interaction of CGO and risk proxies, the interaction between past return and risk proxies (i.e., proxies for information uncertainty in

[9]Moreover, Frazzini (2006) argue that the disposition effect induces underreaction to news, leading to return predictability. In particular, due to the disposition effect, the underreaction effect to good (bad) news is most severe among firms with capital gains (capital losses).

the language of Zhang (2006)) is no longer significant and sometimes carries a negative coefficient. This indicates that the effect of underreaction to information identified by Zhang (2006) might partly be driven by the effect of prospect theory in the risk-return tradeoff.

In addition, Johnson (2004) argues that analyst forecast dispersion can be interpreted as a proxy for idiosyncratic parameter risk. For a levered firm, the negative relation between dispersion and expected return obtains from a general options-pricing result due to convexity. Johnson (2004) shows that after controlling for the interaction of leverage and idiosyncratic risk, dispersion itself no longer forecasts stock returns. If CGO is negatively linked to firm leverage, then it is possible that the significant role of CGO in the risk-return tradeoff is driven, at least partly, by the leverage effect identified by Johnson (2004). Thus, to control for this leverage effect, we include leverage and its interaction with risk proxies into Fama-MacBeth regressions. Regression (3) shows that the interaction between CGO and all risk proxies remains significant even after controlling for the leverage effect.

On the other hand, one could also view idiosyncratic return volatility, cash flow volatility, and firm age as potential proxies for idiosyncratic parameter risk in the sense of Johnson (2004). Table **??**, however, indicates that the interaction between leverage and other proxies such as idiosyncratic risk does not carry a significant negative sign. In fact, many of those interactions have a positive sign, the opposite to the prediction of Johnson (2004). Thus, the leverage effect appears to be specific to the proxy of analyst forecast dispersion, and it does not apply to other proxies for idiosyncratic parameter risk. By sharp contrast, the interaction between CGO and all the risk proxies has a consistent significant positive sign, consistent with our Hypothesis 3.

Furthermore, similar to the underreaction-to-news story, one might argue that CGO itself is a proxy for mispricing as in Grinblatt and Han (2005). Since stocks with high risk tend to have higher arbitrage costs, the mispricing effect is stronger among high-risk firms. This could potentially explain the significant and positive interaction between CGO and risk proxies in Fama-MacBeth regressions. Our proposed mechanism is different since it does not require CGO as a proxy for mispricing. To alleviate this concern, we control directly for the mispricing effect by including a proxy for mispricing in the Fama-MacBeth regression.

Following Stambaugh, Yu, and Yuan (2013), we measure the mispricing score by aggregating 11 key characteristics which are well-known to predict future stock returns. A firm with a high mispricing score tend to be overvalued, and thus has a low subsequent return. Indeed, regression (4) in Table **??** shows that the interaction term between mispricing score and the risk measure is typically significant and negative, consistent with the notion that the mispricing effect is stronger among high-risk firms. However, controlling for the mispricing and its interaction with our risk proxies does not change our conclusions. The interaction of CGO and risk proxies remains statistically significant.[10]

Finally, in regression (5), we control all the previous effects simultaneously, and

[10]Alternatively, one could measure the mispricing score based on more traditional anomalies as in Cao and Han (2010). The results remain similar if this alternative mispricing score is used instead. These results, omitted for brevity, are available upon request.

our main conclusion again remains unaltered. In sum, the Fama-MacBeth regression analysis in this section provides strong and remarkably consistent support to the role of prospect theory in the risk-return tradeoff. This effect is not driven by underreaction to information or the leverage effect.

3.4 Additional Robustness Checks

We now conduct a series of additional tests to assess the robustness of our results under different empirical specifications. We perform both Fama-MacBeth regression analysis and double sorting. To save space, only Fama-MacBeth regression results are reported in the main text, and the results based on double sorting are put in the appendix.

First, to make sure that the pattern in the risk-return tradeoff is not due to the inclusion of NASDAQ stocks. In Table **??**, we repeat the Fama-MacBeth regression analysis in Table **??** by excluding the NASDAQ firms. The results indicate that the pattern in the risk-return tradeoff remains among the NYSE/AMEX stocks. The economic magnitude also remains largely the same. In addition, the double-sorting results without NASDAQ stocks, reported in the appendix, are similar to those in Table **??** obtained with NASDAQ stocks.

Second, previous studies (e.g., Bali et al. (2005)) show that some asset pricing phenomena disappear once illiquid stocks are excluded from the sample. Thus, to ensure that our results are not driven by stocks with extremely low liquidity, we focus on the subset of stocks that can be classified as top 90% liquid stock according to Amihud's

(2002) liquidity measure. Specifically, illiquidity is the average ratio of the daily absolute return to the daily dollar trading volume in the past year. The results in Table **??** show that the pattern in the risk-return tradeoff and the economic magnitude again remains virtually identical. Thus, our results are not driven by highly illiquid stocks.

Third, many strategies in practice focus only on the top $1,000$ largest firms by market capitalization. Thus, we repeat both the Fama-MacBeth regression and the double sorting within the top $1,000$ largest stocks. Again, Table **??** indicates that the results remain virtually the same. In fact, among top $1,000$ largest stocks, high-beta firms earn lower returns on average (not reported), but security market line is upward sloping among firms with large CGO. Thus, our results are not driven by the inclusion of small cap stocks. Double-sorting analysis, reported in the appendix, yields essentially the same conclusion.

Fourth, stocks with a price lower than \$5 are more subject to microstructure effects. Thus, we have excluded those firms from our sample so far. Table **??** shows that our results are robust to the inclusion of penny stocks. Since our idiosyncratic volatility is computed based on daily returns, it might also be subject to microstructure effects. In untabulated analysis, we replace our daily-return-based idiosyncratic volatility measure with monthly-return-based measures, the results remain quantitatively unchanged.

Fifth, Table **??** performs a standard sub-period analysis. The whole sample is divided equally into two sub-periods. Due to a smaller number of observations, the statistical significance for the interaction of CGO and risk measures is slightly lower. However, the general pattern in risk-return tradeoff still emerges in both subperiods: the risk-return relation is more positive among firms with high CGO than among firms with low CGO. Moreover, the slope coefficients on the interaction of CGO and risk proxies do not change significantly across two sub-periods. In addition, we also separate the whole sample into two subsamples based on the median of institutional holdings. We find that the effect of CGO on the risk-return tradeoff is generally stronger among firms with lower institutional holdings. These results are reported in the appendix as Tables A6 and A7 and are consistent with the limits-to-arbitrage effect (e.g., Nagel (2005)).

Overall, the pattern on the risk-return tradeoff is very robust to sub-periods, as well as exclusion/inclusion of highly illiquid stocks, NASDAQ stocks, stocks with low prices, or stocks with small market capitalization.

3.5 Conclusion

The risk-return tradeoff is the fundamental theme in finance. However, there is very weak empirical support for this basic principle. We argue that prospect theory plays a prominent role in the cross-sectional risk-return relation. Among the firms where investors face capital gains, there is a positive, albeit not strong, risk-return association. By sharp contrast, among the firms where investors face capital losses, there is a robust significant inverted risk-return relation. This pattern is consistent with the notion that the presence of PT/MA investors destroys the traditional positive risk-return relation implied under standard preferences.

It would be interesting to investigate the role of prospect theory in other asset pricing phenomena. For example, asset return skewness has gained a substantial amount of attention in recent literature (see, e.g., Zhang (2005), Barberis and Huang (2008), and Boyer, Mitton, and Vorkink (2010)). Similar to risk appetite, individuals' preference on skewness could depend on whether investors are in the loss or gain domain. Indeed, Table **??** provides suggestive evidence that among firms with large CGO, high-skewness firms tend to earn higher subsequent returns, while the opposite holds among firms with low CGO. The difference-in-difference is 60 bps per month with a t-statistics = 2.57. This is consistent with the notion that in the loss domain, investors have a high appetite for positive skewed assets to break even. It seems worthwhile exploring the role of prospect theory in the pricing of skewness. We leave this for future research.

Figure 3.1: Prospect Theory and the Risk-Return Tradeoff Utility: Capital Losses

Assume that investors purchased one share of stocks A and B, each at a price of $20, and the price is now $15 for each. One period later, the price of stock A can be either $20 or $10 with equal probability, and the price of stock B can be either $18 or $12 with equal probability. The figure shows the utility gain (loss) of holding stocks A and B.

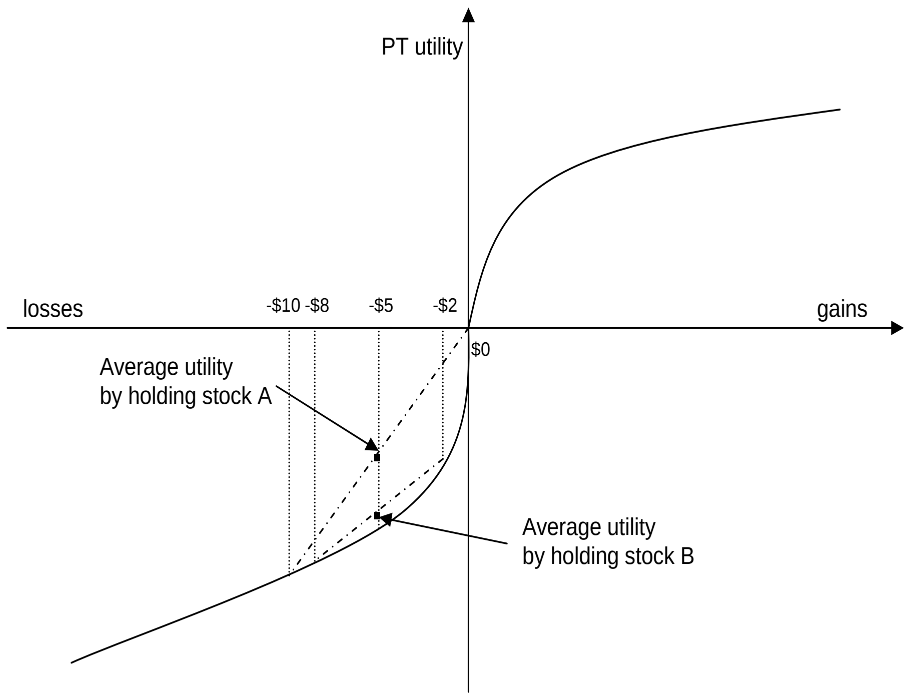


Figure 3.2: Prospect Theory and the Risk-Return Tradeoff Utility: Capital Gains

Assume that investors purchased one share of stocks C and D, each at a price of \$20, and the price is now \$25 for each. Thus, investors are facing capital gains and are risk averse. One period later, stock C has a price of a \$38 or \$23 with equal probability, and stock D has a price of \$40 or \$21 with equal probability. The figure shows the utility gain (loss) of holding stocks C and D.

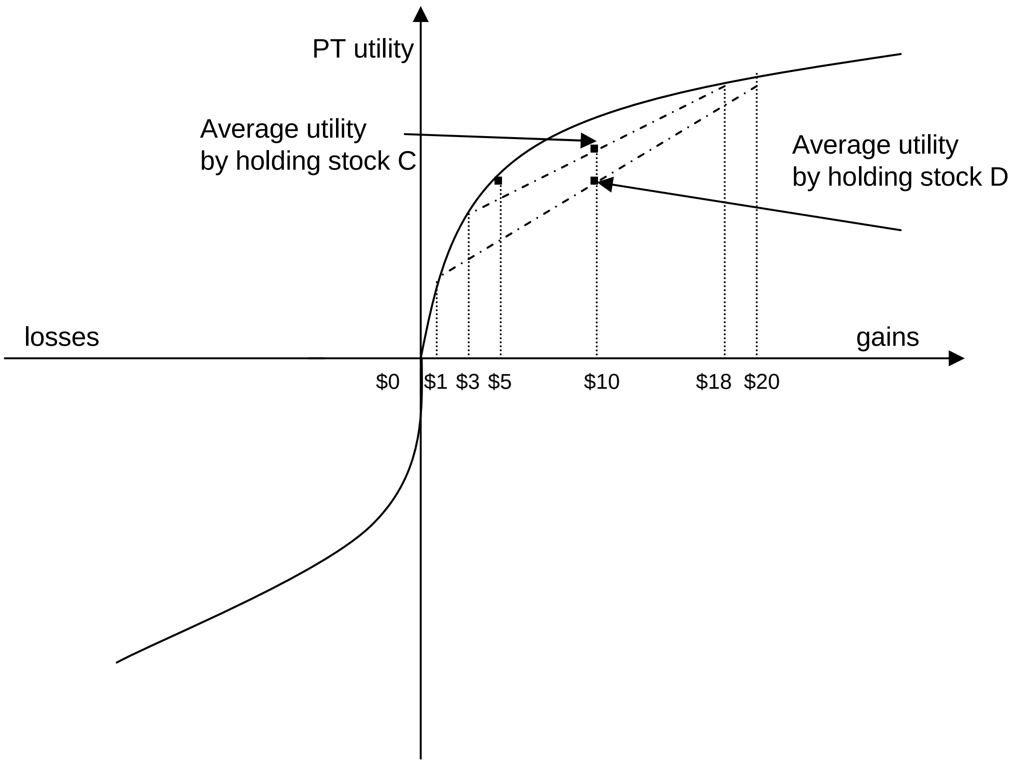


Figure 3.3: Time Series of Cross-Sectional Percentiles of the Capital Gains Overhang

This figure plots the time series of the empirical 10th, 50th, and 90th percentiles of the cross-sectional distribution of the capital gains overhang. The CGO is calculated at a weekly frequency from January 1966 to December 2011. We use all common nonfinancial stocks from NYSE/AMEX/NASDAQ with stock prices of at least $5 and nonnegative book value of equity.

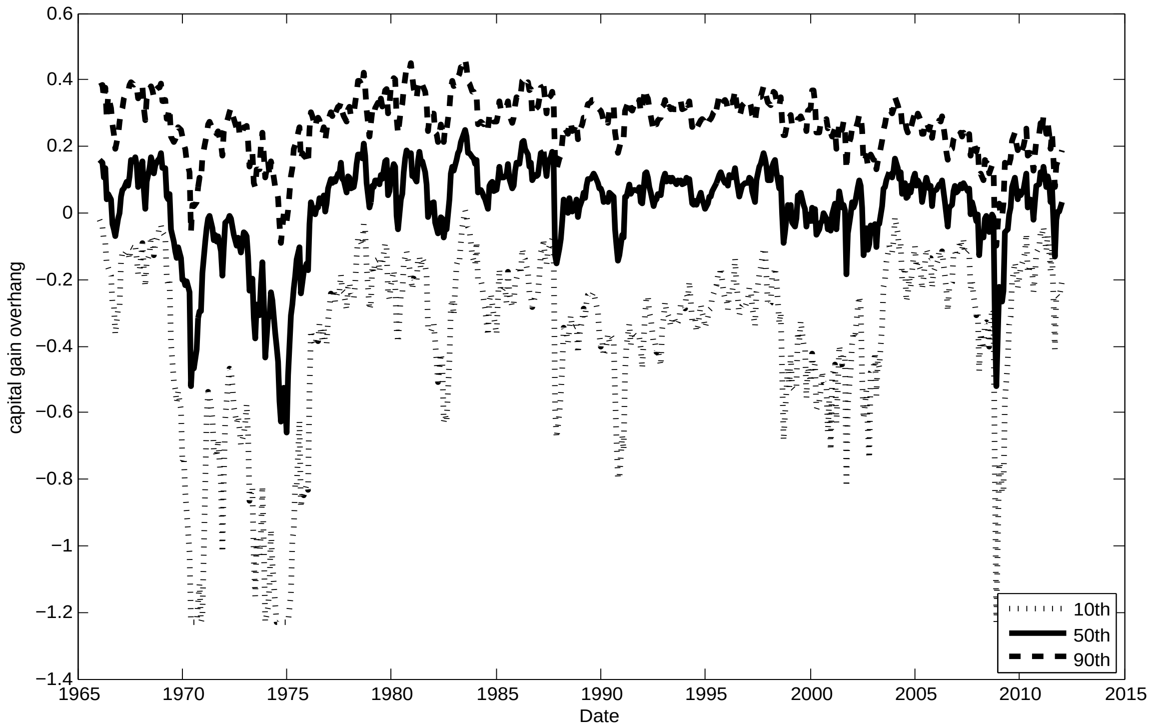


Table 3.1: Summary Statistics

Panel A reports the time-series averages of the monthly equally weighted excess returns for five portfolios sorted by capital gains overhang (CGO), the difference in the excess returns between the high and low CGO portfolio, the standard deviation of excess returns ($\sigma(RET)$), the intercepts of the Fama-French three-factor regression, and the corresponding t-statistics. The last four columns report the excess portfolio returns separately during January and non-January months. At the beginning of every month, we sort NYSE, AMEX, and NASDAQ common nonfinancial stocks with stock prices od at least \$5 and nonnegative book value of equity into five groups based on the quintile of the ranked values of weekly CGO as of the last week of the previous month. CGO at week t is computed as one less the ratio of the beginning of the week t reference price to the end of week $t-1$ price, where the week t reference price is the average cost basis calculated as $RP_t = \sum_{n=1}^{T} \left(V_{t-n} \prod_{\tau=1}^{n-1} (1 - V_{t-n-\tau})\right) P_{t-n}$, and V_t is week t's turnover in the stock and T is the number of weeks in the previous five years. Turnover is calculated as trading volume divided by number of shares outstanding. The portfolio is rebalanced every month. Panel B reports the time-series averages of portfolio characteristics. LOGME is the log of size, BM is the book value of equity divided by market value at the end of last fiscal year, ILLIQ is the illiquidity measure from Amihud (2002) calculated as the average ratio of the daily absolute return to the daily dollar trading volume in the past year, MOM is the cumulative return from month $t-12$ to $t-1$, β is the coefficient of the monthly CAPM regression in the past five years with a minimum of two years of data, and MARKET% is the portion of total market capitalization. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. %(IO) is the fraction of outstanding shares held by institutional investors. #(IO) is the number of institutional investors holding a firm's shares. Monthly excess returns are in percentages and illiquidity is in units of 10^{-6}. The sample period is from January 1966 to December 2011, except for %(IO) and #(IO), which are from January 1980 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12 in Panel A and lag = 36 in Panel B.

	Panel A: Five CGO Portfolio Returns								
	RET	t-stat	$\sigma(RET)$	FF3-α	t-stat	JAN	t-stat	FEB-DEC	t-stat
P1	0.490	1.74	6.726	-0.320	-2.99	5.272	3.74	0.065	0.23
P2	0.512	2.16	5.562	-0.174	-2.09	3.068	2.76	0.285	1.19
P3	0.619	2.90	5.073	0.006	0.10	1.812	2.04	0.513	2.39
P4	0.669	3.07	5.042	0.105	1.79	1.304	1.56	0.613	2.76
P5	1.098	4.49	5.472	0.604	6.84	0.950	1.42	1.111	4.58
P5-P1	0.608	3.53	4.368	0.924	5.62	-4.322	-3.89	1.047	6.23

	Panel B: Five CGO Portfolio Characteristics										
	CGO	LOGME	BM	ILLIQ	MOM	β	MARKET%	LEVERAGE	TURNOVER	%(IO)	#(IO)
P1	-0.406	4.840	0.952	1.090	-0.116	1.250	0.097	0.456	0.070	0.366	59.826
P2	-0.101	5.590	0.878	0.687	0.054	1.119	0.177	0.417	0.076	0.422	101.060
P3	0.025	5.893	0.843	0.551	0.177	1.054	0.223	0.395	0.074	0.427	115.806
P4	0.130	5.984	0.802	0.538	0.319	1.069	0.257	0.355	0.071	0.431	118.868
P5	0.282	5.735	0.751	0.743	0.627	1.088	0.247	0.290	0.057	0.372	84.334
P5-P1	0.688	0.896	-0.201	-0.347	0.743	-0.163	0.150	-0.166	-0.013	0.006	24.508
t-stat	17.78	5.44	-4.44	-2.30	21.99	-3.40	4.04	-9.63	-2.40	0.29	3.04

Table 3.2: Single-Sorted Portfolios by Risk Proxies

This table reports the time-series averages of the monthly value-weighted excess returns for portfolios sorted by our risk proxies, the difference in the excess returns between the high and low portfolio, the intercepts of the Fama-French three-factor regression ($R_{i,t} - R_{ft} = \alpha + b_{i,M}(R_{M,t} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$), and the t-statistics of the differences. We consider six proxies: β is the coefficient of the monthly CAPM regression ($R_{i,t} - R_{ft} = \alpha + \beta_{i,M}(R_{M,t} - R_{ft}) + \varepsilon_{i,t}$) in the past five years with a minimum of two years. Stock volatility (RETVOL) is the standard deviation of monthly returns over the past five years with a minimum of two years. Idiosyncratic volatility (IVOL) is the standard deviation of the residuals from the Fama-French three-factor model using daily excess returns in the past month. Cash flow volatility (CFVOL) is the standard deviation of cash flow from operations in the past five years. Age is the number of years since the firm was first covered by CRSP. Analyst forecast dispersion (DISPER) is the standard deviation of analyst forecasts of one-year earnings from I/B/E/S scaled by the prior year-end stock price to mitigate heteroscedasticity. At the beginning of every month, we sort NYSE, AMEX, and NASDAQ ordinary nonfinancial stocks with stock prices of at least $5 and nonnegative book value of equity into five groups based on the quintile of the ranked values of each proxy. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The excess returns are in percentages. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

Proxy	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
P1	0.422	0.459	0.466	0.475	0.435	0.668
P2	0.466	0.488	0.528	0.524	0.427	0.447
P3	0.496	0.482	0.509	0.561	0.423	0.420
P4	0.443	0.495	0.552	0.418	0.490	0.369
P5	0.405	0.414	0.122	0.346	0.408	0.350
P5-P1	-0.017	-0.044	-0.345	-0.129	-0.027	-0.318
t-stat	-0.06	-0.16	-1.43	-0.76	-0.15	-1.51
FF3-α	-0.225	-0.294	-0.632	-0.132	-0.019	-0.722
t-stat	-1.08	-1.54	-3.69	-1.15	-0.15	-3.36

Table 3.3: Double-Sorted Portfolio Returns

At the beginning of each month, we divide all NYSE/AMEX/NASDAQ common nonfinancial stocks with nonnegative book equity and stock prices of at least $5 into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag =12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.702	0.490	0.489		0.790	0.417	0.450	
P3	0.606	0.531	0.660		0.458	0.450	0.674	
P5	-0.017	0.274	0.776		-0.356	0.364	0.904	
P5-P1	-0.719	-0.216	0.288	1.006	-1.146	-0.054	0.454	1.600
t-stat	-2.20	-0.70	1.03	3.24	-4.02	-0.18	1.57	4.80
FF3-α	-0.958	-0.412	0.154	1.112	-1.346	-0.317	0.229	1.575
t-stat	-3.74	-1.74	0.69	3.44	-5.59	-1.44	0.84	4.23
	Proxy=IVOL				Proxy=CFVOL			
P1	0.943	0.320	0.535		0.769	0.621	0.636	
P3	0.227	0.380	0.835		0.441	0.391	0.809	
P5	-0.848	0.042	0.950		0.267	0.178	0.919	
P5-P1	-1.791	-0.278	0.415	2.205	-0.502	-0.443	0.283	0.785
t-stat	-5.10	-1.04	1.59	6.14	-2.04	-1.90	1.91	3.10
FF3-α	-2.037	-0.480	0.206	2.243	-0.450	-0.439	0.249	0.699
t-stat	-6.79	-2.21	0.81	5.81	-1.79	-2.60	1.84	2.57
	Proxy=1/AGE				Proxy=DISPER			
P1	0.608	0.435	0.481		0.887	0.570	0.974	
P3	0.312	0.472	0.686		0.607	0.587	0.610	
P5	0.162	0.180	1.057		-0.044	0.253	0.584	
P5-P1	-0.448	-0.283	0.584	1.015	-0.931	-0.317	-0.390	0.541
t-stat	-2.07	-1.51	2.95	4.13	-3.42	-1.62	-1.81	2.07
FF3-α	-0.470	-0.319	0.525	0.988	-1.457	-0.642	-0.810	0.646
t-stat	-2.26	-2.14	2.87	3.89	-6.46	-3.14	-4.14	2.42

Table 3.4: Double-Sorted Portfolio Returns during Periods of Low Investor Sentiment

We perform the double-sorting analysis following low levels of investor sentiment, as divided based on the median level of the index of Baker and Wurgler (2006). At the beginning of each low-sentiment month, we divide all NYSE/AMEX/NASDAQ common nonfinancial stocks with stock prices of at least $5 and nonnegative book value of equity into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.535	0.217	0.490		0.700	0.220	0.552	
P3	0.915	0.564	0.924		0.856	0.595	0.925	
P5	0.739	0.796	1.272		0.481	1.027	1.356	
P5-P1	0.204	0.579	0.782	0.578	-0.218	0.808	0.804	1.022
t-stat	0.46	1.46	2.26	1.49	-0.56	2.05	2.37	2.53
FF3-α	-0.337	0.066	0.389	0.726	-0.659	0.253	0.314	0.973
t-stat	-1.07	0.18	1.21	1.90	-2.50	0.70	0.95	2.48
	Proxy=IVOL				Proxy=CFVOL			
P1	0.957	0.224	0.685		0.641	0.526	0.731	
P3	0.569	0.454	0.974		0.801	0.517	1.119	
P5	-0.035	0.629	1.287		0.881	0.285	1.101	
P5-P1	-0.991	0.404	0.601	1.593	0.240	-0.241	0.370	0.130
t-stat	-2.35	1.01	1.96	3.88	0.77	-0.75	1.88	0.41
FF3-α	-1.441	0.020	0.160	1.601	0.217	-0.333	0.250	0.033
t-stat	-4.91	0.06	0.57	3.96	0.72	-1.21	1.26	0.12
	Proxy=1/AGE				Proxy=DISPER			
P1	0.722	0.290	0.638		1.037	0.683	1.175	
P3	0.855	0.707	1.089		0.988	0.565	1.068	
P5	0.528	0.616	1.074		0.659	0.564	1.236	
P5-P1	-0.206	0.271	0.451	0.616	-0.378	-0.120	0.061	0.439
t-stat	-0.76	1.04	2.01	1.98	-0.76	-0.33	0.15	0.97
FF3-α	-0.275	0.101	0.280	0.521	-1.127	-0.577	-0.408	0.719
t-stat	-0.96	0.52	1.47	1.48	-3.18	-1.89	-1.03	1.47

Table 3.5: Fama-MacBeth Regressions

Every month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding, where the volume is the reported value from CRSP for NYSE/AMEX stocks, and 62% of CRSP reported value after 1997 and 50% of that before 1997 for NASDAQ stocks. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The excess returns are in percentages. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12. We only use common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least $5 and nonnegative book equity. The intercept of the regression is not reported.

		PROXY=β					PROXY=RETVOL				
		(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
CGO	1.251	0.504	0.593	0.698	0.298	0.658	-0.662	-1.218	-0.740	-0.627	-1.045
	(6.87)	(2.00)	(2.28)	(2.83)	(1.22)	(2.47)	(-1.88)	(-3.14)	(-2.02)	(-1.75)	(-2.67)
PROXY×CGO		0.697	0.540	0.643	0.580	0.490	16.014	20.047	17.663	14.506	18.128
		(4.07)	(3.13)	(3.84)	(3.39)	(2.72)	(5.77)	(6.74)	(5.59)	(5.08)	(5.66)
PROXY×MOM(-12,-1)			0.019			0.000		-3.608			-3.513
			(0.14)			(0.00)		(-2.32)			(-2.24)
PROXY×LEVERAGE				-0.127		-0.279			10.715		6.914
				-(0.51)		-(1.11)			(2.87)		(1.89)
PROXY×SCORE					-0.005	-0.002				-0.165	-0.122
					(-2.02)	(-0.59)				(-4.18)	(-3.24)
LEVERAGE				0.408		1.080			-0.933		-0.048
				(1.51)		(3.60)			-(2.59)		-(0.12)
LOGBM	0.007	0.000	-0.010	-0.010	-0.004	-0.006	0.000	-0.010	-0.002	-0.004	-0.009
	(0.20)	(0.00)	(-0.38)	(-0.34)	(-0.14)	(-0.19)	(-0.01)	(-0.34)	(-0.08)	(-0.13)	(-0.35)
LOGME	-0.072	-0.070	-0.078	-0.064	-0.097	-0.074	-0.082	-0.076	-0.073	-0.080	-0.061
	(-1.80)	(-1.78)	(-1.99)	(-1.68)	(-2.50)	(-1.98)	(-2.20)	(-2.09)	(-2.10)	(-2.15)	(-1.79)
MOM(-1,0)	-5.220	-5.755	-5.619	-5.951	-5.603	-5.881	-5.633	-5.691	-5.853	-5.741	-5.847
	(-11.16)	(-11.86)	(-11.36)	(-12.50)	(-11.12)	(-12.21)	(-11.76)	(-11.98)	(-12.48)	(-11.89)	(-12.01)
MOM(-12,-1)	0.135	0.138	0.154	0.082	-0.023	-0.073	0.136	0.687	0.117	-0.097	0.453
	(0.85)	(0.95)	(0.68)	(0.54)	(-0.14)	(-0.32)	(0.87)	(2.42)	(0.75)	-(0.62)	(1.63)
MOM(-36,-13)	-0.193	-0.196	-0.224	-0.209	-0.135	-0.097	-0.181	-0.210	-0.184	-0.125	-0.098
	(-3.59)	(-3.86)	(-4.13)	(-4.10)	(-2.64)	(-2.06)	(-3.39)	(-3.76)	(-3.36)	(-2.34)	(-1.87)
PROXY		0.063	0.067	0.136	0.337	0.327	-1.742	-0.947	-5.224	7.009	4.176
		(0.54)	(0.58)	(0.94)	(2.04)	(1.72)	(-0.99)	(-0.53)	(-2.99)	(2.87)	(1.77)
SCORE					-0.020	-0.025				-0.004	-0.010
					(-6.09)	(-5.96)				(-1.01)	(-2.28)
TURNOVER	-2.704	-2.684	-2.792	-2.815	-1.358	-1.427	-2.043	-1.973	-1.963	-1.078	-1.389
	(-1.67)	(-2.13)	(-2.17)	(-2.30)	(-1.05)	(-1.18)	(-1.75)	(-1.75)	(-1.71)	(-0.94)	(-1.21)

	PROXY=IVOL					PROXY=CFVOL				
CGO	-0.746	-1.363	-0.857	-0.638	-1.504	0.600	0.466	0.657	0.460	0.467
	(-2.63)	(-4.77)	(-3.03)	(-2.21)	(-5.25)	(2.54)	(1.91)	(2.84)	(1.91)	(1.87)
PROXY×CGO	82.204	106.418	89.437	68.460	107.534	7.441	10.091	8.667	5.864	7.308
	(8.84)	(9.51)	(8.36)	(6.75)	(8.40)	(4.17)	(4.36)	(4.60)	(3.07)	(3.18)
PROXY×MOM(-12,-1)		-26.080			-34.713		-1.296			-1.503
		(-3.26)			(-4.24)		(-0.60)			(-0.63)
PROXY×LEVERAGE			45.256		41.444			2.732		1.482
			(3.20)		(2.85)			(1.14)		(0.62)
PROXY×SCORE				-0.936	-0.943				-0.113	-0.077
				(-5.35)	(-5.89)				(-3.90)	(-2.39)
LEVERAGE			-0.615		-0.122			0.165		0.659
			(-2.15)		(-0.37)			(0.67)		(2.44)
LOGBM	0.001	-0.009	-0.009	-0.003	-0.002	0.010	-0.012	-0.008	-0.004	-0.006
	(0.02)	(-0.31)	(-0.30)	(-0.10)	(-0.07)	(0.38)	(-0.44)	(-0.32)	(-0.15)	(-0.23)
LOGME	-0.090	-0.084	-0.080	-0.093	-0.076	-0.047	-0.044	-0.034	-0.060	-0.042
	(-2.34)	(-2.23)	(-2.14)	(-2.45)	(-2.08)	(-1.32)	(-1.27)	(-0.99)	(-1.66)	(-1.21)
MOM(-1,0)	-5.124	-5.128	-5.281	-5.267	-5.357	-5.338	-5.466	-5.588	-5.425	-5.505
	(-11.10)	(-11.22)	(-11.63)	(-11.23)	(-11.37)	(-10.48)	(-10.72)	(-11.17)	(-10.52)	(-10.86)
MOM(-12,-1)	0.234	0.851	0.221	0.016	0.844	0.109	0.195	0.070	-0.072	0.019
	(1.49)	(4.12)	(1.40)	(0.10)	(3.71)	(0.59)	(0.86)	(0.37)	-(0.40)	(0.08)
MOM(-36,-13)	-0.155	-0.175	-0.159	-0.100	-0.057	-0.174	-0.205	-0.192	-0.105	-0.079
	(-2.93)	(-3.18)	(-2.92)	(-1.91)	(-1.10)	(-2.75)	(-3.04)	(-2.75)	(-1.64)	(-1.17)
PROXY	-16.082	-12.511	-31.418	29.949	20.438	-1.444	-1.709	-1.762	3.950	1.953
	(-3.65)	(-2.79)	(-4.66)	(3.21)	(2.19)	(-2.17)	(-2.45)	(-1.68)	(2.84)	(1.21)
SCORE				-0.006	-0.006				-0.018	-0.021
				(-1.75)	(-1.47)				(-5.48)	(-5.68)
TURNOVER	-1.908	-1.879	-1.836	-0.577	-0.488	-2.610	-2.536	-2.778	-1.105	-1.125
	(-1.33)	(-1.35)	(-1.31)	(-0.42)	(-0.36)	(-1.59)	(-1.56)	(-1.70)	(-0.68)	(-0.72)

	PROXY=1/AGE					PROXY=DISPER				
CGO	-0.472	-0.784	-0.673	-0.711	-0.715	0.591	0.609	0.825	0.337	0.570
	(-0.86)	(-0.66)	(-0.82)	(-1.15)	(-0.74)	(2.31)	(2.37)	(3.54)	(1.19)	(2.05)
PROXY×CGO	19.945	20.650	22.128	19.215	18.430	35.351	19.677	31.832	16.800	34.502
	(4.53)	(2.15)	(3.39)	(3.77)	(2.31)	(2.23)	(2.08)	(2.35)	(2.02)	(2.05)
PROXY×MOM(-12,-1)		0.537			2.121		-2.249			-9.673
		(0.10)			(0.50)		(-0.23)			(-0.92)
PROXY×LEVERAGE			8.256		5.231			-38.896		-47.915
			(1.79)		(1.42)			(-4.82)		(-4.90)
PROXY×SCORE				-0.188	-0.133				-0.562	0.015
				(-3.82)	(-2.76)				(-2.66)	(0.24)
LEVERAGE			-0.537		0.352			0.582		1.027
			(-1.00)		(0.83)			(1.98)		(3.49)
LOGBM	0.006	-0.006	-0.006	-0.001	-0.001	0.020	0.040	0.046	0.049	0.039
	(0.18)	(-0.21)	(-0.19)	(-0.03)	(-0.04)	(0.66)	(1.50)	(1.70)	(1.63)	(1.35)
LOGME	-0.068	-0.067	-0.059	-0.074	-0.058	-0.111	-0.109	-0.103	-0.131	-0.128
	(-1.69)	(-1.70)	(-1.50)	(-1.87)	(-1.50)	(-2.53)	(-2.51)	(-2.39)	(-3.19)	(-3.13)
MOM(-1,0)	-5.328	-5.413	-5.500	-5.401	-5.460	-4.015	-4.034	-4.269	-3.604	-4.362
	(-11.39)	(-11.74)	(-12.13)	(-11.43)	(-11.81)	(-7.71)	(-7.95)	(-8.54)	(-8.65)	(-9.90)
MOM(-12,-1)	0.111	0.311	0.075	-0.081	-0.091	0.299	0.320	0.222	0.203	0.119
	(0.70)	(0.47)	(0.46)	-(0.51)	-(0.17)	(1.46)	(1.62)	(1.09)	(1.09)	(0.66)
MOM(-36,-13)	-0.199	-0.228	-0.209	-0.141	-0.101	-0.093	-0.110	-0.106	-0.041	-0.026
	(-3.77)	(-4.12)	(-3.87)	(-2.69)	(-1.98)	(-1.44)	(-1.64)	(-1.62)	(-0.66)	(-0.42)
PROXY	-0.625	-0.913	-3.399	8.917	5.678	-21.000	-18.900	1.097	9.247	1.206
	(-0.58)	(-0.75)	(-1.57)	(3.14)	(2.08)	(-5.64)	(-5.15)	(0.73)	(0.89)	(0.35)
SCORE				-0.012	-0.018				-0.017	-0.022
				(-2.27)	(-3.25)				(-6.03)	(-6.86)
TURNOVER	-2.710	-2.634	-2.575	-1.333	-1.007	-0.674	-0.459	-0.404	-0.182	0.238
	(-1.71)	(-1.70)	(-1.66)	(-0.87)	(-0.67)	(-0.49)	(-0.36)	(-0.32)	(-0.13)	(0.18)

Table 3.6: Fama-MacBeth Regressions of NYSE/AMEX Stocks

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use common nonfinancial stocks from NYSE/AMEX with a price of at least \$5 and nonnegative book equity to perform the cross-sectional regression. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.498	-1.117	-1.392	0.155	-0.836	0.409
	(1.72)	(-2.63)	(-3.97)	(0.50)	(-0.86)	(1.40)
PROXY×CGO	0.526	18.547	107.567	10.568	20.048	27.641
	(2.79)	(5.65)	(7.26)	(3.51)	(2.47)	(1.02)
PROXY×MOM(-12,-1)	-0.005	-3.737	-35.472	-3.350	2.328	0.885
	(-0.03)	(-2.15)	(-4.10)	(-1.35)	(0.53)	(0.06)
PROXY×LEVERAGE	-0.253	5.974	40.818	2.005	5.621	-8.018
	(-0.92)	(1.50)	(2.51)	(0.78)	(1.42)	(-0.43)
PROXY×SCORE	-0.003	-0.095	-0.884	-0.109	-0.100	-0.637
	(-0.84)	(-2.07)	(-4.21)	(-3.04)	(-1.69)	(-3.32)
LEVERAGE	1.064	0.151	0.032	0.709	0.355	0.920
	(3.41)	(0.37)	(0.09)	(2.71)	(0.83)	(3.40)
LOGBM	-0.015	0.003	-0.015	-0.031	-0.012	0.040
	(-0.47)	(0.09)	(-0.49)	(-1.04)	(-0.40)	(1.25)
LOGME	-0.070	-0.062	-0.078	-0.042	-0.065	-0.125
	(-1.86)	(-1.81)	(-2.09)	(-1.22)	(-1.70)	(-2.93)
MOM(-1,0)	-5.559	-5.574	-5.056	-5.180	-5.126	-3.856
	(-10.30)	(-10.22)	(-9.34)	(-9.08)	(-9.76)	(-6.42)
MOM(-12,-1)	-0.144	0.404	0.778	0.098	-0.113	0.027
	(-0.65)	(1.32)	(3.34)	(0.38)	(-0.21)	(0.12)
MOM(-36,-13)	-0.078	-0.074	-0.029	-0.061	-0.075	0.004
	(-1.43)	(-1.24)	(-0.50)	(-0.80)	(-1.27)	(0.06)
PROXY	0.309	2.406	15.145	3.125	2.663	4.414
	(1.63)	(0.89)	(1.29)	(1.71)	(0.91)	(1.08)
SCORE	-0.021	-0.012	-0.006	-0.017	-0.017	-0.017
	(-4.71)	(-2.35)	(-1.27)	(-4.07)	(-2.99)	(-4.97)
TURNOVER	-1.537	-1.619	-0.522	-1.452	-1.113	0.031
	(-1.28)	(-1.42)	(-0.39)	(-0.94)	(-0.75)	(0.03)

Table 3.7: Fama-MacBeth Regressions of TOP 90% Liquid Stocks

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use the top 90% liquid common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least $5 and nonnegative book equity to perform the cross-sectional regression. Illiquidity is measured by Amihud's (2010) illiquidity measure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.406	-1.308	-1.787	0.260	-0.868	0.401
	(1.40)	(-3.29)	(-5.72)	(0.98)	(-0.79)	(1.50)
PROXY×CGO	0.637	19.497	118.425	9.233	19.652	22.244
	(3.25)	(6.09)	(9.90)	(3.70)	(2.23)	(2.03)
PROXY×MOM(-12,-1)	-0.063	-4.542	-38.579	-3.132	3.982	-9.154
	(-0.42)	(-2.55)	(-4.39)	(-1.01)	(1.14)	(-1.04)
PROXY×LEVERAGE	-0.351	5.864	39.834	1.984	3.228	24.870
	(-1.36)	(1.55)	(2.29)	(0.70)	(0.87)	(2.06)
PROXY×SCORE	-0.001	-0.119	-1.038	-0.068	-0.086	-0.436
	(-0.35)	(-3.15)	(-6.29)	(-1.88)	(-1.59)	(-1.71)
LEVERAGE	1.059	-0.019	-0.124	0.595	0.448	0.729
	(3.56)	-(0.05)	-(0.35)	(2.09)	(1.10)	(2.38)
LOGBM	0.003	-0.002	0.004	-0.006	0.012	0.015
	(0.09)	(-0.06)	(0.13)	(-0.19)	(0.36)	(0.46)
LOGME	-0.078	-0.069	-0.083	-0.060	-0.064	-0.129
	(-2.15)	(-1.99)	(-2.31)	(-1.69)	(-1.67)	(-3.10)
MOM(-1,0)	-5.648	-5.616	-5.128	-5.211	-5.217	-4.125
	(-11.50)	(-11.41)	(-10.78)	(-9.93)	(-10.89)	(-7.98)
MOM(-12,-1)	0.023	0.611	0.956	0.185	-0.274	0.075
	(0.10)	(2.18)	(3.81)	(0.69)	-(0.64)	(0.37)
MOM(-36,-13)	-0.085	-0.084	-0.037	-0.067	-0.084	-0.050
	(-1.81)	(-1.64)	(-0.73)	(-1.00)	(-1.67)	(-0.91)
PROXY	0.265	3.807	24.583	1.104	2.181	-11.677
	(1.32)	(1.51)	(2.36)	(0.59)	(0.55)	(-0.96)
SCORE	-0.025	-0.009	-0.004	-0.020	-0.022	-0.018
	(-5.56)	(-2.05)	(-0.92)	(-5.17)	(-4.17)	(-5.13)
TURNOVER	-1.732	-1.759	-0.932	-1.834	-1.536	-0.239
	(-1.44)	(-1.57)	(-0.72)	(-1.17)	(-1.06)	(-0.22)

Table 3.8: Fama-MacBeth Regressions of Largest 1,000 Stocks

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use the largest 1,000 common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least $5 and nonnegative book equity to perform the cross-sectional regression. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	-0.698	-1.708	-1.928	-0.011	-1.599	0.116
	(-1.84)	(-3.58)	(-5.20)	(-0.03)	(-1.44)	(0.40)
PROXY×CGO	1.176	21.360	122.400	9.163	23.925	89.621
	(4.55)	(5.41)	(7.44)	(2.78)	(2.57)	(2.08)
PROXY×MOM(-12,-1)	-0.145	-2.050	-36.491	-0.091	2.182	-8.395
	(-0.82)	(-0.92)	(-3.44)	(-0.04)	(0.44)	(-0.52)
PROXY×LEVERAGE	-0.216	4.764	40.191	1.255	2.072	9.939
	(-0.76)	(1.03)	(2.10)	(0.44)	(0.61)	(0.33)
PROXY×SCORE	-0.003	-0.047	-1.000	-0.038	-0.069	-0.379
	(-1.00)	(-1.21)	(-4.48)	(-0.93)	(-1.31)	(-1.49)
LEVERAGE	0.801	0.105	-0.135	0.582	0.499	0.751
	(2.50)	(0.25)	(-0.37)	(2.18)	(1.63)	(2.46)
LOGBM	0.005	0.010	0.014	-0.008	0.012	-0.003
	(0.19)	(0.36)	(0.48)	(-0.23)	(0.41)	(-0.09)
LOGME	-0.094	-0.085	-0.097	-0.072	-0.081	-0.129
	(-2.27)	(-2.07)	(-2.36)	(-1.83)	(-1.87)	(-2.84)
MOM(-1,0)	-5.226	-5.227	-4.706	-5.090	-4.691	-3.823
	(-9.32)	(-9.32)	(-8.52)	(-8.72)	(-8.67)	(-6.60)
MOM(-12,-1)	0.190	0.351	0.958	0.028	0.060	0.114
	(0.72)	(1.05)	(3.67)	(0.11)	(0.10)	(0.55)
MOM(-36,-13)	-0.036	-0.052	-0.007	-0.058	-0.050	-0.005
	(-0.69)	(-0.92)	(-0.13)	(-0.83)	(-0.91)	(-0.08)
PROXY	0.252	0.035	18.120	-0.298	2.193	-26.080
	(1.27)	(0.01)	(1.49)	(-0.15)	(0.78)	(-1.43)
SCORE	-0.018	-0.015	-0.002	-0.019	-0.017	-0.017
	(-4.06)	(-3.27)	(-0.44)	(-5.07)	(-3.06)	(-4.77)
TURNOVER	-1.228	-1.159	-0.329	-1.099	-0.991	0.331
	(-0.98)	(-1.03)	(-0.25)	(-0.70)	(-0.67)	(0.26)

Table 3.9: Fama-MacBeth WLS Regressions

Each month, we run a cross-sectional weighted least squares regression of returns on lagged variables with market equity of last month as the weighting. This table reports the time-series average of the regression coefficients. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. We use all the common nonfinancial stock from NYSE/AMES/NASDAQ with a price of at least $5 and nonnegative book value of equity. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. All variables are winsorized at 1% and 99%. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag =12.

	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	-0.934	-1.358	-1.680	-0.545	-1.021	-0.164
	(-1.73)	(-2.49)	(-3.27)	(-1.04)	(-1.13)	(-0.38)
PROXY×CGO	1.157	15.088	99.380	10.071	16.606	84.772
	(3.02)	(3.90)	(5.24)	(2.10)	(1.98)	(2.16)
PROXY×MOM(-12,-1)	0.189	-0.389	-25.730	-0.338	11.050	-30.558
	(0.72)	(-0.12)	(-1.84)	(-0.11)	(3.26)	(-1.40)
PROXY×LEVERAGE	-0.843	-5.473	30.062	4.060	-2.405	-59.258
	(-2.77)	(-1.05)	(1.22)	(0.91)	(-0.39)	(-3.61)
PROXY×SCORE	0.001	-0.054	-1.225	0.106	0.028	-0.030
	(0.16)	(-0.82)	(-3.79)	(2.02)	(0.28)	(-0.33)
LEVERAGE	1.260	0.877	-0.093	0.275	0.297	0.714
	(3.12)	(1.61)	(-0.18)	(0.68)	(0.40)	(2.24)
LOGBM	0.094	-0.037	0.082	0.072	0.097	0.118
	(1.83)	(-0.73)	(1.61)	(1.33)	(1.96)	(1.57)
LOGME	-0.099	-0.093	-0.114	-0.113	-0.092	-0.093
	(-2.50)	(-2.11)	(-2.88)	(-2.54)	(-2.19)	(-1.85)
MOM(-1,0)	-4.682	-4.587	-4.011	-3.955	-3.846	-2.968
	(-8.62)	(-8.07)	(-6.84)	(-6.59)	(-7.26)	(-4.72)
MOM(-12,-1)	0.227	0.477	0.994	0.472	-0.501	0.401
	(0.62)	(1.18)	(2.76)	(1.33)	(-1.55)	(1.47)
MOM(-36,-13)	0.055	0.020	0.078	0.052	0.003	-0.007
	(0.68)	(0.25)	(0.98)	(0.66)	(0.04)	(-0.10)
PROXY	0.200	4.228	23.832	-9.476	-3.143	5.247
	(0.72)	(1.04)	(1.48)	(-3.55)	(-0.54)	(0.85)
SCORE	-0.018	-0.010	0.004	-0.021	-0.025	-0.015
	(-2.97)	(-1.54)	(0.66)	(-5.23)	(-2.99)	(-3.91)
TURNOVER	-1.546	-2.563	-1.719	-2.568	-2.820	-0.823
	(-0.90)	(-1.75)	(-0.82)	(-1.01)	(-1.33)	(-0.54)

Table 3.10: Fama-MacBeth Regressions: Subperiod Analysis

Each month, we run a cross-sectional regression of returns on lagged variables. This table reports the time-series average of the regression coefficients. Newey-West robust t-statistics are reported in parentheses. Turnover is calculated as monthly trading volume divided by number of shares outstanding. Leverage is calculated as book value of debt over the sum of book value of debt and market value of equity. The mispricing score is calculated based on Stambaugh, Yu, and Yuan (2013). The coefficients are reported in percentages. All variables are winsorized at 1% and 99%. We perform the Fama-MacBeth regression analysis of two subperiods: 1966-1988, and 1989-2011 for all risk proxies except for DISP, for which the two subperiods are 1976-1993 and 1994-2011.

	Panel A: Subperiod: 1966-1988					1976-1993
	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.199	-1.545	-1.725	0.386	-2.527	0.497
	(0.48)	(-2.56)	(-4.96)	(0.94)	(-1.20)	(1.62)
PROXY×CGO	0.892	25.390	137.685	7.603	35.066	0.895
	(3.50)	(4.95)	(6.95)	(1.96)	(2.07)	(0.13)
PROXY×MOM(-12,-1)	0.167	-2.972	-43.944	-2.254	-2.304	-5.387
	(0.78)	(-1.05)	(-3.16)	(-0.46)	(-0.26)	(-0.61)
PROXY×LEVERAGE	-0.143	8.734	46.754	-0.144	5.632	26.525
	(-0.39)	(1.42)	(1.91)	-(0.04)	(1.31)	(1.42)
PROXY×SCORE	0.004	-0.032	-0.681	-0.092	-0.103	-0.414
	(0.72)	(-0.54)	(-2.58)	(-1.83)	(-1.24)	(-2.70)
LEVERAGE	1.226	0.217	0.074	1.225	0.565	1.184
	(2.41)	(0.33)	(0.13)	(3.14)	(1.29)	(3.11)
LOGBM	-0.047	0.026	-0.046	-0.027	-0.038	0.020
	(-0.89)	(0.66)	(-0.91)	(-0.57)	(-0.74)	(0.51)
LOGME	-0.117	-0.115	-0.129	-0.071	-0.109	-0.176
	(-1.85)	(-2.08)	(-2.04)	(-1.21)	(-1.71)	(-2.70)
MOM(-1,0)	-8.218	-8.247	-7.571	-7.258	-7.667	-5.542
	(-18.54)	(-17.59)	(-15.49)	(-12.14)	(-17.41)	(-7.28)
MOM(-12,-1)	-0.167	0.477	1.052	0.292	0.605	0.570
	(-0.46)	(1.24)	(3.39)	(0.85)	(0.55)	(2.59)
MOM(-36,-13)	-0.108	-0.122	-0.042	-0.063	-0.102	0.087
	(-1.47)	(-1.46)	(-0.54)	(-0.51)	(-1.29)	(0.98)
PROXY	0.017	-2.244	-1.677	1.922	2.017	-12.213
	(0.06)	(-0.70)	(-0.11)	(0.69)	(0.43)	(-0.90)
SCORE	-0.032	-0.024	-0.014	-0.025	-0.020	-0.020
	(-5.38)	(-3.77)	(-2.24)	(-4.93)	(-2.10)	(-5.29)
TURNOVER	-3.349	-3.378	-1.985	-3.799	-2.876	-1.184
	(-1.58)	(-1.74)	(-0.83)	(-1.33)	(-1.08)	(-0.58)

	Panel B: Subperiod: 1989-2011					1994-2011
	β	RETVOL	IVOL	CFVOL	1/AGE	DISPER
CGO	0.883	-0.544	-1.283	0.482	0.553	0.480
	(3.28)	(-1.13)	(-2.85)	(1.60)	(1.88)	(1.28)
PROXY×CGO	0.196	10.867	77.383	7.263	6.222	60.431
	(0.88)	(3.38)	(5.69)	(2.70)	(2.09)	(2.09)
PROXY×MOM(-12,-1)	-0.170	-4.055	-25.481	-1.032	2.582	-10.875
	(-1.36)	(-2.98)	(-3.08)	(-0.71)	(1.51)	(-0.53)
PROXY×LEVERAGE	-0.407	5.093	36.134	3.030	2.485	-12.611
	(-1.20)	(1.30)	(2.30)	(0.95)	(0.70)	(-0.60)
PROXY×SCORE	-0.007	-0.212	-1.204	-0.064	-0.197	-0.688
	(-2.00)	(-5.48)	(-7.49)	(-1.54)	(-4.53)	(-3.55)
LEVERAGE	0.917	-0.312	-0.319	0.162	0.434	0.303
	(2.86)	(-0.78)	(-1.13)	(0.48)	(1.10)	(0.63)
LOGBM	0.037	-0.043	0.042	0.012	0.041	0.054
	(1.28)	(-1.51)	(1.53)	(0.44)	(1.45)	(1.40)
LOGME	-0.031	-0.008	-0.024	-0.018	-0.002	-0.093
	(-0.81)	(-0.21)	(-0.72)	(-0.47)	(-0.06)	(-1.63)
MOM(-1,0)	-3.499	-3.446	-3.143	-3.481	-3.173	-3.172
	(-7.50)	(-8.05)	(-7.33)	(-8.20)	(-7.24)	(-5.82)
MOM(-12,-1)	0.041	0.429	0.636	-0.182	-0.351	-0.273
	(0.16)	(1.07)	(1.94)	-(0.55)	(-1.60)	(-0.91)
MOM(-36,-13)	-0.081	-0.075	-0.071	-0.092	-0.090	-0.147
	(-1.43)	(-1.19)	(-1.10)	(-1.35)	(-1.41)	(-2.05)
PROXY	0.624	10.596	42.552	1.925	11.102	6.239
	(2.57)	(3.74)	(4.85)	(1.05)	(6.30)	(1.60)
SCORE	-0.019	0.003	0.002	-0.018	-0.012	-0.016
	(-3.37)	(0.72)	(0.40)	(-3.38)	(-2.54)	(-2.72)
TURNOVER	0.426	0.601	1.008	1.125	0.850	1.681
	(0.44)	(0.57)	(0.85)	(0.81)	(0.66)	(1.29)

Table 3.11: Double-Sorted Portfolio Returns by CGO and Skewness

At the beginning of each month, we divide all common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity into five groups based on lagged CGO; within each of the CGO groups, firms are further divided into five portfolios based on lagged skewness. Monthly skewness is calculated using daily returns within the month. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The sample period is from January 1966 to December 2011. Excess returns are reported in percentages. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff
SKEW1	0.523	0.232	0.421	
SKEW3	0.511	0.354	0.589	
SKEW5	0.154	0.440	0.650	
SKEW5-SKEW1	-0.369	0.209	0.229	0.598
t-stat	-1.98	1.36	1.64	2.57
FF3-α	-0.346	0.201	0.192	0.539
t-stat	-1.78	1.30	1.29	2.11

Appendix: Tables for Additional Robustness Checks

Table A1: Double-Sorted Portfolio Returns of NYSE/AMEX Stocks

At the beginning of each month, we divide all firms into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only the common nonfinancial stocks in NYSE/AMEX with a price of at least $5 and nonnegative book equity are used in the double-sorting procedure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.569	0.427	0.474		0.624	0.353	0.439	
P3	0.549	0.422	0.679		0.291	0.453	0.543	
P5	0.078	0.390	0.744		-0.129	0.595	0.931	
P5-P1	-0.491	-0.037	0.270	0.761	-0.753	0.242	0.492	1.245
t-stat	-1.71	-0.14	1.15	2.66	-2.40	0.82	2.14	4.19
FF3-α	-0.730	-0.263	0.103	0.832	-0.993	-0.061	0.211	1.204
t-stat	-2.82	-1.27	0.53	2.56	-3.96	-0.27	1.02	3.92
	Proxy=IVOL				Proxy=CFVOL			
P1	0.816	0.290	0.553		0.577	0.536	0.556	
P3	0.336	0.468	0.516		0.348	0.321	0.521	
P5	-0.317	0.307	0.772		0.247	0.441	0.785	
P5-P1	-1.134	0.017	0.219	1.353	-0.330	-0.094	0.229	0.559
t-stat	-4.33	0.07	1.06	5.49	-1.36	-0.46	1.40	2.00
FF3-α	-1.402	-0.177	-0.021	1.381	-0.394	-0.098	0.143	0.537
t-stat	-6.79	-0.86	-0.12	5.90	-1.48	-0.64	0.95	1.77
	Proxy=1/AGE				Proxy=DISPER			
P1	0.466	0.421	0.492		0.745	0.662	0.815	
P3	0.550	0.470	0.665		0.548	0.622	0.629	
P5	0.207	0.096	0.999		-0.065	0.213	0.498	
P5-P1	-0.259	-0.324	0.507	0.766	-0.810	-0.449	-0.317	0.493
t-stat	-1.09	-1.48	2.55	2.49	-2.83	-1.93	-1.20	1.91
FF3-α	-0.304	-0.382	0.476	0.780	-1.274	-0.758	-0.734	0.539
t-stat	-1.22	-1.99	2.34	2.36	-5.17	-2.97	-3.02	1.97

Table A2: Double-Sorted Portfolio Returns of Largest 1000 Stocks

At the beginning of each month, we divide all firms into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only the 1,000 largest common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least $5 and nonnegative book equity are used in the double-sorting procedure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.589	0.414	0.456		0.633	0.382	0.483	
P3	0.365	0.349	0.640		0.511	0.229	0.761	
P5	0.052	0.342	0.702		-0.027	0.496	1.031	
P5-P1	-0.536	-0.071	0.246	0.782	-0.660	0.115	0.548	1.208
t-stat	-1.83	-0.24	0.89	3.03	-2.01	0.39	2.07	4.43
FF3-α	-0.752	-0.204	0.161	0.913	-0.867	-0.058	0.366	1.234
t-stat	-3.45	-0.93	0.79	3.46	-3.85	-0.28	1.64	4.66
	Proxy=IVOL				Proxy=CFVOL			
P1	0.863	0.271	0.559		0.583	0.645	0.536	
P3	0.419	0.401	0.724		0.554	0.334	0.607	
P5	-0.376	0.230	0.766		0.319	0.259	0.837	
P5-P1	-1.238	-0.041	0.207	1.445	-0.264	-0.385	0.301	0.565
t-stat	-3.71	-0.18	0.89	4.79	-1.11	-1.72	2.00	2.32
FF3-α	-1.431	-0.192	0.049	1.480	-0.260	-0.277	0.286	0.546
t-stat	-5.53	-1.06	0.22	5.25	-1.07	-1.54	1.86	2.03
	Proxy=1/AGE				Proxy=DISPER			
P1	0.436	0.411	0.532		0.835	0.589	0.993	
P3	0.406	0.383	0.748		0.482	0.580	0.523	
P5	0.288	0.182	1.190		-0.202	0.097	0.530	
P5-P1	-0.148	-0.228	0.658	0.807	-1.037	-0.492	-0.463	0.574
t-stat	-0.55	-1.13	3.39	2.78	-3.96	-2.06	-1.81	2.14
FF3-α	-0.097	-0.195	0.644	0.742	-1.442	-0.751	-0.869	0.574
t-stat	-0.42	-1.19	3.65	2.47	-5.85	-2.82	-3.60	2.07

Table A3: Double-Sorted Portfolio Returns of Top 90% Liquid Stocks

At the beginning of each month, we divide all firms in NYSE/AMEX/NASDAQ into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only the top 90% liquid (using Amihud's (2002) illiquidity measure) common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least $5 and nonnegative book equity are used in the double-sorting procedure. The sample period is from January 1966 to December 2011, except for DISPER, which is from January 1976 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.645	0.431	0.458		0.644	0.359	0.455	
P3	0.411	0.493	0.637		0.324	0.328	0.740	
P5	-0.003	0.217	0.731		-0.190	0.367	1.029	
P5-P1	-0.648	-0.214	0.273	0.921	-0.834	0.008	0.574	1.408
t-stat	-2.19	-0.65	0.96	3.07	-2.94	0.03	1.84	4.08
FF3-α	-0.863	-0.350	0.193	1.056	-1.056	-0.206	0.395	1.451
t-stat	-3.54	-1.48	0.87	3.29	-4.60	-0.93	1.35	3.76
	Proxy=IVOL				Proxy=CFVOL			
P1	0.858	0.299	0.533		0.789	0.542	0.605	
P3	0.371	0.362	0.824		0.380	0.321	0.719	
P5	-0.727	-0.002	1.013		0.419	0.141	0.818	
P5-P1	-1.585	-0.301	0.480	2.065	-0.370	-0.402	0.213	0.583
t-stat	-5.25	-1.23	1.94	6.56	-1.43	-1.81	1.37	2.19
FF3-α	-1.812	-0.464	0.325	2.137	-0.403	-0.317	0.195	0.598
t-stat	-7.50	-2.22	1.37	6.59	-1.63	-1.98	1.31	2.13
	Proxy=1/AGE				Proxy=DISPER			
P1	0.432	0.462	0.519		0.779	0.601	0.978	
P3	0.357	0.409	0.571		0.429	0.457	0.554	
P5	0.202	0.114	1.100		-0.123	0.173	0.534	
P5-P1	-0.230	-0.348	0.581	0.811	-0.902	-0.428	-0.444	0.458
t-stat	-1.05	-1.70	2.94	2.88	-3.67	-1.85	-1.84	1.94
FF3-α	-0.236	-0.360	0.565	0.801	-1.313	-0.727	-0.860	0.454
t-stat	-1.09	-2.31	3.17	2.60	-5.61	-2.84	-3.90	1.73

Table A4: Double-Sorted Portfolio Returns: Subperiod Analysis

At the beginning of each month, we divide all common nonfinancial stocks in NYSE/AMEX/NASDAQ with a price of at least \$5 and nonnegative book equity into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12. We perform the double-sorting analysis for two subperiods, 1966-1988 and 1989-2011, for all risk proxies except for DISP, for which the two subperiods are 1976-1993 and 1994-2011.

	1966-1988				1989-2011			
	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
				Proxy=β				
P1	0.717	0.655	0.375		0.647	0.255	0.546	
P3	0.938	0.823	0.777		0.282	0.079	0.541	
P5	0.191	0.377	0.990		-0.282	0.294	0.567	
P5-P1	-0.527	-0.278	0.615	1.142	-0.929	0.039	0.020	0.950
t-stat	-0.96	-0.53	1.26	2.15	-3.08	0.11	0.08	3.76
FF3-α	-0.894	-0.651	0.312	1.206	-1.112	0.031	-0.013	1.100
t-stat	-2.04	-2.14	0.98	2.23	-4.66	0.09	-0.06	4.30
				Proxy=RETVOL				
P1	0.781	0.690	0.428		0.492	0.048	0.455	
P3	0.276	0.563	1.061		0.205	0.195	0.299	
P5	0.107	0.417	1.319		-0.498	0.398	0.835	
P5-P1	-0.674	-0.273	0.891	1.565	-0.991	0.350	0.380	1.370
t-stat	-1.86	-0.61	1.60	2.67	-2.56	0.91	1.24	3.57
FF3-α	-0.962	-0.692	0.561	1.523	-1.167	0.209	0.206	1.374
t-stat	-2.93	-2.64	1.24	2.45	-3.99	0.68	0.77	3.67
				Proxy=IVOL				
P1	1.073	0.606	0.654		0.666	-0.082	0.419	
P3	0.369	0.499	0.913		0.119	0.271	0.692	
P5	-0.929	-0.163	1.275		-0.614	0.071	0.642	
P5-P1	-2.002	-0.769	0.620	2.622	-1.281	0.153	0.222	1.503
t-stat	-3.55	-1.83	1.31	4.44	-4.38	0.50	0.86	4.86
FF3-α	-2.321	-1.044	0.417	2.739	-1.414	0.027	-0.105	1.309
t-stat	-4.81	-3.26	1.13	4.64	-5.45	0.09	-0.42	4.05

	1966-1988				1990-2011			
	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
				Proxy=CFVOL				
P1	0.699	0.727	0.673		0.607	0.336	0.523	
P3	0.528	0.247	1.067		0.123	0.388	0.392	
P5	0.281	0.138	0.905		0.117	0.319	0.626	
P5-P1	-0.418	-0.590	0.231	0.649	-0.490	-0.017	0.104	0.594
t-stat	-1.19	-1.77	1.01	1.91	-1.57	-0.05	0.60	1.59
FF3-α	-0.480	-0.678	0.107	0.587	-0.445	0.212	0.182	0.627
t-stat	-1.43	-3.12	0.60	1.60	-1.23	0.94	0.93	1.61
				Proxy=1/AGE				
P1	0.645	0.654	0.598		0.430	0.214	0.354	
P3	0.241	0.429	0.966		0.070	0.220	0.428	
P5	0.227	0.352	1.115		0.003	-0.246	1.138	
P5-P1	-0.419	-0.302	0.517	0.936	-0.427	-0.460	0.783	1.210
t-stat	-1.08	-1.06	1.62	2.15	-1.35	-1.31	2.32	2.66
FF3-α	-0.578	-0.459	0.446	1.024	-0.330	-0.339	0.782	1.112
t-stat	-1.67	-2.51	1.78	2.41	-1.11	-1.22	2.16	2.16
	Proxy=DISPER: 1976-1993				Proxy=DISPER: 1994-2011			
P1	0.988	0.523	0.882		0.653	0.596	1.049	
P3	0.388	0.439	0.384		0.464	0.559	0.755	
P5	-0.154	0.344	0.506		-0.001	0.201	0.570	
P5-P1	-1.142	-0.179	-0.376	0.766	-0.654	-0.395	-0.479	0.175
t-stat	-2.74	-0.54	-1.07	2.17	-2.11	-1.59	-1.53	0.58
FF3-α	-1.489	-0.444	-0.775	0.713	-1.376	-0.777	-0.933	0.444
t-stat	-3.88	-1.26	-2.29	1.85	-5.14	-3.41	-3.49	1.33

Table A5: Double-Sorted Portfolio Returns Based on Stocks with Bottom 50% Institution Holding Stocks

At the beginning of each month, we divide all firms into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only stocks with the bottom 50% institutional holdings are used in the double-sorting procedure. Data on institutional holdings are obtained from Thomson Reuters. The sample period is from January 1980 to December 2011. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.722	0.772	0.365		0.819	0.735	0.376	
P3	0.726	0.762	0.724		0.522	0.395	1.340	
P5	0.047	0.585	0.912		-0.360	0.322	1.001	
P5-P1	-0.675	-0.187	0.548	1.223	-1.179	-0.413	0.624	1.804
t-stat	-1.58	-0.46	1.49	2.94	-2.98	-1.06	1.55	3.30
FF3-α	-1.119	-0.569	0.281	1.400	-1.492	-0.852	0.260	1.752
t-stat	-3.04	-2.13	0.94	3.08	-3.94	-2.81	0.67	2.87
	Proxy=IVOL				Proxy=CFVOL			
P1	1.035	0.700	0.453		1.025	0.835	0.520	
P3	0.647	0.421	1.279		0.646	0.513	1.223	
P5	-1.515	-0.107	0.884		-0.014	0.422	0.941	
P5-P1	-2.551	-0.807	0.431	2.982	-1.039	-0.413	0.422	1.460
t-stat	-5.16	-1.96	1.32	6.02	-2.59	-0.90	1.37	2.92
FF3-α	-2.854	-1.177	0.232	3.086	-1.175	-0.677	0.262	1.437
t-stat	-7.34	-3.56	0.72	6.33	-3.04	-2.12	0.82	2.74
	Proxy=1/AGE				Proxy=DISPER			
P1	0.478	0.792	0.374		0.964	0.765	0.896	
P3	0.378	0.484	0.843		0.517	0.768	0.327	
P5	0.203	0.429	1.131		-0.359	0.342	0.340	
P5-P1	-0.274	-0.363	0.757	1.032	-1.323	-0.423	-0.556	0.766
t-stat	-0.99	-1.27	2.87	2.87	-3.61	-1.79	-2.15	2.11
FF3-α	-0.455	-0.423	0.659	1.114	-1.932	-0.661	-0.887	1.045
t-stat	-1.60	-1.69	2.93	2.91	-5.39	-3.06	-3.51	2.51

Table A6: Double-Sorted Portfolio Returns Based on Stocks with Top 50% Institution Holding Stocks

At the beginning of each month, we divide all firms in NYSE/AMEX/NASDAQ into five groups based on lagged CGO; then within each of the CGO groups, firms are further divided into five portfolios based on lagged risk proxies. The portfolio is then held for one month and value-weighted excess returns are calculated. Monthly excess returns are reported in percentages. Only stocks with the top 50% institutional holdings are used in the double-sorting procedure. The sample period is from January 1980 to December 2011. Data on institutional holdings are obtained from Thomson Reuters. The t-statistics are calculated based on Newey-West (1987) adjusted standard errors with lag = 12.

	CGO1	CGO3	CGO5	Diff-in-Diff	CGO1	CGO3	CGO5	Diff-in-Diff
	Proxy=β				Proxy=RETVOL			
P1	0.908	0.670	0.644		0.946	0.699	0.661	
P3	0.928	0.818	0.890		0.752	0.649	1.052	
P5	0.390	0.568	1.004		0.498	0.574	1.433	
P5-P1	-0.518	-0.101	0.359	0.877	-0.448	-0.125	0.772	1.220
t-stat	-1.26	-0.26	0.83	2.01	-1.40	-0.39	1.74	2.51
FF3-α	-0.773	-0.378	0.108	0.881	-0.619	-0.331	0.582	1.201
t-stat	-2.33	-1.21	0.30	1.94	-1.96	-1.27	1.51	2.23
	Proxy=IVOL				Proxy=CFVOL			
P1	1.073	0.615	0.946		1.039	0.756	0.686	
P3	1.031	0.677	0.821		0.478	0.475	1.084	
P5	-0.051	0.474	1.270		0.467	0.587	0.959	
P5-P1	-1.124	-0.141	0.324	1.448	-0.573	-0.170	0.273	0.846
t-stat	-3.34	-0.48	1.01	4.11	-1.93	-0.78	1.16	2.41
FF3-α	-1.330	-0.288	0.215	1.545	-0.571	-0.100	0.226	0.797
t-stat	-4.48	-1.03	0.82	4.50	-1.91	-0.50	1.14	2.07
	Proxy=1/AGE				Proxy=DISPER			
P1	0.814	0.650	0.611		0.956	0.935	1.053	
P3	0.627	0.948	0.932		0.799	0.424	0.608	
P5	0.534	0.372	1.464		-0.037	0.313	0.802	
P5-P1	-0.280	-0.278	0.853	1.133	-0.992	-0.622	-0.251	0.741
t-stat	-0.97	-1.22	3.09	3.17	-3.72	-3.12	-0.84	2.06
FF3-α	-0.199	-0.325	0.901	1.099	-1.342	-0.936	-0.644	0.697
t-stat	-0.70	-1.53	3.79	2.96	-5.48	-4.24	-2.50	1.93

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Chapter 4

Appendices

4.1 Extension of the Berk-Green (2004) Model

In this appendix, I develop a simple variation of the Berk and Green (2004) model by introducing the risk aversion of mutual fund investors. Two propositions derived from the comparative statics analysis are consistent with the empirical findings in the main text.

There are two periods, $t = 1, 2$, and individual investors can only invest in two assets, a risk-free asset and an actively managed fund. The return on the risk-free asset is denoted by $\bar{r}$, and the return earned by fund investors is assumed to have the function form

$$r_t = \alpha - \frac{C(Q_{t-1})}{Q_{t-1}} - f_t + \epsilon_t, \quad t = 1, 2,$$

where α is the constant unobservable managerial skill.[1] $C(Q_{t-1})$ is the costs incurred when actively managing a fund of size Q_{t-1} and is assumed to take the simple quadratic form $C(Q_{t-1}) = \lambda Q_{t-1}^2$, where $\lambda > 0$. This convex cost function captures the idea that larger funds pay higher marginal costs to scale. f_t is the fixed management fee per dollar, and ϵ_t is the idiosyncratic noise independently distributed over time with a normal distribution:

$$\epsilon_t \sim N(0, \sigma_\epsilon^2), \quad t = 1, 2.$$

There is a continuum of infinitesimal fund investors who have constant absolute risk aversion (CARA) utility function over the terminal wealth.

At the beginning of period 1, investors have a total amount of Q_0 in the fund and a prior belief about α, which is assumed to be normally distributed with a mean of α_0 and a variance of σ_0:

$$\alpha \sim N(\alpha_0, \sigma_0^2).$$

At the end of period 1, investors update their prior beliefs based on the realized return

[1] This α includes the convex costs incurred by managing a large fund, so is not the same as the benchmark-adjusted return earned by investors as defined as performance measures in the empirical tests.

r_1 according to the Bayesian rule and reallocate their portfolio between the fund and the risk-free asset. That is, they choose the dollar allocation q_1 to the fund to solve the utility maximization problem: The posterior expectation of α would be:

$$\hat{\alpha} = \alpha | r_1 \sim N(\alpha_1, \sigma_1^2)$$

where

$$\begin{aligned}
\alpha_1 &= \frac{\sigma_\epsilon^2}{\sigma_0^2 + \sigma_\epsilon^2}\alpha_0 + \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\epsilon^2}(r_1 + \lambda Q_0^2 + f_1) \\
\sigma_1^2 &= \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\epsilon^2}\sigma_\epsilon^2
\end{aligned}$$

Based on this updated belief, investors reallocate their wealth between the fund and the risk-free asset. That is, each individual investor chooses the dollar allocation q_1 to the fund to solve the utility maximization problem:

$$\begin{aligned}
&\max_{q_1 \geq 0} E[e^{-\gamma w_2}] \\
\text{s.t.} \quad & w_2 = q_1 r_2 + (w - q_1)\bar{r} \\
& r_2 = \alpha - \lambda Q_1 - f_2 + \epsilon_2,
\end{aligned}$$

where w is the investor's total dollar wealth and Q_1 is the total investment in the fund from all investors, which is taken as given when the representative agent makes an investment decision.

Given CARA utility and the distribution of r_2: $E[r_2|r_1] = \alpha_1 - \lambda Q_1 - f_2$, $Var[r_2|r_1] \equiv \sigma_2^2 = Var[\alpha|r_1] + Var[\epsilon_2] = \sigma_1^2 + \sigma_\epsilon^2$, it is easy to solve the optimal holding q_1^*:

$$q_1^* = \frac{\alpha_1 - \lambda Q_1 - f_2 - \bar{r}}{\gamma \sigma_2^2}$$

Solving this problem and imposing the competitive equilibrium condition $q_1^* = Q_1$, I have:

$$q_1^* = Q_1 = \frac{\alpha_1 - f_2 - \bar{r}}{\gamma\sigma_2^2 + \lambda}.$$

To be consistent with the empirical measure of fund flows, I define flows into the fund at the end of period 1 as

$$F_1 = \begin{cases} \frac{Q_1 - Q_0(1+r_1)}{Q_0} & \text{if } Q_1 > 0 \\ -1 & \text{if } Q_1 = 0 \end{cases}$$

To see how future performance and flow-performance sensitivity change when the convexity of cost functions varies, I proceed to derive cross-partial derivatives of future performance and flows with respect to underlying parameters. After substituting Q_1 and r_1:

$$\frac{\partial^2 E[r_2 - \bar{r}]}{\partial r_1 \partial \lambda} = -\frac{\gamma\sigma_0^2\sigma_2^2}{(\sigma_0^2 + \sigma_\epsilon^2)(\gamma\sigma_2^2 + \lambda)} < 0$$
$$\frac{\partial^2 F_1}{\partial r_1 \partial \lambda} = -\frac{\sigma_0^2}{Q_0(\sigma_0^2 + \sigma_\epsilon^2)(\gamma\sigma_2^2 + \lambda)} < 0.$$

These equations are self-evident and intuitive. The first one suggests that lower costs to scale (i.e., smaller λ) generate more persistent performance. In other words, given the same recent good performance, funds with better scalability and larger capacity can overcome the adverse effects from asset growth more easily and still earn higher returns in the subsequent period. The second equation, from the perspective of rational fund investors, reveals that lower costs to scale help to attract more money inflows. Given that accumulated success in exploration and accumulated success in exploitation correspond to low and high costs to scale in my empirical framework, these relations confirm that previous empirical findings are also consistent with the Berk and Green (2004) model.