Fast and slow arbitrage:

Smart money, dumb money and mispricing in the frequency domain

XI DONG

NAMHO KANG

JOEL PERESS*

February 2019

*Dong: Baruch College, City University of New York, Department of Economics and Finance. Email: Xi.Dong@baruch.cuny.edu. Kang: Bentley University, Finance Department. Email: nkang@bentley.edu. Peress: INSEAD, Boulevard de Constance, 77300 Fontainebleau, France. Email: joel.peress@insead.edu. We thank Stefano Giglio for helpful comments and suggestions.

Fast and slow arbitrage:

Smart money, dumb money and mispricing in the frequency domain

February 2019

Abstract

We conduct a spectral analysis of the relation between capital flows and mispricing. Hedge funds (smart money) and mutual funds (dumb money) both behave as low-pass filters, deploying high-frequency flows towards low-frequency mispricing in opposite directions. But hedge funds attenuate high-frequency flows twice as much as mutual funds do, thus improving market efficiency more slowly than mutual funds exacerbating market inefficiency. Time-series and cross-sectional tests indicate that transaction and implementation costs are the reason hedge funds particularly behave as low-pass filters.

Key words: Pricing anomalies; Market efficiency; Mutual funds; Hedge funds; Slow-moving capital; Transaction costs; Spectral analysis

1. Introduction

A large body of evidence indicates that mutual funds are "dumb money" in that they exacerbate stock market anomalies, whereas hedge funds are "smart money" that attenuates them. Less is known about how the relation between fund flows and mispricing might vary across frequencies, despite good reasons to believe that investors might favour certain frequencies over others.[1] Consider hedge funds. On the one hand, they are reluctant to tie their limited capital for long spells of time. On the other hand, transactions fees of various types make it costly to move in and out of positions frequently. Consistent with the former view, there is ample evidence that high-frequency mispricing is eliminated in fractions of a second (see the growing empirical literature on high-frequency trading). In line with the latter view, capital has been documented to move slowly towards mispricing (see, e.g., the discussion in Duffie (2010) and the illustrations therein).[2]

In this paper, we study whether hedge funds (resp., mutual funds) are more prone to exploit (resp. amplify) pricing anomalies at high or low frequencies. Specifically, we answer three questions. First, are the contributions of flows to mutual and hedge funds' capital spread evenly across frequencies? Second, is mispricing uniformly represented across frequencies? The answer to either question is not *a priori* clear—we provide in Section 2 examples of forces driving these series at either high or low frequency. Finally, and most importantly, how does the relation between fund flows and mispricing vary across frequencies? Putting it differently, does dumb money amplify mispricing at all

[1] A stationary time series can be decomposed into a combination of uncorrelated random waves (or sinusoids) using Fourier analysis. Each wave is characterized by a cycle length (a.k.a. wavelength or period) which measures the length of time required for one full cycle, or equivalently, by a *frequency* which measures the number of cycles per unit time. As an analogy, white light can be decomposed into seven colours (a spectrum), each corresponding to a different frequency, using a prism. This decomposition is known as a series' "spectral representation", and this approach is referred to as "spectral analysis" or analysis in the "frequency domain", in contrast to the time domain approach.

[2] One striking example cited by Duffie (2010) are index exclusions. When a stock is deleted from the S&P500 index, its price declines by approximately 14% over the 7.5 days from the announcement to the effective deletion date. These losses are entirely wiped out over the next 60 days as the price reverts to its pre-announcement level.

frequencies to the same degree? And, does smart money exploit low- and high-frequency mispricing equally effectively? These questions allow to assess whether, and how, market efficiency varies across frequencies, and thus shed light on the sources of inefficiencies. For example, we can tell whether arbitrage capital is slow-moving (and hence pricing anomalies slowly corrected) because capital is slowly supplied to hedge funds (i.e., at low frequency), or because hedge fund managers are slow in deploying their capital towards pricing anomalies (i.e., they choose to slowly correct mispricing).

To answer these questions, we decompose hedge fund flows, mutual fund flows and anomaly returns in the frequency domain, and then study how flows and returns are related. The essence of this frequency decomposition is to identify the slow-moving (i.e., persistent) and fast-moving (i.e., transitory) parts of a time series. We measure smart money and dumb money as the aggregate net flows to hedge funds and mutual funds, respectively. We proxy for mispricing as the returns on the long-minus-short strategy based on the eleven anomalies documented in Stambaugh, Yu and Yuan (2012, 2014), to which we refer as "SYY anomalies".[3] We do not explicitly examine individual stock trades which are hard to assign to specific frequencies, not least because their returns plausibly span more than one frequency;[4] instead, we focus on how asset managers invest/divest capital in response to flows in/out of their funds and on the aggregate return patterns that trades generate. In our analysis, we loosely interpret a group of funds as a "*filter*" that receives capital (flows) over a range of

[3] These anomalies are: Failure Probability (Campbell, Hilscher, and Szilagyi 2008), O-score (Ohlson 1980), Net Stock Issuances (Ritter 1991 and Loughran and Ritter 1995), Composite Equity Issuance (Daniel and Titman 2006), Accruals (Sloan 1996), Net Operating Assets (Hirshleifer, Hou, Teoh, and Zhang 2004), Momentum (Jegadeesh and Titman 1993), Gross Profitability (Novy-Marx 2013), Asset Growth (Cooper, Gulen, and Schill 2008), Return on Assets (Chen, Novy-Marx, and Zhang 2010), and Investment-to-Assets (Titman, Wei, and Xie 2004). We also use, as an alternative proxy for mispricing, returns based on the first seven anomalies of this list which are unrelated to real investment, because these anomalies are shown to be more closely related to mutual and hedge fund flows (Akbas et al. (2015).

[4] A strategy's holding period or rebalancing frequency need not correspond to the frequency at which its returns accrue. Consider, for example, Warren Buffet's investment in a stock, say Apple. Marking-to-market this portfolio leads to profits or losses at all frequencies–including the highest, in synch with fluctuations in Apple's stock price. Yet, as an exemplary long-term investor, Warren Buffet would not adjust his position in Apple in reaction to short-term price variations. On the other hand, consider a successful high-frequency-trader who generates small but consistent profits on her positions. Although the investor's holding period might be a few seconds or less, her profits might accrue over lower frequencies, such as the business-cycle frequency, due, for example, to rising correlations across assets.

frequencies, and selects, through its trading strategies, the frequencies of its profit (returns). In other words, funds select which frequencies to pass on to the equity markets and which ones to attenuate. Consistent with the industry's common practice of evaluating and reporting performance annually, we refer to periods of one year or longer as "low frequency" and to periods below one year as "high frequency"; but our focus is on differences between low and high frequencies regardless of the specific cutoff chosen for classifying frequencies.

Our findings are fourfold. First, studying the frequency profiles of net flows, we document that low-frequency flows account for roughly half (45%) of the total variation of flows for hedge fund, vs. roughly two-thirds (61%) for mutual funds. Thus, smart-money investors supply capital to hedge fund managers roughly equally at low and high frequencies, whereas dumb-money investors supply capital mostly at low frequency. These findings suggest that capital from mutual fund investors moves more slowly than does capital from hedge fund investors.

Second, turning from the filters' input (i.e., flows) to the filters themselves, we find that both types of funds behave, in aggregate, as low-pass filters: time-series regressions of low- and high-frequency anomaly returns on flows yield coefficient estimates that are larger in absolute value for the former than for the later. In other words, fund managers allocate their capital—even capital which flows at high-frequency—predominantly to correct mispricing at low-frequencies. As a comparison, funds would behave as a passthrough filter if they deployed net flows as soon as they receive them, i.e., if coefficient estimates were the same for regressions of low-frequency anomaly returns on low-frequency flows as for regressions of high-frequency anomaly returns on high-frequency flows. In terms of magnitudes, hedge funds correct mispricing at low frequencies five to ten times more than they do at high frequencies. Likewise, mutual funds amplify mispricing 2.6 times more at high frequencies. These findings suggest that flows of both smart and dumb money toward mispriced stocks are slowed down by managers who do not deploy capital immediately.

These estimates lead us to our third finding: hedge funds are a more selective (low-pass) filter than are mutual funds. While both types of funds treat low-frequency flows in a similar way, they differ markedly in the degree to which they attenuate high-frequency flows. Quantitatively, a one standard deviation increase in hedge fund flows leads to a correction in anomaly returns of 41% and 8% of a standard deviation at low and high frequency, respectively. For mutual funds in contrast, a one standard deviation increase in flows leads to an amplification in anomaly returns of 43% and 17% of a standard deviation, at low and high frequency, respectively. Hence, the attenuation factor (i.e., the degree of attenuation of high-frequency flows relative to low-frequency flows) is about twice as large for hedge funds as it is for mutual funds (specifically, 1.9 = (41%/8%)/(43%/17%)). This finding suggests that hedge fund managers deploy capital more slowly than do mutual fund managers, thereby improving the efficiency of financial markets more slowly than mutual funds degrade it.

We hypothesize that funds, particularly hedge funds, behave as a low-pass filter because of transaction and implementation costs. According to theory indeed, partial and gradual trading is optimal in the presence of such costs. For example, traders should adjust their portfolio towards their desired target only partly (e.g., Garleanu and Pedersen 2013, 2016), and smooth trades to reduce price impact if they are superiorly informed (e.g., Kyle 1985; Kyle et al. 2017). The lower attenuation factor we report for mutual funds compared to hedge funds might be caused by the former enjoying less discretion than the latter in timing their trades due to the daily settlement of mutual fund redemptions and purchases.

Therefore, our fourth set of tests investigates the role of transaction and implementation costs in slowing down the deployment of capital. Exploiting variations in transaction costs over time and in the cross-section of hedge funds, we obtain the following results. First, we find that hedge funds' attenuation factor (i.e., their tendency to correct low- rather than high-frequency mispricing) rises in times of low aggregate liquidity, during recessions and under adverse market conditions as measured by high levels of the VIX index or TED spread. Second, we examine how the attenuation factor changes in response to two liquidity shocks, one favorable and the other adverse. We find that the attenuation factor drops sharply following decimalization (which led to improvements in liquidity)[5], whereas it rises strongly during the financial crisis (when liquidity dried up). This pair of findings points to transaction and implementation costs as a likely cause for hedge fund's choice to behave as a low-pass filter. Third, we document that the correction of low-frequency mispricing is mostly attributable to hedge funds with high share restrictions (e.g., lockups), indicating that such restrictions are an effective tool for redirecting high-frequency capital towards low-frequency anomalies. Fourth, carrying out our test on anomalies with signals (namely, one-month industry momentum, one-month return reversal, and one-month industry-adjusted reversal) that are less persistent than those of the SYY anomalies yields insignificant results. This is consistent with the models such as Garleanu and Pedersen (2013, 2016) in which traders' optimal strategy is to curtail trading more when signals persist more. Moreover, we find only weak evidence that transaction costs matter for mutual funds. This is consistent with the aforementioned models to the degree that these models apply to smart (informed) traders, not dumb (noise) traders.

Collectively, our findings suggest that smart money (arbitrage capital) is slow-moving not because hedge fund investors are slow in channelling capital to funds but rather because hedge fund

[5] In 2001 the Securities and Exchange Commission (SEC) reduced the minimum tick size from a sixteenth of a dollar to a hundredth of a dollar. The move to decimalization lead to tighter bid-ask spreads and improved market liquidity significantly (Goldstein and Kavajecz 2000, Bessembinder 2003, Furfine 2003, Chordia, Roll, and Subrahmanyam 2008). Several studies exploit this event to identify the causal impact that liquidity might exert on various aspects of assets and trading (e.g., Chordia, Roll, and Subrahmanyam 2008, Fang et al. 2009).

managers deliberately ignore fast-moving anomalies and target instead slow-moving ones, a behaviour which we interpret as managers being slow in deploying their capital toward pricing anomalies. In other words, arbitrage capital moves relatively quickly from hedge fund investors to hedge fund managers, but slowly from hedge managers to pricing anomalies.

A likely explanation given our evidence is that transactions costs deter managers from frequently moving in and out of anomalies. For mutual funds, capital moves more slowly from investors to managers than for hedge funds, but then its allocation to mispricing is slowed down less by managers. The difference in behaviour between hedge fund and mutual fund managers might plausibly be explained by the latter enjoying less discretion than the former. Indeed, the daily settlement of mutual fund redemptions and purchases makes it costly for mutual fund managers to delay trades.

That hedge fund managers target low-frequency anomalies more than high-frequency ones, and that this bias is more pronounced for hedge fund managers than for mutual fund managers might be viewed as "good news" for market efficiency. Indeed, it suggests that hedge fund managers improve the efficiency of financial markets over long horizons where, presumably, it matters most. In contrast, high-frequency traders are credited for improving market efficiency over fractions of a second, leading critics to question their social value (e.g., Biais et al. 2015, Budish et al. 2015).

The remainder of the paper is organized as follows. Section 2 reviews the related literature and discusses our contribution. Section 3 describes the methodology we employ for our spectral analysis, and Section 4 the data and variables. We present the frequency structures of fund flows and mispricing in Section 5, and of their relation in Section 6. Section 7 investigates the role of transactions cost. Section 8 concludes.

2. Related literature and contribution

Our contribution to the literature on market efficiency is twofold. First, we shed light on the dynamics of market efficiency over different frequencies and on the differential roles played for such dynamics by market participants, namely hedge funds and mutual funds. Our findings imply that mispricing is more likely to be eliminated by arbitrage at low frequency and to survive it at high frequency. Thus, in the context of the market efficiency debate, and given the major role played by hedge funds for arbitrage, our results provide a rationale for higher market efficiency at low frequency than at high frequency.]

We build on the empirical literature documenting that flows to asset managers affect mispricing. Specifically, flows to mutual funds and hedge funds are associated, respectively, with a worsening and a correction of mispricing (e.g., Akbas et al. (2015)). In addition, Agarwal et al. (2009) show that funds with a higher degree of managerial discretion, approximated by longer lockup and redemption notice periods, deliver superior performance, and some of these excess returns can be attributed to the anticipation of mutual fund flows and trades. We add to these studies by examining how these flows, mediated by asset managers, affect market efficiency across different frequencies.

The importance of understanding investments and asset returns in the frequency domain is now recognized by a nascent literature. On the theory front, several models have been recently proposed to work out the implications of trades' frequency profiles for asset pricing (Dew-Becker and Giglio (2016), Crouzet, Dew-Becker, and Nathanson (2017)). On the empirical front, studies conduct spectral analyses of consumption risk (Ortu, Tamoni, and Tebaldi, 2013, Bandi and Tamoni (2014)), of trading activities over various horizons (Chinco and Ye (2016)), and of strategies' alphas and betas (Chaudhuri and Lo (2016, 2018), and Bandi, Chaudhuri, Lo, and Tamoni (2018)). The relation between market efficiency and capital flows to asset managers had not yet been examined through the lens of frequencies. Our spectral analysis contributes not only qualitatively but also quantitively to the understanding of the dynamics of market efficiency and of the distinct roles played by market participants.

Several recent studies point out a puzzle that the returns of anomalies/factors tend to exhibit pervasive positive autocorrelation, i.e., factor momentum that lasts over one year, and call for understanding of this puzzle (See particularly Sina and Linnainmaa (2019), as well as Mclean and Pontiff (2016); Avramov et al. (2017); Arnott et al. (2019)). Such factor momentum can explain important mispricing such as various manifestations of individual stock momentum and industry momentum. Our finding that arbitrage capital persistently corrects anomaly-based mispricing at frequencies higher than one year provides both qualitive and quantitative understanding of this puzzle. It provides one rationale that why anomaly returns exhibit positive autocorrelation and why such time-series factor momentum can last longer than one year.

Our second contribution to the market efficiency literature concerns the importance of transactions/implementation costs in allowing mispricing or anomalies to survive. Indeed, a central question in the market efficiency literature is whether these costs are large enough to deter arbitrage activity. So far, studies disagree on the economic relevance of these costs. Much of the disagreement stems from differences in samples and methodologies used across studies. One strand simulates (in broad datasets such as TAQ) strategies followed by practitioners, often extrapolating price impact estimates from small to large trades, and concludes that these costs are large enough to wipe out arbitrage profits (e.g., Lesmond, Schill, and Zhou (2004), Korajczyk and Sadka (2004), and Novy-Marx and Velikov (2016)). Another strand examines (in proprietary datasets) the actual implementation algorithms followed by selected asset managers and reports that their costs are low, and thus that arbitrage profits are sizeable (e.g., Keim and Madhavan (1997), Engle, Ferstenberg, and Russell (2012), and Frazzini, Israel, and Moskowitz (2018)). One interesting insight by DeMiguel et al. (2018) is that transaction costs do not matter much for exploiting individual anomalies once these anomalies are combined, because the trades in the underlying stocks required to rebalance anomaly portfolios often cancel out. The discussions in this literature centre on the plausibility of the strategies and the costs simulated by the former strand of papers, and the representativeness of the practitioners studied by the latter.

We contribute to this stream of research by identifying the impact of transactions/implementation costs in a broad universe of hedge funds while remaining agnostic on the form and magnitude of these costs. Our spectral decompositions allow us to evaluate the role of transaction costs on arbitrage empirically in the frequency domain. Specifically, under the null hypothesis that transactions/implementation costs do not matter, capital, given its limited supply, should be invested/divested as soon as if flows into/out of funds. As a result, the null predicts that hedge fund flows and their effect on mispricing are in synch: high-frequency (resp., low-frequency) flows are associated with a correction of mispricing at high frequency (resp., low frequency), and at that frequency only. A related null hypothesis is that transaction costs matter little when comparing with alternative economic considerations such as time-sensitive information, competition among the informed, and the fact that fast-decaying anomalies may be more profitable than slow-decaying ones.[6] In that case, arbitrageurs "bite the bullet" and trade quickly before profits are eroded away through public information disclosures or by competitors (e.g., Holden and Subrahmanyam, 1992). This predicts that hedge fund flows mainly correct mispricing at fast frequency or correct fast-decaying mispricing.

[6] For example, Daniel, Hirshleifer, and Sun (2018) show that fast-decaying mispricing has higher Sharpe ratio than slow-decaying mispricing. Hong, Li, Ni, Scheinkman, and Yan (2015) also report that the one-month reversal anomaly appears to have larger alpha and *t*-statistic than the more slowly-decaying anomalies they examine.

Our alternative hypothesis is that costs matter but differently so across frequencies. That is, arbitrageurs prefer correcting mispricing slowly, i.e., at low frequency, irrespective of the frequency at which capital flows in/out of their funds. Indeed, theory indicates that spreading trades over time can lower the trading costs for a given total trading amount over the entire period (e.g., Garleanu and Pedersen (2013, 2016), Kyle et al. (2017), Buss and Dumas (2017). Furthermore, such slow trading implies that arbitrageurs prefer correcting slow-decaying mispricing to correcting fast-decaying mispricing of similar magnitude. According to theory, transactions/implementation costs matter more for price anomalies that decay/mean-revert fast (transient) than they do for those that decay slowly (persistent) (e.g., Garleanu and Pedersen (2013, 2016)). Note that, in this hypothesis, transaction costs need not reduce total trading volume/turnover; arbitrageurs need not reduce their rebalancing frequency either. Arbitrageurs might simply spread their trades over a longer period of time, but their rebalancing/trading direction need be persistent. That is, they rebalance every month for many months ahead by gradually entering and existing mispriced stocks. As a result, the mispricing correction is also gradual and persistent.

Our finding that arbitrage on mispricing concentrates in low frequency, as well as in slow-decaying anomalies, despite arbitrage capital flowing to hedge funds at all frequencies, shed light on not only whether transactions costs hinder arbitrage but also how they hinder arbitrage in the frequency domain; they also explain why mispricing at high frequencies, as well as transient/short horizon mispricing, may be more profitable in the near term as there is insufficient immediate arbitrage capital to eliminate it. Thus, we reconcile the two views described above: transactions costs matter since we observe that arbitrageurs trade in a way to mitigate their burden—namely by not trading on the high-frequency flows they receive, but transactions costs do not explain why low-frequency mispricing survives in spite of arbitrage activity. Our approach borrows the best from each of the two aforementioned strands of research. As the literature that simulates actual trading strategies, it is based on a broad and unbiased universe of arbitrageurs. As in the studies of select asset managers, it does not take a stand on trading strategies nor transactions costs, examining instead the return implications of actual hedge fund trades. In that respect, our approach is close in spirit to a recent working paper of Patton and Weller (2018), who estimate implementation costs through the comparison of actual mutual fund returns with the on-paper returns to factor exposures, without making parametric assumption on transaction costs. In contrast to theirs, our paper sheds light on whether and how costs matter for trading anomalies in the frequency domain.

3. Frequency Decomposition

In this section, we first motivate the spectral decomposition and then describe our methodology and econometric model.

3.1. Motivation

It is not *a priori* clear whether, and how, anomaly returns, fund flows and their relationship vary across frequencies. There are many effects and forces at play. First, mispricing might worsen/correct at any frequency depending on investors' objectives and trading strategies. For example, an algorithmic trader might specialize in high-frequency price fluctuations, while a value investor might be concerned with long-term price movements. Their trades are likely to affect market efficiency only at the frequency at which they operate (Crouzet et al. 2017). Similarly, investment capital is supplied to and redeemed from asset managers over various frequencies. For example, many mutual funds' investors contribute regularly to retirement accounts with restricted redemptions, producing low-frequency flows; on the other hand, particular features of mutual funds, such as openness and mark-to-market, encourage investors to move money at high frequencies. Generally, traders differ considerably in their investment horizons and rebalancing frequencies, leading to differential effects on mispricing across frequencies.

In addition, some economic forces tend to accelerate trading or price formation, while others slow them down. For example, competition among informed traders speeds up the incorporation of information into prices (Holden and Subrahmanyam 1992), whereas transaction costs and limited attention push investors to rebalance infrequently, thereby inducing predictable patterns in prices at specific frequencies (Bogousslavsky 2016; Gao, Han, Li, and Zhou 2018). News too is delivered over various frequencies, generating return cycles matching their delivery frequencies (e.g., quarterly earnings announcement in Linnainmaa and Zhang (2018), and bi-weekly FOMC announcements in Cieslak, Morse, and Vissing-Jorgensen (2018)).

Because of these conflicting effects, it remains an empirical question which frequencies will dominate in the spectra of returns, flows and of their relation. These considerations motivate us to analyze the series in the frequency domain.

3.2. Decomposing Mispricing and Flows

Our analysis relies on decomposing any given stationary time series, X_t (i.e., flows or returns) for t = 1,…, T, as follows:

$$X_t = X_t^L + X_t^H, \tag{1}$$

where X^L_t is the slow-moving (a.k.a. low-frequency) component of X_t, representing cycles longer than a threshold value (e.g., one year in our analysis), and X^H_t is the fast-moving (a.k.a. high-frequency) component that captures shorter cycles. X^L_t and X^H_t are orthogonal, therefore, $Cov(X^L_t, X^H_t)$ is zero.

Such a decomposition can be performed using a Fourier transformation. Specifically, letting $\omega_k = 2\pi k/T$ denote the Fourier frequencies for k = 0,....,N, where N = T-1, the Fourier transform of X_t is given by

$$J_x(\omega_k) = \frac{1}{T}\sum_{t=1}^{T} X_t e^{-i\omega_k t}, \tag{2}$$

where $J_x(\omega_k)$ is the Fourier component of X_t at frequency ω_k. The inverse Fourier transformation allows to recover the original time series such that

$$X_t = \sum_{k=0}^{N} J_x(\omega_k) e^{i\omega_k t}. \tag{3}$$

Now that X_t is expressed as a linear combination of orthogonal components of different frequencies, we can split X_t into distinct time series, each corresponding to a subset of frequencies, or frequency band. First, we create a filter, F_K, a vector of size N, for frequency band K. $F_K(k) = 1$ if k belongs to K, and zero otherwise. We define K = L (resp., H), where L (resp., H) is a low (resp., high) frequency band. In our empirical analysis, we shall consider two frequency bands: Thus, F_L is a low-pass filter, while F_H is a high-pass filter. Next, we apply the filter F_K to X_t to obtain X^K_t as follows:

$$X_t^K = \sum_{k \in K} J_x(\omega_k) e^{i\omega_k t}. \tag{4}$$

The variance of X^K_t can be calculated using either the time-series variance, or the sample spectrum as follow:

$$Var(X_t^K) = \sum_{k \in K} J_x(\omega_k)\overline{J_x(\omega_k)}\,, \tag{5}$$

where the overbar denotes complex conjugate. Thus, $Var(X^K_t)$ is the portion of the sample variance of X_t that can be attributed to the subset of frequencies in K.

To analyse the covariance structure between fund flows and anomaly returns at different frequencies, we estimate the cospectrum. Given another stationary time series, Y_t, the cospectrum between X_t and Y_t is defined as:

$$CO = \frac{1}{T}\sum_{t=1}^{T} X_t Y_t = \sum_{k=0}^{N} J_X(\omega_k)\overline{J_Y(\omega_k)}. \tag{6}$$

The two time series may be in phase (i.e., have peaks and troughs that match) at some frequencies and out of phase at other frequencies. Therefore, even if the covariance between X_t and Y_t is positive, the cospectrum can be negative at certain frequencies. For example, if flows and anomaly returns are in phase at low frequency, then the contribution of that frequency to the covariance between flows and anomaly returns is positive; if they move out of phase, the contribution is negative. The cospectrum for the frequency band K is given by

$$CO_K = \sum_{k \in K} J_X(\omega_k)\overline{J_Y(\omega_k)}. \tag{7}$$

Alternatively, one may adopt a regression approach to evaluate the association between the two variables at various frequencies. Specifically, one can estimate the following regression:

$$Y_t = \alpha + \beta_L X_t^L + \beta_H X_t^H + \varepsilon_t. \tag{8}$$

In this regression, β_K is estimated as $COV(X^K_t, Y_t)/Var(X^K_t)$, where K = L or H. Thus, the beta estimate for each frequency band yields an estimate of the relative contribution of various frequencies to the covariance of the two time series. Since $Y_t = Y^L_t + Y^H_t$, and low-frequency components are orthogonal to high-frequency components, β_K can be experssed as $COV(X^K{}_t, Y^K{}_t)/Var(X^K{}_t) = CO_K/Var(X^K{}_t)$.

The regression approach has several advantages. First, it is intuitive and easy to implement. Second, it extends naturally to a multivariate approach, thus allowing to include control variables in the analysis.

4. Data and Variable Construction

Three main variables are used in our analyses: i) anomaly returns to proxy for aggregate cross-sectional mispricing, ii) aggregate mutual fund flows to proxy for dumb money, and iii) aggregate hedge fund flows to proxy for smart money. In this section, we describe all three variables as well as the control variables used in our tests.

4.1. Anomalies and Mispricing

Mispricing Proxies:

Following Stambaugh, Yu, and Yuan (2012, 2014), we use a set of 11 prominent cross-sectional return anomalies to measure aggregate mispricing. These anomalies include: Failure Probability (Campbell, Hilscher, and Szilagyi 2008), O-score (Ohlson 1980), Net Stock Issuances (Ritter 1991 and Loughran and Ritter 1995), Composite Equity Issuance (Daniel and Titman 2006), Accruals (Sloan 1996), Net Operating Assets (Hirshleifer, Hou, Teoh, and Zhang 2004), Momentum (Jegadeesh and Titman 1993), Gross Profitability (Novy-Marx 2013), Asset Growth (Cooper, Gulen, and Schill 2008), Return on Assets (Chen, Novy-Marx, and Zhang 2010), and Investment-to-Assets (Titman, Wei, and Xie 2004). These anomalies have been extensively shown to generate alpha in standard risk models. Akbas et al. (2015) document that the relation between fund flows and SYY anomaly returns is driven by non-investment anomalies (the first 7 in the above list) rather than by anomalies related to real investments (the last four). Therefore, we also estimate aggregate mispricing using non-investment anomalies only. Henceforth, we refer to these anomalies as "NINV anomalies".

Assuming that at least part of an anomaly's return predictability is due to mispricing, then we can identify the relative degree of mispricing in the cross section by sorting stocks into deciles based on the anomaly characteristic. Stambaugh, Yu, and Yuan (2014) show that returns to the individual anomalies have low correlations with each other, yet are relatively highly correlated with the aggregate returns to a long-short strategy that combines the 11 anomalies into a single signal. This suggests that each of the 11 components captures a different element of cross-sectional mispricing. Therefore, rather than considering individual anomalies, we follow Stambaugh, Yu, and Yuan (2014) and construct an aggregate mispricing measure to identify stocks that are overvalued or undervalued at the end of each calendar month. Using all 11 characteristics together is justified by the fact that hedge funds normally do not trade on single anomalies, and that the aggregate mispricing measure "diversifies away [the] noise in each individual anomaly and… increases precision" (Stambaugh, Yu, and Yuan, 2014).

To construct this aggregate mispricing measure, we proceed in three steps. First, each month, we sort all stocks in our sample according to their future returns as predicted by each of the anomalies. Each stock, therefore, is assigned 11 different deciles ranks each month, one for each anomaly. Second, we compute an aggregate score for each stock and month, based on the equal-weighted average of the decile ranks.

If a stock is mispriced in the current month, the mispricing is expected to be corrected next month on average. Therefore, undervalued (resp., overvalued) stocks are expected to realize high (resp., low) returns in the subsequent month. The scoring is performed in such a way that stocks with higher scores are expected to earn higher average returns over the next month whereas stocks with lower scores are expected to earn lower average returns. Therefore, in the final step of our procedure, we construct a long-short portfolio that takes long positions in the most undervalued stocks (those in the top decile) and short positions in the most overvalued stocks (those in the bottom decile).

Mispricing Correction or Exacerbation

That mispricing is corrected *on average* over time does not imply that it is corrected *every month*. At times, mispricing can be exacerbated. By tracking the returns of the long-short strategy, as well as the long and the short legs during the post-ranking calendar month, we can determine if mispricing becomes corrected or exacerbated.

Specifically, stocks in the short leg are classified as overvalued at the end of month t. If the return to the short leg during month t+1 is positive, then it suggests that overvalued stocks continue appreciate and become even more overvalued. Similarly, stocks in the long leg are classified as undervalued at the end of month t. A negative the return to the long leg in month t+1 therefore indicates that mispricing worsens.

Thus, during months when aggregate mispricing is exacerbated, the long leg realizes negative returns, the short leg realizes positive returns, and the returns of the long-short strategy are negative. Conversely, during months when aggregate mispricing is corrected, the long leg realizes positive returns, the short leg realizes negative returns, and the returns of the long-short strategy are positive.

In the data, the monthly returns to the long leg, the short leg, and the long-short strategy are, *on average*, positive, negative, and positive, respectively. This means that, *post ranking*, the mispricing correction effect dominates the mispricing exacerbation effect. That is, mispricing is attenuated on average during month *t*+1 after it is identified by the aggregate mispricing measure at the end of month *t*.

4.2. Flows to Mutual Funds and Hedge Funds

We use aggregate hedge fund and mutual fund flows to proxy for smart money and dumb money, respectively. Following the literature, the monthly aggregate fund flows to mutual funds (MF) and hedge funds (HF) are computed as

$$MF_t\ (or\ HF_t) = \frac{\sum_{i=1}^{N} TNA_{i,t} - TNA_{i,t-1}\left(1 + R_{i,t}\right)}{\sum_{i=1}^{N} TNA_{i,t-1}}, \tag{9}$$

where $TNA_{i,t}$ is the total net asset of fund *i* in month t, and $R_{i,t}$ is the return of fund *i* over month *t*.

To construct MF, we obtain monthly total net assets and returns from the CRSP Survivor-Bias-Free US Mutual Fund database. We follow the procedure described in Huang, Sialm, and Zhang (2011) to select funds that primarily invest in the U.S. equity market. Specifically, we only choose funds with Lipper objectives that are related to the domestic equity market, therefore eliminate balanced, bond, money market, international, and index funds.

We obtain hedge fund returns and net asset value from Lipper TASS database. As with our mutual fund sample, we focus on hedge funds that primarily trade in the U.S. equity market. Therefore, we only include funds denominated in U.S. dollars and exclude funds whose strategies are emerging market, fixed income, fund of funds and managed futures.

4.3. Control Variables and Other Data

The stock sample includes all common stocks listed on NYSE, AMEX, and Nasdaq over the period from January 1994 to December 2013. The sample period starts in 1994 due to the availability of monthly hedge fund flow data.

For our analyses, we control for aggregate liquidity and commonly used risk factors. *Amihud* is the equally-weighted average Amihud (2002) illiquidity measure of all common stocks listed on the NYSE in month *t*. *Turnover* is the equally-weighted average turnover of all common stocks listed on the NYSE in month *t*. *MKTRF* is the monthly return of the market in excess of the risk-free rate. *HML* and *SMB* are the monthly returns to the value and the size strategies, respectively.

5. Descriptive Statistics and Frequency Structure

5.1. Descriptive Statistics

Table 1 displays summary statistics and the variance decomposition of anomaly returns and fund flows. Panel A shows the descriptive statistics, while Panels B and C report the correlations among main variables. Panel D calculates the variance decomposition of returns and fund flows in the frequency domain.

The average returns on the SYY and NINV anomalies are 2% and 1.6%. per month, respectively. These average returns are statistically significant with t-statistics of 6.28 and 4.08, respectively, indicating a long-minus-short strategy would be profitable before transaction costs. However, variations in anomaly returns over time are sizable, with standard deviations of 4.9% for SYY and 6.1% for NINV. The monthly average flows to mutual funds and hedge funds—0.3% and 0.5% respectively—are relatively similar. In contrast, their standard deviations—0.5% and 1.9% respectively—are not, with flows of hedge fund almost four times more volatile those of mutual fund. This suggests that hedge fund investors supply or withdraw capital much more frequently than do mutual fund investors.

The table also provides descriptive statistics for decomposed time series. Fund flows and anomaly returns are decomposed in the frequency domain based on the methodology in Section 2.

For each time series X_t, we calculate X^L_t and X^H_t as in Equations (1) and (4), where the two components are orthogonal to each other. The variables with the suffix of "-LOW" are the time series that are re-constructed from frequencies that have cycles of one year or longer, while the variables with the suffix of "-HIGH" are re-constructed time series from frequencies that have cycles shorter than one year but equal to or above one month. Due to data limitation (we do not have data on flows at frequencies smaller than a month), our highest frequency is one month.

Panel A shows that anomaly returns are more volatile at high-frequency than at low-frequency. For example, the standard deviation of SYY-LOW is 2.3% vs 4.3% for SYY-HIGH. Figure 1 plots the time series of SYY and NINV, together with their high- and low-frequency components. The low-frequency series allow to spot time patterns that are otherwise difficult to identify. For example, low-frequency anomaly returns increased dramatically after the internet bubble burst in 2000, as mispricing was corrected, and dropped significantly during the financial crisis, implying that mispricing was exacerbated.

The standard deviations of decomposed flows have a different structure from that of decomposed mispricing. The standard deviation of HF-LOW is 1.3%, only slightly smaller than that of HF-HIGH, which is 1.4%. The standard deviation of MF-LOW is 0.4%, higher than that of MF-HIGH, indicating the low-frequency flows is more important in total variation of mutual fund flows. Figure 2 plots the time series of decomposed fund flows. HF-LOW displays patterns similar to those of the low-frequency mispricing series SYY-LOW (e.g., an increase after the internet bubble burst, and a drop during financial crisis). No such similarity is observed for the mutual fund flows series.

Consistent with this observation, Panel B shows that anomaly returns are positively related to hedge fund flows, but negatively related to mutual fund flows. For example, the correlation of SYY with HF is 0.115 (significant at 10%), while its correlation with MF is -0.174 (significant at 1%). The observed correlations are consistent with the notion that hedge funds are smart money while mutual funds are dumb money (For example, Akbas et al., 2015).

Panel C calculates correlations among the low- and high-frequency components of returns and fund flows. While Panel B shows that the correlations between HF and the anomaly returns are positive but only marginally significant, Panel C shows the correlations to be at significantly positive at low frequency. The correlations of HF-LOW with SYY-LOW and NINV-LOW are about twice as big as those reported in Panel B. In contrast, the correlations of HF-HIGH with the high-frequency anomaly returns are indistinguishable from zero, indicating that the positive correlations between HF and the anomaly returns are attributable to low-frequency associations. For MF in contrast, the negative correlations between flows and anomaly returns are mostly driven by high-frequency components.

5.2. Variance Decomposition

The decomposition in Equations (1) and (4) leads to a variance decomposition such that $Var(X_t) = Var(X^L_t) + Var(X^H_t)$ (See Equation (5)). This enables us to estimate the relative contribution of low- and high-frequency bands to the total variance. Panel D reports the variance decomposition results.

The decomposition reveals that our time series have different frequency structures. The variances of anomaly returns are mostly driven by the variance of their high-frequency components. Indeed, the high-frequency components of SYY and NINV anomalies contribute about three times more to the total variance than do their respective low-frequency components. In contrast, for hedge and mutual fund flows, the low-frequency contributions to the total variances is 46% and 61%, respectively. These estimates suggest further that slow-moving components are more important for explaining the variations in mutual fund flows than they are for explaining the variations in hedge fund flows.

Note that percentage flow equals the ratio of dollar flow in month *t* to total net assets (TNA) in month *t*-1. Since the denominator is known in month *t*, the variation of the high- and low-frequency percentage flows in month *t* is driven by the high- and low-frequency dollar flows in month *t*. As a result, the variance contribution of the percentage flows also reflects the contribution of dollar flows.

Figure 3 illustrates the variance decomposition results more in detail. The first column displays the amplitude of each frequency scaled by the sum of all amplitudes, that is, the relative contribution of each frequency to the total variance. The second column displays the cumulative contribution of frequencies. Specifically, for each frequency *k*, $\mathrm{Var}(\Sigma_{k=0}X^{k}_{t})/\mathrm{Var}(X_{t})$ is plotted.

The figure shows that there is a spike in the amplitude at a frequency of 0.3 cycle per year, both for anomaly returns and hedge fund flows, whereas there is no such spike for mutual fund flows. The spike's frequency can be converted into a cycle of 3.3 years, which corresponds approximately to a "business cycle frequency" documented in the real business cycle literature. Thus, the amplitude at that frequency tells us how much monthly variability in returns or hedge fund flows are in sync with the business cycle. For example, the spike at the 0.3 cycle per year contributes more than 10% to the total variance of hedge fund flows.

For the mutual fund flows, the lowest frequency is the most important in explaining total variance, indicating a large portion of mutual fund investors are long-term investors. This observation is sensible, given that a sizeable portion of mutual fund assets under management are tied to retirement accounts, thus restricted from redemption. The low-frequency dominance in the mutual fund flows is displayed also in the second column of the figure. While for anomaly returns the cumulative contribution of frequencies to the total variance is close to the 45-degree line—which corresponds to an equal-contribution benchmark, it is located above the line for fund flows, especially for mutual funds.

6. Frequency Structure of the Relation Between Mispricing and Flows

In this section, we describe our main results on the relation between fund flows and mispricing in the frequency domain. Specifically, as in Equation (8), we regress decomposed returns on decomposed flows and various controls.

Akbas et al. (2015) regress anomaly returns on flows and show that the regression coefficient is positive for hedge funds but negative for mutual funds. Their interpretation is that hedge fund flows correct mispricing, while mutual fund flows exacerbate mispricing. Intuitively, capital inflows (resp., outflows) in a month accompanied by positive anomaly return are an indication that mispricing is corrected (resp., exacerbated). Analyses of funds' trading patterns support this interpretation. Dong, et al. (2018) report that capital supplied to hedge funds is positively related to the intensity of hedge funds' trading on anomalies and to the correction of mispricing. Likewise, many studies document that flow-induced mutual funds' trades exacerbate mispricing (e.g., Coval and Stafford 2007; Frazzini and Lamont 2008; Greenwood and Thesmar 2011; Shive and Yun 2013). Our contribution to that stream of research is to investigate how the relation between fund flows and mispricing might differ over different frequencies. For that purpose, we decompose hedge fund flows, mutual fund flows, and anomaly returns in the frequency domain, and then study their association over distinct frequency bands.

6.1. The Relation Between Fund Flows and Mispricing at Low- and High-Frequency

Table 2 reports the results of regressions of the long-short anomaly returns on fund flows over the low- and high-frequency bands. Panel A uses total fund flows, while Panel B splits them into low- and high-frequency flows. *t*-statistics are calculated based on Newey-West standard errors with 12 lags.

We start by reproducing the findings of Akbas et al. (2015). We regress total anomaly returns on total hedge fund and mutual fund flows, and report the results in the first two columns of Panel A. Both SYY and NINV are significantly and negatively related to mutual fund flows but positively related hedge fund flows, suggesting that mutual funds exacerbate mispricing while hedge funds correct it. These results match those reported in Akbas et al. (2015), both in magnitude and significance.

Next, we decompose anomaly returns into their low- and high-frequency components (SYY-LOW and SYY-HIGH for all 11 anomalies and NINV-LOW and NINV-HIGH for the seven non-investment anomalies) and regress each component on flows. The results in columns three to six of Panel A show that the positive relation between hedge fund flows and anomaly returns in the first two columns is driven by the low-frequency anomaly returns. At high frequency, the positive relation is statistically insignificant and much smaller in magnitude. This suggests that hedge fund flows mainly correct mispricing at low frequency. In contrast, the negative relation between mutual fund flows and anomaly returns obtains for both high- and low-frequency returns with coefficients of comparable magnitudes.

In Panel B, we further decompose fund flows into their low- and high-frequency components, namely HF-LOW and HF-HIGH for hedge funds and MF-LOW and MF-HIGH for mutual funds. The first two columns use the total anomaly returns as the dependent variables. The results indicate that both HF-LOW and HF-HIGH have positive coefficients, indicating that both types of hedge fund flows correct mispricing. However, the effect of HF-HIGH on mispricing is considerably weaker, especially for the NINV anomaly. Turning to mutual funds, both MF-LOW and MF-HIGH have negative coefficients, indicating that both types of flows tend to aggravate mispricing. The effect of MF-HIGH is again weaker than MF-LOW, but the difference across frequencies is smaller than for hedge funds.

The rest of the panel further decomposes mispricing into low- and high-frequency components. The results clearly show that the mispricing correction effect of hedge fund flows occur mainly in the low-frequency band. This difference is more pronounced for NINV anomalies. The regression of NINV-LOW on HF-LOW yields a coefficient estimate of 1.009 with *t*-value of 3.52, compared to (a statistically insignificant) estimate of 0.159 for the regression of NINV-HIGH on HF-HIGH. Turning to SYY anomalies, HF-LOW has the coefficient of 0.730 for SYY-LOW, while the coefficient on HF-HIGH for SYY-HIGH is much smaller at 0.255.

However, unlike hedge fund flows, both low- and high-frequency mutual fund flows exacerbate mispricing. Take SYY for example, at low frequency, MF-LOW has the coefficient of -2.516 with *t*-value of -2.66, while at high frequency, MF-HIGH has coefficient of -2.262 with *t*-value of -2.51. The magnitude of these coefficients are comparable. Since the direct comparison of coefficients can be misleading without accounting for the magnitude of the variation of each variable, we formally evaluate the economic magnitude of coefficients in Table 3.

6.2. Beta Decomposition and Economic Magnitudes

In this section, we interpret the results in Table 2 and discuss the economic magnitude of the coefficient estimates. We start by evaluating the relative importance of these estimates using the following beta decomposition. Consider the regression of a variable Y_t on another variable X_t. Then, the beta of the regression is given by:

$$\beta = \frac{Cov(Y_t, X_t)}{Var(X_t)} = \frac{Cov(Y_t^L, X_t^L) + Cov(Y_t^H, X_t^H)}{Var(X_t)}$$

$$= \frac{Var(X_t^L)Cov(Y_t^L, X_t^L)}{Var(X_t)Var(X_t^L)} + \frac{Var(X_t^H)Cov(Y_t^H, X_t^H)}{Var(X_t)Var(X_t^H)}$$

$$= \frac{Var(X_t^L)}{Var(X_t)}\beta_L + \frac{Var(X_t^H)}{Var(X_t)}\beta_H\,, \tag{10}$$

where $\beta_i \equiv \frac{Cov(Y_t^i, X_t^i)}{Var(X_t^i)}$ for *i=(L, H)* is the beta of the regression of Y_t^i on X_t^i. Thus, the (total) β equals the weighted average of β_L and β_H, where the weights are the contributions of the low- or high-frequency bands to the total variance of X_t. In a regression with no control variable, β, reconstructed from β_L and β_H, is equivalent to β from the univariate regression of Y_t on X_t.[7]

Panel A reports the beta decomposition results, calculating the relative contribution of β_L and β_H to the effect of fund flows on the total mispricing. The panel uses the betas that are reported in the first two columns of Panel B of Table 2. Note that the weight on each beta conforms to the variance decomposition reported in Panel D of Table 1. For example, the weight of HF is 45.9% on β_L and 54.1% on β_H.

The beta decomposition results imply that, for both HF and MF, the low-frequency components are more important to the total fund-flow effect than are high-frequency components. The reconstructed beta on HF for SYY is 0.374, with 67.4% of the effect due to HF-LOW and 32.6% due to HF-HIGH. Likewise, the relative importance of MF-LOW for total effect is much higher partly due to the higher contribution of MF-LOW to the total variance of MF. This implies that the mispricing correction by hedge funds or exacerbation by mutual funds are primarily caused by low-

[7] In our case, adding control variables distorts this relation. We check that we obtain similar results when we exclude control variables from the regressions.

frequency flows. This effect is much more pronounced for NINV, with 86% (73%) of total mispricing correction (worsening) attributable to HF-LOW (MF-LOW).

Panel A displays estimates of the relative magnitudes of low- and high-frequency flows in correcting or exacerbating total mispricing. However, it does not consider the relative size, measured by the standard deviation, of low- and high-frequency mispricing. Thus, in Panel B, we also take into account the proportion of low- and high-frequency in total variance of the mispricing, in calculating the economic magnitudes of fund flow effects.

Specifically, we define the *attenuation factor* as the ratio of the economic magnitude of the fund-flow effect at low frequency to the magnitude at high frequency. The economic magnitude of the fund-flow effect at frequency *i=(L, H)* is calculated as $\beta_i \times \sigma_X^i / \sigma_Y^i$, where σ_X^i and σ_Y^i denote, respectively, the standard deviations of flows and mispricing at frequency *i.* This standard-deviation-adjusted beta measures how much standard-deviation change in mispricing is associated with one standard-deviation increase in flows. The attenuation factor is calculated as $(\beta_L \times \sigma_X^L / \sigma_Y^L) / (\beta_H \times \sigma_X^H / \sigma_Y^H)$, and interpreted as the degree of attenuation of high-frequency flows relative to that of low-frequency flows.

Essentially, the attenuation factor allows us to compare betas on low- and high-frequency flows after accounting for the frequency-specific standard deviation of mispricing. A factor value of one indicates that changes in low- and high-frequency flows of identical magnitudes in terms of standard deviations result in changes in low- and high-frequency anomaly returns of identical magnitudes, again in terms of standard deviations). A value bigger than one means that, all else equal, low-frequency flows lead to a bigger mispricing correction (or exacerbation) than high-frequency flows do. That happens if fund managers behave as a low-pass filter.

That is, upon receiving the high-frequency flows, managers "slow them down" by redirecting some of these flows towards low-frequency mispricing, or putting it differently, convert these high-frequency flows into low-frequency flows. As a result, in a regression in which we do not observe how managers deploy capital (i.e., their trades), mispricing appears to respond more strongly to low-frequency flows than it would if managers only applied low-frequency flows to low-frequency mispricing. Likewise, the mispricing reaction to high-frequency flows appears weaker than it would if all high-frequency flows were used immediately to trade on high-frequency mispricing. This means that, all else equal, the beta of low-frequency anomaly returns on low-frequency flows is larger in (absolute value of) economic magnitude than the beta of high-frequency anomaly returns on high-frequency flows, i.e., the attenuation factor is larger than one.

Panel B shows how the attenuation factors are calculated. Take NINV for example; the beta on HF-LOW equals 1.009, and the coefficient on HF-HIGH equals 0.159. A one-standard deviation increase (1.28%) in HF-LOW is associated with a 1.13% increase in NINV-LOW, which corresponds to 43% of a standard deviation (3.00%). On the other hand, a one-standard deviation increase (1.39%) in HF-HIGH is associated with 0.22% increase in NINV-HIGH, or 4.2% of a standard deviation. The attenuation factor is 10.35, indicating that the effect of a one-standard-deviation shock to low-frequency flows on low-frequency mispricing returns is ten times the size of the effect of a one-standard-deviation shock to high-frequency flows on high-frequency mispricing.

Overall, these results show that both hedge and mutual funds behave as low-pass filters. Hedge funds have an attenuation factor of 5 for SYY anomalies and 10 for NINV anomalies. This implies that hedge funds correct mispricing at low frequencies five to ten times more than they do at high frequencies. Likewise, mutual funds amplify mispricing 2.6 to 2.8 times more than they do at high frequencies.

We then compare hedge funds with mutual funds by computing the ratio of hedge fund's attenuation factor to that of mutual funds. The estimates, reported in Panel B, show that the attenuation factors are 1.9 to 3.8 larger for hedge funds than for mutual funds. This observation suggests that hedge fund managers deploy capital considerably more slowly than do mutual fund managers, thereby improving the markets efficiency more slowly than mutual funds exacerbate market inefficiency. It is important to note that the difference in the attenuation factors is not an artefact of differences in frequency structure between smart and dumb money, but a consequence of how managers filter frequency-specific flows.

6.3. Long and Short Legs

Stambaugh, Yu and Yuan (2012, 2014) show that anomalies are mostly driven by overpricing in the short leg. Thus, in Table 4, we regress the long-leg returns and short-leg returns separately on fund flows. Panel A reports the results of the long-leg returns, while Panel B shows the results of short-leg returns.

Panel A shows that hedge fund flows are not related with the long-leg returns at either frequency band. Both HF-LOW and HF-HIGH are insignificant for returns at both frequencies. On the contrary, MF-LOW is positively related to the low-frequency anomaly returns, but is negatively related to the high-frequency anomaly returns. As a result, the opposing effects cancel out, and the net effect of MF-LOW on the anomaly returns are insignificant (The first and second columns). Similar pattern can be seen for MF-HIGH except that the net effect of MF-HIGH on total anomaly returns is significantly positive. This indicates that the high-frequency mutual fund flows actually correct mispricing in the long leg, albeit with a small degree (relative to their effect on the short leg).

Panel B shows that unlike the long-leg returns, hedge fund flows are significantly and negatively related to the short-leg returns. Comparing the magnitude of the coefficients, we can conclude that the negative relation is mostly due to the low-frequency band. Note that for the short leg, a negative coefficient implies that flows correct mispricing. The result therefore suggests that hedge funds mostly correct overvaluation at the low frequency.

For mutual funds, the pattern observed in Panel A is also present for the short-leg returns. Both MF-LOW and MF-HIGH are significantly and positively related to short-leg returns at corresponding frequencies, but negatively related to returns at opposite frequencies. The net effect is that mutual fund flows exacerbate mispricing at both frequency bands. However, the magnitude of positive coefficients for short-leg returns are much higher than that for long-leg returns, indicating that mutual funds tend to purchase overpriced securities more than they do undervalued ones. For example, for NINV-LOW, MF-LOW has coefficient of 5.416 for the short-leg, while it has coefficient of 1.887 for long-leg, generating a significant negative relation between MF-LOW and the long-short return of NINV-LOW. Overall, the results suggest that the frequency-based mispricing correction (exacerbation) effect of hedge (mutual) fund flows we observed in previous sections are driven by the short leg of anomalies.

6.4. Individual Anomalies and Flows

In Table 5, we further analyze the frequency structure of fund flows and mispricing, by examining the relation between individual anomaly returns and fund flows in the frequency domain.

Panel A uses the total anomaly returns as the dependent variables, while Panels B and C use the low-frequency and high-frequency returns, respectively. Panel A shows that consistent with previous results, the positive relation between HF and the anomaly returns is more prevalent for the low-frequency flows than the high-frequency flows. For seven out of eleven anomalies in SYY, the coefficients for HF-LOW are positive, and four of them are statistically significant. Although there are also some positive coefficients for HF-HIGH, the magnitude of such coefficients, on average, is smaller. For MF side, the negative relation is prevalent both for high- and low-frequency flows.

Panels B and C show the low-frequency and high-frequency anomaly returns, respectively. The mispricing correction by hedge funds at low frequency is again observed for individual anomalies in SYY. HF-LOW has positive relation with eight low-frequency anomaly returns, five of which are statistically significant, while HF-HIGH has a positive relation with six high-frequency anomaly returns, among them only one is significant at 5% level. Overall, these results suggest that our findings are robust and not driven by any particular anomaly.

7. Transaction Costs and Low-Pass Filtering

We hypothesize that one of the reasons why hedge funds particularly choose to be a low-pass filter is the consideration of optimal trading under transaction and implementation costs. In this section, we test this hypothesis directly, exploiting variation of transaction cost and liquidity over time. We also study the difference in fund characteristics that are related to mitigating transaction costs.

7.1. Liquidity

We examine whether the relation between fund flows and the mispricing varies based on the aggregate market illiquidity. Specifically, we measure the aggregate market illiquidity level (denoted ILLIQ) and interact it with fund flows to examine whether the low-frequency mispricing correction is stronger for the periods of high illiquidity. Table 6 shows the results.

We use three measures of illiquidity: Amihud illiquidity, the aggregate illiquidity in Pastor and Stambaugh (PS, 2003), and the permanent variable factor in Sadka (2006). Each of these measures captures a different aspect of illiquidity. The Amihud measure computes volume-related price impacts. The PS measure captures the return reversal post trading, which reflects the compensation paid to liquidity providers (Nagel 2012). The Sadka measure calculates the permanent variable price impact component estimated from bid-ask spreads. Sadka (2010) and Dong, Feng, and Sadka (2017) show that the permanent variable factor is a particularly relevant transaction cost component for hedge funds and mutual funds, respectively. Following the liquidity literature, the aggregate illiquidity measures are obtained by averaging over all individual stocks.[8]

For our analyses, the variable, ILLIQ, is constructed as follows. If the original variable measures the market liquidity, then we convert it to illiquidity by multiplying the variable by minus one. Then, we detrend the illiquidity measures and sort the monthly illiquidity values into quintiles. Finally, we standardize the quintile scores from zero to one to obtain ILLIQ. Thus, the coefficient on the interaction term can be interpret as the difference in the effect between the lowest and the highest market illiquidity period.

In Panel A, we regress anomaly returns on total flows. Panel A shows that while the coefficients on mutual fund flows do not vary much based on the illiquidity level, the results on hedge fund flows are stronger for low-frequency returns, during the period when market illiquidity is high. For example, the interaction term between HF and PS illiquidity is 0.401 and 0.627 for SYY-LOW and NINV-LOW, respectively, and both are statistically significant. This indicates the hedge funds concentrate more correcting mispricing more slowly when market is more illiquid.

[8] We thank Lubos Pastor and Ronnie Sadka for providing the liquidity measures.

This relation is more pronounced in Panel B where the decomposed flows are used as the regressors. The significant interaction term of HF-LOW x ILLIQ indicates that the positive relation between HF-LOW and the low-frequency mispricing is stronger for the period of high market illiquidity. This suggests that hedge funds' low-frequency mispricing correction effect is more driven by the illiquid periods.

In contrast, the interaction of HF-HIGH x ILLIQ is insignificant for high-frequency mispricing and, if anything, negative for two out of the three illiquidity measures, implying hedge funds correct mispricing less at high frequencies during more illiquid period. Further, the interaction of MF-LOW x ILLIQ is mostly negative but not significant, suggesting that mutual funds' low-frequency mispricing exacerbation effect is only weakly related to illiquidity. MF-HIGH x ILLIQ is also insignificant. These results rule out the alternative explanation that the HF-LOW x ILLIQ results are driven by the fact that flow-induced price impact in general (i.e. across assets and across funds) may be higher when market is less liquid.

In other words, our finding is not that flow changes mispricing significantly in general when market is illiquid, but that only one type of flows (HF-LOW) changes mispricing in a particular direction (correction) at a particular frequency (low). The results therefore support that managers choose to filter flows more when costs concern is more important.

To gauge the economic significance, it is useful to calculate the ratio of the total flow effect when ILLIQ is one (top illiquidity quintile) over the flow effect when ILLIQ is zero (bottom illiquidity quintile). A ratio above one means the high illiquidity state is more important in driving the total effect than the low illiquidity state. Take the first column of Panel B for example. The total effect on HF-LOW for SYY-LOW during the high illiquidity states is 0.995 (0.763+0.231), while the effects during the low illiquidity states is 0.231. The ratio is 4.3, implying the low-frequency mispricing correction effect during the high illiquidity state is more than four times of the effect during the low illiquidity state. The ratios calculated for other columns indicate that the effect of HF-LOW on low-frequency mispricing dramatically go up across all illiquidity measures. In contrast, for mutual funds, the increase is much milder with the ratios being about one. Overall, the results suggest that transaction costs are one driving force for hedge funds' frequency filtering.

7.2. Exogenous Shocks to Liquidity

To obtain more direct identification of the effect of transaction costs on hedge fund actions, we explore two natural experiments during which the level of liquidity dramatically shifts. The first one is Decimalization, which is considered as the period of a positive liquidity shock and starts in 08/2000 and ends in 05/2001. Numerous studies use it as an exogenous shock to identify the causal impact of liquidity (e.g., Chordia, Roll, and Subrahmanyam 2008, Fang et al. 2009). The second is the 2007-2009 financial crisis. Many studies also use it as a negative shock to liquidity (Sadka 2010; Aragon and Strahan 2012). Following Akbas et al. (2015), we choose the beginning and end time to be 07/2007 and 12/2009.

During these period the change in liquidity becomes a primary concern for hedge funds, therefore, this setting enable us to more tightly link transaction costs concerns to arbitrageurs' actions. Table 7 examines how the relation between flows and mispricing changes in response to two liquidity shocks; The main variables of interest are the low- and high-frequency fund flows interacted with SHOCK, a dummy variable that equals one if the month t is included in the period of the liquidity shock, zero otherwise.

The results in Panel A shows that during the decimalization period, the low-frequency mispricing correction is much weaker. The coefficient on the interaction term is significantly negative, indicating that hedge funds chose not to be a low-pass filter due to improved liquidity. On the contrary, during the financial crisis period, the attenuation factor increased, evidenced from the significantly positive interaction term.

The results in Panel B are more striking. For decimalization period, the association of HF-LOW with low-frequency returns is weakened significantly (HF-LOW x SHOCK for the low-frequency returns are significantly negative), while the relation between HF-HIGH with high-frequency mispricing is significantly strengthened (HF-HIGH x SHOCK for the high-frequency returns are significantly positive). The results suggest that lower transactions cost allow hedge funds to engage in correcting mispricing at high-frequency domain and that their role of low-pass filters is significantly reduced.

Unlike for systematic liquidity measures in Table 6, mutual funds also strongly react to the decimalization. MF-LOW x SHOCK for the low-frequency returns and for the high frequency returns are significantly positive and negative, respectively, indicating that their low-frequency mispricing exacerbation effect is significantly reduced, while the high-frequency exacerbation is significantly strengthened. The results suggest that mutual funds' frequency filtering is also related to transaction costs but not as strongly as hedge funds'. The opposite changes in the effects on low and high-frequency mispricing for hedge funds and mutual funds rule out the alternative explanation that the results are due to the fact that price impact is smaller when market is more liquid.

However, during the financial crisis period, the relation between HF-LOW and low-frequency returns become stronger, similar to the results in Table 6. The low-frequency mispricing exacerbation effect of mutual funds is significantly stronger, while the high-frequency mutual fund flows is related to the correction of high-frequency mispricing. In sum, results in Tables 6 and7 suggest the transaction and implementation costs are one of important reasons why hedge funds particularly choose to behave as a low-pass filter.

7.3. Market Conditions

To further ensure robustness, in Table 8, we examine whether hedge funds' behaviour alter due to economic or market conditions. We measure the current economic and market condition, using the following three variables; NBER Recession Indicator, TED Spread, and VIX. These variables broadly measures the cost of trading, captureing the market liquidity, funding liquidity, and market volatility. During recessions, for example, the funding liquidity is low, and uncertainty is high, therefore, the costs of trading for arbitrageurs are expected to be higher.

The variable of interest is the low- and high-frequency fund flows interacted with D, which measures the current condition of the market and overall economy. For NBER, D is a dummy variable that equals one if the current month is in a recessionary period, zero otherwise. For TED Spread and VIX, D is a quintile score scaled from zero to one, with higher score indicating higher funding costs and higher uncertainty, respectively. Panel A uses the total flows as the independent variables, while Panel B uses the low- and high-frequency flows.

Panel A shows that HF interacted with D is significantly positive for SYY-LOW or NINV-LOW for all measures of economic conditions, indicating the low-frequency mispricing correction by hedge funds is more significant during the time of adverse market conditions. Interestingly, MF×D has also positive coefficients for low-frequency mispricing.

The results in Panel B provide further insights. While HF-LOW×D is positive and mostly significant for low-frequency anomaly returns, HF-HIGH×D is not significant for the high-frequency anomaly returns. Overall, Table 8 shows that the attenuation factor rises during adverse market condition, suggesting the importance of transaction and implementation costs.

7.4. Fund-Level Constraints

We also investigate fund characteristics to provide further evidence of the transaction costs channel and hedge funds' discretion to be a low-pass filter. We consider two fund characteristics; share restrictions and leverage.

Share restrictions are the sum of the days of the lock-up period, redemption notice period, and payout period. It is widely used in hedge fund studies as a measure of hedge fund illiquidity (Aragon 2007; Sadka 2010; Teo 2011). Funds with high share restrictions are more concerned about illiquidity in their underlying assets. Therefore, transaction costs are a bigger concern for this kind of funds. Further, to exercise the discretion of filtering flows, managers must have the effective device in the first place. Therefore, we expect that funds with higher share-restriction are more likely to be a low-pass filter.

Leverage is the indicator variable that equals one if the hedge fund uses leverage, zero otherwise. Levered funds are more constrained. For example, even if they would like to trade on mispricing slowly, their trading process maybe discontinued by margin calls (LTCM is a famous example; See also Shleifer and Vishny, 1997). Therefore, levered funds are less likely to be able to trade low-frequency mispricing. We expect unlevered funds are more likely to act as a low-pass filter.

Table 9 reports the results of fund characteristics. Each month, based on the median value of the share restrictions (use of leverage), hedge funds are divided into two groups; HFBelow and HFAbove (HFUnLev and HFLev). Then, the fund flows is calculated separately for each group of hedge funds.

First, in Panel A, we examine fund share restrictions. The first and third columns show that the positive relation between mispricing and hedge fund flows are more attributable to funds with high share restrictions (HFAbove). Although both HFBelow and HFAbove have coefficients of similar magnitudes, HFBelow is insignificant. The second and fourth columns show that only the low-frequency flows of high share-restriction hedge funds are significantly positively related to the total anomaly returns, while that of the low-restriction funds are not.

The rest of the panel show that while HFBelow-LOW is negative for the low-frequency anomaly returns, HFAbove-LOW is positive and significant. Although insignificant, HFBelow-HIGH is positive and much larger than HFAbove-HIGH for high-frequency anomaly returns, indicating that hedge funds with high and low restrictions may specialize in different frequencies. Overall, results in Panel A support that funds with more concerns on transaction costs are more likely to correct mispricing slowly. They also suggest that share restrictions are important tool to allow arbitrageurs to redirect capital to low-frequency trading.

In Panel B studies the effect the use of leverage in mispricing correction. First, we look at the total flows for unlevered and levered hedge funds (HFUnLev and HFLev). The positive relation between HF and mispricing is stronger for funds with leverage. However, HFUnLev is strongly positive for low-frequency mispricing, while HFLev is strongly positive for high-frequency mispricing.

This phenomenon becomes clearer once we decompose the flows in the frequency domain. HFUnLev-LOW is significantly positive only with low-frequency mispricing, while HFLev-HIGH is significantly positive with high-frequency mispricing only. This suggests that funds with leverage specialize high-frequency arbitrage, while unlevered funds purse low-frequency arbitrage.

7.5. Transient Anomalies

The anomalies in SYY are formed based on signals over quarter or annual horizons, such as quarterly earnings announcements or annual financial statements. These signals are persistent on a monthly basis. To contrast with these persistent anomaly signals, we also examine three prominent anomalies with transient signals; 1-month industry momentum (Moskowitz and Grinblatt 1999), 1-month return reversal (Jegadeesh and Titman 1993), and 1-month industry-adjusted reversal (Da et al. 2014). These signals for the transient anomalies are fast-decaying and lose their return predictability roughly in one month.

Garleanu and Pedersen (2013, 2016) show theoretically that when trading is costly, the optimal strategy for trading on anomalies is to trade slowly with stepwise rebalancing (i.e., gradually enter and exist a position) and to focus on anomalies with persistent signals. Thus, their theory on the transaction costs-based optimal trading suggests that our main finding, mispricing correction at the low frequencies, may not be observed for transient anomalies which requires frequent and complete rebalancing.

Table 10 reports the regressions of transient anomaly returns on fund flows as in Table 5. Contrary to SYY anomalies, there is no significant coefficient on HF flows for any transient anomalies. Both HF-LOW and HF-HIGH are more often negative but insignificant. The results are consistent with the theory of the optimal trading under high trading costs, and further support that transaction cost is one of the drivers for the low-frequency relation between hedge fund flows and anomaly returns.

8. Conclusion

We examine the frequency structure of fund flows and mispricing. Applying spectral analyses, we show that capital supplied by mutual fund investors moves more slowly than does capital by hedge fund investors. Both types of funds behave, in aggregate, as low-pass filters, suggesting fund managers allocate their capital predominantly to correct or exacerbate mispricing at low-frequencies. In addition, we show that hedge funds are a more selective (low-pass) filter than are mutual funds, attenuating high-frequency flows to larger extent. Finally, we present evidence consistent with transaction and implementation costs as a likely cause of hedge funds' choice to behave as a low-pass filter. Hedge funds' attenuation factor rises in times of low aggregate liquidity, during recessions and under adverse market conditions. The attenuation factor drops sharply following decimalization, whereas it rises strongly during the financial crisis. In addition, we document that the correction of low-frequency mispricing is mostly attributable to hedge funds with high share restrictions, indicating that such restrictions are an effective tool for redirecting high-frequency capital towards low-frequency anomalies. All in all, our work suggests that hedge fund managers improve the efficiency of financial markets over long horizons where, presumably, it is more socially useful.

References

Agarwal V., Daniel, N.D., and Naik, N.Y., 2009, Role of Managerial Incentives and Discretion in Hedge Fund Performance. Journal of Finance 64, 2221-2256.

Akbas, F., Armstrong, W.J., Sorescu, S., and Subrahmanyam, A., 2015, Smart money, dumb money, and capital market anomalies. Journal of Financial Economics 118, 355-382.

Aragon, G.O., 2007, Share restrictions and asset pricing: Evidence from the hedge fund industry. Journal of Financial Economics 83, 33-58.

Bandi, M.F., Chaudhuri, S.E., Lo, A.W., and Tamoni, A., 2018, Measuring Horizon-Specific Systematic Risk via Spectral Betas. Working paper.

Bandi, F.M., and Tamoni, A., 2014, Business-cycle consumption risk and asset prices. Working paper.

Bessembinder, H., 2003, Trade Execution Costs and Market Quality after Decimalization. Journal of Financial and Quantitative Analysis 38, 747-777.

Bogousslavsky, V., 2016, Infrequent rebalancing, return autocorrelation, and seasonality. The Journal of Finance 71, 2967-3006.

Buss, A., and Dumas, B., 2017, The Dynamic Properties of Financial-Market Equilibrium with Trading Fees. Journal of Finance, Forthcoming

Campbell, J.Y., Hilscher, J., and Szilagyi, J., 2008, In search of distress risk. Journal of Finance 63, 2899-2939.

Chaudhuri, S.E., and Lo, A.W., 2016, Spectral Portfolio Theory. Working paper.

Chaudhuri, S.E., and Lo, A.W., 2018, Dynamic Alpha: A Spectral Decomposition of Investment Performance Across Time Horizons. Management Science, Forthcoming.

Chen, L., Novy-Marx, R., and Zhang, L., 2010, An alternative three-factor model. Working paper.

Chinco, A., and Ye, M., 2016, Investment-Horizon Spillovers. Working paper.

Chordia, T., Roll, R., and Subrahmanyam, A., 2008, Liquidity and market efficiency. Journal of Financial Economics 87, 249-268.

Cooper, M.J., Gulen, H., and Schill, M.J., 2008, Asset growth and the cross-section of stock returns. Journal of Finance 63, 1609-1652.

Cieslak, A., Morse, A. and Vissing-Jorgensen, A., 2018, Stock returns over the FOMC cycle. Journal of Finance, Forthcoming.

Coval, J. and Stafford, E., 2007, Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479-512.

Crouzet, N., Dew-Becker, I., and Nathanson, C.G., 2017, Multi-Frequency Trade. Working paper.

Da, Z., Liu, Q., Schaumurg, E., 2014, A closer look at the short-term reversal. Management Science 60, 658-674.

Daniel, K.D., and Titman, S., 2006, Market reactions to tangible and intangible information. Journal of Finance 61, 1605-1643.

Dew-Becker, I., and Giglio, S., 2016, Asset Pricing in the Frequency Domain: Theory and Empirics. Review of Financial Studies 29, 2029-2068

Dong, X., Feng, S., and Sadka, R., 2017, Liquidity Risk and Mutual Fund Performance. Management Science

Dong, X., Liu, Q., Lu, L., Sun, B., and Yan, H., 2018, Anomaly Discovery and Arbitrage Trading. Working paper.

Duffie, D., 2010, Presidential Address: Asset Price Dynamics with Slow-Moving Capital. Journal of Finance 65, 1237-1267.

Engle, R., Ferstenberg, R., and Russell, J., 2012, Measuring and Modeling Execution Cost and Risk. Journal of Portfolio Management, Winter.

Fang, V., Noe, T., and Tice, S., 2009, Stock market liquidity and firm value. Journal of Financial Economics 94, 150-169.

Frazzini, A., Israel, R., and Moskowitz, T.J., 2018, Trading costs. Working paper.

Frazzini, A. and Lamont, O.A., 2008, Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of financial economics 88, 299-322.

Furfine, C.H., 2003, Decimalization and market liquidity. Economic Perspectives 27, 2-12.

Gao, L., Han, Y., Li, S.Z. and Zhou, G., 2018, Market intraday momentum. Journal of Financial Economics 129, 394-414.

Garleanu, N., and Pedersen, L.H., 2013, Dynamic Trading with Predictable Returns and Transaction Costs. Journal of Finance 68, 2309-2340.

Garleanu, N., and Pedersen, L.H., 2016, Dynamic portfolio choice with frictions. Journal of Economic Theory 165, 487-516.

Goldstein, M.A., and Kavajecz, K.A., 2000, Eighths, sixteenths, and market depth: changes in tick size and liquidity provision on the NYSE. Journal of Financial Economics 56, 125-149.

Greenwood, R., and Thesmar, D., 2011, Stock price fragility. Journal of Financial Economics 102, 471-490.

Hirshleifer, D., Hou, K., Teoh, S.H., and Zhang, Y., 2004, Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297-331.

Holden, C.W., and Subrahmanyam, A., 1992, Long-Lived Private Information and Imperfect Competition. Journal of Finance 47, 247-270.

Jegadeesh, N., and Titman, S., 1993, Returns to buying winners and selling losers: Implications for market efficiency. Journal of Finance 48, 65-91.

Keim, D.B., and Madhavan, A., 1997, Transactions costs and investment style: an inter-exchange analysis of institutional equity trades. Journal of Financial Economics 46, 265-292.

Korajczyk, R.A., and Sadka, R., 2004, Are Momentum Profits Robust to Trading Costs? Journal of Finance 59, 1039-1082.

Kyle, A.S., 1985, Continuous Auctions and Insider Trading. Econometrica 53, 1315-1335.

Kyle, A.S., Obizhaeva, A.A., and Wang, Y., 2018, Smooth Trading with Overconfidence and Market Power, Review of Economic Studies 85, 611–662

Lesmond, D.A., Schill, M.J., and Zhou, C., 2004, The illusory nature of momentum profits. Journal of Financial Economics 71, 349-380.

Linnainmaa, J.T., and Zhang, C., 2018, The Earnings Announcement Return Cycle. Working Paper, USC.

Lou, D., 2012, A flow-based explanation for return predictability. Review of Financial Studies 25, 3457-3489.

Loughran, T., and Ritter, J.R., 1995, The new puzzle. Journal of Finance 50, 23-51.

Moskowitz, T.J., and Grinblatt, M., 1999, Do Industries Explain Momentum? Journal of Finance 54, 1249-1290.

Nagel, S., 2012, Evaporating Liquidity. Review of Financial Studies 25, 2005-2039.

Novy-Marx, R., 2013, The other side of value: The gross profitability premium. Journal of Financial Economics 108, 1-28.

Novy-Marx, R., and Velikov, M., 2016, A Taxonomy of Anomalies and Their Trading Costs. Review of Financial Studies 29, 104–147.

Ohlson, J.A., 1980, Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research 18, 109-131.

Ortu, F., Tamoni, A., and Tebaldi, C., 2013, Long-Run Risk and the Persistence of Consumption Shocks. Review of Financial Studies 26, 2876-2915.

Patton, A.J., and Weller, B.M., 2017, What You See is Not What You Get: The Costs of Trading Market Anomalies. Working paper.

Pastor, L., and Stambaugh, R.F., 2003, Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111, 642-685.

Ritter, J.R., 1991, The long-run performance of initial public offerings. Journal of Finance 46, 3-27.

Sadka, R., 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. Journal of Financial Economics 80, 309-349.

Sadka, R., 2010, Liquidity risk and the cross-section of hedge-fund returns. Journal of Financial Economics 98, 54-71.

Shive, S., and Yun, H., 2013, Are mutual funds sitting ducks? Journal of Financial Economics 107, 220-237.

Shleifer, A., and Vishny, R.W., 1997, The Limits of Arbitrage. Journal of Finance 52, 33-55.

Sloan, R.G., 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? The Accounting Review 71, 289-315.

Stambaugh, R.F., Yu, J., and Yuan, Y., 2012, The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104, 288-302.

Stambaugh, R.F., Yu, J., and Yuan, Y., 2015, Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70, 1903-1948.

Stambaugh, R.F., and Yuan, Y., 2016, Mispricing factors. Review of Financial Studies 30, 1270-1315.

Teo, M., 2011, The liquidity risk of liquid hedge funds. Journal of Financial Economics 100, 24-44.

Titman, S., Wei, K.C.J., and Xie, F., 2004, Capital investment and stock returns. Journal of Financial and Quantitative Analysis 39, 677-700.

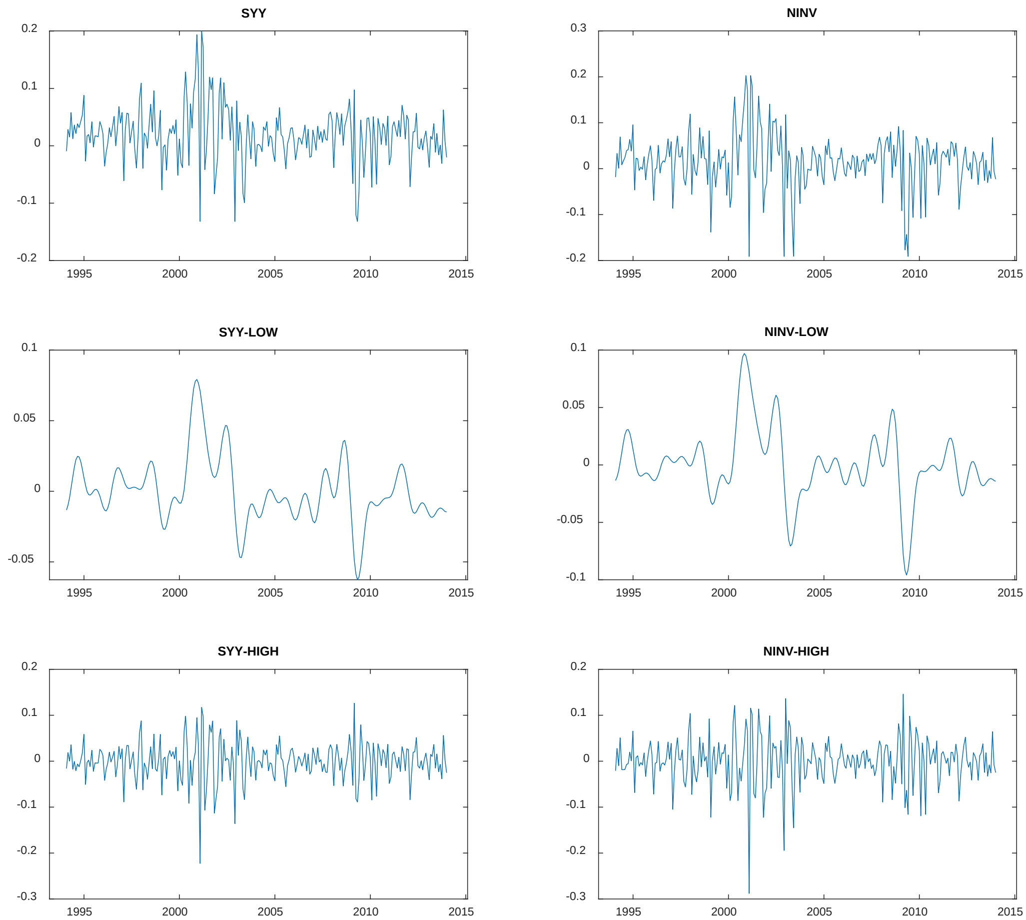

Figure 1. Decomposed Time Series of Anomaly Returns. This figure plots the time series of decomposed anomaly returns. The first row shows the original time series, while the second and third rows plot the low- and high-frequency anomaly returns. A Fourier transformation is applied to anomaly returns to obtain the frequency components. Then, the time series of LOW (HIGH) frequency anomaly returns are reconstructed by an inverse Fourier transformation using only low (high) frequency Fourier components. SYY is the return of the long-minus-short strategy based on eleven anomalies documented in Stambaugh, Yu, and Yuan (2012). NINV is the return of the long-minus-short strategy using seven anomalies in SYY that are not related to corporate investments. The sample period is 1994–2013.

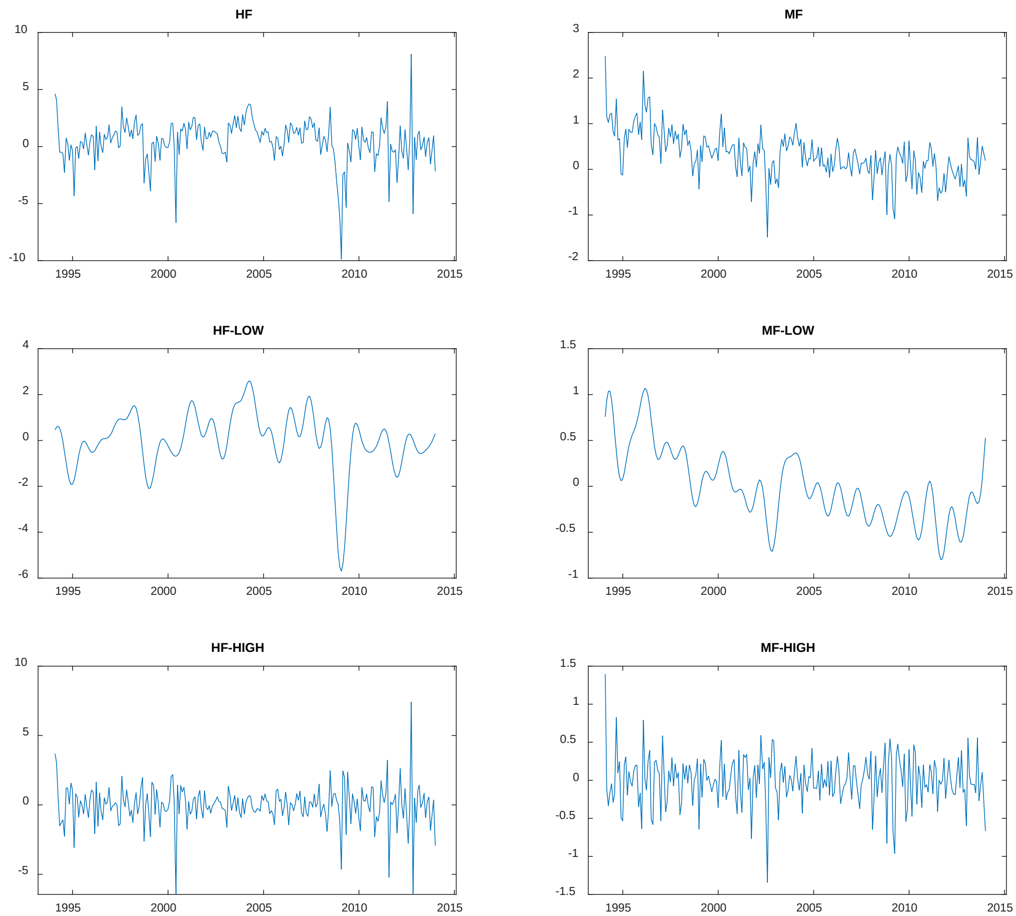

Figure 2. Decomposed Time Series of Fund Flows. The figure shows the time series of decomposed fund flows. The first row shows the original time series, while the second and third rows plot the low- and high-frequency fund flows. A Fourier transformation is applied to fund flows to obtain the frequency components. Then, the time series of LOW (HIGH) frequency flows are reconstructed by an inverse Fourier transformation using only low (high) frequency Fourier components. MF and HF are the monthly aggregate percentage flow of equity mutual funds and equity hedge funds, respectively. The sample period is 1994–2013.

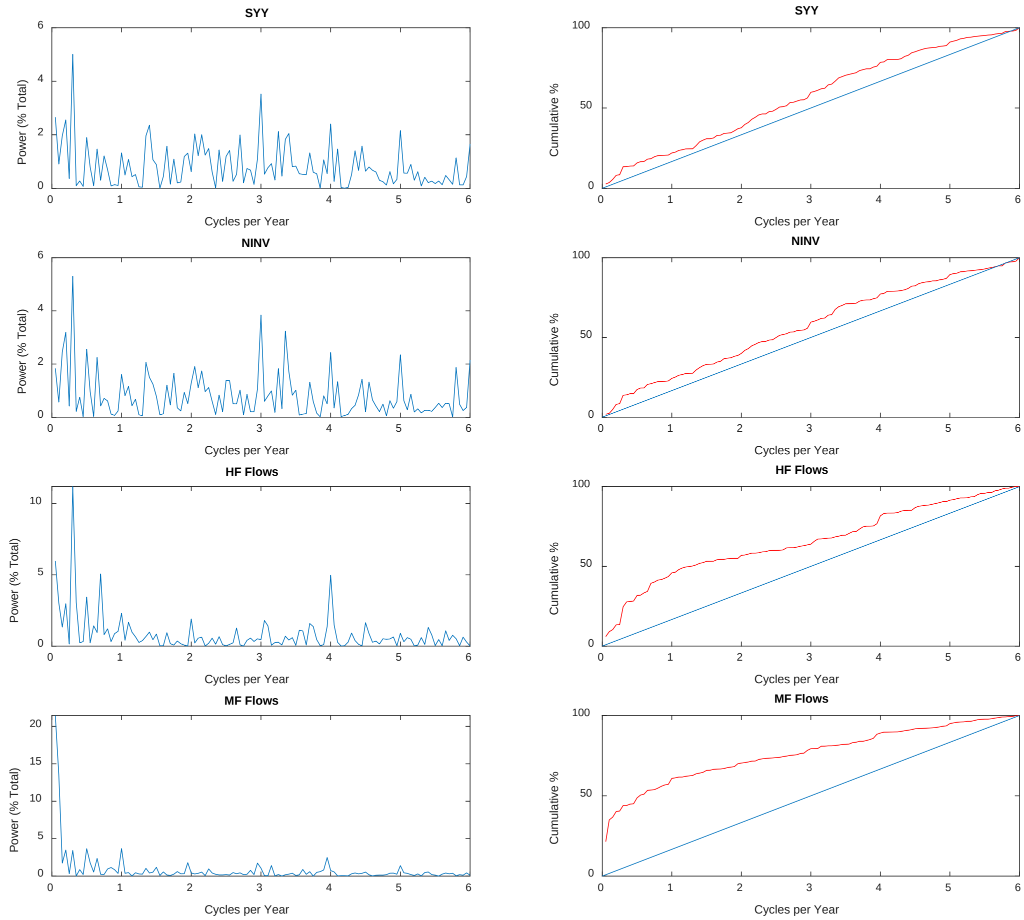

Figure 3. Variance Decomposition. This figure provides the variance decomposition of anomaly returns and fund flows in frequency domain. The first column shows the amplitude of each frequency scaled by the sum of total amplitudes. Therefore, it shows the relative contribution of each frequency to the total variance. The second column shows the cumulative contribution of frequencies. SYY is the return of the long-minus-short strategy based on eleven anomalies documented in Stambaugh, Yu, and Yuan (2012). NINV is the return of the long-minus-short strategy using seven anomalies in SYY that are not related to corporate investments. MF and HF are the monthly aggregate percentage flow of equity mutual funds and equity hedge funds, respectively. The sample period is 1994–2013.

Table 1. Summary Statistics

Panel A shows the descriptive statistics of main variables, and Panel B reports the correlations. Panel C provides the correlations of decomposed returns and fund flows, and Panel D reports the variance decomposition of returns and fund flows in the frequency domain. The upper right corner of Panels B and C reports Pearson correlations and the lower left corner of the panels provides Spearman correlations. SYY is the return of the long-minus-short strategy based on eleven anomalies documented in Stambaugh, Yu, and Yuan (2012). NINV is the return of the long-minus-short strategy using seven anomalies in SYY that are not related to corporate investments. MF and HF are the monthly aggregate percentage flow of equity mutual funds and equity hedge funds, respectively. Amihud is the equally-weighted average Amihud illiquidity measure of all common stocks listed in NYSE in month t. Turnover is the equally-weighted average turnover of all common stocks in NYSE in month t. MKTRF is the monthly return of the market in excess of the risk free rate. HML and SMB are the monthly returns to the value and the size strategies, respectively. We apply spectral analyses to decompose the anomaly returns and fund flows into low- and high-frequency components. The suffixes of -LOW and -HIGH indicate the low- and high-frequency components of the original time series, respectively. The LOW components are time series that are re-constructed from frequencies that have cycles of one year or longer, while the HIGH components are re-constructed time series from frequencies that have cycles shorter than one year. The sample period is 1994–2013.

Panel A: Descriptive Statistics

Variable	N	Mean	Std Dev	Min	Q1	Median	Q3	Max	t Value
SYY	240	0.020	0.049	-0.132	-0.003	0.019	0.044	0.200	6.28
SYY-LOW	240	0.000	0.023	-0.063	-0.012	-0.004	0.011	0.079	0.00
SYY-HIGH	240	0.000	0.043	-0.223	-0.021	0.002	0.024	0.126	0.00
NINV	240	0.016	0.061	-0.191	-0.009	0.021	0.045	0.203	4.08
NINV-LOW	240	0.000	0.030	-0.096	-0.014	-0.002	0.011	0.097	0.00
NINV-HIGH	240	0.000	0.053	-0.288	-0.024	0.003	0.030	0.146	0.00
MF	240	0.003	0.005	-0.015	0.000	0.003	0.006	0.025	10.00
MF-LOW	240	0.000	0.004	-0.008	-0.003	-0.001	0.003	0.011	0.00
MF-HIGH	240	0.000	0.003	-0.013	-0.002	0.000	0.002	0.014	0.00
HF	240	0.005	0.019	-0.099	-0.003	0.007	0.015	0.081	3.88
HF-LOW	240	0.000	0.013	-0.057	-0.005	0.001	0.007	0.026	0.00
HF-HIGH	240	0.000	0.014	-0.064	-0.006	0.001	0.007	0.074	0.00
MKTRF	240	0.006	0.045	-0.172	-0.020	0.013	0.035	0.114	2.12
Amihud	240	0.041	0.024	0.008	0.020	0.037	0.057	0.121	26.72
Turnover	240	0.147	0.074	0.049	0.081	0.133	0.200	0.399	30.83
HML	240	0.002	0.032	-0.111	-0.012	0.001	0.017	0.129	1.21
SMB	240	0.002	0.034	-0.169	-0.017	0.000	0.021	0.217	0.84

Panel B: Pairwise Correlations

	SYY	NINV	MF	HF	MKTRF	Amihud	Turnover	HML	SMB
SYY		0.952	-0.174	0.115	-0.503	0.159	-0.129	0.329	-0.360
		[0.00]	[0.01]	[0.08]	[0.00]	[0.01]	[0.05]	[0.00]	[0.00]
NINV	0.931		-0.167	0.102	-0.398	0.121	-0.124	0.251	-0.311
	[0.00]		[0.01]	[0.11]	[0.00]	[0.06]	[0.06]	[0.00]	[0.00]
MF	-0.198	-0.230		0.200	0.336	0.403	-0.558	0.019	0.140
	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]	[0.00]	[0.77]	[0.03]
HF	0.041	0.039	0.194		0.027	-0.149	-0.174	0.155	0.022
	[0.53]	[0.55]	[0.00]		[0.68]	[0.02]	[0.01]	[0.02]	[0.74]
MKTRF	-0.444	-0.347	0.317	-0.068		-0.042	-0.109	-0.159	0.217
	[0.00]	[0.00]	[0.00]	[0.29]		[0.52]	[0.09]	[0.01]	[0.00]
Amihud	0.203	0.154	0.390	-0.148	-0.032		-0.616	-0.015	-0.106
	[0.00]	[0.02]	[0.00]	[0.02]	[0.62]		[0.00]	[0.81]	[0.10]
Turnover	-0.095	-0.039	-0.600	-0.054	-0.046	-0.709		-0.086	0.020
	[0.14]	[0.55]	[0.00]	[0.40]	[0.47]	[0.00]		[0.19]	[0.76]
HML	0.126	0.023	0.060	0.138	-0.141	-0.040	-0.091		-0.334
	[0.05]	[0.72]	[0.35]	[0.03]	[0.03]	[0.54]	[0.16]		[0.00]
SMB	-0.351	-0.283	0.111	-0.018	0.241	-0.121	0.076	-0.153	
	[0.00]	[0.00]	[0.09]	[0.78]	[0.00]	[0.06]	[0.24]	[0.02]	

Panel C: Correlations - Decomposed Variables

	SYY-LOW	SYY-HIGH	NINV-LOW	NINV-HIGH	MF-LOW	MF-HIGH	HF-LOW	HF-HIGH
SYY-LOW		0.000	0.971	0.000	0.014	0.000	0.216	0.000
		[1.00]	[0.00]	[1.00]	[0.83]	[1.00]	[0.00]	[1.00]
SYY-HIGH	0.003		0.000	0.946	0.000	-0.323	0.000	0.071
	[0.96]		[1.00]	[0.00]	[1.00]	[0.00]	[1.00]	[0.27]
NINV-LOW	0.943	-0.006		0.000	-0.039	0.000	0.256	0.000
	[0.00]	[0.93]		[1.00]	[0.55]	[1.00]	[0.00]	[1.00]
NINV-HIGH	-0.005	0.930	-0.013		0.000	-0.278	0.000	0.027
	[0.94]	[0.00]	[0.84]		[1.00]	[0.00]	[1.00]	[0.68]
MF-LOW	0.056	-0.013	-0.086	-0.019		0.000	0.294	0.000
	[0.39]	[0.84]	[0.19]	[0.77]		[1.00]	[0.00]	[1.00]
MF-HIGH	0.008	-0.356	0.007	-0.294	-0.059		0.000	0.098
	[0.90]	[0.00]	[0.91]	[0.00]	[0.36]		[1.00]	[0.13]
HF-LOW	0.143	0.017	0.161	0.040	0.300	-0.054		0.000
	[0.03]	[0.80]	[0.01]	[0.54]	[0.00]	[0.41]		[1.00]
HF-HIGH	0.018	0.050	0.029	0.005	-0.042	0.081	-0.121	
	[0.78]	[0.44]	[0.66]	[0.94]	[0.52]	[0.21]	[0.06]	

Panel D: Variance Decomposition

Variable	SYY		NINV		MF		HF	
Total Variance (×10000)	23.59	100.0%	37.00	100.0%	0.26	100.0%	3.57	100.0%
Variance-LOW	5.23	22.2%	8.97	24.3%	0.16	60.6%	1.64	45.9%
Variance-HIGH	18.37	77.8%	28.03	75.7%	0.10	39.4%	1.93	54.1%

Table 2: Regressions of Anomaly Returns on Flows

This table reports the results of regressions of the long-short anomaly returns on fund flows. The dependent variable are the long-minus-short returns at month t of two composite anomalies, SYY and NINV, and their respective low- and high-frequency component returns. SYY is the return of the long-minus-short strategy based on eleven anomalies documented in Stambaugh, Yu, and Yuan (2012). NINV is the return of the long-minus-short strategy using seven anomalies in SYY that are not related to corporate investments. The main independent variables are MF and HF at month t, the percentage flows of mutual funds and hedge funds, and their respective low- and high-frequency components. Panel A uses the total fund flows, while Panel B reports the results using the low- and high-frequency fund flows. t-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

Panel A: Total Flows

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		NINV		SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF	-1.773	[-2.26]	-2.479	[-2.44]	-0.714	[-1.35]	-1.001	[-1.61]	-1.059	[-1.72]	-1.478	[-1.84]
HF	0.334	[3.37]	0.370	[2.59]	0.203	[2.17]	0.283	[2.21]	0.131	[1.00]	0.087	[0.53]
MKTRF	-0.418	[-3.73]	-0.395	[-2.75]	-0.113	[-2.29]	-0.153	[-2.40]	-0.305	[-3.65]	-0.242	[-2.35]
Amihud	0.254	[1.66]	0.192	[0.78]	0.255	[1.45]	0.199	[0.83]	-0.001	[-0.01]	-0.007	[-0.05]
Turnover	-0.102	[-2.00]	-0.157	[-1.83]	-0.049	[-0.77]	-0.077	[-0.83]	-0.053	[-1.34]	-0.080	[-1.70]
HML	0.278	[1.39]	0.229	[0.89]	0.126	[1.59]	0.149	[1.49]	0.152	[1.08]	0.080	[0.43]
SMB	-0.248	[-4.00]	-0.300	[-3.79]	0.052	[0.87]	0.050	[0.69]	-0.300	[-5.27]	-0.351	[-4.46]
Intercept	0.031	[2.55]	0.040	[2.02]	0.018	[1.27]	0.022	[1.07]	0.013	[1.35]	0.018	[1.56]
N	240		240		240		240		240		240	
Adj R^2	38.7%		25.7%		20.7%		17.4%		26.0%		14.3%	

Panel B: Decomposed Flows

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		NINV		SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF-LOW	-2.026	[-2.07]	-3.380	[-2.71]	-2.516	[-2.66]	-3.505	[-3.17]	0.489	[0.75]	0.125	[0.16]
MF-HIGH	-1.669	[-1.70]	-1.963	[-1.51]	0.593	[1.78]	0.820	[1.92]	-2.262	[-2.51]	-2.783	[-2.31]
HF-LOW	0.549	[2.78]	0.880	[2.87]	0.730	[3.37]	1.009	[3.52]	-0.180	[-0.83]	-0.129	[-0.47]
HF-HIGH	0.225	[2.11]	0.123	[0.80]	-0.030	[-0.57]	-0.036	[-0.57]	0.255	[2.29]	0.159	[1.01]
MKTRF	-0.419	[-3.68]	-0.399	[-2.73]	-0.127	[-2.63]	-0.173	[-2.77]	-0.291	[-3.43]	-0.227	[-2.16]
Amihud	0.336	[2.25]	0.395	[1.81]	0.489	[2.71]	0.521	[2.32]	-0.152	[-1.05]	-0.126	[-0.69]
Turnover	-0.084	[-1.55]	-0.123	[-1.56]	-0.040	[-0.63]	-0.065	[-0.73]	-0.044	[-0.84]	-0.058	[-0.89]
HML	0.266	[1.35]	0.204	[0.81]	0.106	[1.67]	0.121	[1.51]	0.160	[1.06]	0.083	[0.41]
SMB	-0.250	[-4.12]	-0.307	[-4.03]	0.038	[0.81]	0.031	[0.53]	-0.287	[-5.30]	-0.338	[-4.44]
Intercept	0.025	[1.86]	0.027	[1.47]	0.011	[0.75]	0.011	[0.60]	0.014	[1.08]	0.016	[0.94]
N	240		240		240		240		240		240	
Adj R^2	38.5%		26.1%		32.7%		30.9%		27.5%		14.9%	

Table 3: Beta Decomposition and Economic Magnitudes

Panel A shows the decomposition of coefficients on fund flows shown in Table 2, while Panel B calculates the economic magnitudes of the coefficients. SYY is the return of the long-minus-short strategy based on eleven anomalies documented in Stambaugh, Yu, and Yuan (2012). NINV is the return of the long-minus-short strategy using seven anomalies in SYY that are not related to corporate investments. MF and HF are the monthly aggregate percentage flows of equity mutual funds and equity hedge funds, respectively. The sample period is 1994–2013.

Panel A: Beta Decomposition

Flows\Anomaly	SYY				NINV			
	Coefficient	Weight	Weighted Beta		Coeffient	Weight	Weighted Beta	
MF-LOW	-2.026	60.6%	-1.228	65.1%	-3.380	60.6%	-2.048	72.6%
MF-HIGH	-1.669	39.4%	-0.658	34.9%	-1.963	39.4%	-0.773	27.4%
Total MF			-1.885	100.0%			-2.822	100.0%
HF-LOW	0.549	45.9%	0.252	67.4%	0.880	45.9%	0.404	85.9%
HF-HIGH	0.225	54.1%	0.122	32.6%	0.123	54.1%	0.066	14.1%
Total HF			0.374	100.0%			0.470	100.0%

Panel B: Economic Magnitudes of Coefficients

Flows	Coefficient SYY-LOW	Coefficient SYY-HIGH	STD of Flows (σ_X)	Effect of One σ_X on SYY-LOW	Effect of One σ_X on SYY-HIGH	STD of Returns (σ_Y)	Economic Magnitude (% of σ_Y)	Economic Magnitude Attenuation Factor
MF-LOW	-2.516		0.4%	-1.0%		2.3%	-43.4%	
MF-HIGH		-2.262	0.3%		-0.7%	4.3%	-16.8%	2.59
HF-LOW	0.730		1.3%	0.9%		2.3%	40.8%	
HF-HIGH		0.255	1.4%		0.4%	4.3%	8.3%	4.94
						Ratio (HF/MF)		1.91

Flows	Coefficient NINV-LOW	Coefficient NINV-HIGH	STD of Flows (σ_X)	Effect of One σ_X on NINV-LOW	Effect of One σ_X on NINV-HIGH	STD of Returns (σ_Y)	Economic Magnitude (% of σ_Y)	Economic Magnitude Attenuation Factor
MF-LOW	-3.505		0.4%	-1.4%		3.0%	-46.2%	
MF-HIGH		-2.783	0.3%		-0.9%	5.3%	-16.7%	2.76
HF-LOW	1.009		1.3%	1.3%		3.0%	43.1%	
HF-HIGH		0.159	1.4%		0.2%	5.3%	4.2%	10.35
						Ratio (HF/MF)		3.75

Table 4: Long and Short Returns on Flows

The table reports the results of regressions of the long-leg and short-leg returns of anomalies on fund flows. The dependent variable are the long (decile 10) and short (decile 1) returns at month t of two composite anomalies, SYY and NINV, and their low- and high-frequency components. SYY is the composite anomaly constructed based on eleven anomalies documented in Stambaugh, Yu, and Yuan (2012). NINV is the composite of seven anomalies in SYY that are not related to corporate investments. Panel A reports the results of the long-leg returns, while Panel B shows the results of short-leg returns. The main independent variables are the low- and high-frequency components of fund flows at month t, that is, MF-LOW, MF-HIGH, HF-LOW, and HF-HIGH. t-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

Panel A: Long Returns

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		NINV		SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF-LOW	0.322	[0.98]	-0.084	[-0.23]	2.154	[3.49]	1.887	[3.14]	-1.832	[-3.15]	-1.971	[-3.10]
MF-HIGH	0.945	[2.50]	0.695	[1.94]	-1.177	[-3.36]	-1.162	[-3.29]	2.122	[6.27]	1.857	[4.96]
HF-LOW	-0.058	[-0.59]	-0.002	[-0.02]	-0.066	[-0.30]	-0.087	[-0.39]	0.007	[0.03]	0.085	[0.36]
HF-HIGH	-0.022	[-0.57]	0.023	[0.49]	0.050	[0.98]	0.051	[1.00]	-0.072	[-1.16]	-0.028	[-0.41]
RMRF	0.840	[29.12]	0.888	[30.41]	0.181	[4.24]	0.173	[3.87]	0.659	[15.49]	0.714	[14.35]
Amihud	-0.029	[-0.54]	0.001	[0.02]	-0.233	[-1.49]	-0.231	[-1.53]	0.205	[1.48]	0.232	[1.65]
Turnover	-0.051	[-2.41]	-0.062	[-3.18]	-0.055	[-0.72]	-0.069	[-0.93]	0.004	[0.07]	0.007	[0.11]
HML	0.173	[3.42]	0.039	[0.67]	0.063	[1.20]	0.044	[0.87]	0.110	[1.74]	-0.005	[-0.07]
SMB	0.607	[7.76]	0.617	[7.28]	0.105	[2.32]	0.102	[2.29]	0.502	[7.23]	0.515	[6.86]
Intercept	0.017	[3.34]	0.018	[3.51]	0.026	[1.54]	0.028	[1.72]	-0.008	[-0.60]	-0.010	[-0.71]
N	240		240		240		240		240		240	
Adj R^2	91.8%		92.0%		30.9%		29.9%		79.0%		79.0%	

Panel B: Short Returns

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		NINV		SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF-LOW	2.363	[2.46]	3.320	[2.84]	4.662	[4.03]	5.416	[3.92]	-2.299	[-2.15]	-2.096	[-1.71]
MF-HIGH	2.580	[2.20]	2.649	[1.91]	-1.759	[-2.76]	-1.980	[-2.68]	4.339	[4.17]	4.629	[3.81]
HF-LOW	-0.583	[-2.60]	-0.898	[-2.82]	-0.769	[-2.16]	-1.106	[-2.87]	0.186	[0.53]	0.209	[0.55]
HF-HIGH	-0.223	[-2.06]	-0.100	[-0.68]	0.081	[0.87]	0.088	[0.85]	-0.304	[-2.29]	-0.188	[-1.14]
RMRF	1.246	[12.02]	1.286	[9.03]	0.305	[3.56]	0.346	[3.29]	0.941	[12.59]	0.940	[10.22]
Amihud	-0.393	[-2.61]	-0.402	[-1.84]	-0.739	[-2.56]	-0.758	[-2.22]	0.346	[1.48]	0.355	[1.33]
Turnover	0.022	[0.41]	0.060	[0.73]	-0.023	[-0.18]	-0.005	[-0.03]	0.045	[0.43]	0.064	[0.55]
HML	-0.114	[-0.76]	-0.163	[-0.78]	-0.051	[-0.57]	-0.081	[-0.74]	-0.063	[-0.46]	-0.081	[-0.45]
SMB	0.841	[9.13]	0.920	[10.42]	0.063	[0.80]	0.068	[0.74]	0.778	[9.52]	0.852	[10.40]
Intercept	-0.005	[-0.39]	-0.009	[-0.47]	0.017	[0.59]	0.017	[0.50]	-0.021	[-0.93]	-0.025	[-0.97]
N	240		240		240		240		240		240	
Adj R^2	78.9%		71.0%		28.9%		27.3%		66.8%		59.4%	

Table 5: Returns of Individual Anomalies and Fund Flows

The table shows the results of time-series regressions of the long-minus-short returns of various anomalies on fund flows. The dependent variable are the long-minus-short returns at month t of eleven anomalies in documented in Stambaugh, Yu, and Yuan (2012). Panel A uses the total anomaly returns as the dependent variables, while Panels B and C use the low-frequency and high-frequency return components, respectively. The main independent variables are the low- and high-frequency components of fund flows at month t, that is, MF-LOW, MF-HIGH, HF-LOW, and HF-HIGH. t-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

Panel A: Total Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Anomaly	Total Accruals	Asset Growth	Composite Equity Issue	Investment-to-Asset	Failure Probability	Gross Profitability	Momentum (12m)	Net Operating Asset	Net Stock Issues	O-Score	ROA
MF-LOW	0.826	2.018	-1.173	0.002	-0.304	-2.529	-2.062	-0.238	-0.901	-1.507	-2.808
	[1.26]	[2.63]	[-3.05]	[0.01]	[-0.41]	[-3.06]	[-1.06]	[-0.39]	[-2.45]	[-3.16]	[-2.57]
MF-HIGH	0.768	2.042	-0.449	-0.340	-1.104	-1.255	-6.141	-0.857	-0.626	-0.165	-2.232
	[1.34]	[2.73]	[-1.06]	[-0.82]	[-1.36]	[-1.20]	[-2.22]	[-2.25]	[-1.45]	[-0.26]	[-1.58]
HF-LOW	-0.172	-0.619	0.284	0.166	0.147	0.714	0.519	-0.322	-0.027	0.466	0.838
	[-1.10]	[-1.98]	[2.08]	[1.29]	[0.47]	[3.35]	[0.66]	[-1.65]	[-0.21]	[2.04]	[2.41]
HF-HIGH	0.210	0.204	-0.184	-0.050	0.202	-0.012	0.541	0.292	-0.052	-0.177	-0.137
	[2.22]	[1.63]	[-1.50]	[-0.59]	[1.60]	[-0.07]	[1.53]	[3.02]	[-0.59]	[-1.13]	[-0.75]
MKTRF	0.204	-0.087	-0.438	-0.072	-0.501	-0.031	-0.411	-0.238	-0.319	-0.113	-0.294
	[3.10]	[-0.86]	[-6.74]	[-1.40]	[-5.43]	[-0.36]	[-1.62]	[-4.30]	[-5.55]	[-2.44]	[-2.19]
Amihud	0.155	0.026	0.289	-0.042	-0.007	0.232	-0.572	0.004	0.129	0.536	0.260
	[1.27]	[0.11]	[2.94]	[-0.57]	[-0.05]	[1.72]	[-1.38]	[0.03]	[1.72]	[4.21]	[1.15]
Turnover	0.049	-0.014	0.004	-0.020	-0.097	-0.002	-0.390	-0.129	-0.033	0.078	-0.072
	[1.21]	[-0.16]	[0.10]	[-0.62]	[-2.09]	[-0.06]	[-2.64]	[-2.95]	[-1.02]	[1.63]	[-0.79]
HML	-0.187	0.158	0.604	0.057	-0.185	-0.034	-0.244	-0.071	0.451	0.029	0.584
	[-2.17]	[1.03]	[5.78]	[1.51]	[-0.64]	[-0.31]	[-0.56]	[-0.64]	[6.33]	[0.31]	[3.16]
SMB	0.313	0.522	-0.458	-0.064	-0.318	-0.325	0.073	0.086	-0.271	-0.597	-0.737
	[5.07]	[2.81]	[-9.65]	[-1.40]	[-3.17]	[-1.45]	[0.27]	[0.51]	[-6.58]	[-3.21]	[-5.41]
Intercept	-0.011	0.017	-0.002	0.006	0.026	-0.005	0.092	0.028	0.011	-0.028	0.010
	[-1.06]	[0.80]	[-0.27]	[0.84]	[2.51]	[-0.43]	[2.80]	[2.62]	[1.57]	[-2.43]	[0.48]
N	240	240	240	240	240	240	240	240	240	240	240
Adj R^2	30.1%	16.6%	77.3%	5.9%	29.2%	9.9%	9.6%	17.7%	68.0%	41.0%	36.5%

Panel B: Low Frequency Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Anomaly	Total Accruals	Asset Growth	Composite Equity Issue	Investment-to-Asset	Failure Probability	Gross Profitability	Momentum (12m)	Net Operating Asset	Net Stock Issues	O-Score	ROA
MF-LOW	1.145	1.611	-2.241	-0.122	-1.011	-2.405	-2.762	-0.663	-1.719	-1.651	-2.910
	[1.92]	[2.42]	[-2.91]	[-0.50]	[-2.37]	[-3.30]	[-2.02]	[-1.23]	[-3.59]	[-3.63]	[-2.74]
MF-HIGH	-0.618	-0.852	0.498	0.094	0.435	0.405	0.756	0.061	0.292	0.627	1.077
	[-2.87]	[-2.84]	[2.05]	[0.60]	[1.75]	[1.84]	[1.26]	[0.25]	[1.53]	[2.58]	[2.35]
HF-LOW	-0.313	-0.444	0.544	0.247	0.304	0.606	1.065	-0.343	0.236	0.270	1.092
	[-2.25]	[-2.02]	[2.40]	[2.00]	[1.61]	[3.86]	[2.22]	[-2.37]	[1.45]	[1.56]	[4.04]
HF-HIGH	0.017	0.022	-0.026	-0.005	-0.022	-0.016	-0.002	0.011	-0.015	-0.032	-0.040
	[0.50]	[0.40]	[-0.54]	[-0.26]	[-0.62]	[-0.36]	[-0.02]	[0.28]	[-0.49]	[-0.78]	[-0.55]
MKTRF	0.096	0.108	-0.078	-0.028	-0.088	-0.073	-0.208	-0.051	-0.055	-0.101	-0.165
	[3.13]	[2.67]	[-2.70]	[-1.16]	[-3.95]	[-2.58]	[-2.14]	[-1.32]	[-2.86]	[-3.50]	[-2.66]
Amihud	0.052	0.141	0.409	0.024	0.302	0.161	-0.074	0.014	0.287	0.387	0.346
	[0.46]	[0.75]	[2.68]	[0.44]	[2.94]	[1.64]	[-0.27]	[0.14]	[3.19]	[3.75]	[1.71]
Turnover	0.031	0.012	-0.005	-0.004	0.001	-0.020	-0.244	-0.135	-0.021	0.021	-0.043
	[0.63]	[0.15]	[-0.16]	[-0.13]	[0.01]	[-0.56]	[-1.57]	[-3.67]	[-0.95]	[0.43]	[-0.46]
HML	-0.041	0.034	0.160	-0.001	-0.043	0.017	-0.117	-0.047	0.116	0.049	0.155
	[-0.88]	[0.45]	[2.89]	[-0.04]	[-0.83]	[0.43]	[-1.02]	[-1.21]	[3.51]	[1.36]	[1.55]
SMB	0.059	0.149	0.007	0.018	-0.011	-0.020	-0.037	0.000	0.022	-0.024	-0.072
	[1.84]	[3.48]	[0.15]	[1.22]	[-0.34]	[-0.50]	[-0.55]	[-0.02]	[0.73]	[-0.77]	[-1.15]
Intercept	-0.003	0.008	-0.008	0.001	-0.004	0.000	0.050	0.027	0.001	-0.015	0.002
	[-0.29]	[0.46]	[-0.83]	[0.10]	[-0.42]	[0.05]	[1.63]	[3.33]	[0.22]	[-1.42]	[0.08]
N	240	240	240	240	240	240	240	240	240	240	240
Adj R^2	15.9%	17.8%	30.2%	11.0%	15.9%	20.8%	22.9%	30.0%	28.1%	25.8%	22.2%

Panel C: High Frequency Returns

Anomaly	(1) Total Accruals	(2) Asset Growth	(3) Composite Equity Issue	(4) Investment-to-Asset	(5) Failure Probability	(6) Gross Profitability	(7) Momentum (12m)	(8) Net Operating Asset	(9) Net Stock Issues	(10) O-Score	(11) ROA
MF-LOW	-0.319	0.407	1.067	0.124	0.707	-0.124	-0.071	0.425	0.817	0.144	0.102
	[-0.64]	[0.74]	[1.52]	[0.41]	[1.15]	[-0.32]	[-0.05]	[1.21]	[1.51]	[0.35]	[0.11]
MF-HIGH	1.386	2.894	-0.947	-0.434	-1.540	-1.659	-6.469	-0.918	-0.918	-0.792	-3.309
	[2.58]	[4.36]	[-1.88]	[-1.03]	[-1.92]	[-1.62]	[-2.90]	[-2.61]	[-2.25]	[-1.11]	[-2.42]
HF-LOW	0.141	-0.175	-0.260	-0.081	-0.158	0.108	-0.173	0.021	-0.263	0.195	-0.254
	[1.03]	[-0.71]	[-1.31]	[-1.11]	[-0.56]	[0.61]	[-0.42]	[0.12]	[-1.75]	[1.20]	[-0.80]
HF-HIGH	0.193	0.182	-0.158	-0.045	0.224	0.004	0.547	0.281	-0.037	-0.145	-0.097
	[1.95]	[1.44]	[-1.22]	[-0.54]	[1.71]	[0.02]	[1.69]	[3.03]	[-0.39]	[-0.87]	[-0.51]
MKTRF	0.109	-0.195	-0.360	-0.045	-0.414	0.042	-0.202	-0.187	-0.264	-0.012	-0.128
	[2.14]	[-2.30]	[-4.73]	[-1.39]	[-4.59]	[0.60]	[-1.08]	[-4.10]	[-4.60]	[-0.42]	[-1.39]
Amihud	0.103	-0.115	-0.120	-0.066	-0.309	0.071	-0.284	-0.010	-0.158	0.149	-0.086
	[1.06]	[-0.78]	[-0.90]	[-1.17]	[-1.91]	[0.72]	[-1.03]	[-0.11]	[-1.56]	[1.48]	[-0.40]
Turnover	0.019	-0.027	0.009	-0.016	-0.097	0.017	-0.126	0.006	-0.012	0.057	-0.028
	[0.77]	[-0.69]	[0.22]	[-0.88]	[-1.42]	[0.53]	[-1.63]	[0.24]	[-0.35]	[1.97]	[-0.53]
HML	-0.146	0.124	0.444	0.058	-0.142	-0.051	-0.202	-0.024	0.335	-0.020	0.429
	[-2.04]	[1.14]	[5.75]	[1.56]	[-0.52]	[-0.55]	[-0.63]	[-0.28]	[4.99]	[-0.25]	[2.73]
SMB	0.254	0.373	-0.464	-0.081	-0.306	-0.305	0.180	0.086	-0.293	-0.573	-0.665
	[4.52]	[2.00]	[-11.67]	[-1.77]	[-3.32]	[-1.46]	[0.78]	[0.53]	[-7.74]	[-3.01]	[-4.92]
Intercept	-0.008	0.009	0.006	0.005	0.031	-0.005	0.032	0.001	0.010	-0.013	0.009
	[-1.15]	[0.77]	[0.62]	[1.19]	[2.03]	[-0.61]	[1.51]	[0.07]	[1.31]	[-1.70]	[0.57]
N	240	240	240	240	240	240	240	240	240	240	240
Adj R^2	22.1%	13.8%	65.3%	4.5%	24.0%	5.7%	6.7%	10.2%	58.5%	33.3%	27.5%

Table 6: Market Liquidity, Anomaly Returns, and Fund Flows

This table reports the results of regressions of anomaly returns on the fund flows and its interaction with liquidity variables. The dependent variables are the low- and high-frequency returns at month t of two composite anomalies, SYY and NINV. The main independent variables are the low- and high-frequency fund flows, and their interaction with ILLIQ, which measures the market illiquidity at month t. We use three measures of illiquidity; Amihud illiquidity, the aggregate liquidity in Pastor and Stambaugh (2003), and the permanent variable factor in Sadka (2006). If the original variable measures the market liquidity, then we multiply the variable by minus one. Then, we detrend the illiquidity measures and sort them into quintiles. Finally, we standardize the quintile scores from zero to one to obtain ILLIQ. Panel A uses the total flows as the independent variables, while Panel B uses the low- and high-frequency flows. t-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

Panel A: Total Flows

	Amihud				Aggregate Liquidity (PS)				PV-Level (Sadka)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH
ILLIQ	-0.001	-0.005	0.005	0.007	-0.002	-0.005	-0.001	-0.001	0.001	-0.006	-0.009	-0.011
	[-0.08]	[-0.34]	[0.49]	[0.48]	[-0.52]	[-0.86]	[-0.10]	[-0.04]	[0.10]	[-0.51]	[-1.51]	[-1.43]
MF	-0.644	-1.579	-0.497	-1.051	-0.989	-1.354	-1.154	-1.712	-0.885	-1.554	-0.802	-1.445
	[-1.37]	[-2.54]	[-0.54]	[-0.87]	[-1.42]	[-1.60]	[-1.53]	[-1.85]	[-1.21]	[-1.74]	[-1.14]	[-1.75]
MF × ILLIQ	0.053	1.308	-0.685	-0.536	0.535	0.656	0.166	0.430	0.785	1.457	-1.267	-0.946
	[0.06]	[1.02]	[-0.63]	[-0.32]	[0.64]	[0.61]	[0.12]	[0.23]	[0.81]	[1.20]	[-0.80]	[-0.46]
HF	-0.016	-0.086	-0.093	0.013	0.005	-0.021	0.149	0.165	-0.136	-0.201	0.245	0.280
	[-0.08]	[-0.33]	[-0.39]	[0.04]	[0.06]	[-0.21]	[0.87]	[0.62]	[-1.24]	[-1.48]	[1.44]	[1.18]
HF × ILLIQ	0.331	0.556	0.351	0.128	0.401	0.627	-0.035	-0.161	0.533	0.757	-0.172	-0.292
	[1.34]	[1.64]	[1.29]	[0.29]	[2.27]	[2.69]	[-0.11]	[-0.39]	[2.79]	[2.96]	[-0.60]	[-0.78]
MKTRF	-0.117	-0.160	-0.312	-0.247	-0.107	-0.146	-0.306	-0.245	-0.124	-0.169	-0.300	-0.236
	[-2.27]	[-2.37]	[-3.76]	[-2.39]	[-1.97]	[-2.07]	[-3.66]	[-2.36]	[-2.36]	[-2.44]	[-3.70]	[-2.33]
Amihud	0.239	0.156	-0.069	-0.083	0.274	0.235	0.002	-0.005	0.215	0.210	0.141	0.151
	[1.28]	[0.62]	[-0.40]	[-0.35]	[1.54]	[0.98]	[0.02]	[-0.04]	[1.46]	[1.04]	[1.23]	[0.99]
Turnover	-0.046	-0.071	-0.061	-0.093	-0.036	-0.055	-0.053	-0.084	-0.039	-0.057	-0.048	-0.077
	[-0.58]	[-0.64]	[-1.25]	[-1.52]	[-0.57]	[-0.60]	[-1.25]	[-1.83]	[-0.63]	[-0.65]	[-1.20]	[-1.63]
HML	0.121	0.135	0.147	0.078	0.123	0.143	0.151	0.080	0.105	0.128	0.173	0.108
	[1.58]	[1.38]	[1.02]	[0.41]	[1.57]	[1.46]	[1.05]	[0.42]	[1.49]	[1.38]	[1.10]	[0.53]
SMB	0.044	0.036	-0.307	-0.354	0.049	0.050	-0.300	-0.352	0.035	0.038	-0.258	-0.305
	[0.78]	[0.50]	[-5.27]	[-4.40]	[0.90]	[0.75]	[-5.48]	[-4.54]	[0.83]	[0.73]	[-4.54]	[-3.86]
Intercept	0.020	0.027	0.014	0.020	0.017	0.020	0.013	0.019	0.019	0.023	0.011	0.017
	[1.22]	[1.22]	[1.37]	[1.47]	[1.18]	[0.99]	[1.29]	[1.51]	[1.31]	[1.14]	[1.14]	[1.47]
N	240	240	240	240	240	240	240	240	228	228	228	228
Adj R^2	20.5%	18.6%	25.4%	13.3%	21.9%	19.4%	25.0%	13.2%	21.2%	19.1%	26.4%	14.0%

Panel B: Decomposed Flows

	Amihud				Aggregate Liquidity (PS)				PV-Level (Sadka)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH
ILLIQ	-0.007	-0.016	0.016	0.019	0.001	-0.002	0.000	0.002	0.001	-0.006	-0.013	-0.016
	[-0.66]	[-1.14]	[1.36]	[1.30]	[0.08]	[-0.17]	[-0.02]	[0.13]	[0.09]	[-0.56]	[-2.15]	[-2.08]
MF-LOW	-2.081	-3.583	1.584	1.281	-2.370	-3.368	1.195	1.019	-1.930	-3.057	-0.814	-1.695
	[-2.89]	[-3.40]	[1.79]	[1.24]	[-2.33]	[-2.58]	[1.10]	[0.79]	[-1.79]	[-2.08]	[-1.16]	[-1.86]
MF-HIGH	1.258	1.274	-3.204	-3.968	0.181	0.376	-3.391	-4.365	1.298	1.604	-0.739	-1.006
	[1.70]	[1.40]	[-2.03]	[-1.94]	[0.23]	[0.39]	[-3.02]	[-3.01]	[2.73]	[2.74]	[-0.49]	[-0.56]
MF-LOW × ILLIQ	-0.763	0.265	-1.172	-1.255	-0.271	-0.300	-1.128	-1.456	-0.549	-0.366	1.789	2.850
	[-0.78]	[0.21]	[-1.12]	[-0.74]	[-0.25]	[-0.22]	[-0.84]	[-0.83]	[-0.38]	[-0.20]	[1.28]	[1.46]
MF-HIGH × ILLIQ	-1.054	-0.689	1.894	2.209	0.821	0.922	1.526	2.264	-0.881	-0.987	-2.752	-3.222
	[-0.99]	[-0.49]	[0.84]	[0.74]	[0.66]	[0.62]	[0.65]	[0.77]	[-1.13]	[-1.00]	[-0.92]	[-0.91]
HF-LOW	0.231	0.146	-0.195	-0.022	0.546	0.731	-0.567	-0.434	0.080	0.077	0.076	0.234
	[0.71]	[0.34]	[-0.65]	[-0.06]	[2.02]	[2.31]	[-1.76]	[-0.87]	[0.29]	[0.21]	[0.35]	[0.80]
HF-HIGH	-0.090	-0.073	-0.117	-0.036	-0.151	-0.247	0.497	0.500	-0.009	-0.011	0.263	0.293
	[-0.82]	[-0.54]	[-0.47]	[-0.10]	[-1.21]	[-1.41]	[2.44]	[1.69]	[-0.10]	[-0.11]	[1.28]	[1.07]
HF-LOW × ILLIQ	0.763	1.300	0.095	-0.077	0.277	0.428	0.632	0.501	0.915	1.310	-0.374	-0.549
	[2.45]	[3.15]	[0.25]	[-0.13]	[1.81]	[1.93]	[1.42]	[0.74]	[2.98]	[3.17]	[-0.95]	[-1.05]
HF-HIGH × ILLIQ	0.054	0.000	0.601	0.342	0.340	0.577	-0.519	-0.728	-0.054	-0.076	-0.040	-0.248
	[0.26]	[0.00]	[1.71]	[0.76]	[0.99]	[1.17]	[-1.19]	[-1.39]	[-0.38]	[-0.43]	[-0.11]	[-0.58]
MKTRF	-0.128	-0.173	-0.307	-0.243	-0.123	-0.168	-0.296	-0.233	-0.138	-0.189	-0.290	-0.224
	[-2.73]	[-2.86]	[-3.60]	[-2.31]	[-2.17]	[-2.27]	[-3.32]	[-2.10]	[-2.82]	[-2.92]	[-3.43]	[-2.16]
Amihud	0.579	0.632	-0.320	-0.319	0.478	0.512	-0.154	-0.127	0.437	0.516	-0.017	0.019
	[3.45]	[2.96]	[-1.58]	[-1.17]	[2.67]	[2.37]	[-1.00]	[-0.68]	[2.82]	[2.61]	[-0.13]	[0.11]
Turnover	-0.014	-0.023	-0.067	-0.088	-0.039	-0.061	-0.033	-0.051	-0.027	-0.042	-0.045	-0.062
	[-0.19]	[-0.24]	[-1.10]	[-1.12]	[-0.71]	[-0.82]	[-0.71]	[-0.88]	[-0.45]	[-0.51]	[-0.88]	[-0.95]
HML	0.101	0.106	0.153	0.076	0.106	0.121	0.165	0.086	0.088	0.103	0.180	0.109
	[1.72]	[1.41]	[0.99]	[0.38]	[1.78]	[1.68]	[1.00]	[0.38]	[1.56]	[1.39]	[1.12]	[0.53]
SMB	0.033	0.023	-0.303	-0.350	0.037	0.031	-0.271	-0.321	0.025	0.024	-0.249	-0.294
	[0.80]	[0.43]	[-5.44]	[-4.50]	[0.96]	[0.72]	[-5.51]	[-4.37]	[0.73]	[0.56]	[-4.40]	[-3.88]
Intercept	0.009	0.013	0.015	0.017	0.011	0.012	0.013	0.014	0.012	0.013	0.015	0.018
	[0.58]	[0.63]	[1.07]	[0.90]	[0.87]	[0.76]	[0.92]	[0.75]	[0.82]	[0.71]	[1.18]	[1.09]
N	240	240	240	240	240	240	240	240	228	228	228	228
Adj R^2	33.4%	33.4%	26.9%	13.7%	32.6%	31.3%	26.7%	13.8%	32.6%	32.3%	27.1%	14.1%

Table 7: Liqudity Shocks, Anomaly Returns, and Fund Flows

This table examines the relation between anomaly returns and flow flows during the period of liquidity shocks. The dependent variables are the low- and high-frequency returns at month t of two composite anomalies, SYY and NINV. The main independent variables are the low- and high-frequency fund flows, and their interaction with SHOCK, a dummy variable that equals one if the month t is included in the period of liquidity shock, zero otherwise. We consider two distinct periods of liquidity shock; Decimalization and Financial Crisis. Decimalization is 08/2000–05/2001, and considered as the period of positive liquidity shock. Financial Crisis is 07/2007–12/2009, and considered as the period of negative liquidity shock. Panel A uses the total flows as the independent variables, while Panel B uses the low- and high-frequency flows. t-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

Panel A: Total Flows

	Decimalization				Financial Crisis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH
SHOCK	0.075	0.092	0.029	0.055	-0.001	-0.006	0.005	0.011
	[10.36]	[9.60]	[1.59]	[2.65]	[-0.09]	[-0.42]	[0.67]	[1.15]
MF	-0.320	-0.538	-0.885	-1.168	-0.715	-0.902	-1.354	-1.973
	[-0.86]	[-1.18]	[-1.41]	[-1.48]	[-1.31]	[-1.37]	[-1.97]	[-2.20]
MF × SHOCK	3.757	6.189	-21.708	-26.341	1.052	1.666	2.248	2.902
	[4.08]	[5.64]	[-6.37]	[-5.75]	[1.02]	[1.17]	[1.38]	[1.38]
HF	0.113	0.174	0.219	0.179	0.120	0.105	0.157	0.186
	[1.55]	[1.45]	[2.21]	[1.22]	[0.98]	[0.67]	[1.05]	[0.94]
HF × SHOCK	-1.756	-2.562	0.897	0.602	0.301	0.637	-0.061	-0.298
	[-5.13]	[-6.01]	[0.99]	[0.61]	[1.96]	[3.12]	[-0.31]	[-1.37]
MKTRF	-0.111	-0.152	-0.284	-0.215	-0.123	-0.175	-0.305	-0.235
	[-2.88]	[-3.00]	[-3.69]	[-2.19]	[-2.33]	[-2.50]	[-3.66]	[-2.33]
Amihud	0.126	0.042	0.044	0.021	0.275	0.258	-0.013	-0.050
	[1.01]	[0.23]	[0.41]	[0.15]	[1.67]	[1.21]	[-0.11]	[-0.30]
Turnover	-0.045	-0.072	-0.043	-0.067	-0.037	-0.033	-0.079	-0.138
	[-0.74]	[-0.82]	[-1.19]	[-1.54]	[-0.81]	[-0.59]	[-1.63]	[-1.95]
HML	0.022	0.028	0.089	-0.023	0.118	0.135	0.144	0.074
	[0.44]	[0.40]	[0.73]	[-0.15]	[1.49]	[1.36]	[1.03]	[0.40]
SMB	0.003	-0.006	-0.314	-0.379	0.054	0.056	-0.303	-0.357
	[0.08]	[-0.11]	[-5.00]	[-4.03]	[0.94]	[0.80]	[-5.28]	[-4.57]
Intercept	0.020	0.024	0.010	0.015	0.016	0.015	0.017	0.028
	[1.52]	[1.27]	[1.12]	[1.36]	[1.48]	[1.01]	[1.64]	[1.84]
N	240	240	240	240	240	240	240	240
Adj R^2	42.9%	36.6%	34.7%	22.0%	21.4%	20.5%	25.7%	14.2%

Panel B: Decomposed Flows

	Decimalization				Financial Crisis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH
SHOCK	0.055	0.071	0.101	0.200	0.009	0.007	-0.001	0.004
	[3.61]	[4.19]	[1.47]	[2.21]	[1.19]	[0.82]	[-0.22]	[0.47]
MF-LOW	-1.606	-2.458	0.199	-0.038	-2.412	-3.072	0.543	0.009
	[-2.56]	[-3.21]	[0.32]	[-0.05]	[-2.42]	[-2.63]	[0.79]	[0.01]
MF-HIGH	0.500	0.689	-1.646	-2.041	0.486	0.736	-3.011	-3.737
	[1.65]	[1.72]	[-1.93]	[-1.79]	[1.35]	[1.57]	[-3.14]	[-2.85]
MF-LOW × SHOCK	8.155	10.790	-38.798	-63.705	-17.371	-24.664	10.384	12.533
	[1.84]	[2.41]	[-2.10]	[-2.58]	[-2.72]	[-2.87]	[1.99]	[2.16]
MF-HIGH × SHOCK	2.864	3.643	-28.991	-35.631	-0.629	-0.895	4.519	4.803
	[3.06]	[3.16]	[-8.84]	[-7.42]	[-0.56]	[-0.59]	[2.97]	[1.89]
HF-LOW	0.523	0.781	-0.045	0.001	0.684	0.723	-0.265	-0.114
	[3.00]	[2.78]	[-0.29]	[0.00]	[1.97]	[1.63]	[-0.98]	[-0.36]
HF-HIGH	-0.052	-0.071	0.312	0.225	-0.029	-0.044	0.274	0.260
	[-1.22]	[-1.29]	[2.72]	[1.36]	[-0.50]	[-0.62]	[2.33]	[1.47]
HF-LOW × SHOCK	-1.852	-2.921	-0.546	-2.092	1.014	1.887	-0.361	-0.631
	[-6.38]	[-6.51]	[-0.50]	[-1.42]	[2.14]	[2.99]	[-1.02]	[-1.46]
HF-HIGH × SHOCK	-1.408	-1.593	3.642	3.895	-0.066	-0.117	0.289	-0.233
	[-5.90]	[-5.13]	[4.70]	[4.09]	[-0.34]	[-0.46]	[0.70]	[-0.38]
MKTRF	-0.121	-0.167	-0.271	-0.200	-0.103	-0.150	-0.303	-0.234
	[-3.03]	[-3.18]	[-3.48]	[-2.02]	[-2.57]	[-2.82]	[-3.28]	[-2.09]
Amihud	0.312	0.317	-0.100	-0.096	0.534	0.590	-0.198	-0.192
	[2.79]	[2.01]	[-0.80]	[-0.56]	[3.09]	[2.84]	[-1.24]	[-0.92]
Turnover	-0.036	-0.059	-0.044	-0.056	-0.025	-0.014	-0.058	-0.098
	[-0.59]	[-0.70]	[-0.89]	[-0.92]	[-0.51]	[-0.26]	[-0.86]	[-1.07]
HML	0.020	0.023	0.074	-0.048	0.132	0.163	0.137	0.059
	[0.44]	[0.37]	[0.62]	[-0.31]	[2.34]	[2.36]	[0.85]	[0.28]
SMB	0.003	-0.006	-0.299	-0.360	0.050	0.055	-0.293	-0.347
	[0.07]	[-0.11]	[-4.87]	[-3.86]	[1.13]	[0.99]	[-5.32]	[-4.60]
Intercept	0.014	0.015	0.013	0.015	0.006	0.002	0.018	0.024
	[1.05]	[0.83]	[1.06]	[0.93]	[0.56]	[0.15]	[1.16]	[1.13]
N	240	240	240	240	240	240	240	240
Adj R^2	48.0%	43.6%	35.9%	22.8%	37.0%	37.6%	28.1%	15.1%

Table 8: Economic Conditions, Anomaly Returns, and Fund Flows

The table examines whether the flow-return relation is affected by the economic conditions. The dependent variables are the low- and high-frequency returns at month t of two composite anomalies, SYY and NINV. The main independent variables are the low- and high-frequency fund flows, and their interaction with D, which measures the current condition of the market and overall economy. We use three variables that measure the economic condition; NBER Recession Indicator, TED Spread, and VIX. For NBER, D is a dummy variable that equals one if the current month is in a recessionary period, zero otherwise. For TED Spread and VIX, D is a quintile score scaled from zero to one. Panel A uses the total flows as the independent variables, while Panel B uses the low- and high-frequency flows. t-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

Panel A: Total Flows

	NBER Recession				TED Spread				VIX			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH
D	0.004	0.001	-0.013	-0.011	0.008	0.007	-0.001	0.000	-0.002	-0.011	-0.002	-0.004
	[0.72]	[0.08]	[-2.36]	[-1.71]	[1.03]	[0.74]	[-0.14]	[0.01]	[-0.21]	[-0.97]	[-0.29]	[-0.41]
MF	-0.764	-0.977	-1.089	-1.699	-1.331	-2.067	-0.634	-0.895	-0.962	-1.555	-0.921	-1.441
	[-1.41]	[-1.50]	[-1.60]	[-1.94]	[-2.70]	[-3.53]	[-0.68]	[-0.74]	[-1.68]	[-1.94]	[-1.41]	[-1.98]
MF × D	2.103	2.858	-0.041	1.255	1.331	2.414	-1.021	-1.427	0.853	1.303	-0.424	-0.302
	[2.30]	[2.48]	[-0.02]	[0.58]	[1.58]	[2.23]	[-0.70]	[-0.75]	[0.90]	[1.00]	[-0.28]	[-0.15]
HF	0.107	0.091	0.152	0.158	-0.007	-0.092	0.340	0.372	-0.038	-0.103	0.096	0.074
	[0.97]	[0.63]	[1.15]	[0.85]	[-0.07]	[-0.69]	[1.88]	[1.37]	[-0.30]	[-0.62]	[0.48]	[0.26]
HF × D	0.366	0.707	-0.128	-0.303	0.426	0.738	-0.393	-0.532	0.398	0.639	0.054	0.019
	[2.60]	[3.73]	[-0.60]	[-1.33]	[3.02]	[3.62]	[-1.33]	[-1.54]	[2.42]	[2.60]	[0.19]	[0.05]
MKTRF	-0.127	-0.181	-0.310	-0.245	-0.109	-0.149	-0.305	-0.242	-0.120	-0.171	-0.305	-0.244
	[-2.55]	[-2.72]	[-3.76]	[-2.39]	[-2.05]	[-2.11]	[-3.73]	[-2.40]	[-2.16]	[-2.36]	[-3.61]	[-2.30]
Amihud	0.266	0.242	0.052	0.047	0.230	0.183	-0.009	-0.023	0.268	0.274	0.003	0.013
	[1.53]	[1.05]	[0.46]	[0.32]	[1.45]	[0.88]	[-0.07]	[-0.15]	[1.51]	[1.11]	[0.02]	[0.09]
Turnover	-0.041	-0.043	-0.025	-0.063	-0.033	-0.043	-0.071	-0.105	-0.034	-0.040	-0.050	-0.075
	[-0.72]	[-0.54]	[-0.64]	[-1.31]	[-0.56]	[-0.51]	[-1.84]	[-2.31]	[-0.51]	[-0.44]	[-1.05]	[-1.32]
HML	0.113	0.126	0.158	0.090	0.146	0.176	0.143	0.071	0.109	0.124	0.153	0.083
	[1.40]	[1.25]	[1.12]	[0.49]	[1.79]	[1.68]	[1.06]	[0.40]	[1.42]	[1.26]	[1.02]	[0.42]
SMB	0.041	0.041	-0.287	-0.343	0.076	0.086	-0.313	-0.368	0.044	0.046	-0.295	-0.345
	[0.75]	[0.61]	[-5.05]	[-4.27]	[1.34]	[1.26]	[-5.47]	[-4.85]	[0.84]	[0.71]	[-5.08]	[-4.27]
Intercept	0.017	0.016	0.008	0.015	0.013	0.014	0.016	0.023	0.017	0.020	0.013	0.019
	[1.30]	[0.90]	[0.83]	[1.30]	[0.94]	[0.69]	[1.76]	[1.99]	[1.18]	[1.02]	[1.32]	[1.56]
N	240	240	240	240	240	240	240	240	240	240	240	240
Adj R^2	24.3%	22.9%	25.7%	13.7%	25.9%	24.8%	25.8%	14.1%	21.5%	19.1%	25.1%	13.3%

Panel B: Decomposed Flows

	NBER Recession				TED Spread				VIX			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH	SYY-LOW	NINV-LOW	SYY-HIGH	NINV-HIGH
D	0.018	0.021	0.000	0.003	0.017	0.016	-0.005	-0.002	-0.011	-0.024	0.002	-0.001
	[1.34]	[1.19]	[-0.02]	[0.16]	[1.92]	[1.52]	[-0.69]	[-0.23]	[-1.01]	[-1.73]	[0.28]	[-0.07]
MF-LOW	-2.412	-3.097	0.284	-0.166	-2.322	-3.434	0.990	0.579	-2.811	-4.251	0.580	-0.088
	[-2.44]	[-2.64]	[0.42]	[-0.19]	[-2.47]	[-3.00]	[0.94]	[0.45]	[-2.48]	[-2.78]	[0.70]	[-0.09]
MF-HIGH	0.358	0.568	-2.786	-3.681	-0.112	0.010	-2.119	-2.570	0.385	0.443	-1.954	-2.443
	[1.22]	[1.49]	[-3.04]	[-2.90]	[-0.23]	[0.02]	[-1.68]	[-1.46]	[0.90]	[0.88]	[-2.30]	[-2.35]
MF-LOW × D	-21.316	-31.938	-24.697	-25.487	-0.894	-0.341	-1.007	-1.210	0.740	1.034	0.274	0.713
	[-1.11]	[-1.26]	[-0.87]	[-0.80]	[-0.57]	[-0.19]	[-0.62]	[-0.55]	[0.43]	[0.49]	[0.18]	[0.37]
MF-HIGH × D	1.230	1.541	3.527	5.001	1.312	1.532	-0.410	-0.577	0.435	0.753	-0.500	-0.608
	[2.07]	[1.92]	[2.55]	[2.87]	[1.64]	[1.41]	[-0.17]	[-0.18]	[0.60]	[0.83]	[-0.24]	[-0.23]
HF-LOW	0.631	0.662	-0.130	-0.001	0.506	0.301	-0.128	0.250	0.136	0.064	-0.313	-0.155
	[1.87]	[1.50]	[-0.57]	[0.00]	[1.24]	[0.62]	[-0.34]	[0.53]	[0.51]	[0.19]	[-0.97]	[-0.39]
HF-HIGH	-0.016	-0.025	0.238	0.199	-0.126	-0.143	0.429	0.369	0.050	0.061	0.233	0.168
	[-0.28]	[-0.36]	[2.03]	[1.14]	[-1.37]	[-1.33]	[2.17]	[1.25]	[0.38]	[0.39]	[0.88]	[0.45]
HF-LOW × D	1.319	2.365	1.012	0.906	0.489	1.178	-0.139	-0.572	0.874	1.430	0.163	0.020
	[1.25]	[1.73]	[0.75]	[0.60]	[1.13]	[2.34]	[-0.28]	[-0.90]	[2.97]	[4.24]	[0.46]	[0.04]
HF-HIGH × D	0.073	0.077	0.590	0.333	0.197	0.217	-0.370	-0.445	-0.187	-0.257	0.024	-0.044
	[0.47]	[0.38]	[1.23]	[0.68]	[1.40]	[1.22]	[-1.04]	[-1.01]	[-0.91]	[-1.05]	[0.05]	[-0.07]
MKTRF	-0.103	-0.149	-0.270	-0.197	-0.120	-0.173	-0.295	-0.225	-0.143	-0.205	-0.287	-0.224
	[-3.27]	[-3.54]	[-3.40]	[-1.87]	[-2.48]	[-2.64]	[-3.43]	[-2.13]	[-2.77]	[-3.10]	[-3.32]	[-2.07]
Amihud	0.468	0.498	-0.077	-0.050	0.457	0.469	-0.128	-0.100	0.536	0.654	-0.181	-0.119
	[2.57]	[2.18]	[-0.59]	[-0.28]	[2.81]	[2.32]	[-0.91]	[-0.56]	[2.58]	[2.39]	[-1.10]	[-0.59]
Turnover	-0.048	-0.050	-0.020	-0.043	-0.044	-0.058	-0.051	-0.072	-0.005	0.000	-0.043	-0.053
	[-0.87]	[-0.68]	[-0.40]	[-0.65]	[-0.77]	[-0.73]	[-1.14]	[-1.27]	[-0.07]	[0.00]	[-0.71]	[-0.69]
HML	0.098	0.112	0.148	0.073	0.131	0.154	0.148	0.070	0.087	0.093	0.155	0.079
	[1.44]	[1.29]	[1.02]	[0.38]	[2.06]	[1.89]	[1.03]	[0.37]	[1.58]	[1.36]	[1.00]	[0.39]
SMB	0.029	0.025	-0.280	-0.335	0.064	0.072	-0.300	-0.355	0.030	0.024	-0.290	-0.339
	[0.64]	[0.43]	[-5.04]	[-4.18]	[1.47]	[1.33]	[-5.70]	[-4.87]	[0.73]	[0.49]	[-5.07]	[-4.30]
Intercept	0.012	0.011	0.009	0.011	0.005	0.007	0.017	0.017	0.011	0.013	0.014	0.015
	[0.98]	[0.65]	[0.74]	[0.71]	[0.42]	[0.39]	[1.45]	[1.17]	[0.74]	[0.68]	[1.03]	[0.88]
N	240	240	240	240	240	240	240	240	240	240	240	240
Adj R^2	34.4%	34.6%	27.9%	14.8%	38.6%	38.4%	26.6%	13.9%	34.7%	36.3%	26.0%	13.1%

Table 9: Hedge Fund Flows by Characteristics

This table examines hedge fund characteristics and the flow-return relation. We construct flows of hedge fund based on their share restriction property and the use of leverage. Share restrictions are the sum of the days of the lock-up period, redemption notice period, and payout period. Leverage is the indicator variable that equals one if the hedge fund uses leverage, zero otherwise. Each month, based on the median value of the share restrictions (use of leverage), hedge funds are divided into two groups; HFBelow and HFAbove (HFUnLev and HFLev). Then, the fund flows is calculated separately for each group of hedge funds. The dependent variable are the long-minus-short returns at month *t* of two composite anomalies, SYY and NINV, and their respective low- and high-frequency component returns. Panel A shows the results of the share restriction, while Panel B reports the results of the leverage. *t* -statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

Panel A: Share Restriction

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomalies	SYY		NINV		SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF	-1.852		-2.598		-0.834		-1.172		-1.018		-1.426	
	[-2.25]		[-2.41]		[-1.56]		[-1.85]		[-1.58]		[-1.68]	
HFBelow	0.168		0.212		-0.045		-0.032		0.213		0.243	
	[1.06]		[0.93]		[-0.49]		[-0.26]		[1.17]		[0.95]	
HFAbove	0.196		0.231		0.211		0.288		-0.016		-0.057	
	[2.50]		[1.98]		[2.23]		[2.31]		[-0.17]		[-0.42]	
MF-Low		-2.353		-3.928		-3.017		-4.205		0.664		0.277
		[-2.41]		[-3.23]		[-3.76]		[-4.69]		[1.01]		[0.34]
MF-High		-1.775		-2.104		0.413		0.585		-2.188		-2.689
		[-1.81]		[-1.62]		[1.74]		[1.90]		[-2.26]		[-2.09]
HFBelow-Low		-0.537		-0.769		-0.834		-1.036		0.297		0.267
		[-2.26]		[-2.16]		[-3.05]		[-2.81]		[1.24]		[0.99]
HFAbove-Low		1.094		1.699		1.588		2.112		-0.494		-0.412
		[3.82]		[3.88]		[4.39]		[4.40]		[-1.66]		[-1.19]
HFBelow-High		0.268		0.275		-0.021		-0.024		0.289		0.299
		[1.24]		[0.90]		[-0.39]		[-0.33]		[1.34]		[0.96]
HFAbove-High		0.064		-0.009		-0.038		-0.048		0.102		0.039
		[0.79]		[-0.06]		[-1.07]		[-1.05]		[1.32]		[0.30]
MKTRF	-0.414	-0.381	-0.389	-0.344	-0.103	-0.073	-0.139	-0.102	-0.311	-0.308	-0.250	-0.242
	[-3.69]	[-3.49]	[-2.69]	[-2.52]	[-2.29]	[-2.76]	[-2.37]	[-2.98]	[-3.59]	[-3.18]	[-2.31]	[-2.05]
Amihud	0.253	0.240	0.205	0.265	0.225	0.358	0.166	0.363	0.028	-0.118	0.038	-0.098
	[1.65]	[1.83]	[0.83]	[1.28]	[1.28]	[2.69]	[0.70]	[1.97]	[0.21]	[-0.93]	[0.23]	[-0.60]
Turnover	-0.101	-0.077	-0.152	-0.108	-0.055	-0.027	-0.083	-0.045	-0.046	-0.050	-0.070	-0.064
	[-1.94]	[-1.61]	[-1.76]	[-1.68]	[-0.88]	[-0.76]	[-0.91]	[-0.89]	[-1.13]	[-1.05]	[-1.41]	[-1.04]
HML	0.268	0.265	0.215	0.205	0.126	0.115	0.146	0.130	0.142	0.151	0.069	0.075
	[1.31]	[1.40]	[0.82]	[0.86]	[1.70]	[2.74]	[1.57]	[2.51]	[0.94]	[0.92]	[0.35]	[0.35]
SMB	-0.241	-0.258	-0.292	-0.323	0.055	0.019	0.056	0.007	-0.296	-0.277	-0.348	-0.330
	[-3.90]	[-4.50]	[-3.70]	[-4.54]	[0.91]	[0.51]	[0.75]	[0.15]	[-5.09]	[-5.13]	[-4.34]	[-4.36]
Intercept	0.031	0.023	0.039	0.023	0.001	-0.011	0.008	-0.008	0.010	0.014	0.015	0.015
	[2.41]	[2.11]	[1.89]	[1.44]	[0.04]	[-1.28]	[0.39]	[-0.66]	[1.01]	[1.25]	[1.14]	[1.01]
N	240	240	240	240	240	240	240	240	240	240	240	240
Adj R^2	38.5%	39.7%	25.6%	28.3%	21.4%	49.2%	18.3%	47.9%	26.0%	27.7%	14.3%	14.8%

Panel B: Leverage

	(1)		(2)		(3)		(4)		(5)		(6)	
	SYY		NINV		SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF	-1.798		-2.526		-0.728		-1.026		-1.070		-1.500	
	[-2.24]		[-2.41]		[-1.34]		[-1.58]		[-1.75]		[-1.87]	
HFUnLev	0.071		0.130		0.228		0.324		-0.158		-0.194	
	[0.41]		[0.56]		[2.52]		[2.81]		[-0.77]		[-0.67]	
HFLev	0.335		0.356		0.056		0.081		0.279		0.275	
	[2.36]		[1.71]		[0.61]		[0.68]		[2.35]		[1.61]	
MF-Low		-1.876		-3.184		-2.368		-3.321		0.492		0.137
		[-1.95]		[-2.59]		[-2.50]		[-2.95]		[0.75]		[0.17]
MF-High		-1.617		-1.896		0.653		0.900		-2.270		-2.796
		[-1.65]		[-1.47]		[1.92]		[2.06]		[-2.56]		[-2.36]
HFUnLev-Low		0.821		1.114		0.801		1.089		0.020		0.025
		[2.33]		[2.42]		[2.11]		[2.18]		[0.09]		[0.08]
HFLev-Low		-0.180		-0.095		0.014		0.051		-0.194		-0.146
		[-0.46]		[-0.17]		[0.03]		[0.09]		[-0.76]		[-0.49]
HFUnLev-High		-0.240		-0.365		-0.125		-0.158		-0.115		-0.207
		[-1.03]		[-1.05]		[-1.78]		[-1.76]		[-0.47]		[-0.58]
HFLev-High		0.408		0.377		0.007		0.007		0.401		0.369
		[3.10]		[2.00]		[0.11]		[0.10]		[3.06]		[1.98]
MKTRF	-0.416	-0.428	-0.390	-0.413	-0.105	-0.133	-0.140	-0.179	-0.311	-0.295	-0.249	-0.234
	[-3.62]	[-3.61]	[-2.63]	[-2.69]	[-2.05]	[-2.65]	[-2.14]	[-2.76]	[-3.54]	[-3.31]	[-2.30]	[-2.12]
Amihud	0.276	0.399	0.230	0.482	0.285	0.541	0.244	0.597	-0.009	-0.142	-0.014	-0.115
	[1.82]	[2.53]	[0.93]	[2.07]	[1.53]	[2.90]	[0.97]	[2.50]	[-0.06]	[-0.99]	[-0.08]	[-0.62]
Turnover	-0.096	-0.055	-0.146	-0.083	-0.038	-0.014	-0.060	-0.028	-0.058	-0.042	-0.085	-0.056
	[-1.84]	[-1.01]	[-1.67]	[-1.08]	[-0.58]	[-0.20]	[-0.65]	[-0.30]	[-1.29]	[-0.77]	[-1.56]	[-0.81]
HML	0.263	0.242	0.213	0.175	0.123	0.097	0.145	0.109	0.140	0.144	0.068	0.066
	[1.31]	[1.25]	[0.82]	[0.72]	[1.56]	[1.61]	[1.46]	[1.45]	[0.98]	[0.96]	[0.36]	[0.34]
SMB	-0.241	-0.253	-0.292	-0.314	0.054	0.030	0.054	0.021	-0.295	-0.283	-0.346	-0.336
	[-3.86]	[-4.14]	[-3.68]	[-4.15]	[0.91]	[0.63]	[0.74]	[0.35]	[-5.17]	[-5.21]	[-4.41]	[-4.39]
Intercept	0.029	0.014	0.037	0.011	-0.005	-0.020	0.000	-0.020	0.014	0.014	0.020	0.015
	[2.28]	[1.04]	[1.76]	[0.58]	[-0.34]	[-1.35]	[0.02]	[-1.00]	[1.24]	[1.12]	[1.38]	[0.89]
N	240	240	240	240	240	240	240	240	240	240	240	240
Adj R^2	38.8%	39.3%	25.7%	27.0%	21.6%	35.9%	18.6%	34.6%	26.1%	27.5%	14.3%	14.7%

Table 10: Transient Anomalies

The table shows the results of time-series regressions of the long-minus-short returns of various anomalies on fund flows. The dependent variable are the long-minus-short returns at month *t* of three transient anomalies, and their respective low- and high-frequency returns. The transient anomalies are one-month industry momentum (Moskowitz and Grinblatt 1999), one-month return reversal (Jegadeesh and Titman 1993), and one-month industry-adjusted reversal (Da et al. 2014). The main independent variables are the low- and high-frequency components of fund flows at month *t*, that is, MF-LOW, MF-HIGH, HF-LOW, and HF-HIGH. *t*-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2013.

	Total Returns			Low-Frequency Returns			High-Frequency Returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anomaly	Industry Momentum (1m)	Industry Reversal (1m)	Momemtum (1m)	Industry Momentum (1m)	Industry Reversal (1m)	Momemtum (1m)	Industry Momentum (1m)	Industry Reversal (1m)	Momemtum (1m)
MF-LOW	1.194	-3.020	-3.560	0.798	-2.166	-2.576	0.396	-0.854	-0.984
	[0.80]	[-1.96]	[-2.14]	[0.56]	[-1.76]	[-1.89]	[0.58]	[-1.04]	[-1.10]
MF-HIGH	-0.407	2.079	2.125	-0.107	-0.246	-0.235	-0.301	2.324	2.360
	[-0.30]	[1.37]	[1.26]	[-0.24]	[-0.84]	[-0.69]	[-0.25]	[1.64]	[1.52]
HF-LOW	-0.643	-0.204	-0.010	-0.338	-0.732	-0.576	-0.306	0.529	0.566
	[-1.24]	[-0.26]	[-0.01]	[-0.97]	[-1.69]	[-1.22]	[-0.98]	[1.21]	[1.15]
HF-HIGH	0.102	-0.343	-0.335	-0.003	0.009	0.009	0.105	-0.352	-0.344
	[0.42]	[-1.36]	[-1.10]	[-0.04]	[0.13]	[0.12]	[0.50]	[-1.53]	[-1.26]
MKTRF	-0.244	0.439	0.519	-0.037	0.024	0.036	-0.207	0.416	0.483
	[-1.85]	[4.95]	[4.67]	[-1.00]	[0.68]	[1.02]	[-1.74]	[4.25]	[4.04]
Amihud	-0.120	0.874	0.920	0.063	0.445	0.455	-0.183	0.428	0.465
	[-0.43]	[2.28]	[2.26]	[0.29]	[1.89]	[1.88]	[-1.12]	[1.89]	[1.86]
Turnover	-0.033	0.021	0.033	0.015	-0.095	-0.093	-0.049	0.116	0.126
	[-0.44]	[0.33]	[0.48]	[0.23]	[-1.88]	[-1.78]	[-0.97]	[1.77]	[1.70]
HML	0.086	-0.154	-0.128	-0.178	0.163	0.199	0.264	-0.317	-0.327
	[0.36]	[-0.61]	[-0.42]	[-1.66]	[1.94]	[2.04]	[1.15]	[-1.05]	[-0.93]
SMB	0.332	-0.010	-0.100	0.073	0.061	0.042	0.259	-0.071	-0.142
	[1.09]	[-0.04]	[-0.29]	[0.89]	[0.81]	[0.49]	[0.90]	[-0.27]	[-0.43]
Intercept	0.028	-0.020	-0.027	0.013	0.017	0.012	0.015	-0.036	-0.040
	[1.49]	[-1.00]	[-1.27]	[0.84]	[1.21]	[0.86]	[1.17]	[-2.23]	[-2.17]
N	240	240	240	240	240	240	240	240	240
Adj R^2	1.3%	11.8%	9.3%	5.4%	34.7%	25.5%	1.0%	9.6%	8.2%