TWO ESSAYS ON ASSET PRICING ANOMALIES

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Abstract

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This dissertation investigates the impact of mutual funds in the cross-sectional stock returns and examines a conflict in the existing literature that characterizes momentum. In the first essay, I examine the explanatory power of aggregate mutual fund flows for the profitability of price-based (i.e., momentum and 52-week high) and non-price-based (i.e., earnings surprises, profitability, share issuance, accrual and asset growth) anomalies in the cross-section of returns. I find that the flow-based trading of mutual funds contributes to mispricing as measured by the profits to price-based anomalies, especially at times when market-wide funding costs are high. The effect also exists for non-price-based anomalies, but only through the dependence of their profits on momentum. My findings support the view of Lou (2012) and Vayanos and Woolley (2013) that mutual funds' trading on flows creates feedback that strengthens price-based anomalies, as high-performing funds buy additional shares of high-performing stocks and poorly performing funds sell shares of poorly performing stocks. However, the explanatory power of aggregate mutual fund flows for price-based anomaly returns is only partly attenuated by fund-level variables designed to capture the feedback effect. The flow-induced trading by mutual funds appears to contribute to mispricing for reasons beyond the feedback effect.

The second essay examines the extent to which momentum profits depend on the state of credit markets. The state of credit markets does affect momentum, but the results are not consistent with a credit channel effect on momentum. For non-financial firms, the momentum profits are stronger among portfolios formed under favorable credit conditions. For financial firms, credit conditions do not matter to the momentum profits. Price continuations in financial firms are related to whether the firms are performing poorly, but not whether that performance is attributable to credit conditions that are favorable or poor.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Aggregate Mutual Fund Flows and Cross-Sectional Anomalies

1.1 Introduction

Mutual funds are important participants in equity markets. Investor flows and the economic impact of mutual funds on prices have been extensively studied in recent years.[1] A large body of literature shows that aggregate mutual fund flows have significant effects on stock prices at the aggregate level [e.g., Warther (1995), Edelen and Warner (2001), and Ben-Raphael, Kandel, and Wohl (2012)]. One would expect mutual fund flows also to affect the cross section of stock prices.

From an efficient-markets point of view, if sophisticated mutual fund managers adopt trading strategies to exploit cross-sectional anomalies, the profitability of anomalies will be reduced when capital flows into the mutual fund industry are high. Akbas, Armstrong, Sorescu, and Subrahmanyam (2014a) show that active mutual fund managers do trade on anomalies that have been documented in the academic literature such as momentum, profitability, value, and earnings. They then show that the profitability of a composite-anomaly strategy is lower when there are more inflows to funds whose trading is sensitive to the composite-anomaly strategy.[2]

[1] French (2008) documents that, in the stock market, there is an increase in the holdings of open-end mutual funds, from 4.6% in 1980 to 32.4% in 2007. Stambaugh (2014) points out that the fraction of U.S. equity owned directly by individuals has fallen from 48% in 1980 to around 20% in 2012. Data from the ICI (Investment Company Institute) shows that the sheer size of the open-end domestic equity mutual fund industry is $5.7 trillion at the end of 2013 and the net cash flow into domestic equity mutual funds is $17.9 billion during 2013.

[2] The composite-anomaly strategy is a long-short hedge strategy combining five primary anomalies: mo-

Another set of studies document that flow-induced trading by mutual funds can lead to *mis*pricing in individual stocks. Coval and Stafford (2007) find that purchases (sales) of mutual funds forced by excess inflows (outflows) exert significantly positive (negative) price pressure in individual securities, resulting in transaction prices temporarily deviating from their information-efficient benchmarks. Lou (2012) extends this idea to address how flow-driven trading can potentially *cause* the price momentum documented by Jegadeesh and Titman (1993). Lou's hypothesis is that past winning funds receive capital inflows and expand their existing holdings, which are disproportionately invested in past winning stocks; likewise, past losing funds lose capital and have to liquidate their holdings, which are concentrated in past losing stocks. Since mutual fund flows are persistent and performance chasing, this feedback leads to past winning stocks continuing to outperform past losing stocks in the short term, and mutual fund performance that is persistent.

Vayanos and Woolley (2013; hereafter VW) formalize Lou's hypothesis in a rational continuous-time model where flows between investment funds are driven by changes in investors' views about funds' performance. VW show that the feedback effect of Lou arises *regardless* of the types of investment strategies mutual funds adopt. What is important in VW's model is that fund flows are persistent and performance chasing.[3] Therefore, the extent to which the Lou-VW feedback effect contributes to momentum profits should depend on the sensitivity of flows to funds' performance. Xie (2011) finds that the flow-performance sensitivity is stronger when investors have more capital to allocate, which suggests that the strength of the feedback effect should be positively related to *aggregate* mutual fund flows.

The extent to which the aggregate flows to mutual funds affect the profits to momen-

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mentum, profitability, value, earnings, and reversal. Akbas et al. (2014a) regress returns of all mutual funds on the returns of the composite-anomaly strategy and study the funds with the highest correlation.

[3] Another important assumption in VW's model is that fund managers have to trade individual stocks incrementally over time and put the money (to a large degree) into the securities they already hold when receiving inflows. Coval and Stafford (2007), Lou (2012) and Shive and Yun (2013) find that mutual funds tend to expand and contract their portfolios in their existing proportions.

tum strategies has not been studied. Moreover, whether there is a relationship between aggregate mutual fund flows and the profitability of individual *non*-price-based anomalies is also an open question. This paper fills this gap by examining the significance of mutual fund flows as determinants of the profitability of a large set of anomalies. I consider (and contrast) price-based and non-price-based strategies because the feedback effect of Lou-VW should only affect price-based anomalies—it makes no prediction regarding non-price-based strategies. For price-based anomalies, I examine strategies based on past six-month returns and nearness to the 52-week high (MOM and 52-Wk, respectively). The variables I examine for non-price-based anomalies are standardized unexpected earnings (SUE), return on equity (ROE), share issuance (SI), accruals (ACC), and asset growth (AG).[4]

I begin by investigating the relationship between mutual fund trading strategies and fund-level flows to understand whether mutual fund managers engage in anomaly-based strategies when they encounter inflows and outflows. I construct measures from mutual fund holdings data of the degree to which the holdings changes of individual funds conform to the long and short legs of anomaly-based strategies. Then for each anomaly, I estimate panel regressions of these measures on the flows to individual mutual funds. The results indicate that mutual funds do trade on both the price-based and non-price-based anomalies, particularly the long legs of the strategies; and that these measures are sensitive to fund-level flows, suggesting that trading on anomalies is (at least partly) how funds deal with flows. I then use the measures of anomaly-based trading as controls in estimating the flow-performance relation across funds. I find that fund-level flows remain significantly positively related to the past performance of mutual funds even with these controls.[5] This affirms the strength of the performance-chasing feature of flows that is necessary for Lou and VW's

[4]For studies of the individual strategies see: MOM, Jegadeesh and Titman (1993); 52-Wk, George and Hwang (2004); SUE, Bernard and Thomas (1989); ROE, Fama and French (2006); SI, Loughran and Ritter (1995); ACC, Sloan (1996); AG, Cooper, Gulen, and Schill (2008).

[5]Sapp and Tiwari (2004) find that investors do not select funds based on a momentum investing style, but rather simply chase funds that were recent winners.

feedback effect to exist.

Next, I test whether trading by mutual funds attenuates or reinforces the profits to trading on anomalies. If mutual funds' trading corrects cross-sectional mispricing, the returns to anomaly-strategy portfolios are lower following high aggregate inflows; in contrast, if trading by mutual funds increases mispricing, the returns to anomaly strategies are higher following greater capital flows into mutual funds.[6]

This analysis is done both unconditionally, and conditional on macroeconomic measures of funding conditions that capture market-wide financing costs. The conditional analysis is intended to make the impact of mutual funds more visible in the data. Mutual fund trading is likely to exert a greater influence on prices when other sources of investment capital are scarcer, such as when overall borrowing costs are high. The effect of aggregate mutual fund flows on the profitability of anomaly-based strategies might therefore be easier to detect in periods of relative financial stress.[7] I use the excess bond premium (EBP) in Gilchrist and Zakrajšek (2012; hereafter GZ) to proxy for macro funding conditions.[8] I estimate a two-state Markov regime-switching model to identify regimes of macro funding conditions: "Favorable" ("Poor") macro funding conditions are periods when EBP is low (high).

In the analysis of price-based strategies, the unconditional results show that aggregate mutual fund flows have a strong and positive influence on the future returns to the MOM and 52-Wk strategies. Aggregate mutual fund flows account for about 40% (30%)

[6] Akbas et al. (2014a, 2014b) also examine the effect of aggregate flows on future returns to their composite-anomaly strategy to test whether mutual funds exacerbate or attenuate mispricing in the cross-section.

[7] The empirical evidence in Ben-David, Franzoni, and Moussawi (2012) supports this approach. They find that, unlike hedge funds, mutual funds did not significantly reduce their equity holdings during the recent financial crisis.

[8] The EBP is a residual component of GZ's credit spread index—the "GZ credit spread". An increase in the EBP reflects a reduction in the effective risk-bearing capacity of the financial sector and a contraction in the supply of credit. I thank Egon Zakrajšek for providing the time-series of data for the GZ credit spread and the EBP.

of Fama-French risk-adjusted returns of the MOM (52-Wk) strategy. The magnitude of the sensitivity of price-based strategies to aggregate mutual fund flows is striking. A one standard deviation increase in aggregate mutual fund flows is associated with an increase in future returns of 0.86% and 0.73% per month for MOM and 52-Wk, respectively. The conditional results are even more striking. When funding conditions are poor, the sensitivities of profits of the MOM and 52-Wk strategies to aggregate mutual fund flows are *three times* as large as under the unconditional scenarios, and they are highly significant. In fact, the results suggest that the total profits of the MOM and 52-Wk strategies under poor funding conditions are attributable to mutual fund trading—those strategies' profits are insignificant after controlling for aggregate mutual fund flows. In stark contrast, under favorable macro funding conditions, the profits of the MOM and 52-Wk strategies are not explained by aggregate mutual funds flows, and remain statistically significant regardless of the magnitude and direction of aggregate mutual fund flows. All these results hold for both the winner and loser components of price-based anomaly returns (i.e., the long and short legs of the strategies).

These findings suggest that mutual funds' trading enhances the profits to price-based strategies, as the Lou-VW feedback effect predicts. This is driven by periods when funding conditions are poor. It also provides cross-sectional evidence that reinforces existing findings that aggregate mutual fund flows contribute to *mis*pricing. For example, Ben-Raphael, Kandel and Wohl (2012) find that the positive contemporaneous relation between aggregate mutual fund flows and stock market returns reverses within ten months. They interpret this reversal pattern as evidence of aggregate mutual funds flows inducing mispricing into market returns (i.e., at the aggregate level).

To scrutinize the Lou-VW feedback effect at a more "micro" level, I examine directly the changes in the stock holdings of funds that experience inflows and outflows. I construct two flow-induced trading measures: *Buy* and *Sell* from mutual fund holdings data. *Buy* measures the intensity with which mutual funds that experience inflows buy past winner over past loser stocks; *Sell* measures the intensity with which funds experiencing outflows sell past loser over winner stocks. The Lou-VW mechanism predicts that momentum profits should be positively related to *Buy* and *Sell*.

The unconditional analysis shows that *Buy* and *Sell* do affect the future returns to both the MOM and 52-Wk strategies with the correct signs. However, their impacts are not significant when aggregate flows are also taken into account. Under poor funding conditions, *Buy* and *Sell* partly explain why aggregate flows matter to the MOM strategy returns, but they do not explain it for the 52-Wk strategy returns. Specifically, for MOM, *Buy*, *Sell* and aggregate flows all affect profits. For 52-Wk, only aggregate flows matter. When macro funding conditions are favorable, the profits to both the MOM and 52-Wk strategies remain strong, and they are not related to *Buy*, *Sell* or aggregate flows. The Lou-VW effect as captured by *Buy* and *Sell* does have explanatory power. Nonetheless, the effect of aggregate flows remains significant after controlling for *Buy* and *Sell* suggesting there are aspects of flow-based trading by mutual funds that contribute to mispricing that go beyond the Lou-VW effect.

I conduct the same analysis for non-price-based strategies, and the results are quite different, especially after controlling for the contribution momentum makes to those strategies' returns. Without controlling for momentum, aggregate flows have significant positive impacts on the future profits of SUE, SI and AG. However, these relations are not significant once momentum is also controlled for. This evidence is also consistent with the implications of the Lou-VW effect. The flow-based trading of mutual fund flows seems to affect the profits of the non-price-based anomalies *through* its effect on price-based strategies.

In other tests, I examine whether my findings are robust to market-wide variables that have been used in the literature to explain momentum profits: market return, market volatility, market illiquidity, and the Baker and Wurgler (2006) sentiment index.[9] Since the existing literature has linked aggregate mutual fund flows to market-wide variables, the

[9] See Cooper, Gutierrez, and Hameed (2004), Wang and Xu (2011), Avramov, Cheng, and Hameed (2013), and Stambaugh, Yu, and Yuan (2012).

results described above could merely reflect the results in previous studies.[10] To examine this, I run a horserace between aggregate mutual fund flows and these variables. It turns out that my finding explains theirs—those variables are insignificant after accounting for aggregate mutual fund flows.

To sum up, the main contribution of this paper is to explore the role of aggregate mutual fund flows to the profitability of several anomalies related to stock prices and other well-known non-price-based variables. The empirical evidence broadly supports the view of Lou (2012) and Vayanos and Woolley (2013) that mutual funds' trading on flows strengthens price-based anomalies. This is driven primarily by periods when funding conditions are poor, suggesting the price pressure generated by mutual fund trading plays a crucial role when capital is relatively scarce. However, the overall explanatory power of *aggregate* mutual fund flows for price-based anomaly returns is only partly explained by variables designed to focus narrowly on the Lou-VW feedback effect, even when funding conditions are poor. This suggests there are aspects of funds' flow-based trading that contribute to mispricing that lie outside the Lou-VW explanation.

The rest of paper is organized as follows: Section 1.2 reviews the existing literature. Section 1.3 describes the data and methodology. Section 1.4 analyses the mutual fund trading strategies and the characteristics of mutual fund flows. Section 1.5 analyzes the impact of aggregate mutual fund flows and Lou's flow-based mechanism on price-based strategy returns. Section 1.6 examines the non-price-based strategies. Section 1.7 conducts robustness checks, and Section 1.8 concludes.

1.2 Relevant Literature

This study connects and contributes to several strands of literature. First, it is related to literature that links mutual fund trading to cross-sectional mispricing in equity markets.

[10] For example, Warther (1995), Jank (2012), and Ben-Raphael, Kandel, and Wohl (2012) document that stock market returns and flows into equity funds are contemporaneously correlated; Cao, Chang, and Wang (2008) find that market volatility is negatively related to aggregate flows.

Vayanos and Wooley (2013) offer a model of momentum and reversal returns due to delegated management. They argue that flows between funds can give rise to momentum effects because flows are persistent and performance chasing and eventually push prices away from fundamentals causing reversals. Lou (2012) empirically finds that the flow-induced trading of mutual funds can cause stock-level momentum. Coval and Stafford (2007) and Hau and Lai (2013) document that the distressed selling of mutual funds experiencing extreme outflows leads to temporary price pressures that subsequently reverse. Frazzini (2006) produces evidence linking the disposition effect of mutual fund managers to post-earnings announcement drift. Akbas et al. (2014b) find that aggregate mutual fund flows appear to exacerbate cross-sectional mispricing because future returns of a composite-anomaly strategy are higher when there are more aggregate inflows to the entire mutual fund industry. This paper differs from Akbas et al. (2014b) in showing that only returns to price-based anomalies positively vary with aggregate mutual fund flows, and the impact of aggregate mutual fund flows is driven primarily by periods when capital is relatively scarce.

Second, this paper expands the literature that investigates the relation between aggregate mutual fund flows and aggregate stock market returns. Warther (1995) documents a significant contemporaneous correlation between stock market returns and mutual fund flows. Jank (2012) studies the relationship between mutual fund flows, stock market returns, and the real economy. Ben-Raphael, Kandel, and Wohl (2012) not only find a significant, positive contemporaneous relation between aggregate mutual fund flows and stock market excess returns but also show that about 85% of these price changes are reversed within four months. Jotikasthira, Lundblad, and Ramadorai (2012) find that movements in investor flows of global equity fund portfolios related to emerging markets affect equity prices of emerging markets at the aggregate market level.

Additionally, the empirical results support the view that there is time-variation in momentum profits and provide explanations beyond behavioral stories. From perspectives of behavioral biases, Cooper, Gutierrez, and Hameed (2004), Wang and Xu (2011), Avramov, Cheng, and Hameed (2013), and Stambaugh, Yu, and Yuan (2012) find that momentum profits can be explained by market return, market volatility, market illiquidity, and the Baker and Wurgler (2006) sentiment index, respectively. Daniel and Moskowitz (2013) find that the momentum return is negatively related to market volatility and to other market stress measures. Furthermore, Daniel, Jagannathan, and Kim (2012) suggest that momentum returns may arise from a mixture of normal distributions and characterize these risk spikes with a two-state hidden Markov model, with "turbulent" and "calm" states. They find that momentum returns are more volatile and lower during turbulent months. This study extends the literature by showing that aggregate mutual fund flows contribute to momentum, and momentum is weaker when macro funding conditions are poor and aggregate mutual fund flows are outbound.

1.3 Data and Methodology

1.3.1 Stock Data

The data consist of common stocks traded on the all NYSE/AMEX/NASDAQ common stocks (share code 10 or 11). Data on stock returns and prices is obtained from the Center for Research in Security Prices (CRSP) monthly files. The baseline sample spans the period from January 1984 to December 2012. Throughout the paper, in computing holding period returns, the CRSP delisting return is used whenever a stock drops out of the sample to avoid potential delisting biases.[11] Financial firms (SIC code between 6000 and 6999) and penny stocks (price below $5) are excluded. The accounting variables are obtained from Compustat.

[11] If the delisting return is missing, the Beavera, McNicholsa, and Price (2007) methodology is utilized. The associate SAS code is available on Richard Price's website: http://richardp.bus.usu.edu/research.

1.3.2 Mutual Fund Data

Mutual Fund Holdings Data

Mutual fund holdings data are obtained from the Thompson Financial CDA/Spectrum database for the period from 1980 to 2012. Although mutual funds are only required to report their holdings semiannually, most of them report holdings quarterly. Total net assets, net monthly returns, and other characteristics of mutual funds are obtained from the CRSP Survivor-Bias-Free Mutual Fund Database. Because some mutual funds have multiple share classes, the total net assets (TNA) in all share classes are combined for each fund. Net returns and expense ratios of the funds are calculated as TNA-weighted averages across all share classes. Finally, the MFLinks file is used to merge the CDA/Spectrum and the CRSP mutual fund databases.

I follow the procedure of Lou (2012) to choose domestic equity mutual funds. Specifically, I require the investment objective code of the mutual funds reported by CDA/Spectrum to be aggressive growth, growth, growth and income, and unclassified or missing and select the funds with a ratio of equity holdings to total net assets of at least 70% to exclude funds that are misclassified as equity funds.[12] I require a minimum fund size of $1 million and that the TNAs reported by CDA/Spectrum and CRSP do not differ too much (i.e., $0.5 < TNACDA/TNACRSP < 2$) to ensure data quality. The final sample contains 125,448 fund-quarter observations with 3,361 distinct mutual funds.

Table 1.1 summarizes the number and total net assets of all active domestic equity funds in the sample at the end of each year. The number of funds increases from 232 in 1980 to 2,013 in 2007 but decreases to 1,395 in 2012 after the recent financial crisis. The percentage of the equity market value held by domestic equity mutual funds in the sample rises steadily from 2.32% in 1980 to 15.86% in 2012.

[12] The results are qualitatively unchanged when index funds are excluded.

Aggregate Mutual Fund Flows

Data on aggregate monthly flows into the domestic equity fund industry are provided by the Investment Company Institute (ICI).[13] I follow Warther (1995) and Jank (2012) to calculate monthly net flows as new sales minus redemptions plus exchanges-in minus exchanges-out, and then I standardize flows by the total market value of the previous month using the CRSP stock market index from CRSP.[14] The sample spans the period from January 1984 to December 2012. Table 1.2 reports summary statistics of aggregate mutual fund flows and how aggregate mutual fund flows vary with macro funding conditions. Figure 1.1 plots the dynamics of aggregate mutual fund flows over time. It shows that outflows occur more frequently in poor macro funding conditions, and aggregate flows under favorable states are significantly greater than under poor states at \$3.17 billion per month.[15]

1.3.3 Estimating Returns to Anomalies

I examine seven well-known anomalies in this paper: MOM, 52-Wk, SUE, ROE, SI, AG, and ACC.[16] Then I follow the Fama–MacBeth (1973) style regression approach in George and Hwang (2004) and Grinblatt and Moskowitz (2004) to measure and compare the returns to different investment strategies. To compute returns to the k-month holding period investment strategy, I estimate k cross-sectional regressions (for $j = 2,\ldots,k+1$) of the following form in each month t:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R_{i,t-1} + b_{4jt} Short_{i,t-j} + b_{5jt} Long_{i,t-j} + \varepsilon_{ijt} \quad (1.1)$$

[13] ICI data cover about 98 percent of assets in the mutual fund industry [e.g., ICI – Trends in Mutual Fund Investing (July 2012)], and I thank Doug Richardson for providing monthly flow data.

[14] The inferences are qualitatively the same when I standardize flows by the total market value of mutual funds of the previous month.

[15] See Section 1.3.3 for details about macro funding conditions.

[16] See Appendix A for details about anomalies.

where R_{it} is the return on stock i in month t and $size_{i,t}$ and $BM_{i,t}$ are the market capitalization and the book-to-market ratio of stock i at end of month t. Lagged equity market capitalization, book-to-market ratio, and return are included in the regressions to mitigate the effect of size and book-to-market on returns and to control for bid-ask bounce.

In each month, I sort stocks into quintile portfolios based on the anomaly variables discussed above. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if stock i is ranked in the short (long) leg of the above anomalies in month *t-j*. Annual (quarterly) accounting information are based on the most recent fiscal year (quarter) end financial statements whose closing date is at least six (three) months prior to the end of month t-1 and t-j, respectively. Because *Short* and *Long* are dummy variables, the estimates of coefficients b_{4jt} and b_{5jt} represent the returns on short and long portfolios in excess of the intercept term after hedging out the effects of lagged returns, size, and book-to-market. The raw return in month t to short and long portfolios of a given strategy is the average of coefficient estimates over $j = 2,\ldots,k+1$. Thus, the returns to a given strategy in month t are computed as $(1/k)\sum_{j=2}^{k+1}(b_{5jt} - b_{4jt})$.

1.3.4 Macro Funding Conditions

Funding is created by the financial sector in the form of credit. Because the effective risk-bearing capacity of the financial sector affects the supply of credit, I use a measure of macro funding conditions linked to the compensation that the financial sector demands to supply funding, which is the excess bond premium (EBP) in GZ.[17]

The GZ credit spread is an arithmetic average of the credit spreads on outstanding corporate bonds. GZ decompose this credit spread into (1) a predicted component reflecting the firm-specific information on default risk and (2) a residual component representing the effective risk-bearing capacity of the financial sector. The EBP is the residual component. An increase in the EBP reflects a reduction in the effective risk-bearing capacity of the

[17] Details of how to construct the excess bond premium (EBP) in GZ are described in Appendix B.

financial sector and a contraction in the supply of credit.

The sample period for EBP is between January 1973 and December 2012, at a monthly frequency. Figure 1.2 suggests that the fluctuations in EBP are a leading indicator of changes in economic states. EBP increases significantly prior to or during all cyclical downturns of the business cycle (except for the 1990–1991 recession period). Beginning in late 2003, EBP fell and remained at a historic low for several years. This period is characterized by lax credit standards, excessive credit growth, and unsustainable asset price appreciation. However, during the 2007–2009 financial crisis, EBP achieved its highest level, a period characterized by very high financing costs.

I use a two-state Markov regime-switching model to identify regimes implied by EBP and a maximum likelihood method through an EM algorithm proposed by Hamilton (1994) for estimation. The model allows EBP to have different means and variances across the two regimes as follows

$$EBP_t = \mu_{S_t} + \varepsilon_t, \ \varepsilon_t \sim N(0, \sigma^2_{S_t}), \text{ where } S_t \in \{1, 2\} \tag{1.2}$$

The estimation technique will pick up state 1 as the state at which EBP has lower mean and variance. I define state 1 as a "favorable" and state 2 as a "poor" state because a higher level of EBP indicates worsening macro funding conditions. [18] Panel A of Table 1.3 documents the date of each state over sample periods. Of the 480 observations, 344 observations are flagged as favorable states and 136 as poor states, compared to 408 and 72 for expansions and recessions, respectively. Panel B verifies that poor funding conditions indeed represent the time at which investors suffer in financial markets. The TED spread, which is defined as the difference between the three-month London Interbank Offer Rate (LIBOR) and the three-month Treasury Bill interest rate as a measure of banks' and traders' funding liquidity, is significantly wider in poor funding conditions, with 34 bps per month. The monthly VIX and returns on the S&P 500 Index in poor funding conditions are significantly 7.24% higher and 1.31% lower than those in favorable funding conditions.

[18] The null hypothesis σ_1 equal to σ_2 is rejected in the likelihood ratio test.

Moreover, the levels and innovations of Pastor and Stambaugh (2003) liquidity measures are significantly lower during poor funding conditions, supporting the prediction of Brunnermeier and Pedersen (2009) that tightening funding liquidity will have a negative impact on market liquidity. The states identified in the estimation are matched with the plot in Figure 1.2. It shows that poor macro funding conditions are different from NBER recessions, and the correlation between these two states is 0.41.

1.4 Mutual Fund Trading and Capital Flows

1.4.1 Anomaly-based Trading of Mutual Funds

The previous literature documents that mutual fund managers actually trade based on anomalies that have been documented in the academic literature. For instance, Grinblatt, Titman, and Wermers (1995) and Lou (2012) show that mutual funds adopt momentum strategies. In this section, I explore whether mutual funds trade on price-based (MOM and 52-Wk) and non-price-based (SUE, ROE, SI, ACC, and AG) anomalies, and then I examine the extent to which mutual funds trade on these anomalies when fund flows occur.

To quantify how actively mutual funds trade on strategies, I construct measures from mutual fund holdings data in the following steps. First, I keep fund-quarter observations for which the fund holdings at the end of the previous quarter are also available, so holding changes can be computed over the consecutive quarter. Second, since mutual funds could trade at any point during a quarter, I follow Lou (2012) to assume that fund managers trade at the end of each quarter and pick stocks based on the information at the end of the previous quarter in order to mitigate the look-ahead bias. Take the momentum strategy (MOM) as an example. The winner (loser) stocks that fund j trades in quarter t are stocks in the long (short) leg of MOM at the end of quarter t-1. Finally, measures applied to capture the propensity that fund j buys stocks in the long or short leg of MOM in quarter t are defined as

$$PRO\_Buy_{j,t}^{Long}(MOM) = \frac{\left(\sum_{\{i \in \text{long leg of MOM in } t\text{-}1\}} \max\{0, \Delta Holdings_{i,j,t} P_{i,t}\}\right)}{\sum_i |\Delta Holdings_{i,j,t}| P_{i,t}}$$

$$PRO\_Buy_{j,t}^{Short}(MOM) = \frac{\left(\sum_{\{i \in \text{short leg of MOM in } t\text{-}1\}} \max\{0, \Delta Holdings_{i,j,t} P_{i,t}\}\right)}{\sum_i |\Delta Holdings_{i,j,t}| P_{i,t}} \quad (1.3)$$

where $P_{i,t}$ is the price of stock i in quarter t, $\Delta Holdings_{i,j,t}$ is the shares of stock i traded by fund j in quarter t. For instance, the numerator of $PRO\_Buy_{j,t}^{Long}(MOM)$ is the total dollar value that fund j buys winner stocks in quarter t, and the denominator is fund j's total trading value in quarter t. Similarly, the following measures are computed to gauge the the propensity that fund j sells stocks in the long or short leg of MOM:

$$PRO\_Sell_{j,t}^{Long}(MOM) = \frac{\left(\sum_{\{i \in \text{long leg of MOM in } t\text{-}1\}} \max\{0, -\Delta Holdings_{i,j,t} P_{i,t}\}\right)}{\sum_i |\Delta Holdings_{i,j,t}| P_{i,t}}$$

$$PRO\_Sell_{j,t}^{Short}(MOM) = \frac{\left(\sum_{\{i \in \text{short leg of MOM in } t\text{-}1\}} \max\{0, -\Delta Holdings_{i,j,t} P_{i,t}\}\right)}{\sum_i |\Delta Holdings_{i,j,t}| P_{i,t}} \quad (1.4)$$

I then define $LTrade_{j,t}(MOM)$ as $PRO\_Buy_{j,t}^{Long}(MOM) - PRO\_Buy_{j,t}^{Short}(MOM)$ and $STrade_{j,t}(MOM)$ as $PRO\_Sell_{j,t}^{Short}(MOM) - PRO\_Sell_{j,t}^{Long}(MOM)$ to measure the degree to which fund j buys winner over loser stocks and fund j sells loser over winner stocks, respectively. Thus, $LTrade_{j,t}(MOM)$ and $STrade_{j,t}(MOM)$ proxy for the extent to which fund j participates in the long side and the short side of MOM in quarter t. If fund j engages in the long side and short side of MOM, the signs of $LTrade_{j,t}(MOM)$ as and $STrade_{j,t}(MOM)$ are supposed to be positive. Following the same procedure, I compute $LTrade_{j,t}$ and $STrade_{j,t}$ for the rest strategies (i.e., 52-WK, SUE, ROE, SI, ACC, and AG) to capture fund j's long-side and short-side trading activities.

I follow the prior literature [e.g., Sirri and Tufano (1998); Lou (2012)] to define flows to fund j in quarter t as

$$flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1} \times (1 + ret_{j,t}) - MGN_{j,t}}{TNA_{j,t-1}} \tag{1.5}$$

where $TNA_{j,t}$ is the total net assets of fund j in quarter t, $ret_{j,t}$ is the total return of fund j in quarter t, and $MGN_{j,t}$ is the increase in total net assets from fund mergers in quarter t.

In order to examine the extent to which fund j adopts the long side and short side of a given trading strategy s in quarter t when capital flows occur, I estimate the following panel regressions for each strategy:

$$LTrade_{j,t}(s) = b_0 + b_1 flow_{j,t} + b_2 IOC\text{-}qtr\text{-}dum_{j,t} + b_3 Stytle\text{-}qtr\text{-}dum_{j,t} + \varepsilon_{j,t} \tag{1.6}$$

$$STrade_{j,t}(s) = b_0 + b_1 flow_{j,t} + b_2 IOC\text{-}qtr\text{-}dum_{j,t} + b_3 Stytle\text{-}qtr\text{-}dum_{j,t} + \varepsilon_{j,t} \tag{1.7}$$

To account for a fund's trading behavior that is common for a fund's "investment objective" and a fund's "style" in a given quarter, I include objective-quarter fixed effects based on the Thomson Investment Objective Code classification (*IOC-qtr-dum*) and fund style-quarter fixed effects based on a three-by-three matrix of size and book-to-market ratio (*Style-qtr-dum*). Standard errors are clustered by fund and quarter.

Panel A and Panel B of Table 1.4 report the estimation results of the long side and the short side, respectively. In Panel A, the estimated intercept in the first column of each strategy is significantly positive for all trading strategies except AG. Moreover, except for AG, the estimated coefficients of fund-level flows are positive and significant in most cases. The results are by and large unchanged when fixed effects are taken into account. Take the momentum strategy (MOM), for example. Fund managers on average buy more winner stocks than loser stocks. In column 1 of MOM, the estimated intercept is around 1.85% (t-statistic of 3.66), which suggests that of the total trading value, fund managers purchase 1.85% more winner stocks than loser stocks after controlling for fund-level flows. Furthermore, the loadings on *flow* are significantly positive in both columns of MOM. For instance, it is 0.022 (t-statistic of 2.98) after adding objective-quarter and fund style-quarter fixed effects. It suggests that capital flows in a given quarter also induce a greater buying of winner stocks than loser stocks. Mutual fund managers prefer to inject new capital into stocks with better past performances. The inferences are similar for strategies 52-Wk, SUE, ROE, SI and ACC. The findings indicate that, except for AG, mutual fund managers indeed follow the long side of both price-based and non-price-based strategies and invest more in these strategies when receiving positive flows from fund investors.

The results in Panel B of Table 1.4 suggest that mutual funds only engage in trading on the short side of the AG. The estimated intercept in the first column of each strategy is significantly negative, except for AG which is positive at 3.88% (t-statistic of 14.30). In the second column of AG, the magnitude of the sensitivity of selling stocks in the short leg of AG to fund-level flows is significantly negative for AG (coefficient of -0.024 with t-statistic of -7.70), suggesting that fund managers are more likely to participate in the short-side investment of AG when outflows happen.

For the rest of the strategies, the data do not support the view that fund managers trade on the short side. Panel B of Table 1.4 shows that the intercepts of the non-AG strategies are significantly negative and the loadings on *flow* are significantly positive, which suggests that fund managers tend to sell stocks in the long leg of the non-AG strategies and are more likely to sell stocks in the long leg when mutual fund investors extract money from mutual funds. Together with findings in Panel A of Table 1.4, the evidence indicates that mutual funds invest in the non-AG strategies by trading on the long side only. The results are also consistent with the findings in Grinblatt, Titman, and Wermers (1995) that mutual funds follow the momentum strategy by buying past winner stocks, but that they do not systematically sell past loser stocks.

To sum up, the results suggest that mutual funds appear to adopt strategies to exploit both price-based and non-price-based anomalies, particularly investing in the long side of them. Furthermore, the magnitudes of those investments are significantly sensitive to fund-level flows.

1.4.2 Analysis of Mutual Fund Flows

VW's model predicts that the price-based return predictability in individual stocks is *independent* of the types of strategies mutual funds adopt. Crucial elements of VW's model are that fund flows are persistent and that fund flows are performance chasing. To test these hypotheses, I examine whether the flow persistence and performance-chasing behavior of mutual fund investors exist even after the anomaly-based trading of mutual funds is taken into account. The regression model is specified by the following equation:

$$\begin{aligned} flow_{j,t} &= b_o + b_1 flow_{j,t-1} + b_2 Alpha_{j,t-1} + b_3 Alpha^2_{j,t-1} \\ &+ b_4 LnTNA_{j,t-1} + b_5 LnAge_{j,t-1} + b_6 Expense_{j,t-1} + b_7 IOC\text{-}qtr\text{-}dum_{j,t} \\ &+ b_8 Stytle\text{-}qtr\text{-}dum_{j,t} + \sum_s c_s LTrade_{j,t-1}(s) + \sum_s d_s STrade_{j,t-1}(s) + \varepsilon_{j,t} \end{aligned} \tag{1.8}$$

The main independent variables of interest are *Alpha* and *flow* in the previous quarter, which are intended to account for the flow-performance relationship and the flow persistence, respectively. *Alpha* is the monthly Carhart four-factor alpha computed from the fund's returns in the previous year. $Alpha^2$ is added to account for the convexity in the flow-return relation [Sirri and Tufano (1998)]. I include other controls related to funds' characteristics: the size of the fund's asset base defined as the natural logarithm of TNA ($LnTNA$); the natural logarithm of age ($LnAge$) measured as year of quarter t minus the year the fund first appears in CRSP; and the weighted average of all share class expense ratios (*Expense*). To account for the independent effect of a fund's investment objective and a fund's style on flows, I include *IOC-qtr-dum* and *Style-qtr-dum.* As defined in Soltes, Solomon, and Sosyura (2014), *IOC-qtr-dum* are the investment objective fixed effects based on the Thomson Investment Objective Code classification. *Style-qtr-dum* are fund style dummies that capture a fund's style based on a three-by-three matrix of stock size (small, medium, and large) and valuation (value, mixed, and growth), constructed based on the holdings' average percentile rankings relative to the CRSP stock universe. I include the *LTrade* and *STrade* measures of each anomaly to control for the effect of mutual fund anomaly-based trading on flows. Standard errors are clustered by fund and quarter.

Panel A in Table 1.5 shows that fund flows are persistent and performance-chasing. Before considering trading styles of mutual funds, both $flow_{t-1}$ and $Alpha_{t-1}$ have significantly positive coefficients across Columns 1 and 2. For instance, when fixed effects are taken into account, the coefficients of $flow_{t-1}$ and $Alpha_{t-1}$ in Column 2 are 0.1647 and 2.5299 (t-statistics of 8.05 and 10.64), respectively. In Columns 3–4 of Table 1.5, Panel A, I test whether anomaly-based trading styles of mutual funds affect the impact of past flows and performance on flows. *Anomaly_ Trading* in Table 1.5 represents whether *LTrade* and *STrade* measures of all anomalies are included in the panel regression.[19] I find that the coefficients of $flow_{t-1}$ and $Alpha_{t-1}$ remain positive and reliably significant at the 1% level (t-statistics range from 7.80 to 11.05) after controlling for trading styles.

Furthermore, mutual fund investors are more likely to chase the past performance of mutual funds when they have more capital to allocate in the mutual fund industry [Xie (2011)]. I examine the extent to which the flow-performance sensitivity varies with the level of aggregate flows. I define Low_AF_t ($High\_AF_t$) as a dummy variable that equals 1 if the level of aggregate flows in quarter t is among the bottom (top) 30% over the whole sample period. I add Low_AF_t, $High\_AF_t$, Low_AF_t*$flow_{t-1}$, $High\_AF_t$*$flow_{t-1}$, Low_AF_t*$Alpha_{t-1}$, and $High\_AF_t$*$Alpha_{t-1}$ into the Equation (1.8).

All controls and fixed effects are included in Column 4 of Panel B in Table 1.5. The coefficients of Low_AF_t ($High\_AF_t$) are significantly negative (positive), suggesting that the level of aggregate flows exerts a positive influence on fund-level flows. Moreover, the level of aggregate flows also has positive effects on the flow-performance sensitivity. Although the coefficients are not significant, when the level of aggregate flows is high, the flow-performance sensitivity is 3.8895 ($2.5531+1.3364 = 3.8895$), compared with 1.7684 ($2.5531-0.7847 = 1.7684$) during the periods of low aggregate flows, and the difference (3.8895-1.7684 = 2.1211) is significant at the 1% level (t-statistic of 5.98). These results are consistent with

[19] For brevity, Columns 3 and 4 in Panel A and Panel B of Table 1.5 do not report coefficients of each anomaly's *LTrade* and *STrade* measures. The untabulated results show that all anomaly-based trading strategies, except SUE, have impacts on flows. The results are available upon request.

the findings in Xie (2011) that the flow-performance sensitivity is stronger when aggregate mutual fund flows are higher.

In summary, the findings suggest that mutual funds do trade on anomalies, but that differences in their trading styles do not eliminate or explain away the persistence and performance-chasing nature of mutual fund investors' decisions about allocating money across funds. These are the crucial elements to the Lou-VW feedback effect. The conditional results further imply that their feedback effect should be positively related to aggregate mutual fund flows because the flow-performance sensitivity is stronger when there are more aggregate inflows.

1.5 Price-based Anomalies

In this section, I examine the extent to which aggregate mutual fund flows contribute to the profits of price-based strategies—MOM and 52-Wk—because VW's model predicts that aggregate mutual fund flows should only have effects on *price*-based anomalies. I conduct an unconditional analysis and an analysis that conditions on macro funding conditions. Furthermore, I examine the extent to which Lou's flow-based mechanism accounts for the explanatory power of aggregate mutual fund flows in MOM and 52-Wk.

1.5.1 Unconditional Analysis

In order to investigate whether aggregate mutual fund flows exacerbate or attenuate profits of cross-sectional anomalies, I examine the effect of aggregate mutual fund flows on returns to anomalies in periods subsequent to measurement of aggregate flows. The time period of aggregate mutual fund flows is aligned with the time when strategies are *implemented*. Since the return to short, long or long-short portfolios in month t of a k-month holding period investment strategy is the average of month-t returns to k subportfolios formed in previous months, t-2,...,t-k-1, I use the average of aggregate mutual fund flows measured at previous months, t-2,...,t-k-1, to examine the effect of aggregate mutual fund flows on future portfolio returns. For short, long, or long-short portfolios of MOM and 52-Wk with

k-month holding periods, I estimate the following time-series regression model for each of them:

$$R_t^P = a^P + \sum_{i\,=\,1}^{3} b_i^P f_{it} + b_4^P AF_t^{avg} + \varepsilon_t,\ \text{where } P \in \{Short,\ Long \text{ or } LS\} \tag{1.9}$$

$$R_t^{Short} = 1/k \sum_{j\,=\,2}^{k\,+\,1} b_{4jt} \text{ and } R_t^{Long} = 1/k \sum_{j\,=\,2}^{k\,+\,1} b_{5jt}$$

$$R_t^{LS} = R_t^{Long} - R_t^{Short} \text{ and } AF_t^{avg} = 1/k \sum_{j\,=\,2}^{k\,+\,1} AF_{t-j}$$

R_t^{Short} is the month-t return to short portfolios, R_t^{Long} is the month-t return to long portfolios, R_t^{LS} is the month-t return to long-short (LS) portfolios, f_{it} are returns to the three Fama–French factors in month t, AF_t^{avg} is the average aggregate mutual fund flows in month t, and AF_{t-j} is the aggregate mutual fund flows in month t-j.

Table 1.6 reports the estimation results of MOM and 52-Wk. The holding periods of both momentum strategies considered are 3, 6, 9, and 12 months. Because the January effect has a great impact on momentum profits, Table 6 reports results for both January-included and January-excluded samples.[20] In Model 1, returns are regressed only on the three Fama-French factors (FF3) and the estimated intercepts in Model 1 are FF3 risk-adjusted returns. For both strategies, FF3 risk-adjusted returns are positive and significant at the 1% level across different holding periods with and without January.

In Table 1.6, Model 2 denotes the regression models in Equation (1.9). The estimation results show that aggregate mutual fund flows exert a strong and positive influence on future returns to MOM and 52-Wk. This inference is uniform across all eight variations of the procedure for calculating returns—with and without January and using four different holding periods. The positive signs of the coefficients of AF^{avg} suggests that the flow-based trading of mutual funds contributes to mispricing as measured by the profits to price-based anomalies. Moreover, when aggregate mutual fund flows are taken into account, a large

[20] George and Hwang (2004) and Chou, Ko, and Lin (2010) emphasize the impact of the January effect on momentum profits. As a consequence of tax loss selling, loser stocks rebound in January months, which weakens momentum profits.

portion of average momentum profits is attributable to variation in aggregate mutual fund flows. For example, FF3 alphas are around 40% to 44% smaller for MOM after including aggregate mutual fund flows. For 52-Wk, aggregate mutual fund flows account for about 30% to 32% of FF3 alphas. The magnitude of the sensitivity of momentum to aggregate mutual fund flows is striking. Based on the point estimate for MOM with three-month holding periods, a one standard deviation increase in the AF^{avg} (0.086%) is associated with an increase in momentum returns of 0.86% (0.086% * 10.05 = 0.86%) per month, while the FF3 alpha is 1.10%. For 52-Wk, a one standard deviation increase in the aggregate mutual fund flows is associated with an increase in momentum returns of 0.73% per month. The results are the same for the long leg and short leg of MOM and 52-Wk. The loadings of long (short) portfolios on AF^{avg} are positive (negative) and are significant at the 1% level in most specifications for calculating returns.

Overall, the evidence suggests that aggregate mutual fund flows are an important driving force behind price-based anomalies. In the next section, I condition the analysis on macro funding conditions defined by regimes of the EBP. The reason for doing this is to help make the impact of mutual funds more visible in the data. Mutual funds are likely to exert a greater influence on prices relative to retail investors or professional investors that follow highly levered strategies when overall borrowing costs are high, because mutual funds have limited reliance on leverage.

1.5.2 Conditional Analysis

The conditional analysis in this section is to make the impact of mutual funds more visible in the data. Mutual fund trading is likely to exert a greater influence on prices when other sources of investment capital are scarcer, such as when overall borrowing costs are high. The effect of aggregate mutual fund flows on the profitability of anomaly-based strategies might therefore be easier to detect in periods of relative financial stress. Periods of favorable or poor macro funding conditions vary according to the time periods shown in Panel A of Table 1.3.

I compute conditional portfolio returns based on macro funding conditions at which the portfolios are formed and conduct the conditional analysis by regressing conditional returns on aggregate mutual fund flows. The following methodology is applied to calculate holding-period returns to the short, long, and LS portfolios dependent on the state when strategies are implemented. In any given month t, the short or long portfolios have k subportfolios formed in previous months, t-2,...,t-k-1, and these k subportfolios are formed in either favorable or poor states. Then for the short or long portfolios, k subportfolios are divided into two categories according to the state at formation time. For example, in month t, some of the k subportfolios of the long portfolios belong to the favorable group if they are formed under favorable funding conditions; then these "favorable" subportfolios are equally weighted averaged to obtain month-t "favorable" returns to the long portfolio. By equally weighted averaging other "poor" subportfolios in the poor group, the month-t return conditional on poor states is also obtained. Specifically, the conditional month-t return to portfolios under poor funding conditions with k-month holding periods can be expressed as

$$R_t^{Short}(poor) = \frac{\sum_{j=2}^{k+1} b_{4jt} D_{t-j}}{\sum_{j=2}^{k+1} D_{t-j}} \text{ and } R_t^{Long}(poor) = \frac{\sum_{j=2}^{k+1} b_{5jt} D_{t-j}}{\sum_{j=2}^{k+1} D_{t-j}}$$

$$R_t^{LS}(poor) = R_t^{Long}(poor) - R_t^{Short}(poor) \tag{1.10}$$

where D_{t-j} is a dummy variable that equals 1 if month t-j is in the poor state and 0 otherwise. If $\sum_{j=2}^{k+1} D_{t-j} = 0$, then no poor-state months contribute to the returns in month t. The same methodology is applied to compute the conditional month-t return to portfolios under favorable funding conditions. The advantage of this method is to avoid overlapping returns while allowing the tractability to examine whether portfolio returns depend on the state in formation months. The following conditional regression model is used to examine the effect of aggregate mutual fund flows on future momentum profits when the strategy is implemented in the poor state:

$$R_t^P(poor) = a^P + \sum_{i=1}^{3} b_i^P f_{it} + b_4^P AF_t^{avg}(poor) + \varepsilon_t, \text{ where } P \in [Short, Long \text{ or } LS] \tag{1.11}$$

$$AF_t^{avg}(poor) = \frac{\sum_{j=2}^{k+1} AF_{t-j}D_{t-j}}{\sum_{j=2}^{k+1} D_{t-j}}$$

There are several interesting findings in Table 1.7.[21] Panel A shows that aggregate mutual fund flows have less influence on momentum profits under favorable macro funding conditions. The impact of aggregate flows on momentum only exists for three-month holding periods, but the magnitude is only 50% as large as the effect in the unconditional results in Table 1.6. The coefficients of AF^{avg} are not significant in the rest of scenarios. FF3 alphas of both strategies formed under favorable funding conditions are stronger and remain statistically significant even after controlling for aggregate flows.

Panel B shows the results under poor macro funding conditions.[22] In stark contrast, momentum disappears after controlling for aggregate mutual fund flows, and the coefficients of AF^{avg} are not only highly significant but three times as large as in the unconditional tests. Take MOM for example. The coefficients of AF^{avg} vary from 19.28 (t-statistic of 3.76) to 30.85 (t-statistic of 4.32) across four specifications of computing returns. Furthermore, the estimated intercepts of Model 2 are insignificant for different holding periods, ranging from 0.25% (t-statistic of 0.57) to 0.43% (t-statistic of 1.34). The results suggest that profits of MOM under poor finding conditions are explained by aggregate mutual fund flows. The inferences are the same for 52-Wk.

The results are robust across winners and losers. The effect of aggregate mutual funds flows on winners and losers is mainly concentrated in poor states. After controlling for FF3 and aggregate flows, both winners and losers are insignificant if formed under poor funding conditions, but they are significant when formed in favorable funding conditions.

[21] The more appropriate and informative estimation results of momentum strategies are results outside of January [see George and Hwang (2004)]. For brevity, Table 1.7 only reports results without January. The inferences are by and large unchanged when January is included.

[22] Panel B of Table 1.7 shows that FF3 risk-adjusted returns are insignificant for short-term momentum strategies. This is because momentum strategies performed poorly during the recent financial crisis. The results are robust when excluding the recent financial crisis from the sample.

To sum up, the impact of aggregate mutual fund flows on profits of MOM and 52-Wk varies with macro funding conditions and is much stronger under poor macro funding conditions. Focusing on poor funding conditions is intended to clarify the impact of mutual funds on equity prices. These results suggest that flow related trading of mutual funds exerts a strong influence on prices, which results in momentum.

1.5.3 Analysis of the Lou-VW Feedback Effect

In this session, I examine how the Lou-VW feedback effect relates to my results on aggregate mutual fund flows. Lou (2012) finds that *cross-sectional* flow-induced trading of mutual funds matters to momentum profits. His mechanism is that past winning funds receive capital inflows and expand their existing holdings, which are disproportionately invested in past winning stocks; at the same time, past losing funds lose capital and have to liquidate their holdings, which are concentrated in past losing stocks. Because mutual fund flows are persistent and performance chasing, the trading patterns of mutual funds can lead past winning stocks to keep outperforming past losing stocks in the short term. It is possible that the impact of aggregate mutual fund flows on momentum is proxying for this *cross-sectional* flow-induced trading of mutual funds. In order to investigate whether the Lou-VW mechanism can explain why momentum profits are related to *aggregate* flows, the methodology in section 1.4.1 is modified to construct aggregate measures based on the Lou-VW feedback effect.

In each quarter t, mutual funds are sorted into quintiles based on quarter t flows; inflow (outflow) funds are funds in the top (bottom) quintile. All stocks in quarter t are assigned to the long leg or short leg of a price-based strategy according to the past momentum ranking in the formation quarter t-1.[23] I use the following measures to capture the extent to which

[23] Rankings are based on past six-month stock returns because the flow-based mechanism in Lou (2012) is for explaining profits of traditional momentum strategies. In the untabulated results, I find that the measures based on nearness to the 52-week high have no explanatory power.

inflow funds tend to purchase stocks in the long and short legs:

$$PRO\_Buy_t^{Long} = \frac{\sum\limits_{\{j \in \text{Inflow Funds}\}} \left[\sum\limits_{\{i \in \text{long leg in } t-1\}} \max\{0, \Delta Holdings_{i,j,t} P_{i,t}\} \right]}{\sum\limits_{\{j \in \text{Inflow Funds}\}} \left[\sum\limits_i |\Delta Holdings_{i,j,t}| P_{i,t} \right]}$$

$$PRO\_Buy_t^{Short} = \frac{\sum\limits_{\{j \in \text{Inflow Funds}\}} \left[\sum\limits_{\{i \in \text{short leg in } t-1\}} \max\{0, \Delta Holdings_{i,j,t} P_{i,t}\} \right]}{\sum\limits_{\{j \in \text{Inflow Funds}\}} \left[\sum\limits_i |\Delta Holdings_{i,j,t}| P_{i,t} \right]} \tag{1.12}$$

For instance, the numerator of $PRO\_Buy_t^{Long}$ is the total dollar value that inflow funds purchase of past winners in quarter t, and the denominator is the total dollar trading volume of inflow funds in quarter t. Similarly, for outflow funds, I use the following measures to capture the degree to which outflow funds sell stocks in the long and short legs:

$$PRO\_Sell_t^{Long} = \frac{\sum\limits_{\{j \in \text{Outflow Funds}\}} \left[\sum\limits_{\{i \in \text{long leg in } t-1\}} \max\{0, -\Delta Holdings_{i,j,t} P_{i,t}\} \right]}{\sum\limits_{\{j \in \text{Outflow Funds}\}} \left[\sum\limits_i |\Delta Holdings_{i,j,t}| P_{i,t} \right]}$$

$$PRO\_Sell_t^{Short} = \frac{\sum\limits_{\{j \in \text{Outflow Funds}\}} \left[\sum\limits_{\{i \in \text{short leg in } t-1\}} \max\{0, -\Delta Holdings_{i,j,t} P_{i,t}\} \right]}{\sum\limits_{\{j \in \text{Outflow Funds}\}} \left[\sum\limits_i |\Delta Holdings_{i,j,t}| P_{i,t} \right]} \tag{1.13}$$

I then define Buy_t as $PRO\_Buy_t^{Long} - PRO\_Buy_t^{Short}$ to measure the degree to which inflow funds buy past winner stocks over past loser stocks in quarter t. Similarly, $Sell_t$ defined as $PRO\_Sell_t^{Short} - PRO\_Sell_t^{Long}$ is used to gauge the extent to which outflow funds sell past loser over winner stocks in quarter t. If the Lou-VW mechanism can explain why momentum profits are related to aggregate flows, *Buy* and *Sell* should have the explanatory power on future momentum profits when included in the regression, and and the impact of aggregate flows on momentum profits should be attenuated when *Buy* and *Sell* are included in the regression.

Because the mutual fund holdings data have a quarterly frequency, I assume that *Buy* and *Sell* measures take the same value each month before quarterly updates. Although data on aggregate mutual fund flows have a monthly frequency, I align data frequency to fairly compare the explanatory power of *Buy* and *Sell* to aggregate mutual fund flows. Therefore, aggregate mutual fund flows are measured over the period of one quarter and are assumed to be uniform in each month of a quarter.[24]

In the unconditional analysis, I include Buy_t^{avg} and $Sell_t^{avg}$ in regression Equation (1.9). In the conditional analysis, if macro funding conditions are poor, I include $Buy_t^{avg}(poor)$ and $Sell_t^{avg}(poor)$ into the regression model in Equation (1.11). These variables are defined as

$$Buy_t^{avg} = 1/k \sum_{j=2}^{k+1} Buy_{t-j} \quad \text{and} \quad Sell_t^{avg} = 1/k \sum_{j=2}^{k+1} Sell_{t-j}$$

$$Buy_t^{avg}(poor) = \frac{\sum_{j=2}^{k+1} Buy_{t-j} D_{t-j}}{\sum_{j=2}^{k+1} D_{t-j}} \quad \text{and} \quad Sell_t^{avg}(poor) = \frac{\sum_{j=2}^{k+1} Sell_{t-j} D_{t-j}}{\sum_{j=2}^{k+1} D_{t-j}} \tag{1.14}$$

where Buy_{t-j} and $Sell_{t-j}$ are *Buy* and *Sell* measures in month *t-j*. D_{t-j} is a dummy variable that equals one if month *t-j* is in the poor state and zero otherwise.[25]

If the flow-based mechanism has an impact on momentum profits, the sign of the loadings of winner portfolios on Buy^{avg} should be positive because the prices of winner stocks will go up when inflow funds buy more winner stocks than loser stocks in existing portfolios. Similarly, the sign of the loadings of loser portfolios on $Sell^{avg}$ should be negative because the prices of loser stocks will go down when outflow funds sell more loser stocks than winner stocks in existing portfolios. Therefore, the sign of the sensitivity of momentum profits to Buy^{avg} and $Sell^{avg}$ should be positive.

Panel A of Table 1.8 documents the unconditional results for the long-short portfolio of MOM and 52-Wk. When Buy^{avg} and $Sell^{avg}$ are included in the time-series regression without AF^{avg}, the loadings of momentum profits on Buy^{avg} and $Sell^{avg}$ have the correct signs, but only the loadings on Buy^{avg} are significant. Moreover, compared with FF3 risk-

[24] In the unreported results, I find that the inference remains the same when I use monthly standardized flows.

[25] The purpose of this section is to compare explanatory power of *Buy* and *Sell* to aggregate mutual fund flows on future momentum profits, so independent variables are constructed at the formation periods.

adjusted returns of Model 1 in Table 1.6, FF3 alphas of Model 2 in Panel A are around 40% (30%) smaller for MOM (52-Wk) after including Buy^{avg} and $Sell^{avg}$ in the regression, suggesting that Buy^{avg} and $Sell^{avg}$ have explanatory power on momentum profits. The results are consistent with Lou's story that mutual funds' flow-induced trading can generate price continuation. The impact of the flow-based mechanism on both momentum strategies, however, does not exist when AF^{avg} is included in the regression. The sensitivity of momentum profits to Buy^{avg} and $Sell^{avg}$ turns insignificant in Model 3, but AF^{avg} still has a significant positive coefficient as before in Table 6.

Panels B and C of Table 1.8 report results for favorable and poor funding conditions, respectively. For both strategies in favorable states, the estimation results of Model 2 in Panel B show that the loadings of long-short portfolios on Buy^{avg} and $Sell^{avg}$ are insignificant, and the estimated intercepts remain significant. After including AF^{avg} into regressions, both strategies remain profitable, and all mutual fund-related variables do not have impacts on momentum profits. This means that the flow related trading of mutual funds has no influence on equity prices under favorable macro funding conditions.

In contrast, Panel C shows that under poor macro funding conditions, before controlling for AF^{avg}, the loadings of MOM and 52-Wk on Buy^{avg} and $Sell^{avg}$ have the correct signs and are significant, and momentum profits are mainly explained by these propensity measures, suggesting that the flow-induced trading behavior of mutual funds has a strong impact on momentum profits at the times of poor funding conditions when mutual funds are likely to exert a greater influence on equity prices.

The results of the two strategies are different when AF^{avg} is also included in the regression, however. For MOM, the loadings on Buy^{avg} and $Sell^{avg}$ remain significant when holding periods are three months, and the coefficients of AF^{avg} are significant in all scenarios.[26] The findings suggest that both Lou's flow-based mechanism and aggregate flows affect momentum profits when mutual funds are relatively active in equity markets. For

[26] Table 9 in Lou (2012) shows that his flow-based mechanism accounts for a larger fraction of momentum profits with shorter holding periods.

52-Wk, the impact of flow-induced trading is subsumed by aggregate flows. The loadings on Buy^{avg} and $Sell^{avg}$ become insignificant after AF^{avg} is included in the regression, but the loadings on AF^{avg} are significant in all scenarios.

Overall, the empirical evidence suggests that the Lou-VW theory does have explanatory power. However, the effect of aggregate flows on momentum as described above does not entirely come from the cross-sectional flow-induced trading in Lou's story. The effect of aggregate flows remains significant after controlling for measures related to the Lou-VW mechanism. Thus, there is something about trading by institutional investors captured by aggregate flows outside the Lou-VW mechanism that leads to momentum.

1.6 Non-price-based Anomalies

1.6.1 Unconditional Analysis

In this section, I examine whether aggregate mutual fund flows have effects on non-price-based anomalies: SUE, ROE, SI, ACC, and AG. First, the returns to each strategy are estimated by the methodology described in section 1.3.3, in which momentum effects on individual stocks are not controlled. Then I adopt the same regression model specified in Equation (1.9) to investigate the role of aggregate mutual fund flows to future profits of non-price-based anomalies.

Table 1.9 reports unconditional findings for the long-short portfolio of each non-price-based anomaly. In Panel A of the table, returns to long-short portfolios are estimated without controlling for momentum effects. Panel A indicates that the FF3 risk-adjusted returns of each strategy are positive and significant across all four variations of the procedure for calculating returns—with and without January and using six-month and twelve-month holding periods. The estimation results of Model 2 show that aggregate mutual fund flows affect future returns to some strategies. For SUE and AG, the loadings on AF^{avg} are significantly positive in some specifications for computing returns. Aggregate flows have greater impacts on the profits of SUE when January is excluded. Returns to AG are more sensitive to aggregate flows for shorter holding periods with January. For SI, the effects of aggregate flows are significant across all specifications.

Because VW's model predicts that mutual fund flows will *only* have impacts on price-based strategies and aggregate flows are crucial for returns to price-based anomalies, I control for momentum effects when estimating returns and re-do the examination. The purpose is to examine whether the impact of aggregate flows on non-price-based anomalies arises from their interactions with price-based anomalies. For each non-price-based anomaly, I use the following model to control for momentum effects when computing returns:

$$R_{it} = b_{ojt} + b_{1jt}size_{i,t-1} + b_{2jt}BM_{i,t-1} + b_{3jt}R6_{i,t-1} + b_{4jt}MOML_{i,t-j}$$
$$+b_{5jt}MOMW_{i,t-j} + b_{6jt}52L_{i,t-j} + b_{7jt}52W_{i,t-j} + b_{8jt}Short_{i,t-j} + b_{9jt}Long_{i,t-j} + \varepsilon_{ijt} \quad (1.15)$$

where $R6_{i,t-1}$ is the past six-month returns of stock i at the end of month t-1 (I use t-2 to t-7 returns to measure the past six-month returns, skipping a month to avoid bid-ask bounce), $MOML_{i,t-j}$ ($MOMW_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of MOM in month t-j, and $52L_{i,t-j}$ ($52W_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of 52-Wk in month t-j. Since *Short* and *Long* are dummy variables, the estimates of coefficients b_{8jt} and b_{9jt} represent the returns on the short and long portfolios in excess of the intercept term after hedging out the effects of past returns, size and book-to-market, and momentum effects. Thus, for k-month holding periods, "momentum-effect-controlled" returns to a given strategy in month t are computed as $1/k \sum_{j=2}^{k+1}(b_{9jt} - b_{8jt})$.

I use the time-series regression model in Equation (1.9) to investigate the impact of aggregate mutual fund flows on "momentum-effect-controlled" returns to non-price-based anomalies. The findings in Panel B of Table 1.9 are interesting. The FF3 risk-adjusted returns of each strategy are reduced when momentum effects are controlled, but they are still significantly positive. The striking result is that the impact of aggregate flows on SUE, SI, and AG disappears. The coefficients of AF^{avg} are *in*significant for all non-price-based anomalies across all specifications. The results suggest that the impact of aggregate flows on non-price-based anomalies arises from their interactions with price-based anomalies. The empirical evidence is consistent with the implication of VW's model that the price pressure induced by mutual fund flows will only affect returns to price-based anomalies.

1.6.2 Conditional Analysis

I follow the procedure described in section 1.5.2 to condition my analysis on macro funding conditions. For brevity, I only keep one specification for computing returns of non-price-based anomalies: six-month holding periods and excluding January because Panel A of Table 1.9 shows that the impact of aggregate flows on non-price-based strategies is the strongest in this specification when momentum effects are not controlled.[27]

Panels A and B of Table 1.10 report results for favorable and poor funding conditions, respectively. In Panel A, before controlling for momentum effects, aggregate mutual fund flows only affect returns to *SI* under favorable funding conditions (coefficient of 3.16 with *t*-statistic of 3.12). Nonetheless, AF^{avg} still has a significant positive coefficient of 1.98 (*t*-statistic of 2.28) for *SI* even after momentum effects are controlled. The findings suggest that aggregate mutual fund flows have less influence on momentum effects, and the effect of aggregate mutual fund flows on *SI* under favorable conditions does not arise from its interactions with price-based anomalies.

In contrast, Panel B of Table 1.10 shows that under poor funding conditions, the effect of aggregate flows on non-price-based anomalies mainly results from the dependence of profits to non-price-based anomalies on price-based anomalies. Before controlling for momentum effects, aggregate flows have significant and positive impacts on returns to all non-price-based anomalies except ACC. When momentum effects are controlled, the effect of aggregate flows on non-price-based anomalies is attenuated, and the coefficients of AF^{avg} become *in*significant for most non-price-based anomalies.

To sum up, the results suggest that the flow-based trading of mutual funds has a strong influence on momentum effects under poor funding conditions and affects the profits of the

[27] The inferences remain unchanged when considering other variations of computing returns.

non-price-based anomalies *through* its effect on price-based strategies, which are consistent with findings in Table 1.7 that aggregate mutual fund flows have a great impact on price-based anomalies at the times of poor funding conditions.

1.7 Robustness Tests

1.7.1 Aggregate Mutual Fund Flows *vs.* Market-wide Variables

I examine whether my findings are robust to controlling for other market-wide variables that are used to explain future momentum profits in the literature: market return, market volatility, market illiquidity, and Baker and Wurgler's (2006) sentiment index. Panel A of Table 1.11 reports the estimation results for the long-short portfolio without conditioning on macro funding conditions.[28] *Lagmkt* is the lagged 36-month return on the CRSP value-weighted index. *MktVol* is the standard deviation of the daily CRSP value-weighted market return. *MktIlliq* is the value-weighted average of the Amihud (2002) stock-level illiquidity measure for all NYSE and AMEX stocks. *Sen* is the Baker and Wurgler (2006) sentiment index. I include each of these variables in Equation (1.9) and run a horse race between aggregate flows and these variables. The findings show that the impact of aggregate flows on MOM and 52-Wk is robust to these variables and loadings on AF^{avg} remain significantly positive. For other market-wide variables, only loadings on $Lagmkt^{avg}$ and Sen^{avg} are significant with positive signs as documented in Cooper, Gutierrez, and Hameed (2004) and Stambaugh, Yu, and Yuan (2012), respectively.

Panel B of Table 1.11 reports the estimation results when macro funding conditions are taken into account. When macro funding conditions are favorable, momentum remains strong after controlling for aggregate flows and other variables, and the effect of aggregate flows on momentum profits is only one-third as large as the effect in the unconditional results in Panel A of Table 1.11. When macro funding conditions are poor, aggregate mutual

[28] I only consider six-month holding periods to save spaces and exclude January to have more informative inferences. The results are similar for other holding periods.

fund flows have a much greater impact on momentum profits than other variables. For MOM, loadings on AF^{avg} are significantly positive, which range from 19.26 (t-statistic of 2.59) to 24.70 (t-statistic of 2.83). For 52-Wk, the coefficients of AF^{avg} are significant from 18.81 (t-statistic of 2.58) to 26.01 (t-statistic of 2.99). In contrast, loadings on other market-wide variables are insignificantly different from zero. Although loadings on $Lagmkt^{avg}$ and Sen^{avg} are significant in the unconditional analysis, they turn insignificant for both momentum strategies under poor funding conditions. To sum up, market-wide variables used to proxy for behavior bias or sentiment do have explanatory power on momentum profits, but their explanatory power are subsumed by aggregate mutual fund flows under poor funding conditions, suggesting the flow-based trading of mutual fund is the main driving force to momentum when mutual funds are relatively active.

1.7.2 Different Specifications of Macro Funding Conditions

One of my main findings is that the effect of aggregate flows on returns to price-based strategies is concentrated in periods when market-wide financing costs are high. So far, I use the EBP to proxy for funding conditions and define favorable and poor states based on the regimes of the EBP. In this section, I examine whether my results are robust when different specifications of macro funding conditions are applied.

Panel A of Table 1.12 presents results from the analysis conditional on poor macro funding conditions according to regimes of the EBP when the periods of recent financial crisis are excluded. Panel B reports results from the analysis conditional on poor macro funding conditions with respect to regimes of the EBP without periods of NBER recessions. The findings show that loadings on AF^{avg} are significantly positive for both momentum strategies.

Next, I applied the same two-state Markov regime switching model to identify regimes of favorable (poor) macro funding conditions based on whether TED or VIX is low (high).[29]

[29] The sample period of TED is from January 1986 to December 2012, and the time period of VIX is from June 1986 to December 2012. In Panel C, of the 324 observations, 133 observations are flagged as poor

Panel C reports results from the analysis conditional on macro funding conditions defined by TED. Panel D presents results from the analysis conditional on macro funding conditions defined by VIX. Panel C and Panel D show that for both momentum strategies, loadings on AF^{avg} are significantly positive in both states, but the magnitude is stronger when strategies are formed in poor states. Furthermore, the findings are robust to long and short legs of both momentum strategies.

1.7.3 Aggregate Flows to Funds with Different Characteristics

I further examine whether the impact of aggregate flows on momentum profits varies with fund characteristics. VW's model predicts that the price-based return predictability in individual stocks is *independent* of the types of strategies mutual funds adopt. The results in section 1.4.2 show that the trading styles of mutual funds do not explain away the persistence and performance-chasing nature of mutual fund investors, which are the crucial elements to the Lou-VW feedback effect. Therefore, if the prediction of VW's theory is valid, aggregate flows to funds that actively seek investment opportunities should also have positive effects on momentum profits. Da, Gao, and Jagannathan (2011) find that the active trading is more important for growth-oriented funds than income-oriented funds, so I calculate aggregate flows to funds with different investment objectives: aggressive growth (AGG), growth (Grow), or growth and income (GNI), and examine the effect of aggregate flows on momentum profits based on funds' investment objectives.

Following Akbas et al. (2014a), I construct measures of aggregate mutual fund flows to funds with different characteristics by obtaining monthly total net assets and returns from the CRSP Survivor-Bias-Free US Mutual Fund Database. Measures of monthly aggregate mutual fund flows to funds with characteristic c are computed as:

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states. In Panel D, there are 183 months of the 319 observations marked as poor states.

$$AF(c)_t = \frac{\sum_{j=1}^{N_c} [TNA_{j,t} - TNA_{j,t-1}(1 + ret_{j,t})]}{\sum_{j=1}^{N_c} TNA_{j,t-1}} \tag{1.16}$$

where $TNA_{j,t}$ is the total net assets of fund j in month t, $ret_{j,t}$ is the total return of fund j in month t, and N_c is the number of funds with characteristic c in month t. Since monthly total net assets are available from the end of 1990, measures of monthly aggregate mutual fund flows are available from January 1991 to December 2012.

Panel A of Table 1.13 presents the unconditional and conditional loadings of momentum profits on aggregate flows to funds based on different investment objectives. The results show that for all investment objectives, aggregate flows have strong and positive impacts on momentum profits, and such influence is concentrated under poor funding conditions. Overall, the evidence suggests that the flow related trading of mutual funds exerts a strong influence on momentum profits *regardless* of investment strategies mutual funds adopt.

Moreover, I consider funds with respect to different momentum trading styles. The impact of aggregate flows on price-based anomalies could arise from that returns to momentum strategies are positively auto-correlated.[30] When momentum strategies perform well recently, there are more flows to mutual funds whose returns are highly correlated with returns to momentum strategies. Because momentum profits are persistent, aggregate flows to momentum-oriented funds could be positively related to future momentum profits. If only aggregate flows to momentum-oriented funds have impacts on price-based anomalies, previous results based on aggregate flows to the entire equity mutual fund industry are not robust.

I follow Sapp and Tiwari (2004) to rank funds each month into deciles based on their exposure to the momentum factor (UMD) factor loadings estimated from individual fund four-factor regressions that use data from the prior 36 months. HM (LM) funds are funds in the top (bottom) 30% and MM funds are funds in the middle 40%. I use Equation (1.16)

[30] For example, the first autocorrelation of the momentum factor is 0.08 (t-statistic of 2.67) for the sample period of 1927 to 2012.

to compute flows to funds with respect to different momentum trading styles.

Panel B of Table 1.13 shows the unconditional and conditional results. Aggregate flows to each category have strong and positive effects on momentum profits, especially under poor funding conditions. However, the effect of HM funds on momentum profits is weaker than funds that are less sensitive to UMD. For instance, for MOM, under poor funding conditions, the loading of MM funds on aggregate flows is 6.09 (t-statistic of 2.78), compared with 2.58 of HM funds (t-statistic of 1.89). To sum up, the persistence in momentum profits cannot explain the effect of aggregate mutual fund flows on price-based anomalies.

1.8 Conclusion

The fact that aggregate mutual fund flows have significant effects on stock prices at the aggregate level has been extensively documented in the literature. In this paper, I examine whether aggregate mutual fund flows affect the *cross-section* of stock prices by exploring the role of aggregate mutual fund flows to the profitability of a large set of anomalies, some of which are identified with price continuation and others based on non-price variables.

I conduct an unconditional analysis and an analysis conditional on macro funding conditions measured by the EBP because mutual fund trading is likely to exert a greater influence on prices when other sources of investment capital are scarce. The results show that aggregate mutual fund flows have a strong and positive influence on returns to price-based anomalies. In the unconditional analysis of price-based anomalies, a one standard deviation increase in the aggregate mutual fund flows is associated with an increase in price-based anomaly returns of 0.86% and 0.73% per month for MOM and 52-Wk, respectively. When controlling for aggregate flows under poor macro funding conditions, the profits of price-based strategies are insignificant, and the sensitivity of price-based anomaly returns to aggregate flows is three times as large as under unconditional scenarios. In contrast, the profits of price-based anomalies in favorable macro funding conditions remain statistically significant even after controlling for variation in aggregate mutual fund flows, and the loadings on aggregate flows are insignificant in most cases. These findings suggest that mutual funds exert a strong influence on the profits of price-based anomalies, and the impact is stronger at times when mutual funds are relatively active. The results are robust after controlling for other market-wide variables and using different specifications of macro funding conditions.

Interestingly, the effect of aggregate flows on non-price-based anomalies occurs through the dependence of profits to non-price-based anomalies on price-based anomalies. After controlling for this dependence, the profits to non-price-based anomalies are unrelated to aggregate flows. The empirical evidence supports the view of Lou (2012) and VW that mutual fund flows will only have impacts on price-based anomalies. I further find that the effect of aggregate flows remains significant after controlling for variables designed to focus narrowly on the Lou-VW feedback effect. Thus, there are aspects of the trading behavior of mutual funds that lie outside the Lou-VW effect and that also help to explain momentum and mispricing.

Appendix A. Description of Anomalies

A.1 Price-based Anomalies

Return momentum (MOM)

MOM is the traditional momentum strategy documented in Jegadeesh and Titman (1993). All stocks are ranked based on their past six-month returns, and stocks in the top (bottom) quintile are in the long (short) legs.

52-week high momentum (52-Wk)

52-Wk is constructed based on George and Hwang (2004). All stocks are ranked based on the nearness to 52-week high: $P_{i,t-j}/high_{i,t-j}$, where $P_{i,t-j}$ is the price of stock i at the end of month *t-j* and $high_{i,t-j}$ is the highest price of stock i during the 12-month period that ends on the last day of month *t-j*. Both $P_{i,t-j}$ and $high_{i,t-j}$ are adjusted for stock splits and stock dividends. Stocks in the top (bottom) quintile are in the long (short) legs.

A.2 Non-price-based Anomalies

Earnings (SUE)

Post-Earnings Announcement Drift (PEAD) is the tendency for a stock's cumulative abnormal returns to drift in the direction of an earnings surprise for several weeks following an earnings announcement [Bernard and Thomas (1989)]. Standardized unexpected earnings (SUE) is defined as in Chan, Jegadeesh and Lakonishok (1996) and Chordia and Shivakumar (2006), which is $(e_q\text{-}e_{q-4})/\sigma_q$, where e_q is the most recently announced earnings, e_{q-4} is earnings in the same quarter of the previous year, and σ_q is the standard deviation of the difference $(e_q\text{-}e_{q-4})$ over the prior eight quarters. All stocks are ranked by SUE, and stocks in the top (bottom) quintile are in the long (short) legs.

Profitability (ROE)

Fama and French (2006) and Novy-Marx (2013) find that more profitable firms have higher expected returns than less profitable firms. Wang and Yu (2013) find that the anomaly exists primarily among firms with high arbitrage costs and high information uncertainty. Profitability is defined as return on equity (ROE) which is calculated as quarterly net income divided by one-quarter lagged book-equity: $\text{IBQ}_t/\text{BEQ}_{t-1}$. All stocks are ranked by ROE, and stocks in the top (bottom) quintile are in the long (short) legs.

Stock issuance (SI)

The stock issuing market has been long viewed as producing an anomaly arising from sentiment-driven mispricing. Loughran and Ritter (1995) and Pontiff and Woodgate (2008) show that, in post-issue years, equity issuers underperform matching nonissuers with similar characteristics. Following Pontiff and Woodgate (2008), in each month t, share issuance issues (SI) is defined as the natural log of the ratio of the split-adjusted shares outstanding in month t divided by the split-adjusted shares outstanding in month t-11. In order to be conservative and ensure that the shares outstanding numbers are available to investors, the 6 month-old CRSP data are utilized in the formation period. The split adjusted shares outstanding is CRSP shares outstanding times the CRSP cumulative factor to adjust shares. All stocks are ranked by SI, and stocks in the bottom (top) quintile are in the long (short) legs.

Accruals (ACC)

Sloan (1996) shows that firms with high accruals earn abnormal lower returns on average than firms with low accruals, and suggests that investors overestimate the persistence of the accrual component of earnings when forming earnings expectations. The study of Hirshleifer, Hou, and Teoh (2012) indicates that it is the accrual characteristic rather than the accrual factor loading that predicts returns. Their findings suggest that investors misvalue the accrual characteristic and cast doubt on the rational risk explanation. Accruals (ACC) are calculated as current assets, less the change in current liabilities, less depreciation expense scaled by average total assets as in Sloan (1996). All stocks are ranked by ACC, and stocks in the bottom (top) quintile are in the long (short) legs.

Asset growth (AG)

Cooper, Gulen, and Schill (2008) find companies that grow their total asset more earn lower subsequent returns. They suggest that this phenomenon is due to investors' initial overreaction to changes in future business prospects implied by asset expansions. Lam and Wei (2011) empirically evaluate the predictions of the mispricing hypothesis with limits-to-arbitrage and the q-theory with investment frictions on the negative relation between asset growth and average stock returns and show that each hypothesis is supported by a fair and similar amount of evidence. Total asset growth (AG) is defined as the growth rate of firm's total assets from year t-1 to year t. All stocks are ranked by AG, and stocks in the bottom (top) quintile are in the long (short) legs.

Appendix B. Description of the Excess Bond Premium

If $S_{it}[k]$ is the credit spread on bond k (issued by firm i) in month t, the GZ credit spread is

$$S_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k S_{it}[k] \tag{B.1}$$

where N_t is the number of bond/firm observations in month t; therefore, the GZ credit spread is simply an arithmetic average of the credit spreads on outstanding bonds in any given month t.

Since fluctuations in credit spreads may not only represent changes of firm-specific credit risks but also reflect shifts in the effective supply of funds offered by financial intermediaries, the GZ credit spread is decomposed into two parts: (1) a predicted component reflecting the available firm-specific information on default risk; and, (2) a residual component representing the financial health of the issuer. GZ assume that the log of the credit spread on bond k (issued by firm i) at time t is assumed to be related linearly to a firm-specific measure of expected default (DFT_{it}) and a vector of bond-specific characteristics ($Z_{it}[k]$), according to

$$\ln S_{it}[k] = \beta DFT_{it} + \gamma\prime Z_{it}[k] + \varepsilon_{it}[k] \tag{B.2}$$

The regression is estimated by OLS. The DFT_{it} is the distance-to-default as described in Merton (1974). The bond-specific characteristics are those variables which could influence bond yields through either term or liquidity premiums. Thus, the components of $Z_{it}[k]$ include (1) the bond's duration; (2) the amount outstanding; (3) the coupon rate; (4) the issue age; and (5) an indicator variable equaling one if the bond is callable and zero otherwise. Therefore, the predicted component of the GZ credit spread is an arithmetic average of the fitted value of credit spreads:

$$\hat{S}_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k \hat{S}_{it}[k] \tag{B.3}$$

The excess bond premium (EBP) in time t is defined by the following linear decomposition:

$$EBP_t = S_t^{GZ} - \hat{S}_t^{GZ} \tag{B.4}$$

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Chapter 2

Momentum and Credit Conditions

2.1 Introduction

Jegadeesh and Titman (1993) document that a strategy of buying top decile (winner) and selling bottom decile (loser) stocks ranked by returns during the past 6 months earns an average return over the next six months that is statistically and economically significant.[1] An extensive literature attempts to explain these "momentum" profits.[2] The theoretical and empirical literature that seeks a rational or risk-based explanation has met with limited success, leading others to consider explanations based on behavioral biases of investors.[3] Price continuation in individual stocks is a feature of financial markets that poses a challenge to financial economists. This paper examines a conflict in the existing literature that

[1] Jegadeesh and Titman (2001) show that momentum strategy is still profitable after the period covered by the 1993 study. Griffin, Ji, and Martin (2003) document that momentum profits around the world are economically large and statistically reliable.

[2] For a partial list of explanations on momentum, see Conrad and Kaul (1998), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), Berk, Green, and Naik (1999), Chordia and Shivakumar (2002), Johnson (2002), George and Hwang (2004), Cooper, Gutierrez, and Hameed (2004), Grinblatt and Han (2005), Avramov et al. (2007), Sagi and Seasholes (2007), Liu and Zhang (2008), and, Garlappi and Yan (2011).

[3] Fama and French (1996) show that the momentum profitability is unexplained by the unconditional three-factor model. Grundy and Martin (2001) and Avramov and Chordia (2006) find that controlling for time-varying exposures to common risk factors does not affect momentum profits. The behavioral theories are referred to Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999), who focus on imperfect formation and revision of investor expectations in response to new information.

characterizes momentum, with the hope that doing so will shed some light on the source of momentum profits.

The conflict is that momentum is stronger in the time-series during stock market booms, but stronger in the cross-section among stocks with high default risk. Cooper, Gutierrez, and Hameed (2004; hereafter CGH) find that momentum returns are reliably positive among portfolios formed in UP markets and insignificant among portfolios formed in DOWN market.[4] In the cross-section, Avramov, Chordia, Jostova, and Philipov (2007) show that momentum is profitable only among stocks with low credit ratings. Similarly, Garlappi and Yan (2011) find that momentum is stronger among firms with high default probabilities as measured by the Expected Default Frequency (EDF). The pro-cyclical nature of momentum profits seems at odds with the cross-sectional findings. If default risk is an important determinant of risk or mispricing, one would expect it to be more important in downturns than in booms. Correspondingly, if mispricing or differences in risk are more extreme in bull markets, it seems puzzling that its effect would be stronger among stocks with higher risk of default. Presumably, credit risk is less relevant to firms' financial condition in booms than in downturns.

This study addresses whether there is, in fact, a "credit channel" that affects momentum by examining whether momentum profits depend on the state of credit markets. In contrast to bull and bear stock markets, the effect of credit risk on firms should be related specifically to conditions in credit markets. By focusing specifically on credit conditions at the macro level, I hope to determine whether the dependence of momentum on default risk in the cross-section arises because there is a credit channel effect on mispricing or equity risk and hence profits to momentum strategies. If there is not, then there is a strong possibility that the cross section of default risk proxies for something else that affects momentum.

[4] Following CGH, UP markets are the periods when the lagged 3-year stock market return is positive; DOWN markets are the periods when the lagged 3-year stock market return is negative. Moreover, CGH find that the future returns of the momentum portfolio are mainly explained by past market returns and its square.

Measuring the credit conditions with different proxies, Lown and Morgan (2006) and Gilchrist and Zakrajšek (2011; hereafter GZ) both use VAR analysis and find that a contraction in the supply of credit will cause significant adverse consequences for the macroeconomy. Since the proxy of GZ is at the monthly frequency and not a survey data with timing misalignment, their measure of credit conditions is utilized.[5] Additionally, a two-state Markov regime switching model is used to identify regimes of GZ's measure as either: "Favorable" credit conditions are periods when credit markets are willing to supply credit to firms at lower cost, or "Poor" credit conditions when firms face higher financing costs.

The results are not consistent with a credit channel effect on momentum. Since previous cross-sectional studies of default risk only focus on non-financial firms, I first investigate momentum in non-financial firms across credit conditions. If tight credit accentuates mispricing or risk-based causes of momentum, then profits should be greater when momentum portfolios are created under "poor" credit conditions than under "favorable" credit conditions. I find the opposite. Both raw and risk-adjusted (using Fama-French (1993)) momentum profits are higher among portfolios formed under favorable credit conditions than those under poor credit conditions. Furthermore, if market states are taken into accounts, momentum profits are only significant when momentum strategies are implemented in favorable credit conditions. Moreover, this is robust across both the winner and loser components of the strategy. After controlling for the three Fama-French factors and market states, both winners and losers exhibit significant momentum when formed during favorable credit conditions, and insignificant momentum if formed when credit conditions are poor. Thus, for non-financial firms, the results are opposite to what is expected if tight credit enhances momentum.

Next I examine financial firms. Any effects of credit conditions on momentum should affect financial firms more strongly than non-financials because financials rely on credit

[5] I thank Egon Zakrajšek for providing the time-series of data for the GZ credit spread and the excess bind premium. These variables are described by Gilchrist and Zakrajšek (2011). The details of the excess bond premium are described in Section 2.3.1.

markets as both a source of funding and a source of revenue. These results also are not consistent with a credit channel effect on momentum. I find that without conditioning on credit conditions, financial firms exhibit momentum that is similar to non-financials. However, this pattern is unaffected by whether credit conditions are favorable or poor—credit conditions do not matter to the momentum profits of financial firms. The Fama-French risk-adjusted momentum profits of financial firms are significant in both regimes. Furthermore, in both regimes it is the loser stocks that exhibit the strongest momentum, suggesting that momentum among financial firms is related to whether the firms are performing poorly, but not whether that performance is attributable to credit conditions that are favorable or poor. I also find that market states explain momentum profits of financial firms more than do credit conditions.

To sum up, the empirical evidence shows that there is no "credit channel" effect on momentum profits by investigating the relationship between momentum profits of non-financial/financial firms and credit conditions. For non-financial firms, the momentum profits are stronger among portfolios formed under favorable credit conditions. For financial firms, credit conditions do not matter to the momentum profits. The results suggest that the cross section of credit risk proxies for other unknown source that affects momentum.

The rest of paper is organized as follows: Section 2.2 reviews the existing literature that is most relevant to this study. Section 2.3 describes the data and methodology. Section 2.4 examines the role of credit conditions. Section 2.5 conducts some robustness checks. Finally, Section 2.6 concludes the paper.

2.2 Relevant Literature

Credit risk usually refers to the likelihood that a levered firm will not be able to serve its debt obligations and has a great impact on stock returns. Most of the existing empirical literatures document that stocks of companies with a higher probability of default usually earn lower returns when various measures of the probability of default are taken into account. Using Ohlson (1980) O-score and Altman (1968) Z-score to proxy for the likelihood of default, Dichev (1998) and Griffin and Lemmon (2002) document an inverse relationship between stock returns and default probability. Campbell, Hilscher, and Szilagyi (2008) use a hazard model approach to predict corporate bankruptcy and find that firms with a high probability of bankruptcy are likely to earn low average returns. Garlappi, Shu, and Yan (2008) use the Expected Default Frequency (EDF) of Moody's KMV, and also document that higher default probabilities are not associated with higher expected stock returns.

Many recent literatures address this negative relationship in different ways. Garlappi, Shu, and Yan (2008) suggest that within a model of bargaining between equity holders and debt holders in default, the relationship between default probability and equity return depends on the shareholder advantage. George and Hwang (2010) argue that when market frictions exist, low-leverage firms have the greatest exposure to systematic risk relating to distress costs. Moreover, by choosing low leverage, high-cost firms achieve low probabilities of financial distress, so expected returns are negatively related to distress measures as well.

Recent works add a new dimension to explain momentum anomaly by relating the profitability of momentum strategies to the default risk. Avramov et al. (2007) find that the momentum strategy is profitable only among stocks with low credit ratings, and the results are robust after controlling firm size, firm age, analyst forecast dispersion, leverage, return volatility, and cash flow volatility.

Garlappi and Yan (2011) show that their model is capable of predicting stronger momentum profits for nearly distressed firms when shareholder recovery is taken into account. Measuring default probability with the market-based Expected Default Frequency (EDF), they empirically find that the momentum profits are more pronounced among firms with high default probability. In particular, after adjusting for traditional risk factors, the enhanced momentum profits are significantly positive only among firms that rank in top EDF quintiles.

Chou, Ko, and Lin (2010) catalog a simple version of the augmented five-factor model to explain the momentum anomaly. The augmented five-factor model incorporates two risk factors related to default risk proposed by Ferguson and Shockley (2003) into the Fama-

French three-factor model: (1) relative leverage (based on the ratio of debt-to-equity, D/E) and (2) relative distress (based on Altman's (1968) Z score). They find that the explanatory power of past returns becomes insignificant when individual stock returns are risk-adjusted by the conditional version of the augmented five-factor model.

Other than the cross-sectional variation of the momentum profits, the momentum profits also exhibit the time-variation properties. Chordia and Shivakumar (2002; hereafter CS) show that a set of commonly applied macroeconomic instruments for measuring macroeconomic conditions can explain a significant portion of momentum profits and document that momentum payoffs are large during expansions and nonexistent during recessions. CGH also find that subsequent momentum payoffs are only reliably positive following UP markets and are insignificant following DOWN markets. They argue this is consistent with the prediction of overreaction theory because investors become more overconfident following UP markets, which causes good or bad news incorporated into stock prices more slowly. Daniel, Jagannathan and Kim (2012) suggest that momentum returns may be drawn from a mixture of normal distributions. They develop a variation of the two state hidden Markov regime switching model (HMM) of Hamilton (1989), where the market is calm in one state and turbulent in the other, and find that momentum returns are more volatilite and average -0.65 % per month during turbulent months.

However, the pro-cyclical nature of momentum profits seems at odds with cross-sectional findings because default concerns are potentially greater during bad economic states. This study attempts to resolve this confliction by examining whether momentum profits depend on the state of credit markets. If the dependence of momentum on default risk in the cross-section arises because there is a credit channel effect on mispricing and hence profits to momentum strategies, then risk adjustments for momentum returns should include a default risk factor. If there is not, then there is a strong possibility that the cross section of default risk proxies for something else that affects momentum.

The reasons for why momentum profits would depend on credit conditions are as follows. First, the credit-market conditions are not at the same phase with the economic states or market states. Moreover, the fluctuation of credit conditions is a leading indicator for the business conditions. Lown and Morgan (2006) create a credit standards index (*Standards*) as a net percentage of banks tightening credit based on the survey data obtained from the Federal Reserve's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). *Standards* is computed as the number of banks reporting tightening standards less the number of banks reporting easing standards divided by the total number reporting.[6] GZ use the excess bond premium as their proxy for credit conditions, which is a residual component of their new credit spread index—the "GZ credit spread". Both Lown and Morgan (2006) and GZ find that changes in the credit conditions can influence the course of the business cycle and future economic states.

Second, CS argue that momentum payoffs are attributable to cross-sectional differences in conditionally expected returns predicted by macroeconomic variables. However, this study differs from CS because it focuses on variables that are related to the credit conditions. The factors that affect aggregate credit conditions are identified as critical sources to drive future stock returns. Theoretical studies predict that changing credit market conditions will have great impacts on expected stock returns (e.g., Bernanke and Gertler (1989), Gertler and Gilchrist (1994), and Kiyotaki and Moore (1997), Bolton, Chen, and Wang (2011)). Supporting these theories, Perez-Quiros and Timmermann (2000) document larger variations in risk factor loadings across credit cycles for small firms compared to large firms. Chava et al. (2010) empirically recorded that tight credit predicts lower future stock returns.[7]

Third, Chou, Ko, and Lin (2010) document that only the conditional version of their augmented five-factor model can explain the momentum anomaly. Since the impact of distress and leverage risk on firms varies with macro credit conditions, firm's factor loadings on relative leverage risk and relative distress risk should condition on the state of credit markets. Therefore, momentum profits are expected to be conditional on credit conditions, and

[6] See http://www.federalreserve.gov/boarddocs/SnLoanSurvey/ to get the more information of SLOOS.

[7] Chava et al. (2010) use Lown and Morgan (2006) proxy for measuring credit conditions.

if there is a credit channel effect that mispricing or risk-based factors related to credit risk are intensified during credit crunches, momentum profits should be greater when strategies are implemented under poor credit conditions.

2.3 Data and Methodology

2.3.1 Credit Conditions

The measure of aggregate supply-side credit conditions used in this paper is the excess bond premium, the residual component of "GZ credit spread". GZ construct a new credit spread index—the "GZ credit spread" to examine the role of credit conditions in macroeconomy. This highly informative financial indicator is constructed by using prices of individual corporate bonds traded in the secondary market. If $S_{it}[k]$ is the credit spread on bond k (issued by firm i) in month t, the GZ credit spread is

$$S_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k S_{it}[k] \tag{2.1}$$

where N_t is the number of bond/firm observations in month t; therefore, the GZ credit spread is simply an arithmetic average of the credit spreads on outstanding bonds in any given month t.

Since fluctuations in credit spreads may not only represent changes of firm-specific credit risks but also reflect shifts in the effective supply of funds offered by financial intermediaries, the GZ credit spread is decomposed into two parts: (1) a predicted component reflecting the available firm-specific information on default risk; and, (2) a residual component representing the financial health of the issuer. GZ assume that the log of the credit spread on bond k (issued by firm i) at time t is assumed to be related linearly to a firm-specific measure of expected default (DFT_{it}) and a vector of bond-specific characteristics ($Z_{it}[k]$), according to

$$\ln S_{it}[k] = \beta DFT_{it} + \gamma\prime Z_{it}[k] + \varepsilon_{it}[k] \tag{2.2}$$

The regression (2.1) is estimated by OLS. The DFT_{it} is the distance-to-default as described in Merton (1974). The bond-specific characteristics are those variables which could influence bond yields through either term or liquidity premiums. Thus, the components of $Z_{it}[k]$ include (1) the bond's duration; (2) the amount outstanding; (3) the coupon rate; (4) the issue age; and (5) an indicator variable equaling one if the bond is callable and zero otherwise. Therefore, the predicted component of the GZ credit spread is an arithmetic average of the fitted value of credit spreads:

$$\hat{S}_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k \hat{S}_{it}[k] \tag{2.3}$$

The excess bond premium (EBP) in time t is defined by the following linear decomposition:

$$EBP_t = S_t^{GZ} - \hat{S}_t^{GZ} \tag{2.4}$$

GZ's analysis concludes that EBP accounts for much of the predictive power of the GZ credit spread for economic activities. Shocks to EBP lead to economically and statistically significant declines in consumption, investment, and a sharp fall in the broad stock market. Moreover, GZ provide evidence to support the link between EBP and risk attitudes and balance sheet conditions of financial intermediaries. An increase in the excess bond premium reflects a reduction in the effective risk-bearing capacity of the financial sector and, as a result, a contraction in the supply of credit. The results of GZ suggest that EBP is an informative proxy for the external financing environment and that the credit market is tighter when the level of EBP is higher.

The sample period of EBP is between January 1973 and September 2010 with monthly frequency. Panels A and B of Figure 2.1 compare EBP to the economic and market states, respectively, showing that the credit conditions are not in the same phase as the economic or market states. Furthermore, credit condition fluctuation seems to be a leading indicator for the economic and market states. The sample data indicates that EBP increases significantly prior to or during all cyclical downturns of the business cycle (except for the 1990-1991 recession period) and prior to or during all DOWN markets. The pattern of EBP is also consistent with situations of the credit market in the real world. Beginning in late 2003 EBP fell and remained at a historic low for several years; this period is characterized by lax credit standards, excessive credit growth, and unsustainable asset price appreciation; however, during 2007-2009 financial crisis EBP achieves its highest level; a period characterized by very high financing costs.

Regarding methodology of identifying regimes, a two-state Markov regime switching model is utilized to find regimes implied by EBP and a Maximum Likelihood method through an EM algorithm proposed by Hamilton (1994) is used for estimation. Two alternative models are considered before choosing the benchmark model: Model 1 represents EBP has different mean and variance across two regimes, and Model 2 denotes EBP has different mean but the same variance across two regimes. In order to determine which one is the final benchmark model, a likelihood ratio (LR) test is implemented. Two models are described as follows

$$\text{Model 1: } EBP_t = \mu_{S_t} + \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma^2_{S_t}), \text{ where } S_t \in \{1,2\} \tag{2.5}$$

$$\text{Model 2: } EBP_t = \mu_{S_t} + \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma^2), \text{ where } S_t \in \{1,2\} \tag{2.6}$$

where S_t is the latent state variable.

Panel A of Table 2.1 provides the estimation results of both models. Since the LR-statistic equals 66.24 (significant at 5% significance level), the null hypothesis that σ_1^2 equals to σ_2^2 is rejected; therefore, Model 1 is the final benchmark model. The estimated transition probability matrix of the benchmark model is $\hat{p}_{11} = 0.98$ and $\hat{p}_{22} = 0.96$. The estimation technique will pick lower level of EBP as state 1 and higher level as state 2. I define state 1 as a favorable and state 2 as poor state because the higher level of EBP indicates worsening credit conditions.

Panel B of Table 2.1 documents the credit conditions over different time periods. It shows that the poor states in credit markets are different from NBER recessions, and the correlation between these two states is 0.39. The poor credit conditions do not equal to DOWN markets defined by CGH, and the correlation is 0.21. Moreover, there are more poor credit conditions during the whole sample period. Of the total 453 observations, 314 observations are flagged as favorable states and 139 as poor states, compared to 381 and 72 for expansions and recessions, respectively. For market states, there are 378 months marked as UP markets and 75 as DOWN markets.

2.3.2 Momentum Strategies

Data on stock returns is obtained from the Center for Research in Security Prices (CRSP) monthly files. The information utilized is all NYSE/AMEX/Nasdaq common stocks (share code 10 or 11). The baseline sample spans from January 1972 to December 2010.

To construct momentum portfolios, the commonly used overlapping period approach proposed by Jegadeesh and Titman (1993) is utilized. At the end of each month t, all stocks are ranked based on their past six-month returns t-5 to t and then are grouped into five equally-weighted portfolios. The top quintile of the firms is assigned to the "winner" portfolio and firms in the bottom quintile are assigned to the "loser" portfolio. Quintile portfolios are formed monthly and their returns are computed by weighing equally all firms in that quintile ranking. Each month's momentum strategy involves buying the winner portfolio and selling the loser portfolio. Moreover, this study considers the methodological adjustments that take account of microstructural concerns.[8] First, one month is skipped between the end of the formation month t and the beginning of the first holding-period month t+2, that is, t+1 is skipped. Second, the same price screen filter used by Jegadeesh and Titman (2001) is implemented: stocks priced below $5 (penny stocks) at the beginning of the holding period and stocks with market capitalizations that would place them in the smallest NYSE decile are excluded from the sample. Then, each portfolio is held for the next six months, t+2,...,t+7. Because the six-month holding period is used while the portfolio is formed monthly, six sub-portfolios exist for each quintile in a given holding month. These six sub-portfolios are equal-weight averaged to obtain monthly returns of a given quintile. Throughout the paper, in computing holding period returns, the CRSP delisting return is used whenever a stock drops out of the sample to avoid potential delisting biases. If

[8] Griffin et al. (2003) and CGH show that CS results are not robust to this adjustment. Bhootra (2011) also highlights the critical importance of using microstructure screens in empirical momentum studies.

the delisting return is missing, the Beavera, McNicholsa and Price (2007) methodology is utilized.[9] In order to match the sample period of EBP which begins from January 1973 and lasts until September 2010, the first formation month is January 1973 and the last formation month is September 2010.

Panel A of Table 2.2 provides raw returns to each momentum quintile. Panel B of Table 2.2 reports the alphas returns to each momentum quintile estimated by regressing the monthly momentum returns (less the risk-free rate except for the zero investment WML portfolio) on the monthly returns of the three Fama-French factors. Since the January effect has a great impact on momentum profits, Table II reports results for both January included and January excluded samples.[10] The momentum strategy is profitable in both samples: past winners outperform past losers by 0.96% per month (t-statistic=4.38) in all months and 1.14% per month (t-statistic=5.35) in non-January months. The Fama-French alphas of WML are 1.10% (t-statistic=5.31) and 1.26% (t-statistic=6.07) in all months and non-January months, respectively. These results are similar to Jegadeesh and Titman (2001).

The main point of this study is to addresses whether there is a "credit channel" that affects momentum by examining whether momentum profits depend on credit conditions; therefore, the following methodology is applied to calculate holding-period returns to each quintile conditional on the state when the momentum strategy is implemented.

In any given month t, each of five ranking portfolios has six sub-portfolios formed in previous months, t-2,...,t-7, and these six sub-portfolios are formed in either favorable or poor states. Then, for each quintile, six sub-portfolios are grouped into two categories according to the state in formation time. For example, in month t, some of six sub-portfolios of a given quintile k will belong to the favorable group if they are formed under favorable

[9] The SAS code is available on Richard Price's website: http://richardp.bus.usu.edu/research

[10] George and Hwang (2004) and Chou, Ko, and Lin (2010) emphasize the impact of January effect on momentum profits. As a consequence of tax loss selling, loser stocks are rebounding in January months. Therefore, the returns of loser stocks are smaller in non-January months; in turn, momentum profits are larger in non-January months.

credit conditions; then, these "favorable" sub-portfolios are equally-weighted averaged to obtain quintile k's month-t "favorable" return. By equally-weighted averaging other "poor" sub-portfolios in the poor group, the month-t return conditional on the poor state is also obtained. Specifically, the month-t return to any quintile k conditional on the state i can be expressed as

$$r_t^k(i) = \frac{\sum\limits_{j=2}^{7} r_{t-j,t}^k D_{t-j}}{\sum\limits_{j=2}^{7} D_{t-j}} \tag{2.7}$$

where D_{t-j} is the month-t return to a sub-portfolio of quintile k which is formed in month t-j, and D_{t-j} is a dummy variable that equals one if month t-j is in the state i and zero otherwise. If $\sum\limits_{j=2}^{7} D_{t-j} = 0$, then no state i months contribute to the returns in month t.

This method is different from CGH's: in CGH, if quintile k is formed in month t which is the UP market, the monthly return of quintile k conditional on UP markets is calculated as one-sixth of the cumulative payoff for the holding period over months t+2 to t+7. The CGH method has an overlapping problem that is corrected by this paper's methodology. Additionally, this methodology does not lose the tractability to examine whether momentum profits depend on the state of formation months.

2.4 Empirical Results

Previous cross-sectional studies of default risk mainly focus on non-financial firms because the leverage of financial firms is limited by regulations that do not apply to non-financial companies.[11] However, the impact of credit channel on momentum profits should be to a greater extent on financial firms than on non-financial firms because the financial firm performance is highly dependent on the state of credit markets. Correspondingly, GZ find a clear link between EBP and the profitability of financial intermediaries. GZ also document that there is a co-movement between EBP and the CDS spread of financial firms. Thus,

[11] Financial firms are firms whose Standard Industrial Classification (SIC) code is between 6000 and 6999.

this paper divides the examination into two independent parts based on non-financial and financial companies.

At the end of formation month all firms are ranked together, then non-financial (financial) firms are equally weighted within each quintile ranking to obtain non-financial (financial) quintile portfolios. The monthly return to any non-financial (financial) quintile k conditional on favorable or poor state is computed as described in Equation (2.7).

2.4.1 Analysis on Non-financial Firms

Panel A and Panel B of Table 2.3 reports raw and Fama-French risk-adjusted momentum profits in each scenario for non-financial firms. In addition, CGH argue that lagged market returns could be a proxy for aggregate investor confidence (Daniel, Hirshleifer and Subrahmanyam, 1998) or aggregate risk aversion, which causes greater delayed overreaction and momentum as in Hong and Stein (1999). Moreover, CGH find that the future returns of the momentum portfolio are mainly explained by past market returns and its square. Panel C of Table 2.3 presents the results after controlling for market states.

I apply the modified empirical strategy of CGH to examine the impact of credit conditions on momentum profits when market states are taken into accounts. As in section 2.3.2, in each month, conditional returns to quintile k are simple averages of returns to quintile k portfolios that are formed in favorable or poor states. As a result, the time period of lagged market returns is supposed to be aligned with the time period of conditional portfolio returns. The lagged market returns are measured at the time of portfolio formation, and I follow the methodology in section 2.3.2 to calculate the conditional average lagged 36 month market return as the average of past lagged market returns based on the states at the formation time. Then I regress the conditional returns to portfolios on Fama-French 3 factors, the conditional average lagged 36 month market return and its square as follows

$$r_t^k(i) - r_{ft} = \alpha + \sum_{i\,=\,1}^{3} \beta_i f_{it} + \beta_4 lagmkt_t^{avg}(i) + \beta_5 [lagmkt_t^{avg}(i)]^2 + \varepsilon_t \tag{2.8}$$

$$lagmkt_t^{avg}(i) = \frac{\sum_{j=2}^{7} lagmkt_{t-j} D_{t-j}}{\sum_{j=2}^{7} D_{t-j}}$$

where f_{it} are returns to month-t Fama-French three factors, $lagmkt_t^{avg}(i)$ is the month-t conditional average lagged 36 month market return, $lagmkt_{t-j}$ is the lagged 36 month market returns in month t-j, and D_{t-j} is a dummy variable that equals one if month t-j is in the state i and zero otherwise. If $\sum_{j=2}^{7} D_{t-j} = 0$, then there is no $lagmkt_t^{avg}(i)$ in month t.

Panel C of Table 2.3 reports the alphas from the regression (2.8). Without conditioning on credit conditions, both raw and Fama-French risk-adjusted returns to WML are significant in all months and non-January months. However, after lagged market-related variables are included in the regression, a large portion of unconditional momentum profits is explained by these two factors, lagged month market return and its square. For example, in non-January months, the average WML payoff is 1.07% per month (t-statistic=5.11), the Fama-French alpha of WML is 1.18% (t-statistic=5.80), but the alpha from regression (8) turns out to be statistically insignificant (0.37% and with 1.13 t-statistic). Moreover, the coefficient of the lagged market return is significant positive, which is consistent with CGH's finding that momentum profits are positive correlated with lagged market returns.[12]

After considering credit conditions at the formation time, Table 2.3 shows that the momentum profitability in non-financial firms is robust and stronger following favorable credit conditions. When portfolios are formed in the favorable state, returns to WML are significant and higher than those to portfolios formed in the poor state. In non-January months, for instance, the raw returns to WML are 1.11% per month (t-statistic=5.35) if credit conditions are favorable at the formation time, and become 0.89% per month (t-statistic=2.05) when portfolios are created in the poor state. This also holds for Fama-French alphas. The Fama-French three-factor alpha of WML is 1.14% (t-statistic=5.37) when formed under favorable credit conditions compared to 0.95% (t-statistic=2.25) under poor credit con-

[12] The loadings of WML on lagged market returns are 0.77 (t-statistic=3.31) and 0.93 (t-statistic=3.90) when January is included and excluded, respectively.

ditions. Even though non-January raw and Fama-French risk-adjusted returns to WML are slightly significant under poor credit conditions, Panel C finds that the non-January momentum under poor states is mainly explained by market-state variables . The lagged market return and its square, however, cannot explain the momentum under favorable credit conditions. Therefore, after considering market states, momentum profits are only significant only among portfolios formed in favorable credit conditions. The non-January alphas to WML from regression (2.8) are 0.88% (t-statistic=3.08) for favorable credit conditions compared to -0.04% (t-statistic=-0.07) for poor states. The loadings of WML on lagged market returns are only significant under poor states.[13] Furthermore, this is robust across winners and losers. Under the favorable state, the non-January Fama-French and market-state adjusted returns to winners and losers are 0.38% (t-statistic=1.87) and -0.50% (t-statistic=-3.01), respectively. In contrast, neither winners nor losers exhibit momentum when constructed in the poor state. The non-January alphas of winners and losers in poor states are -0.18% (t-statistic=-0.34) and -0.06% (t-statistic=-0.14), respectively.

In Panel D, I provide results for testing the equality of raw, Fama-French risk-adjusted and Fama-French factors plus market-state adjusted returns to WML across favorable and poor states. In each month, adjusted returns under favorable (poor) credit conditions are fitted values of the intercept estimated from Fama-French factors or the regression (2.8). Then, the t-test is utilized to assess whether the means of two credit-condition groups are statistically different from each other. Momentum profits are not statistically greater following favorable credit conditions for both raw and Fama-French risk-adjusted returns. This is because momentum profits under poor states are mainly explained by lagged market returns. After controlling for market-state variables, for instance, non-January profits to WML under favorable states are significantly greater than under poor states with 92 basis points per month (t-statistic=2.08).

If mispricing or risk-based factors of momentum are intensified during worsening credit

[13] When January is excluded, the loadings of WML on lagged market returns are 0.24 (t-statistic=1.09) in favorable states compared to 1.16 (t-statistic=3.65) in poor states.

conditions and there is a credit channel effect, then momentum profits should be greater when strategies are implemented under poor credit conditions than under favorable credit conditions. Nevertheless, the results show the opposite effect, and the momentum under poor credit conditions are more related to market states than credit conditions. Thus, the above observations indicate that there is no credit channel that has an impact on momentum for non-financial firms because the actual results are the opposite of the expected.

2.4.2 Analysis on Financial Firms

Table 2.4 documents the empirical results for financial firms. Both raw and Fama-French risk-adjusted momentum profits are statistically significant regardless of credit states in which the portfolios are formed. For example, the unconditional Fama-French risk-adjusted returns to WML are 1.38% (t-statistic=5.82) in non-January months; conditional on favorable and poor states, non-January Fama-French risk-adjusted returns to WML are 1.26% (t-statistic=5.17) and 1.34% (t-statistic=2.71), respectively. Moreover, the losers exhibit the strongest momentum in all conditions. The unconditional non-January Fama-French three-factor alphas of loser stocks are -1.10% (t-statistic=-5.56), and the conditional ones are -1.11% (t-statistic=-5.98) and -1.19% (t-statistic=-2.66) when formed under favorable and poor credit conditions, respectively. In contrast, winners do not contribute to momentum profits of financial firms. Interestingly, when market states are taken into accounts, Panel C shows that in both states, a large portion of momentum profits disappears when market states are considered. In each condition, alphas to WML become less statistically significant, so it is possibly the market state not the credit condition that has an impact on momentum profits of financial firms. Since the coefficient of lagged market returns is positive, the momentum profits to financial firms are positively related to market states.[14]

[14] When January is excluded, the loadings of WML on lagged market returns are 0.31 (t-statistic=2.13) without controlling for credit conditions. Under favorable conditions, the coefficient of WML on lagged market returns is 0.29 (t-statistic=2.10); under poor conditions, the coefficient of WML on lagged market returns is 0.39 (t-statistic=2.37)

Panel D also reports that the difference of raw, Fama-French risk-adjusted and Fama-French factors plus market-state adjusted returns to WML between favorable and poor states is statistically insignificant for financial firms.

If the credit channel effect exists, any effect of the credit channel on momentum should affect financial firms more so than non-financial firms because financial firm operations rely heavily on credit markets. The evidence, however, shows that credit conditions do not matter for momentum profits of financial firms. The above results also suggest that momentum among financial firms relates to whether bad news arrives during formation time and does not relate to whether poor performance occurs under favorable or poor credit conditions. Furthermore, what matters more for momentum profits of financial firms is market states, not credit conditions. Thus, there is no credit channel effect for momentum of financial firms.

2.5 Robustness Tests

2.5.1 Alternative Momentum Strategies

This paper documents that there is no credit channel effect on momentum for both non-financial and financial firms when (6,1,6) momentum strategy is executed—the strategy based on past performance over the previous six months and holding stocks for six months after the formation periods with skip-a-month filter. Further evidence presents that the results are robust to the alternative (6,1,12) momentum strategy.

Panel A and Panel B of Table 2.5 documents the Fama-French factors plus market-state adjusted returns to the winner, loser, and WML portfolios of both non-financial and financial firms when (6,1,12) momentum strategy is implemented. The inferences are the same as before. For non-financial companies, momentum only appears when portfolios are formed under favorable credit conditions. For example, the non-January alphas to WML conditional on favorable states are 0.79% (t-statistic=2.66) compared to -0.20% (t-statistic=-0.47) when formed in poor states. Furthermore, Panel C shows that after controlling market states, momentum in non-financial firms under favorable states are significantly greater than under poor states when (6,1,12) momentum strategy is implemented. Even though the non-January adjusted returns to WML of financial firms are significant under favorable credit conditions (0.95%, t-statistic=2.62) and insignificant (0.57%, t-statistic=1.17) under poor credit conditions, the difference of adjusted returns to WML between favorable and poor states is statistically insignificant for the (6,1,12) momentum strategy. Moreover, the mispricing in financial firms arising in favorable states enforces the inference that there is no credit channel in momentum profits of financial firms

2.5.2 Controlling for Credit Shocks

GZ mention that the innovation to credit conditions has a great impact on economic activities. Positive innovations to EBP will cause significant adverse consequences for the macroeconomy. Thus, an examination is required to determine if the results of this study are robust if credit shocks are taken into account.

The AR(2) model is applied to EBP and the credit shock in each month is the difference between the actual value and the fitted value of EBP. All shocks are ranked into three groups based on magnitude. Month t is labeled as either: "Improving" state when the value of month-t shock is in the bottom tercile, "Neutral" state when the value of month-t shock is in the medium tercile, or "Deteriorating" state when the value of month-t shock is in the top tercile.

Table 2.6 presents the alphas from regression (2.8) for sorts independently on original states of credit markets and credit shocks. Panel A shows that the adjusted momentum profits of non-financial firms within each credit-shock groups are more profitable under favorable credit conditions. The non-January adjusted returns to WML conditional on favorable states are 0.92% (t-statistic=2.96), 0.96% (t-statistic=2.74), and 0.75% (t-statistic=1.92) across "Improving", "Neutral" and "Deteriorating" groups, respectively; when formed under poor credit conditions, the adjusted returns to WML are 0.67% (t-statistic=0.99), -0.05% (t-statistic=-0.07), and -0.46% (t-statistic=-0.70). As a result, the effect of credit shocks is subsumed by the previous conditioning set.

The results in Panel B further indicate that the profitability of momentum in financial firms is not related to credit conditions. Under favorable credit conditions, momentum profits of financial firms does not exist when "Improving" shocks occur, but the alphas to WML are significant in the "Neutral" and "Deteriorating" groups. In contrast, momentum of financial firms under poor credit conditions becomes stronger when there "Improving" shocks in poor states. Therefore, it suggests that credit conditions do not matter to momentum profits of financial firms, but return continuation in financial firms is more likely to happen during the period when the regime of credit markets is most likely to change.

2.5.3 Controlling for Macroeconomic Factors

CS find that momentum profits are pro-cyclical over business cycles. They show that momentum profits can mainly be explained by commonly-used macroeconomic variables used for measuring macroeconomic conditions. After controlling for cross-sectional differences in returns predicted by lagged macroeconomic variables, the portfolios of past winners and past losers do not exhibit short term return momentum. Since credit conditions are related to macroeconomic conditions to some extent, in this section, I want to examine whether the conditional variation of momentum in non-financial firms is robust after controlling for the macroeconomic variables. Moreover, the robustness of that momentum profits of financial firms are not related to credit conditions is investigated as well.

At the end of each month t, all stocks are first sorted into quintiles based on their six-month predicted returns from the four-factor model: lagged dividend yield of CRSP value weighted index (DIV), lagged yield spread for Baa bonds over Aaa bonds (DEF), lagged yield spread for 10-year Treasury over three-month Treasury (TERM), and lagged yield on a T-bill with three months until maturity (YLD).[15] The coefficients for each stock on the four macroeconomic factors are calculated with a time-series regression of stock returns on the four factors and an intercept using 60-month window. The loadings are updated

[15] The macroeconomic data are acquired from Amit Goyal's website: http://www.hec.unil.ch/agoyal/

monthly. Stocks are excluded if there are less than 12 observations within the 60-month window. The monthly predicted returns are fitted values from the model using lagged factor realizations and coefficient, and a six-month (t-5 to t) factor-model predicted return is compound from these predicted returns. Stocks are then sorted into quintiles based on their six-month predicted returns, and each of these quintiles is further sorted into quintiles based on lagged six-month raw returns. To avoid potential microstructure biases, one month is skipped between the end of the formation month t and the beginning of the first holding-period month. Each portfolio is held for the next six months. To ensure that the results are not influenced by small and illiquid stocks, the same price screen filter is utilized. Then, non-financial (financial) firms are equally weighted within each 25 portfolios to obtain non-financial (financial) 25 portfolios, and the monthly conditional return to any of non-financial (financial) 25 is computed as described in section 2.3.2. With these two-way sorts, I can examine the extent to which the cross-sectional variation in returns predicted by the macroeconomic factor model captures the conditional variation in the momentum profits. Table 2.7 reports non-January alphas from the regression (2.8) for both non-financial and financial firms conditional on favorable or poor credit conditions.

Panel A shows that the macroeconomic model has no ability to explain the conditional variation in the momentum profits of non-financial firms. The alphas to WML are significantly different from zero within each quintile of the factor-model predicted returns following favorable credit conditions. Although the alpha in second quintile is not as significant as other quintiles, it is still 48 basis points greater in favorable states than in poor states. In contrast, the alphas to WML are insignificant within each predict-return quintile in poor states, so market states still explain a large portion of momentum in non-financial firms under poor credit conditions even after controlling for macroeconomic variables. The results in Panel B also suggest that the impact of credit conditions on momentum profits of financial firms is subsumed by market states. The alphas to WML are insignificant within most of predict-return quintile in both favorable and poor states. Moreover, under both credit conditions, the momentum of financial firms is stronger among the lower predict-return quintile.

2.6 Conclusion

The financial literature has struggled with finding rational or risk-based sources behind abnormal returns of momentum strategies. Although Avramov, Chordia, Jostova, and Philipov (2007) and Garlappi and Yan (2011) unveil that the momentum is profitable only among firms with higher distress levels, the pro-cyclical nature of momentum in CGH appears to be contradicting to former cross-sectional findings. This paper examines this conflict by investigating whether there is a "credit channel" effect on momentum profits.

This paper shows that there is no credit channel effect. Measuring credit conditions with the excess bond premium, I find that the impact of credit risk on momentum profits does not arise during poor credit conditions, the period when credit risk is more relevant to firms' financial conditions. For non-financial firms, after controlling for market states, momentum profits are significant only among portfolios formed under favorable credit conditions; this is robust to winner and loser stocks. The results also suggest that what matters to momentum profits of financial firms is the market state, not the credit condition. The profitability of momentum exists because the market underestimates the implications of bad news. Although the dependence of momentum on default risk in the cross-section is not related to the state of credit market, the possibility that high relative distress firms are responsible for momentum profits is not ruled out. It is possible that the cross section of default risk proxies for other unknown risk factor in another form not tested here that affects momentum profits. Therefore, seeking for reasonable explanations for momentum profits, and addressing the puzzle between time-series and cross-sectional patterns are still important for future works.

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Table 1.1: Summary Statistics of the Mutual Fund Sample (1980-2012)

This table reports the summary statistics of domestic equity mutual funds sample as of December in each year. The CRSP mutual fund database and the CDA/Spectrum database are merged by MFLinks. *Num Funds* is the number of funds at the end of each year. *TNA* is the total net assets reported by CRSP. *Total Stock Hld* and *Num Stock Hld* are the total dollar value of stocks and the number of stocks held by a mutual fund obtained from CDA/Spectrum, respectively. *% of Mkt* is the fraction of the U.S. equity market that is held by the mutual funds in this sample.

Year	Num Funds	TNA ($million)		Total Stock Hld ($million)		Num Stock Hld		% of Mkt
		Medium	Mean	Medium	Mean	Medium	Mean	
1980	232	51.48	158.55	45.70	132.88	45	55.11	2.33%
1981	229	53.91	148.58	42.02	119.80	44	55.33	2.23%
1982	233	72.50	185.61	59.45	148.29	45	57.36	2.44%
1983	259	104.78	233.50	80.84	192.85	48	65.74	2.86%
1984	273	86.23	235.30	74.35	191.73	50	65.48	3.10%
1985	305	115.63	292.22	90.35	233.74	55	69.17	3.39%
1986	349	103.92	316.19	88.18	247.27	51	69.92	3.61%
1987	395	85.20	296.34	69.72	240.25	50	73.34	4.07%
1988	428	79.91	300.58	65.31	243.15	50	76.75	4.10%
1989	467	93.96	359.40	72.82	277.58	50	78.57	4.21%
1990	510	83.68	326.95	62.77	253.64	50	77.62	4.68%
1991	612	103.55	425.73	81.50	335.89	53	85.09	5.49%
1992	716	119.87	475.46	98.01	368.48	57	95.57	6.38%
1993	958	111.90	489.18	85.66	371.40	60	106.97	7.57%
1994	1089	105.47	478.78	84.03	371.11	62	111.00	8.67%
1995	1188	140.81	676.02	117.82	531.90	63	113.48	9.94%
1996	1329	153.58	821.03	127.66	663.68	68	115.38	11.37%
1997	1492	172.21	1013.65	145.18	832.78	66	114.66	12.26%
1998	1577	185.20	1217.55	163.00	1059.60	63	111.67	13.36%
1999	1754	206.75	1485.29	178.26	1296.71	66	122.31	14.26%
2000	2015	184.05	1294.07	154.83	1097.51	66	125.45	15.26%
2001	2117	157.00	1089.64	138.59	919.59	69	132.91	15.25%
2002	2193	109.40	810.97	95.20	682.76	69	133.62	15.08%
2003	2217	153.30	1045.19	136.90	910.29	73	138.97	15.60%
2004	2189	174.20	1208.96	155.07	1038.14	71	141.08	15.83%
2005	2149	200.00	1313.13	179.18	1118.82	71	141.89	16.13%
2006	2021	232.20	1539.12	209.81	1295.74	69	141.36	15.81%
2007	2013	244.20	1615.31	214.81	1333.77	69	145.62	16.17%
2008	1911	148.00	996.65	131.63	830.20	68	148.91	15.78%
2009	1779	202.50	1373.92	181.21	1166.88	73	154.59	16.42%
2010	1587	298.00	1711.96	259.78	1468.24	72	150.93	15.93%
2011	1456	302.70	1753.78	268.48	1525.97	70	144.50	15.71%
2012	1395	352.80	2026.86	304.55	1804.06	70	147.84	15.86%

Table 1.2: Summary Statistics of Aggregate Mutual Fund Flows

This table reports summary statistics of aggregate monthly flows into domestic equity funds provided by the Investment Company Institute (ICI). Standardized flows are net flows standardized by the market value of the previous month using the CRSP stock market index from CRSP. Favorable and Poor represent macro funding conditions defined by the Excess Bond Premium (EBP).The sample period is from January 1984 to December 2012. The Newey-West *t*-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

	Net Flow (in $billions)			Standardized Flow (in %)		
	All	Favorable	Poor	All	Favorable	Poor
Mean	2.915	3.789	0.621	0.048	0.059	0.019
Std	11.201	10.317	13.026	0.098	0.095	0.101
Min	-48.730	-29.315	-48.730	-0.395	-0.151	-0.395
Max	34.193	34.193	31.190	0.294	0.294	0.212
%>0	66.95%	67.86%	64.58%	66.95%	67.86%	64.58%
N	348	252	96	348	252	96
Mean Diff	3.168**			0.040***		
(Fav-Poor)	(2.14)			(3.36)		

Table 1.3: Summary of Macro Funding Conditions

Panel A: Time Periods of Macro Funding Conditions

Regimes of the EBP are picked by the two-state Markov regime switching models as described in equation (1.2). Panel A reports the date of each state over sample periods. The sample period is January 1973 to December 2012.

Favorable Periods	Poor Periods
01/1973–05/1974	06/1974–09/1975
10/1975–03/1981	04/1981–03/1983
04/1983–07/1985	08/1985–11/1987
12/1987–02/1989	03/1989–03/1990
04/1990–03/2000	04/2000–02/2003
03/2003–10/2007	11/2007–06/2009
07/2009–12/2012	

Panel B: Market Variables across Macro Funding Conditions

Panel B reports numbers of different market variables across macro funding conditions. TED is the TED spread, which is the difference between the three-month London Interbank Offer Rate (LIBOR) and the three-month Treasury Bill interest rate. VIX is Chicago Board Options Exchange Market Volatility Index. S&P 500 Ret. is the monthly S&P 500 Index return. PS Levels and PS Innovations are the levels and innovations of Pastor and Stambaugh (2003) liquidity measures, respectively. Favorable and Poor represent macro funding conditions defined by Excess Bond Premium (EBP). The sample period is from January 1973 to December 2012. The Newey-West *t*-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

	TED (%) (starting 1986/01)		VIX (%) (starting 1986/06)		S&P 500 Ret. (%) (starting 1973/01)		PS Levels (starting 1973/01)		PS Innovations (starting 1973/01)	
	Favorable	Poor	Favorable	Poor	Favorable	Poor	Favorable	Poor	Favorable	Poor
Mean	0.54	0.88	18.85	26.09	0.99	-0.31	-0.02	-0.05	0.01	-0.02
Std	0.33	0.57	6.27	9.41	3.78	5.93	0.05	0.08	0.05	0.07
Min	0.12	0.16	10.42	15.99	-14.58	-21.76	-0.30	-0.46	-0.27	-0.38
Max	2.21	3.35	44.28	61.41	11.83	16.30	0.20	0.10	0.29	0.13
N	233	91	233	86	344	136	344	136	344	136
Mean Diff	-0.34***		-7.24***		1.31**		0.03***		0.03***	
(Fav-Poor)	(-5.37)		(-6.61)		(2.39)		(3.86)		(3.08)	

Table 1.4: Anomaly-based Trading of Mutual Funds

This table presents ordinary least squares regressions of fund's trading activity of each anomaly on quarterly fund flows. For each strategy, the dependent variable in Panel A is *LTrade* measure which is used to proxy for fund's long-side trading activity.The dependent variable in Panel B is *STrade* measure which is used to proxy for fund's short-side trading activity. Definitions of *LTrade* and *STrade* are described in section 1.4.1. *flow* is the quarterly fund flow. *Objective-qtr* FE and *Style-qtr* FE denote fixed effects for the fund's investment objective category and investment style, respectively, which are specific to each quarter (*IOC-qtr-dum* and *Style-qtr-dum*). Details about trading strategies are in Appendix A. The sample period is from 1980 to 2012. Reported *t*-statistics (in parentheses) are based on standard errors clustered by fund and quarter. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively. The numbers of intercepts are in percent per month. Nob is the number of observations.

Panel A: Long-side of Strategies

	Dependent variable = $LTrade_t$													
	MOM		52-Wk		SUE		ROE		SI		ACC		AG	
Intercept	1.854***		4.706***		4.820***		10.271***		3.164***		0.829***		-4.000***	
	(3.66)		(8.47)		(18.56)		(45.46)		(7.83)		(4.73)		(-15.96)	
$flow_t$	0.023***	0.022***	0.038***	0.042***	0.027***	0.028***	0.058***	0.063***	0.0120	0.017**	0.004**	0.007***	-0.025***	-0.022***
	(2.90)	(2.98)	(4.52)	(5.02)	(6.66)	(6.52)	(7.09)	(7.20)	(1.46)	(2.09)	(2.10)	(3.26)	(-5.77)	(-5.18)
Obj-qtr and *Style-qtr* FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Nob.	86482	86482	86328	86328	90180	90180	84713	84713	89641	89641	87842	87842	88063	88063
Adj R^2	0.16%	7.90%	0.40%	7.61%	0.31%	7.88%	1.20%	13.76%	0.05%	13.14%	0.01%	2.46%	0.30%	8.51%

Panel B: Short-side of Strategies

	Dependent variable = $STrade_t$													
	MOM		52-Wk		SUE		ROE		SI		ACC		AG	
Intercept	-3.189***		-6.808***		-5.406***		-11.087***		-4.827***		-0.902***		3.884***	
	(-5.63)		(-10.48)		(-18.55)		(-39.66)		(-10.05)		(-4.82)		(14.30)	
$flow_t$	0.0070	0.010**	0.044***	0.040***	0.035***	0.033***	0.072***	0.067***	0.050***	0.043***	0.006***	0.003**	-0.021***	-0.024***
	(1.52)	(2.06)	(6.10)	(5.45)	(7.54)	(8.41)	(8.52)	(8.61)	(7.24)	(6.36)	(3.67)	(2.14)	(-5.32)	(-7.70)
Obj-qtr and *Style-qtr* FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Nob.	86482	86482	86328	86328	90180	90180	84713	84713	89641	89641	87842	87842	88063	88063
Adj R^2	0.02%	1.95%	0.52%	3.42%	0.43%	6.69%	1.74%	13.62%	0.60%	15.57%	0.02%	2.51%	0.18%	14.08%

Table 1.5: Persistency, Performances, Anomaly-based Trading, and Fund Flows

This table presents ordinary least squares regressions of quarterly fund flows on fund's past flows and past performances. The dependent variable is quarterly fund flows (*flow*). Panel A examines whether the flow persistency and performance chasing behavior of mutual fund flows exist after trading styles of mutual funds are taken into accounts. *Alpha* is the monthly Carhart four-factor alpha computed from the fund's returns in the previous year. As other controls related to funds' characteristics, *LnTNA* is the natural logarithm of the total net asset, *LnAge* is the natural logarithm of age which is measured as year of quarter *t*-1 minus the year of birth in CRSP, and *Expense* is the weighted average of all share classes expenses ratio. *Anomaly_ Trading* represents whether *LTrade* and *STrade* measures of each anomaly are included in the panel regression. Definitions of *LTrade* and *STrade* are described in section 1.4.1. *Objective-qtr* FE and *Style-qtr* FE denote fixed effects for the fund's investment objective category and investment style, respectively, which are specific to each quarter (*IOC-qtr-dum* and *Style-qtr-dum*). Panel B conditions the analysis on the level of aggregate flows. *Low_AF* is a dummy variable that equals to one if the level of aggregate flows in quarter *t* is among bottom 30% over the whole sample period. *High_AF* is a dummy variable that equals to one if the level of aggregate flows in quarter *t* is among top 30% over the whole sample period. The sample period in Panel A is from 1980 to 2012. The sample period in Panel B is from 1984 to 2012. Reported *t*-statistics (in parentheses) are based on standard errors clustered by fund and quarter. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively. Nob is the number of observations.

Panel A

	Dependent variable = quarterly fund flow ($flow_t$)			
	(1)	(2)	(3)	(4)
$flow_{t-1}$	0.1656***	0.1647***	0.1566***	0.1569***
	(8.08)	(8.05)	(7.83)	(7.80)
$Alpha_{t-1}$	2.5529***	2.5299***	2.5388***	2.5124***
	(10.80)	(10.64)	(11.05)	(10.83)
$Alpha^2_{t-1}$	2.2927	0.9373	2.1060	1.3546
	(0.28)	(0.12)	(0.26)	(0.17)
Anomaly_ Trading	No	No	Yes	Yes
Control for Fund Characteristics	Yes	Yes	Yes	Yes
Obj-qtr and *Style-qtr* FE	No	Yes	No	Yes
Nob.	89418	89418	89418	89418
Adj R^2	8.16%	8.30%	8.50%	8.63%

Panel B

	Dependent variable = quarterly fund flow (*$flow_t$*)			
	(1)	(2)	(3)	(4)
$flow_{t-1}$	0.1432***	0.1430***	0.1352***	0.1348***
	(4.69)	(4.69)	(4.64)	(3.87)
$Alpha_{t-1}$	2.5535***	2.5519***	2.5598***	2.5531***
	(6.94)	(7.00)	(7.15)	(7.20)
$Alpha^2_{t-1}$	19.4418*	18.7212*	20.6314*	16.5031*
	(1.76)	(1.69)	(1.88)	(1.68)
$flow_{t-1}$*Low_AF_t	0.0229	0.0227	0.0138	0.0137
	(0.60)	(0.59)	(0.38)	(0.38)
$flow_{t-1}$*$High\_AF_t$	0.0412	0.0416	0.0445	0.0447
	(0.93)	(0.94)	(1.04)	(1.05)
$Alpha_{t-1}$*Low_AF_t	-0.7370*	-0.7435*	-0.7739*	-0.7847*
	(-1.65)	(-1.68)	(-1.77)	(-1.80)
$Alpha_{t-1}$*$High\_AF_t$	1.3751	1.3832	1.3242	1.3364
	(1.56)	(1.57)	(1.51)	(1.53)
Low_AF_t	-0.0164***	-0.0166***	-0.0163***	-0.0167***
	(-5.32)	(-5.17)	(-5.38)	(-5.26)
$High\_AF_t$	0.0199***	0.0201***	0.0197***	0.0201***
	(3.93)	(4.07)	(3.86)	(4.01)
Anomaly_ Trading	No	No	Yes	Yes
Control for Fund Characteristics	Yes	Yes	Yes	Yes
Obj-qtr and *Style-qtr* FE	No	Yes	No	Yes
Nob.	86027	86027	86027	86027
Adj R^2	9.35%	9.40%	9.69%	9.75%

Table 1.6: Unconditional Analysis on Effects of Aggregate Mutual Fund Flows on Price-based Anomalies

Each month between January 1984 and December 2012, k (*j*= 2,……,*k*+1) cross-sectional regressions of the following form are estimated:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R_{i,t-1} + b_{4jt} Short_{i,t-j} + b_{5jt} Long_{i,t-j} + \varepsilon_{ijt}$$

R_{it} is the return on stock *i* in month *t*, $size_{i,t}$ and $BM_{i,t}$ are the market capitalization and book-to-market ratio of stock *i* at end of month *t*. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if the stock *i* is ranked in the short (long) leg of MOM or 52-Wk in month *t-j*. Details about MOM and 52-Wk are in Appendix A. This table presents results from the time series regressions of the form:

$$R_t^P = a^P + \sum_{i=1}^{3} b_i^P f_{it} + b_4^P AF_t^{avg} + \varepsilon_t, \text{ where } P \in \{Short, Long \text{ or } LS\}$$

$$R_t^{Short} = 1/k \sum_{j=2}^{k+1} b_{4jt}, \; R_t^{Long} = 1/k \sum_{j=2}^{k+1} b_{5jt}, \; AF_t^{avg} = 1/k \sum_{j=2}^{k+1} AF_{t-j}$$

f_{it} are returns to month *t* Fama-French three factors. AF_{t-j} is the aggregate mutual fund flows in month *t-j*. The numbers of intercepts are in percent per month. The sample period is from January 1984 to December 2012. The Newey-West *t*-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

		MOM							
		Jan. Incl.							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-0.64***	-0.45***	-0.64***	-0.47***	-0.61***	-0.46***	-0.52***	-0.41***
		(-5.94)	(-3.46)	(-6.31)	(-3.34)	(-6.12)	(-3.26)	(-5.33)	(-3.01)
	AF^{avg}		-4.17***		-3.65**		-2.94*		-2.09
			(-2.66)		(-2.05)		(-1.72)		(-1.34)
Long	*Intercept*	0.46***	0.17	0.39***	0.12	0.28***	0.07	0.17**	0.00
		(3.84)	(1.64)	(3.51)	(0.92)	(2.97)	(0.62)	(2.22)	(0.04)
	AF^{avg}		5.88***		5.71***		4.22***		3.22***
			(4.05)		(3.42)		(3.19)		(3.17)
LS	*Intercept*	1.10***	0.62***	1.04***	0.58**	0.89***	0.53**	0.69***	0.41**
		(5.65)	(3.12)	(5.75)	(2.46)	(5.50)	(2.36)	(4.89)	(2.11)
	AF^{avg}		10.05***		9.35***		7.16**		5.31**
			(3.75)		(2.93)		(2.57)		(2.36)
		Jan. Excl.							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-0.77***	-0.54***	-0.78***	-0.56***	-0.74***	-0.55***	-0.64***	-0.48***
		(-6.29)	(-3.42)	(-6.95)	(-3.45)	(-7.16)	(-3.66)	(-6.54)	(-3.47)
	AF^{avg}		-4.65***		-4.39**		-3.77**		-2.98*
			(-2.66)		(-2.25)		(-2.11)		(-1.89)
Long	*Intercept*	0.51***	0.22*	0.43***	0.15	0.29***	0.09	0.16*	0.01
		(3.85)	(1.81)	(3.56)	(1.09)	(2.94)	(0.77)	(1.94)	(0.09)
	AF^{avg}		5.84***		5.60***		3.99***		2.83***
			(3.70)		(3.13)		(2.90)		(2.78)
LS	*Intercept*	1.28***	0.76***	1.21***	0.71**	1.03***	0.64***	0.80***	0.49**
		(5.64)	(3.08)	(5.90)	(2.59)	(5.94)	(2.67)	(5.37)	(2.43)
	AF^{avg}		10.49***		9.99***		7.76***		5.82**
			(3.53)		(2.85)		(2.65)		(2.51)

		52-Wk							
		Jan. Incl.							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-0.93***	-0.66***	-0.84***	-0.61***	-0.73***	-0.54***	-0.61***	-0.46***
		(-6.81)	(-3.99)	(-6.54)	(-3.37)	(-5.75)	(-3.03)	(-4.92)	(-2.72)
	AF^{avg}		-5.66***		-4.81**		-3.76*		-2.89
			(-3.04)		(-2.28)		(-1.90)		(-1.58)
Long	*Intercept*	0.32***	0.19**	0.33***	0.18*	0.29***	0.16	0.24***	0.14*
		(4.16)	(1.99)	(4.63)	(1.74)	(4.39)	(1.59)	(4.41)	(1.75)
	AF^{avg}		2.80***		2.99**		2.72**		2.03**
			(2.89)		(2.44)		(2.40)		(2.34)
LS	*Intercept*	1.25***	0.85***	1.17***	0.79***	1.02***	0.70***	0.85***	0.60**
		(6.42)	(3.61)	(6.30)	(2.94)	(5.67)	(2.66)	(5.11)	(2.55)
	AF^{avg}		8.46***		7.80**		6.49**		4.92*
			(3.29)		(2.43)		(2.17)		(1.92)
		Jan. Excl.							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-1.09***	-0.79***	-1.02***	-0.75***	-0.91***	-0.67***	-0.79***	-0.59***
		(-7.34)	(-4.12)	(-7.40)	(-3.76)	(-7.09)	(-3.65)	(-6.31)	(-3.38)
	AF^{avg}		-6.09***		-5.57**		-4.85**		-3.99**
			(-2.93)		(-2.44)		(-2.35)		(-2.14)
Long	*Intercept*	0.41***	0.26**	0.39***	0.23**	0.35***	0.21*	0.29***	0.18*
		(4.64)	(2.42)	(5.01)	(1.99)	(4.78)	(1.84)	(4.76)	(1.96)
	AF^{avg}		2.99***		3.20**		2.98**		2.19**
			(2.81)		(2.35)		(2.37)		(2.27)
LS	*Intercept*	1.50***	1.05***	1.42***	0.98***	1.27***	0.88***	1.08***	0.77***
		(6.91)	(3.81)	(6.98)	(3.26)	(6.72)	(3.14)	(6.27)	(3.07)
	AF^{avg}		9.08***		8.77**		7.83**		6.18**
			(3.16)		(2.48)		(2.45)		(2.29)

Table 1.7: Conditional Analysis on Effects of Aggregate Mutual Fund Flows on Price-based Anomalies

Each month between January 1984 and December 2012, k (j= 2,……,k+1) cross-sectional regressions of the following form are estimated:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R_{i,t-1} + b_{4jt} Short_{i,t-j} + b_{5jt} Long_{i,t-j} + \varepsilon_{ijt},$$

R_{it} is the return on stock i in month t, $size_{i,t}$ and $BM_{i,t}$ are the market capitalization and book-to-market ratio of stock i at end of month t. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of MOM or 52-Wk in month t-j. Details about MOM and 52-Wk are in Appendix A. This table presents results from the analysis conditional on macro funding conditions according to the time periods in Panel A of Table 1.3. The results are obtained from the conditional regression model of the form:

$$R_t^P(m) = a^P + \sum_{i=1}^{3} b_i^P f_{it} + b_4^P AF_t^{avg}(m) + \varepsilon_t, \text{ where } P \in \{Short, Long \text{ or } LS\}$$

$$R_t^{Short}(m) = \sum_{j=2}^{k+1} b_{4jt} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}, \; R_t^{Long} = 1/k \sum_{j=2}^{k+1} b_{5jt}(m) = \sum_{j=2}^{k+1} b_{5jt} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

$$R_t^{LS}(m) = R_t^{Long}(m) - R_t^{Short}(m), \; AF_t^{avg}(m) = \sum_{j=2}^{k+1} AF_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

D_{t-j} is a dummy variable that equals one if month t-j is in the state m and zero otherwise. f_{it} are returns to month t Fama-French three factors. AF_{t-j} is the aggregate mutual fund flows in month t-j. The numbers of intercepts are in percent per month. The sample period is from January 1984 to December 2012. The Newey-West t-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

Panel A: Favorable Macro Funding Conditions (Jan. Excl.)

		MOM							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-0.72***	-0.62***	-0.74***	-0.70***	-0.69***	-0.69***	-0.62***	-0.68***
		(-6.98)	(-5.70)	(-8.57)	(-7.32)	(-9.29)	(-8.58)	(-8.69)	(-9.27)
	AF^{avg}		-1.50		-0.69		0.03		1.03
			(-1.31)		(-0.70)		(0.03)		(1.17)
Long	*Intercept*	0.59***	0.37***	0.47***	0.32***	0.25**	0.20**	0.09	0.09
		(5.22)	(3.62)	(4.55)	(3.45)	(2.51)	(2.34)	(1.10)	(1.09)
	AF^{avg}		3.55***		2.53**		0.78		0.09
			(3.03)		(2.23)		(0.65)		(0.08)
LS	*Intercept*	1.31***	1.00***	1.21***	1.02***	0.94***	0.90***	0.72***	0.77***
		(6.91)	(5.72)	(7.37)	(6.62)	(6.33)	(6.61)	(5.42)	(6.04)
	AF^{avg}		5.04***		3.22*		0.76		-0.94
			(2.60)		(1.84)		(0.43)		(-0.56)
		52-Wk							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-1.08***	-0.95***	-1.01***	-0.93***	-0.87***	-0.83***	-0.75***	-0.75***
		(-9.70)	(-8.47)	(-10.72)	(-9.47)	(-10.51)	(-9.79)	(-9.66)	(-10.11)
	AF^{avg}		-2.06*		-1.40		-0.70		0.05
			(-1.79)		(-1.33)		(-0.72)		(0.06)
Long	*Intercept*	0.49***	0.40***	0.45***	0.39***	0.37***	0.30***	0.28***	0.25***
		(6.75)	(5.20)	(7.72)	(6.37)	(6.61)	(5.07)	(5.59)	(4.49)
	AF^{avg}		1.41*		1.00		1.19*		0.45
			(1.89)		(1.57)		(1.85)		(0.80)
LS	*Intercept*	1.56***	1.35***	1.47***	1.32***	1.24***	1.14***	1.03***	1.00***
		(9.71)	(8.16)	(10.62)	(9.53)	(10.18)	(9.06)	(9.46)	(9.19)
	AF^{avg}		3.47**		2.40		1.89		0.40
			(2.14)		(1.62)		(1.31)		(0.29)

Panel B: Poor Macro Funding Conditions (Jan. Excl.)

		MOM							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-0.61*	-0.35	-0.57**	-0.35	-0.68***	-0.40*	-0.49**	-0.31
		(-1.83)	(-0.99)	(-2.00)	(-1.11)	(-2.69)	(-1.71)	(-2.28)	(-1.51)
	AF^{avg}		-14.63***		-13.79**		-16.81***		-12.63***
			(-2.83)		(-2.44)		(-4.43)		(-3.56)
Long	*Intercept*	0.13	-0.04	0.08	-0.10	0.25	0.02	0.04	-0.06
		(0.56)	(-0.16)	(0.45)	(-0.52)	(1.32)	(0.15)	(0.31)	(-0.50)
	AF^{avg}		9.48***		11.08***		14.04***		6.65**
			(2.82)		(2.88)		(2.90)		(2.34)
LS	*Intercept*	0.74	0.32	0.65	0.25	0.93**	0.43	0.53*	0.25
		(1.52)	(0.62)	(1.64)	(0.57)	(2.51)	(1.34)	(1.96)	(0.98)
	AF^{avg}		24.12***		24.87***		30.85***		19.28***
			(3.21)		(2.87)		(4.32)		(3.76)
		52-Wk							
		k=3		k=6		k=9		k=12	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Short	*Intercept*	-0.82**	-0.49	-0.69**	-0.41	-0.71**	-0.44	-0.60**	-0.38
		(-2.06)	(-1.23)	(-2.04)	(-1.16)	(-2.42)	(-1.56)	(-2.25)	(-1.50)
	AF^{avg}		-18.93***		-17.61***		-16.39***		-15.12***
			(-3.47)		(-2.98)		(-3.76)		(-3.62)
Long	*Intercept*	0.10	-0.03	0.14	-0.00	0.23*	0.12	0.18*	0.11
		(0.54)	(-0.17)	(0.91)	(-0.02)	(1.75)	(0.84)	(1.83)	(0.98)
	AF^{avg}		7.30***		8.55***		6.65**		5.41**
			(2.89)		(2.64)		(2.60)		(2.55)
LS	*Intercept*	0.92*	0.45	0.83*	0.41	0.94**	0.56	0.78**	0.48
		(1.74)	(0.85)	(1.82)	(0.83)	(2.40)	(1.44)	(2.33)	(1.47)
	AF^{avg}		26.24***		26.16***		23.04***		20.53***
			(3.62)		(3.00)		(3.64)		(3.64)

Table 1.8: Effects of Aggregate Mutual Fund Flows and the Flow-based Mechanism on Price-based Anomalies

Each month between January 1984 and December 2012, k (j= 2,……,k+1) cross-sectional regressions of the following form are estimated:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R_{i,t-1} + b_{4jt} Short_{i,t-j} + b_{5jt} Long_{i,t-j} + \varepsilon_{ijt},$$

R_{it} is the return on stock i in month t, $size_{i,t}$ and $BM_{i,t}$ are the market capitalization and book-to-market ratio of stock i at end of month t. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of MOM or 52-Wk in month t-j. Details about MOM and 52-Wk are in Appendix A. Panel A reports the unconditional results from the time series regressions of the form:

$$R_t^{LS} = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg} + b_5 Buy_t^{avg} + b_6 Sell_t^{avg} + \varepsilon_t$$

$$R_t^{LS} = 1/k \sum_{j=2}^{k+1} (b_{5jt} - b_{4jt}),\ AF_t^{avg} = 1/k \sum_{j=2}^{k+1} AF_{t-j},\ Buy_t^{avg} = 1/k \sum_{j=2}^{k+1} Buy_{t-j},\ Sell_t^{avg} = 1/k \sum_{j=2}^{k+1} Sell_{t-j}$$

f_{it} are returns to month t Fama-French three factors. AF_{t-j} is the aggregate mutual fund flows in month t-j. Buy_{t-j} and $Sell_{t-j}$ are *Buy* and *Sell* measures in month t-j. *Buy* and *Sell* are measures to proxy for Lou's flow-based mechanism. Definitions of *Buy* and *Sell* are described in section 1.5.3. Panel B and Panel C present results from the analysis conditional on macro funding conditions according to the time periods in Panel A of Table 1.3. The results are obtained from the conditional regression model of the form:

$$R_t^{LS}(m) = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg}(m) + b_5 Buy_t^{avg}(m) + b_6 Sell_t^{avg}(m) + \varepsilon_t$$

$$R_t^{LS}(m) = \sum_{j=2}^{k+1} (b_{5jt} - b_{4jt}) D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j},\ AF_t^{avg}(m) = \sum_{j=2}^{k+1} AF_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

$$Buy_t^{avg}(m) = \sum_{j=2}^{k+1} Buy_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j},\ Sell_t^{avg}(m) = \sum_{j=2}^{k+1} Sell_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

D_{t-j} is a dummy variable that equals one if month t-j is in the state m and zero otherwise. The numbers of intercepts are in percent per month. The sample period is from January 1984 to December 2012. The Newey-West t-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

Panel A: Unconditional (Jan. Excl.)

	MOM											
	k=3			k=6			k=9			k=12		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	0.73***	0.73***	0.60**	0.71***	0.66**	0.57**	0.63***	0.59**	0.54**	0.48**	0.51**	0.50**
	(2.75)	(2.68)	(2.39)	(2.59)	(2.42)	(2.16)	(2.67)	(2.39)	(2.30)	(2.42)	(2.27)	(2.31)
AF^{avg}	11.82***		11.25***	10.59***		10.02**	8.22***		8.01**	6.21**		6.15*
	(3.36)		(2.70)	(2.88)		(2.36)	(2.68)		(2.19)	(2.57)		(1.92)
Buy^{avg}		0.08**	0.01		0.08***	0.01		0.07***	0.01		0.05**	0.00
		(2.54)	(0.31)		(2.81)	(0.40)		(2.79)	(0.24)		(2.47)	(0.01)
$Sell^{avg}$		0.06	-0.02		0.07	-0.02		0.07	-0.02		0.07	-0.00
		(1.29)	(-0.44)		(1.61)	(-0.52)		(1.40)	(-0.64)		(1.54)	(-0.06)
	52-Wk											
	k=3			k=6			k=9			k=12		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	1.01***	1.21***	1.08***	0.97***	1.08***	0.99***	0.87***	0.95***	0.91***	0.76***	0.87***	0.86***
	(3.49)	(3.86)	(3.61)	(3.26)	(3.44)	(3.25)	(3.14)	(3.15)	(3.09)	(3.07)	(3.04)	(3.09)
AF^{avg}	10.38***		11.31***	9.45**		9.78**	8.34**		8.46**	6.60**		6.75*
	(3.02)		(2.68)	(2.54)		(2.17)	(2.48)		(2.09)	(2.34)		(1.86)
Buy^{avg}		0.05*	-0.02		0.06*	-0.01		0.06**	-0.00		0.05**	-0.01
		(1.71)	(-0.52)		(1.95)	(-0.16)		(2.17)	(-0.10)		(2.04)	(-0.21)
$Sell^{avg}$		0.06	-0.02		0.09*	-0.01		0.10*	0.01		0.10*	0.02
		(1.40)	(-0.42)		(1.84)	(-0.11)		(1.85)	(0.11)		(1.91)	(0.43)

Panel B: Favorable Macro Funding Conditions (Jan. Excl.)

	MOM											
	k=3			k=6			k=9			k=12		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	1.01***	1.08***	1.02***	1.03***	1.06***	1.03***	0.89***	1.01***	0.99***	0.75***	0.95***	0.95***
	(5.11)	(4.58)	(4.56)	(5.94)	(4.72)	(4.83)	(6.40)	(4.32)	(4.41)	(5.51)	(4.43)	(4.49)
AF^{avg}	5.04***		5.64**	3.21*		4.41*	0.81		3.69	-0.87		3.27
	(2.70)		(2.26)	(1.90)		(1.91)	(0.46)		(1.46)	(-0.47)		(1.26)
Buy^{avg}		0.03	-0.01		0.02	-0.02		-0.01	-0.04		-0.04	-0.06
		(1.10)	(-0.28)		(0.63)	(-0.47)		(-0.38)	(-0.90)		(-1.15)	(-1.36)
$Sell^{avg}$		0.03	-0.02		0.01	-0.04		-0.03	-0.07		-0.05	-0.09
		(0.74)	(-0.43)		(0.27)	(-0.82)		(-0.58)	(-1.18)		(-1.16)	(-1.44)
	52-Wk											
	k=3			k=6			k=9			k=12		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	1.35***	1.52***	1.48***	1.34***	1.45***	1.43***	1.14***	1.23***	1.22***	1.01***	1.20***	1.20***
	(6.95)	(7.55)	(7.46)	(8.36)	(8.72)	(8.81)	(7.48)	(7.75)	(7.76)	(7.45)	(8.72)	(8.85)
AF^{avg}	3.54**		4.35*	2.28		2.58	2.01		2.01	0.36		2.13
	(2.17)		(1.90)	(1.57)		(1.21)	(1.42)		(0.99)	(0.27)		(1.02)
Buy^{avg}		0.01	-0.02		0.01	-0.01		0.01	-0.00		-0.01	-0.03
		(0.68)	(-0.59)		(0.72)	(-0.34)		(0.68)	(-0.13)		(-0.69)	(-1.14)
$Sell^{avg}$		0.05	0.01		0.05	0.02		0.05	0.02		0.02	-0.00
		(1.44)	(0.16)		(1.51)	(0.44)		(1.62)	(0.61)		(0.84)	(-0.12)

Panel C: Poor Macro Funding Conditions (Jan. Excl.)

	MOM											
	k=3			k=6			k=9			k=12		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	0.29	0.15	-0.07	0.27	0.29	0.08	0.47	0.42	0.23	0.24	0.34	0.20
	(0.62)	(0.27)	(-0.13)	(0.63)	(0.61)	(0.17)	(1.37)	(1.05)	(0.63)	(0.91)	(1.06)	(0.69)
AF^{avg}	30.09***		27.18***	28.08***		26.28***	32.22***		27.45***	21.96***		18.60***
	(4.13)		(3.30)	(3.25)		(2.95)	(3.96)		(4.28)	(3.77)		(3.47)
Buy^{avg}		0.19***	0.14***		0.14**	0.06		0.21***	0.10*		0.14***	0.07
		(3.62)	(3.10)		(2.59)	(1.22)		(3.40)	(1.87)		(3.44)	(1.50)
$Sell^{avg}$		0.14*	0.11*		0.13*	0.04		0.22***	0.09		0.18***	0.09*
		(1.70)	(1.71)		(1.79)	(0.52)		(2.76)	(1.20)		(3.34)	(1.65)
	52-Wk											
	k=3			k=6			k=9			k=12		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	0.45	0.54	0.30	0.42	0.59	0.36	0.55	0.74	0.55	0.47	0.70	0.55
	(0.93)	(0.85)	(0.56)	(0.94)	(1.01)	(0.66)	(1.42)	(1.46)	(1.18)	(1.39)	(1.56)	(1.29)
AF^{avg}	31.50***		30.09***	29.58***		28.74***	26.28***		25.65***	23.58***		21.16***
	(4.89)		(3.65)	(3.57)		(3.16)	(3.86)		(3.46)	(3.83)		(3.61)
Buy^{avg}		0.14**	0.08		0.11*	0.03		0.11***	0.01		0.13***	0.04
		(2.55)	(1.44)		(1.93)	(0.47)		(2.72)	(0.24)		(2.77)	(0.87)
$Sell^{avg}$		0.13	0.09		0.12	0.02		0.14**	0.02		0.19***	0.08
		(1.44)	(1.17)		(1.48)	(0.26)		(2.32)	(0.26)		(3.04)	(1.41)

Table 1.9: Unconditional Effects of Aggregate Mutual Fund Flows on Non-price-based Anomalies

In Panel A, each month between January 1984 and December 2012, k (j= 2,……,k+1) cross-sectional regressions of the following form are estimated when momentum effects are not controlled for:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R_{i,t-1} + b_{4jt} Short_{i,t-j} + b_{5jt} Long_{i,t-j} + \varepsilon_{ijt},$$

R_{it} is the return on stock i in month t, $size_{i,t}$ and $BM_{i,t}$ are the market capitalization and book-to-market ratio of stock i at end of month t. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of non-price-based anomalies (SUE, ROE, SI, ACC and AG) in month t-j. Details about SUE, ROE, SI, ACC and AG are in Appendix A. Panel A reports the unconditional results from the time series regressions of the form:

$$R_t^{LS} = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg} + \varepsilon_t$$

$$R_t^{LS} = 1/k \sum_{j=2}^{k+1} (b_{5jt} - b_{4jt}),\ AF_t^{avg} = 1/k \sum_{j=2}^{k+1} AF_{t-j}$$

f_{it} are returns to month t Fama-French three factors. AF_{t-j} is the aggregate mutual fund flows in month t-j. The numbers of intercepts are in percent per month. The sample period is from January 1984 to December 2012. The Newey-West t-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

In Panel B, each month between January 1984 and December 2012, k (j= 2,……,k+1) cross-sectional regressions of the following form are estimated when momentum effects are controlled for:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R6_{i,t-1} + b_{4jt} MOML_{i,t-j} + b_{5jt} MOMW_{i,t-j} + b_{6jt} 52L_{i,t-j} + b_{7jt} 52W_{i,t-j} + b_{8jt} Short_{i,t-j} + b_{9jt} Long_{i,t-j} + \varepsilon_{ijt},$$

$R6_{i,t-1}$ is the past six-month returns of stock i at end of month t-1. $size_{i,t}$ and $BM_{i,t}$ are the market capitalization of and book-to-market ratio of stock i at end month t. $MOML_{i,t-j}$ ($MOMW_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of MOM in month t-j, and $52L_{i,t-j}$ ($52W_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of 52-Wk in month t-j. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of non-price-based strategies (SUE, ROE, SI, ACC and AG) in month t-j. Details about MOM, 52-Wk, SUE, ROE, SI, ACC and AG are in Appendix A. Panel B reports the unconditional results from the time series regressions of the form:

$$R_t^{LS} = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg} + \varepsilon_t$$

$$R_t^{LS} = 1/k \sum_{j=2}^{k+1} (b_{9jt} - b_{8jt}),\ AF_t^{avg} = 1/k \sum_{j=2}^{k+1} AF_{t-j}$$

f_{it} are returns to month t Fama-French three factors. AF_{t-j} is the aggregate mutual fund flows in month t-j. The numbers of intercepts are in percent per month. The sample period is from January 1984 to December 2012. The Newey-West t-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

Panel A: Without Controlling for Momentum Effects

		k=6									
		SUE		ROE		SI		ACC		AG	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Jan. Incl.	*Intercept*	0.55***	0.46***	1.07***	1.04***	0.71***	0.57***	0.21***	0.15*	0.50***	0.36***
		(5.52)	(4.12)	(5.88)	(5.98)	(5.94)	(4.68)	(2.61)	(1.70)	(3.94)	(2.87)
	AF^{avg}		1.78*		0.61		2.86***		1.41*		3.03**
			(1.72)		(0.36)		(2.71)		(1.71)		(2.07)
Jan. Excl.	*Intercept*	0.60***	0.48***	1.17***	1.05***	0.81***	0.63***	0.22**	0.15*	0.53***	0.39***
		(5.77)	(3.88)	(6.46)	(6.28)	(6.61)	(4.94)	(2.58)	(1.72)	(4.38)	(3.40)
	AF^{avg}		2.45**		2.26		3.41***		1.35		2.81*
			(2.14)		(1.28)		(3.07)		(1.60)		(1.96)
		k=12									
		SUE		ROE		SI		ACC		AG	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Jan. Incl.	*Intercept*	0.34***	0.27***	0.73***	0.66***	0.70***	0.56***	0.21***	0.17**	0.42***	0.31***
		(3.62)	(2.86)	(4.09)	(3.89)	(5.72)	(4.30)	(2.87)	(2.03)	(4.02)	(2.89)
	AF^{avg}		1.27		1.10		2.55**		0.71		2.25*
			(1.39)		(0.63)		(2.21)		(0.86)		(1.93)
Jan. Excl.	*Intercept*	0.40***	0.30***	0.84***	0.69***	0.80***	0.62***	0.21***	0.17**	0.45***	0.35***
		(4.19)	(3.01)	(4.74)	(4.22)	(6.51)	(4.53)	(2.78)	(1.99)	(4.28)	(3.24)
	AF^{avg}		1.90**		2.75		3.42***		0.88		2.22*
			(2.02)		(1.47)		(2.91)		(1.03)		(1.86)

Panel B: Controlling for Momentum Effects

		k=6									
		SUE		ROE		SI		ACC		AG	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Jan. Incl.	*Intercept*	0.36***	0.32***	0.85***	0.87***	0.50***	0.44***	0.16**	0.12	0.34***	0.28***
		(4.11)	(3.27)	(5.44)	(5.97)	(5.66)	(4.46)	(2.14)	(1.46)	(3.26)	(2.81)
	AF^{avg}		0.96		-0.43		1.35		0.87		1.27
			(0.98)		(-0.28)		(1.61)		(1.21)		(1.12)
Jan. Excl.	*Intercept*	0.37***	0.30***	0.91***	0.85***	0.55***	0.47***	0.15*	0.11	0.34***	0.30***
		(4.13)	(2.84)	(6.06)	(6.13)	(5.96)	(4.50)	(1.95)	(1.32)	(3.44)	(3.19)
	AF^{avg}		1.49		1.13		1.51*		0.80		0.81
			(1.46)		(0.75)		(1.67)		(1.05)		(0.73)

		k=12									
		SUE		ROE		SI		ACC		AG	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Jan. Incl.	*Intercept*	0.22***	0.17**	0.59***	0.57***	0.51***	0.44***	0.16**	0.14*	0.28***	0.24***
		(2.83)	(2.14)	(4.01)	(4.13)	(5.86)	(4.36)	(2.36)	(1.74)	(3.35)	(2.78)
	AF^{avg}		1.07		0.21		1.22		0.43		0.98
			(1.24)		(0.14)		(1.34)		(0.58)		(1.00)
Jan. Excl.	*Intercept*	0.25***	0.17**	0.66***	0.57***	0.55***	0.46***	0.16**	0.13	0.28***	0.25***
		(3.16)	(2.08)	(4.63)	(4.27)	(6.19)	(4.32)	(2.19)	(1.58)	(3.25)	(2.83)
	AF^{avg}		1.54*		1.65		1.58		0.58		0.69
			(1.81)		(1.06)		(1.61)		(0.77)		(0.68)

Table 1.10: Conditional Effects of Aggregate Mutual Fund Flows on Non-price-based Anomalies

Each month between January 1984 and December 2012, k (*j*= 2,……,*k*+1) cross-sectional regressions of the following form are estimated without controlling for momentum effects:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R_{i,t-1} + b_{4jt} Short_{i,t-j} + b_{5jt} Long_{i,t-j} + \varepsilon_{ijt},$$

R_{it} is the return on stock *i* in month *t*, $size_{i,t}$ and $BM_{i,t}$ are the market capitalization and book-to-market ratio of stock *i* at end of month *t*. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if the stock *i* is ranked in the short (long) leg of non-price-based anomalies (SUE, ROE, SI, ACC and AG) in month *t-j*. On the other hand, k (*j*= 2,……,*k*+1) cross-sectional regressions of the following form are estimated with controlling for momentum effects:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R6_{i,t-1} + b_{4jt} MOML_{i,t-j} + b_{5jt} MOMW_{i,t-j} + b_{6jt} 52L_{i,t-j} + b_{7jt} 52W_{i,t-j} + b_{8jt} Short_{i,t-j} + b_{9jt} Long_{i,t-j} + \varepsilon_{ijt},$$

$R6_{i,t-1}$ is the past six-month returns of stock *i* at end of month *t*-1. $MOML_{i,t-j}$ ($MOMW_{i,t-j}$) is a dummy variable that equals 1 if the stock *i* is ranked in the short (long) leg of MOM in month *t-j*, and $52L_{i,t-j}$ ($52W_{i,t-j}$) is a dummy variable that equals 1 if the stock *i* is ranked in the short (long) leg of 52-Wk in month *t-j*. Details about MOM, 52-Wk, SUE, ROE, SI, ACC and AG are in Appendix A. This table present results from the analysis conditional on macro funding conditions according to the time periods in Panel A of Table 1.3. If returns to strategies are estimated without controlling for momentum effects, the results are obtained from the conditional regression model of the form:

$$R_t^{LS}(m) = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg}(m) + \varepsilon_t$$

$$R_t^{LS}(m) = \sum_{j=2}^{k+1} (b_{5jt} - b_{4jt}) D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}, \quad AF_t^{avg}(m) = \sum_{j=2}^{k+1} AF_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

If returns to strategies are estimated with controlling for momentum effects, the results are obtained from the conditional regression model of the form:

$$R_t^{LS}(m) = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg}(m) + \varepsilon_t, \quad R_t^{LS}(m) = \sum_{j=2}^{k+1} (b_{9jt} - b_{8jt}) D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

f_{it} are returns to month *t* Fama-French three factors. AF_{t-j} is the aggregate mutual fund flows in month *t-j*. D_{t-j} is a dummy variable that equals one if month *t-j* is in the state *m* and zero otherwise. The numbers of intercepts are in percent per month. The sample period is from January 1984 to December 2012. The Newey-West *t*-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

Panel A: Favorable Macro Funding Conditions (Jan. Excl.)

		k=6									
		SUE		ROE		SI		ACC		AG	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Without Controlling for Momentum Effects	*Intercept*	0.50***	0.45***	0.88***	0.76***	0.74***	0.55***	0.17*	0.10	0.48***	0.38***
		(5.70)	(4.67)	(6.06)	(5.35)	(7.37)	(4.80)	(1.88)	(0.98)	(3.74)	(2.98)
	AF^{avg}		0.83		2.05		3.16***		1.12		1.61
			(1.08)		(1.42)		(3.12)		(1.17)		(1.27)
Controlling for Momentum Effects	*Intercept*	0.28***	0.24**	0.64***	0.57***	0.49***	0.37***	0.10	0.07	0.31***	0.28**
		(3.15)	(2.54)	(4.38)	(4.07)	(5.57)	(3.55)	(1.23)	(0.68)	(2.72)	(2.32)
	AF^{avg}		0.58		1.15		1.98**		0.60		0.62
			(0.76)		(0.83)		(2.28)		(0.70)		(0.56)

Panel B: Poor Macro Funding Conditions (Jan. Excl.)

		k=6									
		SUE		ROE		SI		ACC		AG	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Without Controlling for Momentum Effects	*Intercept*	0.70***	0.53***	1.61***	1.42***	0.78***	0.67***	0.37***	0.34**	0.45**	0.35*
		(3.55)	(2.82)	(4.64)	(4.32)	(3.26)	(2.79)	(2.73)	(2.47)	(2.44)	(1.98)
	AF^{avg}		10.53***		11.26**		6.83*		2.28		6.17**
			(3.86)		(2.34)		(1.87)		(1.20)		(2.22)
Controlling for Momentum Effects	*Intercept*	0.50***	0.38**	1.32***	1.21***	0.62***	0.57***	0.30**	0.27**	0.32**	0.29**
		(3.19)	(2.40)	(5.17)	(5.12)	(3.61)	(3.15)	(2.24)	(2.00)	(2.29)	(2.10)
	AF^{avg}		7.43***		6.73*		2.95		2.25		1.57
			(2.94)		(1.93)		(1.01)		(1.27)		(0.76)

Table 1.11: Momentum Returns, Aggregate Mutual Fund Flows, Market Returns, Market Volatility, Market Illiquidity and Sentiment Index

Each month between January 1984 and December 2012, k (j= 2,……,k+1) cross-sectional regressions of the following form are estimated:

$$R_{it} = b_{ojt} + b_{1jt} size_{i,t-1} + b_{2jt} BM_{i,t-1} + b_{3jt} R_{i,t-1} + b_{4jt} Short_{i,t-j} + b_{5jt} Long_{i,t-j} + \varepsilon_{ijt},$$

R_{it} is the return on stock i in month t, $size_{i,t}$ and $BM_{i,t}$ are the market capitalization and book-to-market ratio of stock i at end of month t. $Short_{i,t-j}$ ($Long_{i,t-j}$) is a dummy variable that equals 1 if the stock i is ranked in the short (long) leg of MOM or 52-Wk in month t-j. Details about MOM and 52-Wk are in Appendix A. Panel A reports the unconditional results from the time series regressions of the form:

$$R_t^{LS} = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg} + b_5 MktVar_t^{avg} + \varepsilon_t$$

$$R_t^{LS} = 1/k \sum_{j=2}^{k+1} (b_{5jt} - b_{4jt}),\ AF_t^{avg} = 1/k \sum_{j=2}^{k+1} AF_{t-j},\ MktVar_t^{avg} = 1/k \sum_{j=2}^{k+1} MktVar_{t-j}$$

f_{it} are returns to month t Fama-French three factors. AF_{t-j} is the aggregate mutual fund flows in month t-j. $MktVar_{t-j}$ is one of market variables (*Lagmkt*, *MktVol*, *MktIlliq* and *Sen*) in month t-j. *Lagmkt* is the lagged 36-month return on the CRSP value-weighted index. *MktVol* is the standard deviation of daily CRSP value-weighted market return. *MktIlliq* is the value-weighted average of the Amihud (2002) stock-level illiquidity measure for all NYSE and AMEX stocks. *Sen* is the Baker and Wurgler (2006) sentiment index. Panel B presents results from the analysis conditional on macro funding conditions according to the time periods in Panel A of Table 1.3. The results are obtained from the conditional regression model of the form:

$$R_t^{LS}(m) = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg}(m) + b_5 MktVar_t^{avg}(m) + \varepsilon_t,\ R_t^{LS}(m) = \sum_{j=2}^{k+1} (b_{5jt} - b_{4jt}) D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

$$AF_t^{avg}(m) = \sum_{j=2}^{k+1} AF_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j},\ MktVar_t^{avg}(m) = \sum_{j=2}^{k+1} MktVar_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j}$$

D_{t-j} is a dummy variable that equals one if month t-j is in the state m and zero otherwise. The numbers of intercepts are in percent per month. The sample period spans from January 1984 to December 2012. For Model 4, the sample period ends at December 2010 because the last month of *Sen* is December 2010. The Newey-West t-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

Panel A: Unconditional Analysis (Jan. Excl.)

	MOM (k=6)				52-Wk (k=6)			
	Model 1	Model 2	Model 3	Model 4†	Model 1	Model 2	Model 3	Model 4†
Intercept	0.20	1.99**	0.66*	0.40	0.53	2.63***	0.90**	0.53
	(0.57)	(2.41)	(1.86)	(1.23)	(1.33)	(3.44)	(2.35)	(1.61)
AF^{avg}	6.99**	6.95**	9.97***	11.96***	6.14**	4.83*	8.72**	11.62***
	(2.58)	(2.46)	(2.86)	(3.09)	(2.20)	(1.83)	(2.48)	(3.09)
$Lagmkt^{avg}$	0.77***				0.67**			
	(3.15)				(2.29)			
$MktVol^{avg}$		-1.21				-1.56*		
		(-1.35)				(-1.90)		
$MktIlliq^{avg}$			2.08				3.60	
			(0.27)				(0.45)	
Sen^{avg}				0.97***				1.16***
				(3.36)				(4.00)

†: The sample period is from 1984 to 2010.

Panel B: Conditional Analysis (Jan. Excl.)

Favorable Macro Funding Conditions

	MOM (k=6)				52-Wk (k=6)			
	Model 1	Model 2	Model 3	Model 4†	Model 1	Model 2	Model 3	Model 4†
Intercept	0.73***	1.09*	1.00***	0.96***	1.13***	1.53***	1.29***	1.08***
	(3.17)	(1.66)	(4.73)	(6.12)	(6.66)	(3.28)	(7.13)	(8.72)
AF^{avg}	2.32	3.14	3.21*	3.92*	1.81	2.18	2.40	4.46***
	(1.41)	(1.47)	(1.83)	(1.94)	(1.28)	(1.35)	(1.61)	(2.90)
$Lagmkt^{avg}$	0.35				0.23			
	(1.52)				(1.22)			
$MktVol^{avg}$		-0.09				-0.24		
		(-0.11)				(-0.44)		
$MktIlliq^{avg}$			0.93				1.29	
			(0.13)				(0.22)	
Sen^{avg}				0.63**				0.86***
				(2.25)				(4.41)

†: The sample period is from 1984 to 2010.

Poor Macro Funding Conditions

	MOM (k=6)				52-Wk (k=6)			
	Model 1	Model 2	Model 3	Model 4†	Model 1	Model 2	Model 3	Model 4†
Intercept	0.01	1.57	0.15	0.10	0.11	2.13*	0.32	0.14
	(0.02)	(1.47)	(0.20)	(0.23)	(0.22)	(1.91)	(0.40)	(0.28)
AF^{avg}	20.50**	19.26**	24.70***	22.46**	20.87**	18.81**	26.01***	21.81**
	(2.41)	(2.59)	(2.83)	(2.54)	(2.38)	(2.58)	(2.99)	(2.41)
$Lagmkt^{avg}$	0.56				0.68			
	(1.62)				(1.57)			
$MktVol^{avg}$		-0.95				-1.24		
		(-1.10)				(-1.46)		
$MktIlliq^{avg}$			4.90				4.13	
			(0.21)				(0.16)	
Sen^{avg}				0.56				1.01
				(1.15)				(1.48)

†: The sample period is from 1984 to 2010.

Table 1.12: Different Specifications of Macro Funding Conditions

Panel A presents results from the analysis conditional on poor macro funding conditions according to the time periods in Panel A of Table 1.3 but excluding 2008-2009 periods. Panel B presents results from the analysis conditional on poor macro funding conditions according to the time periods in Panel A of Table 1.3 without NBER recessions. Panel C presents results from the analysis conditional on macro funding conditions defined by TED. Panel D presents results from the analysis conditional on macro funding conditions defined by VIX. The sample period of Panel A and Panel B is from January 1984 to December 2012. The sample period of Panel C is from January 1986 to December 2012. The sample period of Panel D is from June 1986 to December 2012. The Newey-West *t*-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

	MOM (k=6)			52-Wk (k=6)		
Panel A: Poor Macro Funding Conditions without 2008-2009 (Jan. Excl.)						
	Short	Long	LS	Short	Long	LS
AF^{avg}	-8.98***	5.79*	14.77***	-12.47***	3.40**	15.88***
	(-2.71)	(1.97)	(3.02)	(-2.88)	(2.00)	(2.99)
Panel B: Poor Macro Funding Conditions without NBER Recessions (Jan. Excl.)						
	MOM (k=6)			52-Wk (k=6)		
	Short	Long	LS	Short	Long	LS
AF^{avg}	-7.25*	3.73	10.98**	-12.63***	1.85	14.48**
	(-1.93)	(1.37)	(2.01)	(-2.99)	(0.89)	(2.49)
Panel C: Regimes defined by TED (Jan. Excl.)						
	Favorable States					
	MOM (k=6)			52-Wk (k=6)		
	Short	Long	LS	Short	Long	LS
AF^{avg}	-2.49	2.94***	5.43***	-3.03	1.54**	4.57*
	(-1.61)	(3.23)	(2.70)	(-1.54)	(2.24)	(1.84)
	Poor States					
	MOM (k=6)			52-Wk (k=6)		
	Short	Long	LS	Short	Long	LS
AF^{avg}	-10.32**	12.07***	22.39***	-12.57***	7.41**	19.98***
	(-2.56)	(3.18)	(3.05)	(-2.75)	(2.43)	(2.71)
Panel D: Regimes defined by VIX (Jan. Excl.)						
	Favorable States					
	MOM (k=6)			52-Wk (k=6)		
	Short	Long	LS	Short	Long	LS
AF^{avg}	-2.69**	1.71*	4.40***	-2.83**	1.43**	4.26***
	(-2.60)	(1.66)	(2.72)	(-2.57)	(2.42)	(2.92)
	Poor States					
	MOM (k=6)			52-Wk (k=6)		
	Short	Long	LS	Short	Long	LS
AF^{avg}	-6.79**	8.17**	14.96***	-8.99***	4.58**	13.57**
	(-2.32)	(1.98)	(2.80)	(-2.66)	(2.15)	(2.56)

Table 1.13: Aggregate Flows to Funds with Different Characteristics

Panel A presents the loadings of momentum profits on aggregate flows to funds with respect to different investment objectives. I choose funds that are self-reported as aggressive growth (AGG), growth (Grow), or growth and income (GNI). Panel B presents results from the analysis funds with respect to different momentum trading styles. Mutual funds are sorted each month into decile portfolios based on momentum (UMD) factor loadings estimated from individual fund four-factor regressions that use data from the prior 36 months. Funds not having at least 30 months of prior data are excluded. *LM* (*HM*) represents funds in the bottom (top) 30%, and *MM* is funds in the middle 40%. The results in both panels are obtained from the regression model of the form and the conditional analysis is based on macro funding conditions according to the time periods in Panel A of Table 1.3:

Unconditional: $R_t^{LS} = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF(c)_t^{avg} + \varepsilon_t, \ \ AF(c)_t^{avg} = 1/k \sum_{j=2}^{k+1} AF(c)_{t-j},$

Conditional: $R_t^{LS}(m) = a + \sum_{i=1}^{3} b_i f_{it} + b_4 AF_t^{avg}(c,m) + \varepsilon_t, \ \ AF_t^{avg}(c,m) = \sum_{j=2}^{k+1} AF(c)_{t-j} D_{t-j} \Big/ \sum_{j=2}^{k+1} D_{t-j},$

$D_{t\text{-}j}$ is a dummy variable that equals one if month *t-j* is in the state *m* and zero otherwise. f_{it} are returns to month *t* Fama-French three factors. $AF(c)_{t\text{-}j}$ is the aggregate mutual fund flows to mutual funds with some characteristic *c* in month *t-j*. The sample period of Panel A and Panel B is from January 1991 to December 2012. The Newey-West *t*-statistics are reported in parentheses. Significance levels at 10%, 5%, and 1% are indicated by *, ** and ***, respectively.

Panel A: Funds with Different Investment Objectives (Jan. Excl.)

	MOM (k=6)			52-Wk (k=6)		
	AGG	Grow	GNI	AGG	Grow	GNI
Unconditional	0.54**	1.46**	0.76	0.48**	1.27**	0.86
	(2.47)	(2.77)	(1.39)	(2.31)	(2.33)	(1.64)
Favorable	0.21**	0.50**	0.40	0.21**	0.33	0.21
	(2.05)	(2.17)	(1.42)	(2.53)	(1.48)	(1.04)
Poor	2.83**	4.72***	5.09**	2.43**	4.60***	6.09***
	(2.63)	(2.87)	(2.06)	(2.49)	(2.92)	(2.95)

Panel B: Funds with Different Momentum Trading Styles (Jan. Excl.)

	MOM (k=6)			52-Wk (k=6)		
	LM	MM	HM	LM	MM	HM
Unconditional	0.68	1.18***	0.73**	0.87*	1.03**	0.59**
	(1.34)	(2.65)	(2.37)	(1.76)	(2.22)	(2.00)
Favorable	0.21	0.53**	0.28**	0.14	0.29	0.23**
	(0.81)	(2.37)	(2.00)	(0.69)	(1.41)	(2.11)
Poor	2.06**	6.09***	2.58*	2.48**	6.15***	1.92
	(2.02)	(2.78)	(1.89)	(2.57)	(2.43)	(1.39)

Table 2.1
Regimes of Credit Conditions
Panel A: Estimation Results of Regime Switching Models

The two-state Markov regime switching models are estimated using Maximum Likelihood method through EM algorithm proposed by Hamilton (1994). Panel A presents the estimation results of Model 1 and Model 2 as described in Equation (2.) and (2.6), respectively. The sample period is January 1973 to September 2010. The standard errors are in parentheses.

Panel 1: Model 1						
$\hat{\mu}_1$	$\hat{\mu}_2$	$\hat{\sigma}_1^2$	$\hat{\sigma}_2^2$	$\hat{p}_{11}$	$\hat{p}_{22}$	Log Likelihoods
-0.2080	0.5662	0.0693	0.2273	0.98	0.96	1923.2590
(0.0153)	(0.0505)	(0.0049)	(0.0191)	(0.06)	(0.08)	
Panel 2: Model 2						
$\hat{\mu}_1$	$\hat{\mu}_2$	$\hat{\sigma}^2$	$\hat{p}_{11}$	$\hat{p}_{22}$		Log Likelihoods
-0.1819	0.6485	0.1146	0.98	0.94		1890.1374
(0.0215)	(0.0304)	(0.0054)	(0.05)	(0.09)		

Panel B: Time Periods of Credit Conditions

The regime credit conditions are picked by Model 1 of Panel A. State 1 is the favorable state, and state 2 is the poor state. The sample period is January 1973 to September 2010.

Favorable Periods	Poor Periods
01/1973–05/1974	06/1974–10/1975
11/1975–01/1981	02/1981–03/1983
04/1983–06/1985	07/1985–09/1987
10/1987–01/1989	02/1989–03/1990
04/1990–03/2000	04/2000–02/2003
03/2003–10/2007	11/2007–06/2009
07/2009–09/2010	

Table 2.2
Momentum Portfolio Returns

At the end of each month *t*, all stocks are allocated into quintile portfolios on the basis of their past six-month returns (from *t*-5 to *t*). Quintile portfolios are formed monthly and their returns are computed by weighing equally all firms in that quintile ranking. The momentum strategy involves buying the winner portfolio and selling the loser portfolio. To avoid potential microstructure biases, one month is skipped between the end of the formation month *t* and the beginning of the first holding-period month, *t*+2. Each portfolio is held for the next six months (*t*+2 through *t*+7). To ensure that the results are not influenced by small and illiquid stocks, the price screen filter is utilized. Panel A reports monthly raw returns. Panel B documents the intercepts of each portfolio from the Fama-French three factor model regression. The first formation month is January 1973 and the last one is September 2010. The *t* statistics are reported in parentheses. The * (**) denotes significance at the 5% (10%) level.

Panel A: Average Monthly Returns						
	P1 (Loser)	P2	P3	P4	P5 (Winner)	P5-P1 (WML)
Jan. Incl.	0.57	1.07	1.21	1.32	1.52	0.96
	(1.60)	(4.12)*	(5.14)*	(5.54)*	(4.94)*	(4.38)*
Jan. Excl.	0.24	0.88	1.07	1.20	1.38	1.14
	(0.68)	(3.37)*	(4.50)*	(4.94)*	(4.33)*	(5.35)*
Panel B: Fama-French Risk-adjusted Returns						
	P1 (Loser)	P2	P3	P4	P5 (Winner)	P5-P1 (WML)
Jan. Incl.	-0.67	-0.11	0.06	0.23	0.43	1.10
	(-4.47)*	(-1.38)	(1.02)	(4.35)*	(4.20)*	(5.31)*
Jan. Excl.	-0.82	-0.14	0.07	0.25	0.44	1.26
	(-5.80)*	(-1.83)**	(1.20)	(4.88)*	(4.38)*	(6.07)*

Table 2.3
Momentum Profits of Non-Financial Firms

At the end of each month *t*, all stocks are allocated into quintile portfolios on the basis of their past six-month returns. The top quintile of the firms is assigned to the “winner” portfolio and firms in the bottom quintile are assigned to the “loser” portfolio. Then, non-financial (financial) firms are equally weighted within each quintile ranking to obtain non-financial (financial) quintile portfolios. Financial firms are identified as firms whose SIC code is between 6000 and 6999. To avoid potential microstructure biases, one month is skipped between the end of the formation month *t* and the beginning of the first holding-period month, *t*+2. Each portfolio is held for the next six months. To ensure that the results are not influenced by small and illiquid stocks, the price screen filter is utilized. Measuring credit conditions with the excess bond premium, the state of credit conditions in each formation month is detected by two-state Markov regime switching model. For each quintile, six sub-portfolios are grouped into two categories according to the state of credit conditions in formation time. Monthly profits of quintile portfolios conditional on the favorable (poor) state is computed by equally-weighted averaging sub-portfolios in the favorable (poor) group. Panel A reports monthly raw returns. Panel B documents the intercepts of each portfolio from the Fama-French three factor model regression. Panel C reports alphas from a regression of portfolio returns on Fama-French three factors and past 36 months market return and its square. Panel D reports the results for the test of the equality of momentum profits of Panel A, Panel B and Panel C across favorable and poor credit conditions. The first formation month is January 1973 and the last one is September 2010. The *t* statistics are reported in parentheses. The * (**) denotes significance at the 5% (10%) level.

Panel A: Average Monthly Profits						
	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	0.62	0.30	1.51	1.37	0.89	1.07
	(1.75)	(0.85)	(4.73)*	(4.12)*	(4.16)*	(5.11)*
Favorable	0.72	0.48	1.73	1.59	1.01	1.11
	(2.27)*	(1.46)	(4.89)*	(4.28)*	(5.06)*	(5.35)*
Poor	0.37	-0.10	0.91	0.79	0.53	0.89
	(0.49)	(-0.13)	(1.55)	(1.33)	(1.16)	(2.05)*
Panel B: Fama-French Risk-adjusted Returns						
	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	-0.58	-0.73	0.44	0.45	1.02	1.18
	(-3.90)*	(-5.23)*	(4.05)*	(4.17)*	(5.04)*	(5.80)*
Favorable	-0.66	-0.72	0.42	0.41	1.07	1.14
	(-5.25)*	(-5.42)*	(3.38)*	(3.22)*	(5.26)*	(5.37)*
Poor	-0.36	-0.63	0.24	0.32	0.61	0.95
	(-1.16)	(-2.14)*	(1.48)	(1.79)**	(1.45)	(2.25)*

Panel C: Fama-French Factors plus Market-state Adjusted Returns						
	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	-0.25	-0.22	0.17	0.15	0.41	0.37
	(-1.10)	(-0.96)	(1.20)	(1.00)	(1.31)	(1.13)
Favorable	-0.52	-0.50	0.39	0.38	0.91	0.88
	(-3.18)*	(-3.01)*	(2.12)*	(1.87)**	(3.38)*	(3.08)*
Poor	0.04	-0.06	-0.14	-0.09	-0.18	-0.04
	(0.11)	(-0.14)	(-0.66)	(-0.42)	(-0.34)	(-0.07)

Panel D: Test for Equality (Favorable – Poor = 0)		
	WML	
	Jan. Incl.	Jan. Excl.
Panel A	0.48	0.22
	(0.96)	(0.47)
Panel B	0.46	0.19
	(0.98)	(0.42)
Panel C	1.09	0.92
	(2.33)*	(2.08)*

Table 2.4
Momentum Profits of Financial Firms

At the end of each month *t*, all stocks are allocated into quintile portfolios on the basis of their past six-month returns. The top quintile of the firms is assigned to the “winner” portfolio and firms in the bottom quintile are assigned to the “loser” portfolio. Then, non-financial (financial) firms are equally weighted within each quintile ranking to obtain non-financial (financial) quintile portfolios. Financial firms are identified as firms whose SIC code is between 6000 and 6999. To avoid potential microstructure biases, one month is skipped between the end of the formation month *t* and the beginning of the first holding-period month, *t*+2. Each portfolio is held for the next six months. To ensure that the results are not influenced by small and illiquid stocks, the price screen filter is utilized. Measuring credit conditions with the excess bond premium, the state of credit conditions in each formation month is detected by two-state Markov regime switching model. For each quintile, six sub-portfolios are grouped into two categories according to the state of credit conditions in formation time. Monthly profits of quintile portfolios conditional on the favorable (poor) state is computed by equally-weighted averaging sub-portfolios in the favorable (poor) group. Panel A reports monthly raw returns. Panel B documents the intercepts of each portfolio from the Fama-French three factor model regression. Panel C reports alphas from a regression of portfolio returns on Fama-French three factors and past 36 months market return and its square. Panel D reports the results for the test of the equality of momentum profits of Panel A, Panel B and Panel C across favorable and poor credit conditions. The first formation month is January 1973 and the last one is September 2010. The *t* statistics are reported in parentheses. The * (**) denotes significance at the 5% (10%) level.

Panel A: Average Monthly Profits

	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	0.47	0.18	1.38	1.29	0.91	1.10
	(1.32)	(0.52)	(5.31)*	(4.81)*	(3.57)*	(4.46)*
Favorable	0.53	0.21	1.48	1.32	0.95	1.11
	(1.73)*	(0.67)	(5.12)*	(4.38)*	(4.31)*	(4.87)*
Poor	0.10	-0.25	0.93	0.90	0.84	1.14
	(0.13)	(-0.32)	(2.06)*	(1.98)*	(1.46)	(2.12)*

Panel B: Fama-French Risk-adjusted Returns

	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	-0.99	-1.10	0.23	0.28	1.23	1.38
	(-4.90)*	(-5.56)*	(1.64)	(1.98)*	(5.05)*	(5.82)*
Favorable	-1.00	-1.11	0.15	0.14	1.15	1.26
	(-5.50)*	(-5.98)*	(0.96)	(0.90)	(4.94)*	(5.17)*
Poor	-1.01	-1.19	0.06	0.15	1.07	1.34
	(-2.18)*	(-2.66)*	(0.22)	(0.61)	(2.01)*	(2.71)*

Panel C: Fama-French Factors plus Market-state Adjusted Returns						
	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	-0.56	-0.37	0.15	0.17	0.70	0.54
	(-1.76)**	(-1.16)	(0.63)	(0.74)	(1.68)**	(1.32)
Favorable	-0.60	-0.57	0.02	0.09	0.69	0.63
	(-2.33)*	(-2.15)*	(0.07)	(0.36)	(1.88)**	(1.71)**
Poor	-0.75	-0.60	0.07	0.21	0.82	0.82
	(-1.27)	(-1.03)	(0.21)	(0.63)	(1.20)	(1.25)

Panel D: Test for Equality (Favorable – Poor = 0)		
	WML	
	Jan. Incl.	Jan. Excl.
Panel A	0.10	-0.03
	(0.17)	(-0.06)
Panel B	0.08	-0.08
	(0.14)	(-0.16)
Panel C	-0.13	-0.19
	(-0.23)	(-0.37)

Table 2.5
Alternative Momentum Strategies

At the end of each month *t*, all stocks are allocated into quintile portfolios on the basis of their past six-month returns. The top quintile of the firms is assigned to the “winner” portfolio and firms in the bottom quintile are assigned to the “loser” portfolio. Then, non-financial (financial) firms are equally weighted within each quintile ranking to obtain non-financial (financial) quintile portfolios. Financial firms are identified as firms whose SIC code is between 6000 and 6999. To avoid potential microstructure biases, one month is skipped between the end of the formation month *t* and the beginning of the first holding-period month, *t*+2. Each portfolio is held for the next twelve months. To ensure that the results are not influenced by small and illiquid stocks, the price screen filter is utilized. Measuring credit conditions with the excess bond premium, the state of credit conditions in each formation month is detected by two-state Markov regime switching model. This table reports alphas from a regression of portfolio returns on Fama-French three factors plus past 36 months market return and its square under different credit conditions for both non-financial and financial firms. Panel A documents the results of non-financial firms. Panel B reports the results of financial firms. Panel C reports the results for the test of the equality of momentum profits across favorable and poor credit conditions. The first formation month is January 1973 and the last one is September 2010. The *t* statistics are reported in parentheses. The * (**) denotes significance at the 5% (10%) level.

Panel A: Non-Financial Firms						
	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	-0.25	-0.20	0.11	0.10	0.36	0.30
	(-1.21)	(-0.95)	(0.95)	(0.81)	(1.40)	(1.14)
Favorable	-0.53	-0.48	0.26	0.31	0.79	0.79
	(-3.14)*	(-2.83)*	(1.53)	(1.61)	(2.87)*	(2.66)*
Poor	0.17	0.09	-0.16	-0.11	-0.32	-0.20
	(0.53)	(0.27)	(-0.92)	(-0.63)	(-0.78)	(-0.47)
Panel B: Financial Firms						
	Loser		Winner		WML	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Unconditional	-0.73	-0.54	0.22	0.24	0.95	0.78
	(-2.65)*	(-1.93)**	(1.08)	(1.20)	(2.72)*	(2.28)*
Favorable	-0.92	-0.86	0.07	0.09	1.00	0.95
	(-3.65)*	(-3.37)*	(0.29)	(0.35)	(2.80)*	(2.62)*
Poor	-0.70	-0.52	-0.06	0.05	0.64	0.57
	(-1.54)	(-1.16)	(-0.23)	(0.18)	(1.26)	(1.17)

Panel C: Test for Equality (Favorable – Poor = 0)		
	WML	
	Jan. Incl.	Jan. Excl.
Non-Financial Firms	1.12	0.99
	(3.12)*	(2.96)*
Financial Firms	0.36	0.38
	(0.84)	(0.96)

Table 2.6

Independent Sorts by Original States and Credit Shocks

The state in each month is independently sorted by original two states and credit shocks. Fitting the excess bond premium with AR(2) model, the credit shock in each month is the difference between the actual value and the fitted value. All shocks are ranked into three group based on their magnitudes. Each month is labeled as: either “Improving” state when the value of shock is in the bottom tercile, “Neutral” state when the value of shock is in the medium tercile, or “Deteriorating” state when the value of shock is in the top tercile. For each quintile, six sub-portfolios are grouped into six categories according to the state in formation time. Monthly profits of quintile portfolios conditional on specific state are computed by equally-weighted averaging sub-portfolios in that group. This table reports alphas from a regression of portfolio returns on Fama-French three factors plus past 36 months market return and its square under different credit conditions for both non-financial and financial firms. Panel A documents the results of non-financial firms. Panel B reports the results of financial firms. The first formation month is January 1973 and the last one is September 2010. The *t* statistics are reported in parentheses. The * (**) denotes significance at the 5% (10%) level.

Panel A: Non-Financial Firms						
	Loser					
	Improving		Neutral		Deteriorating	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Favorable	-0.54	-0.54	-0.63	-0.61	-0.43	-0.39
	(-3.09)*	(-2.91)*	(-3.48)*	(-3.41)*	(-1.86)**	(-1.63)
Poor	-0.51	-0.52	-0.04	0.10	0.27	0.23
	(-1.16)	(-1.13)	(-0.08)	(0.18)	(0.59)	(0.48)
	Winner					
	Improving		Neutral		Deteriorating	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Favorable	0.43	0.38	0.37	0.35	0.38	0.36
	(2.32)*	(1.83)**	(1.54)	(1.36)	(1.76)**	(1.43)
Poor	0.16	0.15	0.04	0.04	-0.28	-0.23
	(0.56)	(0.50)	(0.13)	(0.13)	(-1.10)	(-0.88)
	WML					
	Improving		Neutral		Deteriorating	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Favorable	0.97	0.92	1.00	0.96	0.81	0.75
	(3.39)*	(2.96)*	(3.02)*	(2.74)*	(2.27)*	(1.92)**
Poor	0.68	0.67	0.08	-0.05	-0.55	-0.46
	(1.05)	(0.99)	(0.11)	(-0.07)	(-0.88)	(-0.70)

Panel B: Financial Firms						
	Loser					
	Improving		Neutral		Deteriorating	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Favorable	-0.44	-0.44	-0.97	-0.96	-0.47	-0.54
	(-1.60)	(-1.53)	(-3.25)*	(-3.09)*	(-1.33)	(-1.52)
Poor	-0.60	-0.48	-0.12	0.22	-0.57	-0.12
	(-0.92)	(-0.72)	(-0.13)	(0.22)	(-0.70)	(-0.16)
	Winner					
	Improving		Neutral		Deteriorating	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Favorable	-0.13	-0.21	0.07	0.01	0.55	0.53
	(-0.55)	(-0.85)	(0.29)	(0.06)	(1.60)	(1.54)
Poor	0.53	0.68	0.00	-0.03	0.20	0.38
	(1.29)	(1.69)**	(0.01)	(-0.07)	(0.46)	(0.84)
	WML					
	Improving		Neutral		Deteriorating	
	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.	Jan. Incl.	Jan. Excl.
Favorable	0.31	0.23	1.04	0.97	1.02	1.08
	(0.82)	(0.62)	(2.50)*	(2.29)*	(2.25)*	(2.41)*
Poor	1.13	1.16	0.13	-0.25	0.77	0.51
	(1.60)	(1.67)**	(0.11)	(-0.21)	(0.81)	(0.58)

Table 2.7
Two-Way Dependent Sorts: Six-Month Factor-Model Predicted Returns and Then Lagged Six-Month Returns in Favorable and Poor Credit Conditions

In each month *t*, all stocks are first sorted into quintiles based on their six-month (*t*-5 to *t*) predicted returns from the four-factor model: lagged dividend yield of CRSP value weighted index (DIV), lagged yield spread for Baa bonds over Aaa bonds (DEF), lagged yield spread for 10-year Treasury over three-month Treasury (TERM), and lagged yield on a T-bill with three months until maturity (YLD). Each predicted-return quintile is then further sorted into quintiles based on lagged six-month returns. Then, non-financial (financial) firms are equally weighted within each 25 portfolios to obtain non-financial (financial) 25 portfolios. Financial firms are identified as firms whose SIC code is between 6000 and 6999. To avoid potential microstructure biases, one month is skipped between the end of the formation month *t* and the beginning of the first holding-period month, *t*+2. Each portfolio is held for the next six months. To ensure that the results are not influenced by small and illiquid stocks, the price screen filter is utilized. Measuring credit conditions with the excess bond premium, the state of credit conditions in each formation month is detected by two-state Markov regime switching model. This table reports alphas from a regression of portfolio returns on Fama-French three factors plus past 36 months market return and its square under different credit conditions for both non-financial and financial firms. Panel A documents the results of non-financial firms. Panel B reports the results of financial firms. The first formation month is January 1973 and the last one is September 2010. The *t* statistics are reported in parentheses. The * (**) denotes significance at the 5% (10%) level.

Panel A: Non-Financial Firms							
Favorable Credit Conditions							
Sort	Lagged Six-Month Returns						
Macro-Model Predicted Returns	1 Low	2	3	4	5 High	High-Low	*t-stat* (High-Low)
1	-0.85	-0.55	-0.15	-0.15	-0.02	0.82	2.96*
2	-0.31	-0.06	-0.09	0.06	0.15	0.46	1.94**
3	-0.15	0.11	0.14	0.15	0.33	0.48	2.06*
4	-0.15	0.13	0.12	0.46	0.42	0.57	2.39*
5	-0.23	0.12	0.31	0.43	0.42	0.65	1.96*
Poor Credit Conditions							
Sort	Lagged Six-Month Returns						
Macro-Model Predicted Returns	1 Low	2	3	4	5 High	High-Low	*t-stat* (High-Low)
1	-0.22	0.08	0.32	0.33	0.42	0.64	0.99
2	0.19	0.32	0.38	0.31	0.16	-0.02	-0.06
3	0.06	0.42	0.47	0.37	0.17	0.10	0.25
4	-0.26	0.12	0.27	0.31	0.04	0.29	0.68
5	-0.54	-0.19	-0.24	-0.20	-0.10	0.44	0.73

Panel B: Financial Firms							
Favorable Credit Conditions							
Sort	Lagged Six-Month Returns						
Macro-Model Predicted Returns	1 Low	2	3	4	5 High	High-Low	*t-stat* (High-Low)
1	-1.21	-0.51	-0.11	-0.22	-0.52	0.69	1.05
2	-0.46	-0.31	-0.07	-0.35	0.15	0.61	1.62
3	-0.52	-0.42	0.02	-0.15	0.16	0.68	1.91**
4	-0.01	-0.01	0.01	-0.14	-0.20	-0.20	-0.48
5	0.33	0.32	0.05	0.34	0.31	-0.03	-0.04
Poor Credit Conditions							
Sort	Lagged Six-Month Returns						
Macro-Model Predicted Returns	1 Low	2	3	4	5 High	High-Low	*t-stat* (High-Low)
1	-1.13	-1.16	-0.41	-0.10	0.26	1.38	1.11
2	-0.50	-0.32	0.29	0.04	0.23	0.73	1.28
3	-0.31	0.08	0.33	0.33	0.18	0.49	0.92
4	-0.25	-0.09	0.28	0.16	0.04	0.29	0.75
5	0.39	0.18	0.77	-0.28	0.36	-0.03	-0.03

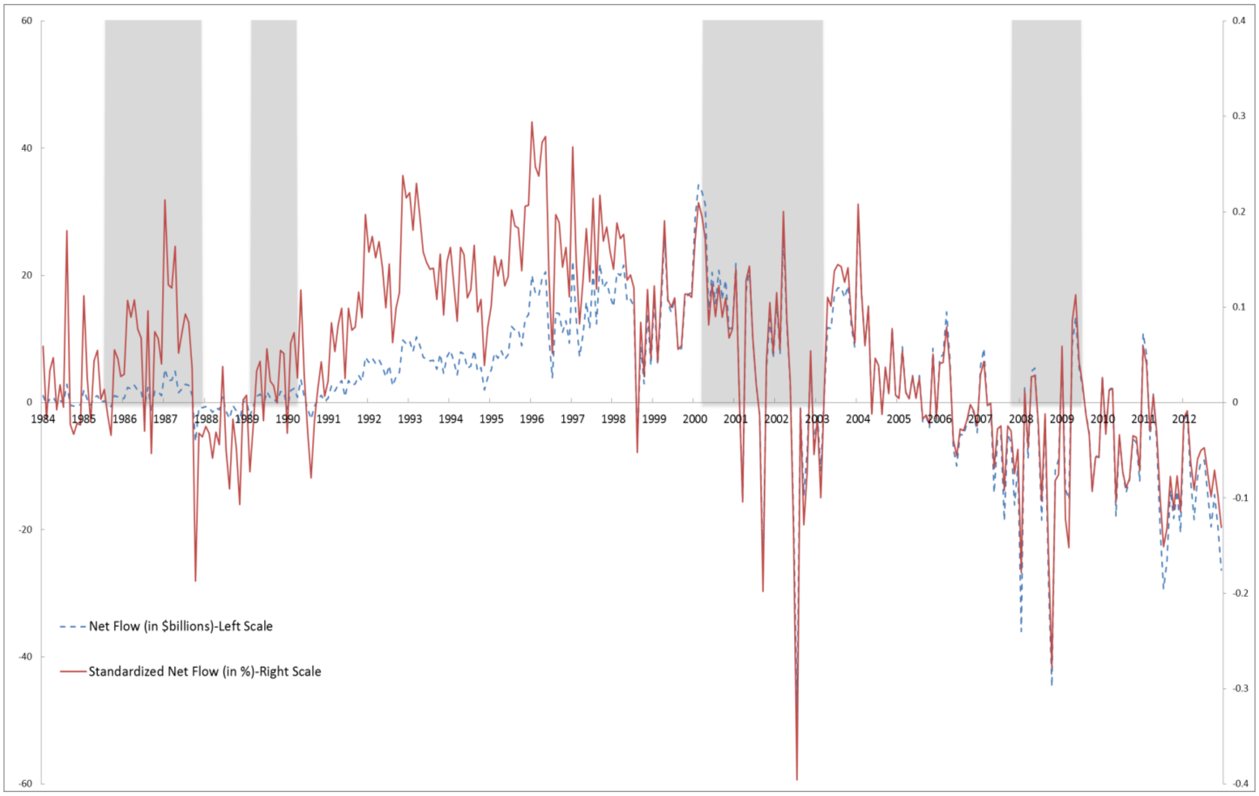


Figure 1.1. Aggregate Mutual Fund Flows and Macro Funding Conditions. This figure plots the dynamic of net and standardized monthly flows into domestic equity funds provided by the Investment Company Institute (ICI). I standardize flows by the total market value of the previous month using the CRSP stock market index from CRSP. The sample period is from January 1984 to December 2012. The shaded vertical bars represent poor macro funding states defined by Excess Bond Premium (EBP).

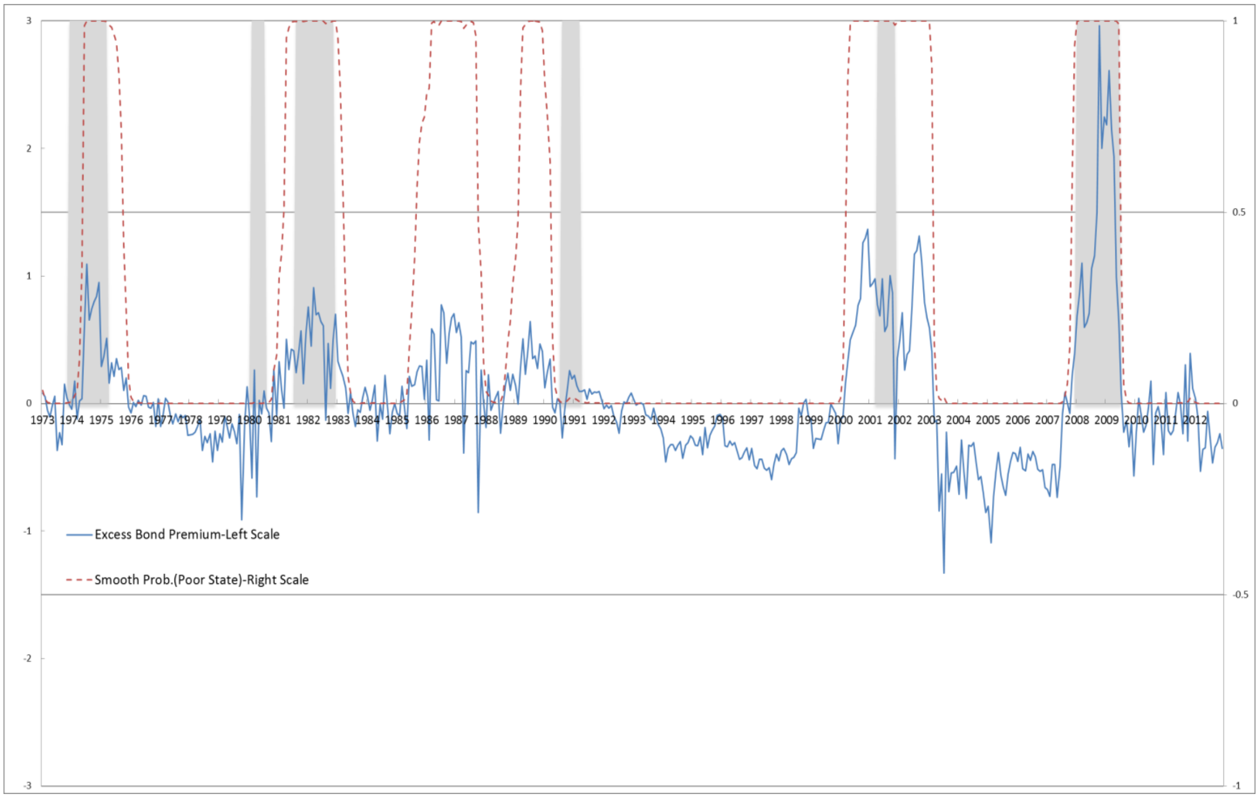
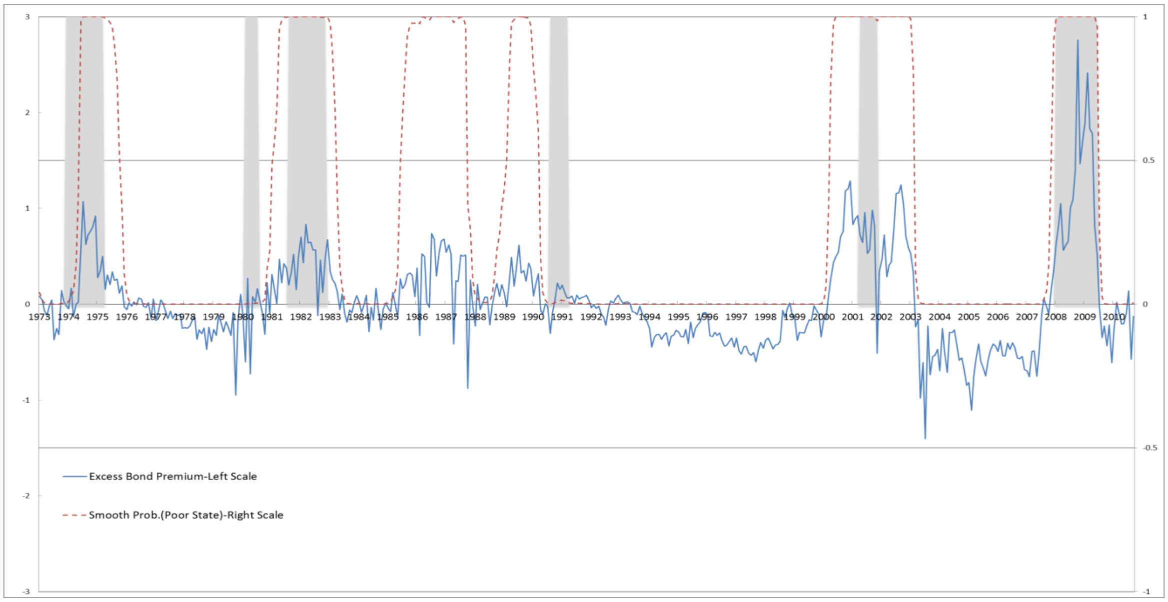


Figure 1.2. Excess Bond Premium and Macro Funding Conditions. The solid line depicts the excess bond premium. The dashed line the probabilities of poor macro funding conditions which is detected by two-state Markov regime switching model. The shaded vertical bars denote the NBER-dated recessions. The sample period is January 1973 to December 2012. The units of left scale are percentage points.

Panel A: Credit Conditions and Business Cycle



Panel B: Credit Conditions and Market States

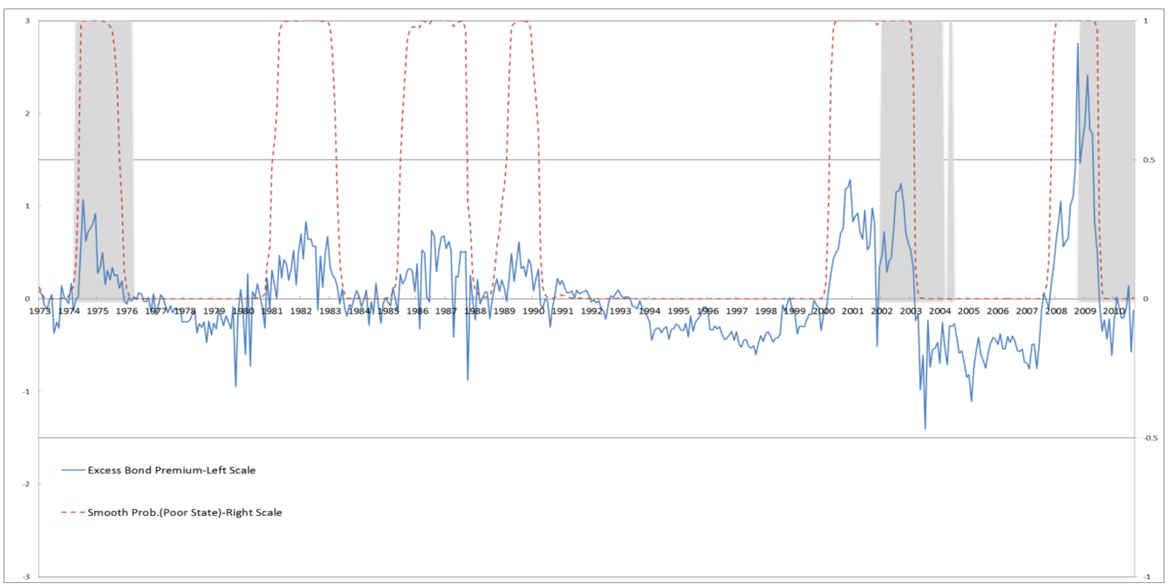


Figure 2.1. Excess Bond Premium and Credit Conditions. The solid line in both panels depicts the excess bond premium. The dashed line in both panels depicts the probabilities of poor credit conditions which is detected by two-state Markov regime switching model. The shaded vertical bars in Panel A denote the NBER-dated recessions. The shaded vertical bars in Panel B denote DOWN markets, the periods when the lagged 3-year stock market return is negative. The sample period is January 1973 to September 2010. The units of left scale are percentage points.