Slow Arbitrage:
Fund Flows and Mispricing in the Frequency Domain

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Abstract

We conduct a spectral analysis of the relation between fund flows and mispricing. Hedge funds and mutual funds both behave as low-pass filters, deploying high-frequency flows toward low-frequency mispricing. But hedge funds attenuate high-frequency flows more than do mutual funds, thus improving market efficiency 2 to 7 times more slowly than mutual funds worsen efficiency. Time-series and cross-sectional tests indicate that risk, limited access to capital, and implementation costs explain why hedge funds behave as low-pass filters. We propose a model to rationalize these results, which highlight the frequency-dependent effects of (especially arbitrage) capital on market efficiency.

Keywords: pricing anomalies; market efficiency; mutual funds; hedge funds; slow-moving capital; transaction costs; limits to arbitrage; spectral analysis

1. Introduction

A large body of evidence points to hedge funds being "smart money" that attenuates stock market anomalies (e.g., Akbas, Armstrong, Sorescu, and Subrahmanyam 2015; Kokkonen and Suominen 2015) and to mutual funds being "dumb money" that exacerbate them (e.g., Frazzini and Lamont 2008). Yet fund flows and anomalies comprise components of varying frequencies (or persistence), with some moving slowly and others more rapidly. It is not known how these components interact with one another—in other words, how the relation between flows and mispricing varies across frequencies—despite reasons to believe that investors might favor certain frequencies over others. On the one hand, investors are reluctant to tie up their limited capital for long periods in the face of such frictions as fundamental risk and limited funding. On the other hand, trading frictions of various types make it costly to move in and out of positions frequently. In line 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, Duffie (2010) describes many instances of capital moving slowly toward mispricing.[1]

In this paper we study the relation between hedge fund flows and pricing anomalies in the frequency domain, and we contrast it with the relation between mutual fund flows and anomalies. We ask four questions. First, are flows to hedge and mutual funds spread evenly across frequencies? Second, is mispricing uniformly represented across frequencies? The answer to either question is not clear a priori—Section 2 gives examples of forces that drive these series at either high or low frequency. Third, and most importantly, how does the relation between fund flows and mispricing vary across frequencies? Put differently, are hedge (resp. mutual) funds equally smart (resp. dumb) across all frequencies, or do they specialize in specific frequency bands? Fourth, what economic forces (frictions) make the relation between fund flows and mispricing frequency dependent? These questions allow to assess whether, and how, market efficiency varies across frequencies and thereby to shed light on the sources of inefficiencies. For example, addressing these issues helps us understand whether and why arbitrage capital is slow-moving (and hence why pricing anomalies are only slowly corrected). Is it because capital is slowly supplied to hedge funds or rather because hedge fund managers are slow in deploying their capital toward pricing anomalies (i.e., they choose to correct mispricing slowly)?

To answer these questions, we employ Fourier analysis to decompose hedge fund flows, mutual fund flows, and anomaly returns in the frequency domain and then study how flows and returns are related. Fourier analysis enables one to decompose any (stationary) time series into a combination of uncorrelated

[1] One striking example cited by Duffie (2010) is that of 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 recovered entirely over the next 60 days as the price reverts to its pre-announcement level.

random waves (or sinusoids). Each wave is characterized by a cycle length (a.k.a. a wavelength or period) that measures how much time is required for one full cycle or, equivalently, by a frequency that measures the number of cycles per unit time. Low-frequency waves are slow-moving (i.e., persistent) whereas high-frequency waves are fast-moving (i.e., transitory).[2]

Using such a spectral decomposition, we study how flows and returns are related at different frequencies. We measure smart money and dumb money as aggregate net flows to hedge funds and mutual funds, respectively. Our proxy for mispricing is the returns on the long-minus-short strategy based on the eleven anomalies documented by Stambaugh, Yu, and Yuan (2012, 2015), or the "SYY anomalies". We also consider a subset of seven anomalies that are unrelated to real investment—so-called non-investment (NINV) anomalies—because they are more closely related to mutual and hedge fund flows (Akbas et al. 2015).

Our spectral decomposition is based on a notion of frequency that differs from those previously studied. In particular, our use of "frequency" should be distinguished from the frequency of trading, which refers to how often a portfolio is rebalanced (a.k.a. portfolio turnover) and also from the closely related notion of a holding horizon.[3] It also differs from the frequency of measurement, which reflects how often a time series is sampled. Instead, our focus is on the frequency at which returns accrue and at which capital flows—that is, on how persistent these time series are. Yet our notion of frequency reflects economically meaningful concepts—such as the lengths of different cycles comprising these series—which are not easily captured with a single persistence parameter. Indeed, our decomposition identifies prominent cycles related to real and financial activity that have been reported in the literature; examples include the business cycle (with a period from 2 to 8 years), firm/fund annual and quarterly fiscal and reporting cycles, the one-year

[2] This approach is widely used in physical science and engineering and is analogous to using a prism to separate white light into its component colors, each corresponding to a different frequency. The resulting 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).

[3] To illustrate why the rebalancing frequency or holding period of an asset manager's strategy need not correspond to the frequency at which its returns accrue, consider Warren Buffet's investment in a particular stock (say, Apple). Marking-to-market these holdings yields 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, Buffet does not adjust his position in Apple in reaction to short-term price variations. Now consider a high-frequency convergence trader whose holding period is a few seconds or less. The returns to her strategy might be persistent and therefore evolve at much lower frequencies—for example, because they depend on cross-asset correlations that are known to vary along the business cycle. Take, for instance, an underpriced asset: if arbitrageurs persistently buy the asset at high frequency, then the asset's return is likely to be persistent and thus to display low frequency movement; if instead arbitrageurs make high-frequency trades in the asset but those trades do not have a persistent direction, then the asset's return is likely not to be persistent either (displaying high-frequency movement). It follows that trading frequency and return frequency are different concepts. Moreover, the frequencies of capital flows and trading can be related in various ways. For example, both long- and short-term investors can contribute capital either to a high-frequency trading shop or to a buy-and-hold mutual fund manager.

asset allocation cycle (Kamstra et al. 2003, 2017), seasonal momentum and reversal (Heston and Sadka 2008; Keloharju, Linnainmaa, and Nyberg 2019), and the quarterly earnings announcement return cycle (Linnainmaa and Zhang 2019). Studying how the cycles comprising anomaly returns and fund flows relate to one another improves our understanding of market (in)efficiency.

We focus on how asset managers invest and divest capital in response to flows in and out of their funds as well as 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 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 to attenuate. In accord with the industry's common practice of evaluating and reporting performance annually, we refer to periods of one year or more as "low frequency" and to periods of less than one year as "high frequency".

Our four key findings are as follows. First, our study of the frequency profiles of net flows documents that low-frequency flows account for roughly half of the total variation of flows for hedge funds—versus two thirds 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 frequencies. This result suggests 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 latter. In other words, fund managers appear to allocate their capital—even capital that flows at a high frequency—mainly to correct mispricing at low frequencies. In comparison, funds would behave as a "passthrough" filter 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 9–24 times more than they do at high frequencies; mutual funds similarly amplify mispricing 4 times more at low frequencies. These findings indicate that the flows of both smart and dumb money toward mispriced stocks are slowed down by managers.

The estimates lead to our third set of findings: hedge funds are a more selective (low-pass) filter than are mutual funds. Although both types of funds treat low-frequency flows in a similar way, they differ markedly in the extent to which they attenuate high-frequency flows. From a quantitative perspective, a one–standard deviation (1-SD) increase in hedge fund flows leads to a correction in SYY anomaly returns amounting to 43.1% of a standard deviation at low frequency, yet to only 5.0% of a standard deviation at high frequency. For mutual funds, in contrast, a 1-SD increase in flows leads to an amplification in anomaly returns of 54.6% and 15.5% of a standard deviation at (respectively) low and high frequencies. Hence the attenuation factor (i.e., the extent of attenuation in high-frequency flows relative to low-frequency flows) is 2.4 times as large for hedge funds as it is for mutual funds: (43.1%/5.0%) / (54.6%/15.5%) = 2.4. With regard to NINV anomalies, the attenuation factor is 7 times larger for hedge funds than for mutual funds. Put differently, at low frequency we observe that a 1-SD increase in hedge fund flows corrects 80% of the mispricing implied by a 1-SD increase in mutual fund flows; at high frequency, this figure drops to 12%.

Moreover, examining the attenuation factor over the entire spectrum reveals that, for both hedge and mutual funds, this factor is constant for frequencies of less than one cycle per year but then gradually diminishes beyond that threshold (again, the diminution is steeper for hedge funds). Hence our findings suggest that one year is an important threshold, although they also confirm that our high–low frequency contrasts are insensitive to the choice of a one-year cutoff for classifying frequencies as low or high. Overall, then, our third set of results indicates that hedge fund managers deploy capital toward improving market efficiency more slowly than do mutual fund managers toward reducing efficiency.

We hypothesize that the reasons for funds' (and especially hedge funds') behavior as a low-pass filter are related to frictions that limit arbitrage activity over specific frequency bands. Our fourth set of tests accordingly investigates the role of these frictions in slowing down the deployment of capital. We consider three types of frictions: fundamental risk, limited arbitrage capital, and implementation costs.[4] Exploiting variations in 14 proxies for these frictions—over time and in the cross section of hedge funds—yields evidence that all three frictions matter; in particular, we obtain the following four sets of results.

First, we find that hedge funds' tendency to correct low-frequency (rather than high-frequency) mispricing increases during periods of elevated fundamental risk—as proxied by the National Bureau of Economic Research (NBER) recession indicator, the Chicago Board Options Exchange volatility index (VIX), the financial uncertainty index of Jurado, Ludvigson, and Ng (2015), and the economic uncertainty index of Bekaert, Engstrom, and Xu (2019). Second, this tendency rises under adverse market conditions, as captured by the T-bill–eurodollar (TED) spread and the risk aversion index of Bekaert et al. (2019). The effect is due primarily to unleveraged hedge funds, which tend to have a relatively limited risk-bearing capacity (e.g., Adrian and Shin 2013). Third, the tendency to correct low-frequency mispricing intensifies in times of low aggregate liquidity, as captured by various systematic liquidity measures: those of Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), and Hu, Pan, and Wang (2013). This tendency is also concentrated among funds with illiquid investments, as reflected in the share restrictions imposed on fund investors (Aragon 2007). Thus, implementation costs are a likely contributor to hedge funds' behaving as low-pass filters.

[4] Strictly speaking, risk is not a friction. Rather, any limitation on investors' ability to diversify risk is a friction. We abuse notation slightly by bundling risk with genuine frictions.

Finally, to sharpen causal inferences regarding the role of frictions, we use the most recent financial crisis as an exogenous shock that increased fundamental risk, worsened funding conditions (Aragon and Strahan 2012), and/or impaired market liquidity (Sadka, 2010). We report that the tendency to favor low-frequency mispricing corrections rose dramatically during the crisis. Using decimalization as an exogenous, liquidity-improving shock[5] similarly reveals that this tendency is considerably weakened following decimalization—thanks to an amplification in the correction of high-frequency mispricing. These results support the importance of all three frictions in hindering arbitrage activity. Furthermore, we find no evidence that these frictions matter for mutual funds. This outcome is consistent with the notion that the rational consideration of market frictions is typical of smart (informed) managers but not of dumb (noise) managers.

We perform two additional tests to confirm that the filterlike behavior we report is linked to the investment decisions of active managers. First, we investigate whether passive funds behave like the hedge funds and mutual funds we have considered so far; we find that they do not. Instead, passive funds behave as a passthrough filter. Second, within our sample we identify a small subset of mutual funds that are skilled using common performance proxies. Subjecting these mutual funds to our spectral analysis, we find that they actually behave more like hedge funds. The implication is that our findings (i) are driven by active managers rather than by flows being passively passed through, and (ii) are due not to structural or institutional differences between hedge funds and mutual funds but rather to smart investing.

Collectively, our findings suggest that smart money (arbitrage capital) is slow-moving not because hedge fund investors are slow in channelling capital to hedge fund managers but rather because hedge fund managers deliberately prioritize slow-moving over fast-moving mispricing. We interpret this pattern as managers being slow in deploying their capital toward anomalies. In other words, arbitrage capital moves fairly quickly from hedge fund investors to hedge fund managers, but it moves slowly from hedge fund managers to capital market anomalies. 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, could be viewed as "good news" for market efficiency. Indeed, it suggests that hedge fund managers improve the efficiency of financial markets over long horizons—for which, presumably, it matters most. In contrast, high-frequency traders are credited for improving market efficiency over fractions of a second, leading critics (e.g., Biais, Foucault, and Sophie Moinas 2015; Budish, Cramton, and Shim 2015) to question their social value.

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

We propose a simple model that ties together our evidence and illustrates how the three frictions that play a central role in the data can, in theory, produce the patterns we document. The model—an extension of Garleanu and Pedersen (2013, 2016) to an equilibrium setting—describes the dynamics of returns when the factors driving those returns decay at different speeds. The economy features two agents: noise traders (dumb money), who have a temporary excess demand for assets; and arbitrageurs (smart money), who accommodate that demand. Our economy also features two assets, one with slowly decaying excess demand and another a fast-decaying excess demand; these assets represent (respectively) low-frequency and high-frequency mispricing. Finally, it incorporates the three aforementioned frictions, namely fundamental risk, a limited supply of arbitrage capital, and transaction costs. Arbitrageurs receive flows that expand their risk-bearing capacity (and more so for more persistent flows) and that they invest in the two assets subject to a transaction cost. We use the model to compute the coefficient from regressing asset returns on flows, and we derive five predictions that are consistent with our empirical results.

The first of these predictions is that the regression coefficient is positive; this is simply a reflection of the mispricing corrections that occur when arbitrageurs see their risk capacity expand. Second, and of greater interest, the regression coefficient is larger for the slower-decaying asset. This prediction reflects two factors: (i) arbitrageurs are exposed for longer to the slower asset and so they demand a larger premium; and (ii) they trade that asset more slowly and so incur lower transaction costs. As a result, the slower asset is more mispriced and hence more responsive to fluctuations in arbitrage capital. Our final three predictions are that the regression coefficient is more sensitive to the speed of decay when fundamentals are riskier, when arbitrageurs' risk-bearing capacity is lower, and when transaction costs are greater. Any one of these conditions will widen the gap between the prices of the two assets and so will magnify the differential effect of decay speed. The model proposed here thus demonstrates that our diverse empirical findings can be rationalized within a unified framework featuring limited risk bearing and transaction costs.

The rest of our paper proceeds as follows. Section 2 reviews the related literature and discusses our contribution. Section 3 presents the methodology employed for our spectral analysis. Section 4 describes the data and variables. Section 5 discusses the frequency structures of fund flows and of mispricing and their relation. Section 6 investigates the role of frictions. Section 7 presents our theoretical model. Section 8 concludes with a brief summary.

2. Related literature and contribution

We make three major contributions to the literature, the first two of which concern the market efficiency debate. First, we build on the empirical literature documenting that flows to asset managers affect market efficiency. Among those studies, Akbas et al. (2015), Akbas, Armstrong, Sorescu, and Subrahmanyam (2016), and Kokkonen and Suominen (2015) report that flows to hedge funds and mutual funds are associated with (respectively) a correction and a worsening of mispricing.[6] We add to this debate by examining how these associations between capital flows and mispricing vary across frequencies. In so doing, we shed light on the dynamics of market efficiency (anomalies) and on the differential roles played in such dynamics by hedge funds and mutual funds. More recently, Koijen et al. (2019) and Koijen and Yogo (2019) emphasize the importance for asset pricing of distinguishing among types of institutions. In a theory paper, Crouzet, Dew-Becker, and Nathanson (forthcoming) establish that, in equilibrium, investors specialize in specific frequencies. Daniel, Hirshleifer, and Sun (forthcoming) report that anomaly returns are shaped by forces with various degrees of persistence. Our findings imply that hedge funds correct mispricing at low frequency more than they do at high frequency; thus they contribute to market efficiency, especially at frequencies lower than one year. In contrast, mutual funds exacerbate mispricing over the entire spectrum of frequencies—and slightly more so (in comparison with hedge funds) for frequencies lower than one cycle per year. Hence hedge funds are instrumental in shaping anomaly returns for frequencies greater than one year, whereas mutual funds exert influence across the entire spectrum.

These results help explain why anomaly returns are surprisingly persistent—in particular, why "factor momentum" can last for a year or even longer (e.g., Ehsani and Linnainmaa 2019).[7] Our findings can likewise help us understand the predictive power of hedge funds' infrequently reported holdings for stock returns over long horizons (Agarwal, Jiang, Tang, and Yang. 2013; Aragon, Hertzel, and Shi 2013) and alsothe cross-predictability between equity and bond markets over such horizons (Pitkäjärvi, Suominen, and Vaittinen, forthcoming).

Our second contribution to the market efficiency debate concerns the effects of frictions on mispricing. In contrast to theoretical work, the empirical literature has not yet reached a consensus on which frictions actually matter. We evaluate the relevance of three categories of frictions (risk, limited access to capital, and implementation costs) by examining how their effects on the relation between market efficiency and arbitrage activity varies across frequencies. That arbitrageurs prefer to correct mispricing at low rather than high frequencies (irrespective of the frequency at which their capital flows)—and that this preference strengthens when frictions are more severe—is evidence not only that such frictions do matter but also of why they matter. Consider, for example, our results for implementation costs. There is substantial disagreement on their importance in hindering arbitrage, where contrary views reflect differences in the

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[6] Shive and Yun (2013) document that hedge funds profit from flows to mutual funds, and Brunnermeier and Pedersen (2005) as well as Chen, Hanson, Hong, and Stein (2008) find that hedge funds "prey on" distressed mutual funds. Coval and Stafford (2007, Frazzini and Lamont (2008), and Lou (2012), among others, focus on the relationship between flows and mutual funds.

[7] McLean and Pontiff (2016), Avramov, Cheng, Schreiber, and Shemer (2017), and Arnott, Clements, Kalesnik, and Linnainmaa (2019) document varying degrees of persistence in anomaly returns.

samples and methodologies used across studies. One strand of papers uses broad data sets, such as the New York Stock Exchange Trade and Quote (TAQ), to simulate strategies that are followed by practitioners. These studies typically extrapolate price impact estimates from small to large trades and conclude that implementation costs are high enough to wipe out arbitrage profits. Another strand of research examines, in proprietary data sets, the actual implementation algorithms followed by selected asset managers; this work reports that their costs are low and so arbitrage profits are sizable.[8] The debates center on (a) the plausibility of the strategies and costs simulated by the former strand of papers and (b) the representativeness of the practitioners studied by the latter. The approach we adopt borrows from both of these research streams. As in the literature that simulates trading strategies, our approach is based on a broad and unbiased universe of arbitrageurs. And as in studies of select asset managers, we neither take a stand on trading strategies nor rely on particular parameterizations of costs; instead, we examine the return implications of actual hedge fund trades.[9] Our findings imply that implementation costs matter, since we observe more attenuation of arbitrage capital flows when these costs are elevated, and they also shed light on the effects of those costs—namely to deter arbitrageurs from trading on the high-frequency flows they receive.

Finally, our work is part of a growing group of papers that import new methodologies (e.g., statistical and machine learning) into the field of finance. Much like other techniques—such as instrumented principal component analysis (e.g., Kelly, Pruitt, and Su 2019) or partial least squares (e.g., Huang et al. 2015)—spectral analysis is essentially a way of understanding the covariance structure of variables, here by focusing on cycle-like variations. With cycles at the heart of so many economic variables, spectral analysis is a promising tool. In fact, a nascent literature has begun to examine investments and asset returns through the lens of frequencies. From a theoretical perspective, models have been proposed to work out the implications of trades' frequency profiles for asset pricing (Dew-Becker and Giglio 2016; Crouzet et al. forthcoming). On the empirical front, studies have conducted frequency analyses of concepts such as news (Calvet and Fisher 2007), consumption risk (Ortu, Tamoni, and Tebaldi 2013; Bandi and Tamoni 2017), risk prices (Dew-Becker and Giglio 2016), investment strategies' alphas and betas (Bandi, Chaudhuri, Lo, and Tamoni 2018; Chaudhuri and Lo 2018), and market return (Schneider 2019).

[8] Papers in the first stream of literature include Lesmond, Schill, and Zhou (2004), Korajczyk and Sadka (2004), Novy-Marx and Velikov (2016), and DeMiguel et al. (2019). Among the second are Keim and Madhavan (1997), Engle, Ferstenberg, and Russell (2012), and Frazzini, Israel, and Moskowitz (2018).

[9] In that respect, our approach is close in spirit to a recent working paper of Patton and Weller (forthcoming), who estimate implementation costs by comparing actual mutual fund returns with the on-paper returns to factor exposure but making any parametric assumptions about transaction costs.

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 evident a priori whether (and how) anomaly returns, fund flows and their relationship vary across frequencies. There are many forces at play. First, mispricing might worsen/correct at any frequency depending on investors' objectives and trading strategies. For instance, an algorithmic trader might specialize in high-frequency price fluctuations while a value investor could be more concerned with long-term price movements. These investors' trades are likely to affect market efficiency only at the frequency at which they operate (Crouzet et al. forthcoming). Similarly, investment capital is supplied to and redeemed from asset managers over various frequencies. On the one hand, many mutual fund investors contribute regularly to retirement accounts with restricted redemptions, producing low-frequency flows; on the other hand, mutual funds exhibit features—such as open-endedness, liquidity, and marking-to-market—that encourage investors to move money at high frequencies. Generally, investors tend to differ considerably in their investment horizons and rebalancing frequencies, which results in differential effects on mispricing across frequencies.

In addition, some economic forces tend to accelerate trading or price discovery while other forces hinder them. For example, competition among informed traders speeds up the incorporation of information into prices (Holden and Subrahmanyam 1992), whereas market segmentation (Pitkäjärvi et al. 2019) and market frictions that impair investors' ability to bear risk (Lou, Yan, and Zhang 2013; Etula, Rinne, Suominen, and Vaittinen 2019) generate slow return cycles; transaction costs and limited attention also induce investors to rebalance infrequently, which leads to predictable patterns in prices at certain frequencies (Bogousslavsky 2016; Gao, Han, Li, and Zhou 2018). News, too, is delivered over various frequencies, generating return cycles that match their delivery frequencies—for example, the quarterly earnings announcement cycle in Linnainmaa and Zhang (2018) and the biweekly Federal Open Market Committee (FOMC) announcement cycle in Cieslak, Morse, and Vissing-Jorgensen (2018).

3.2. Decomposition of mispricing and flows

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

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

here X_t^L is the slow-moving (low-frequency) component of X_t, representing cycles longer than a threshold value (e.g., one year in our analysis), and X_t^H is the fast-moving (high-frequency) component that captures shorter cycles. Both X_t^L and X_t^H are orthogonal, from which it follows that $\text{Cov}(X_t^L, X_t^H) = 0$.

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

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

for $J_x(\omega_k)$ the Fourier component of X_t at frequency ω_k. The inverse Fourier transformation allows us to recover the original time series:

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

Now that X_t is expressed as a linear combination of orthogonal components of different frequencies, we can split it into distinct time series—each corresponding to a subset of frequencies, or a "frequency band". First, we create a filter F_K, a vector of size $N + 1$, for frequency band K. Here $F_K(k)$ is set to 1 only if k belongs to K; otherwise, $F_K(k) = 0$. We define $K = L$ (resp. H), where L (resp. H) is a low-frequency (resp. high-frequency) band. In the empirical analysis, we shall consider two frequency bands: F_L, a low-pass filter; and F_H, a high-pass filter. Next we apply the filter F_K to X_t to obtain X_t^K as follows:

$$X_t^K = \sum_{k=0}^{N} F_K(k) J_x(\omega_k) e^{i\omega_k t}. \tag{4}$$

The variance of X_t^K can be calculated using the time-series variance; it can also be calculated using the sample spectrum:

$$\text{Var}(X_t^K) = \sum_{k=0}^{N} F_K(k) J_x(\omega_k) \overline{J_x(\omega_k)}\,; \tag{5}$$

in this expression the overline denotes complex conjugate. Thus $\text{Var}(X_t^K)$ is that portion of of X_t's sample variance that can be attributed to the subset of frequencies in K.

To analyze 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:

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

The two time series may be in phase (i.e., have peaks and troughs that match) at some frequencies yet be out of phase at other frequencies. So even if the covariance between X_t and Y_t is positive, the cospectrum could 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 are out of phase, then the contribution is negative. The cospectrum for frequency band K is given by

$$\mathrm{CO}_K = \sum_{k=0}^{N} F_K(k) J_X(\omega_k) \overline{J_Y(\omega_k)}. \tag{7}$$

One could, as an alternative, adopt a regression approach to evaluating the association between these two variables at various frequencies. More specifically, we 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 $\mathrm{Cov}(X_t^K, Y_t)/\mathrm{Var}(X_t^K)$, 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 $Y_t = Y_t^L + Y_t^H$ and since low-frequency components are orthogonal to high-frequency components, it follows that β_K can be expressed as $\mathrm{Cov}(X_t^K, Y_t^K)/\mathrm{Var}(X_t^K) = \mathrm{CO}_K/\mathrm{Var}(X_t^K)$.

The regression approach described by Equation (8) has several advantages. First, it is intuitive and easy to implement. Second, it extends naturally to a multivariate approach and so enables the analysis to incorporate control variables. Third, we can further expand the regression to include more refined frequency bands (beyond H and L) and thereby obtain a continuous frequency structure of the relation between Y and X—in other words, the spectrum of that relation.

4. Data and variable construction

Three main variables are used in our analyses: (i) anomaly returns, which proxy for aggregate cross-sectional mispricing; (ii) aggregate mutual fund flows, our proxy for dumb money; and (iii) aggregate hedge fund flows, a 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

4.1.1. Mispricing proxies

Following Stambaugh et al. (2012, 2015), 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), the O-score (Ohlson 1980), net stock issuances (Ritter 1991; 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 the ratio of investments to assets (Titman, Wei, and Xie 2004). These anomalies have been 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 of those just listed) and not by anomalies related to real investments (the last 4). Hence, we also estimate aggregate mispricing with respect to NINV anomalies only.

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 under study. Stambaugh et al. (2015) show that returns to the individual anomalies have low correlations with each other but have relatively high correlations with aggregate returns to a long–short strategy that combines the 11 anomalies into a single signal. This result suggests that each of the 11 components captures a different element of cross-sectional mispricing. So rather than considering individual anomalies, we follow Stambaugh et al. (2015) and construct an aggregate mispricing measure to identify overvalued/undervalued stocks at the end of each calendar month. Using all 11 characteristics together is justified given that (a) hedge funds seldom trade on single anomalies and (b) the aggregate mispricing measure "diversifies away [the] noise in each individual anomaly and … increases precision" (Stambaugh et al. 2015). Stambaugh and Yuan (2016) show that their mispricing metric performs well in explaining a set of 73 anomalies.

To construct this aggregate mispricing measure, we proceed in three steps. First, for each month we assign all sample stocks to deciles that reflect degrees of mispricing, based on their next-month returns as predicted by each of the anomalies. Thus, each stock is associated with 11 different decile ranks each month, one for each anomaly. Second, we compute an aggregate score—for each stock and month—that is based on the equal-weighted average of the decile ranks. If a stock is mispriced in the current month, that mispricing is expected to be corrected next month, on average. This means that 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. So, 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).

4.1.2. Correction versus exacerbation of mispricing

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 of that strategy during the post-ranking calendar month—we can determine whether mispricing is corrected or exacerbated. For this purpose, we classify stocks in the short leg as being overvalued at the end of month t. If the return to the short leg during month $t + 1$ is positive, then the implication is that overvalued stocks continue to appreciate and become even more overvalued. Analogously, stocks in the long leg are classified as undervalued at the end of month t. Hence a negative return on the long leg in month $t + 1$ indicates that mispricing worsens. For months during which aggregate mispricing is exacerbated, the long leg yields lower returns than does the short leg and so the returns on the long–short strategy are negative. Conversely, for months during which aggregate mispricing is corrected, the long leg realizes higher returns than the short leg, and so returns on the long–short strategy are positive.

The data reveal that, on average, monthly returns to the long leg, the short leg, and the long–short strategy are (respectively) positive, negative, and positive. This means that, post ranking, the correction of mispricing dominates its exacerbation. In other words, mispricing is attenuated on average during month $t + 1$ after it is identified—at the end of month t—by the aggregate mispricing measure.

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 actively managed mutual funds (MF) and hedge funds (HF) are computed as

$$\mathrm{MF}_t \text{ (or } \mathrm{HF}_t) = \frac{\sum_{i=1}^{N} \mathrm{TNA}_{i,t} - \mathrm{TNA}_{i,t-1}\left(1 + R_{i,t}\right)}{\sum_{i=1}^{N} \mathrm{TNA}_{i,t-1}}, \tag{9}$$

where $\mathrm{TNA}_{i,t}$ represents the total net assets of fund i in month t and where $R_{i,t}$ is the return on 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 actively managed mutual funds that primarily invest in the US equity market. Thus, we choose only those funds whose Lipper investment objectives are related to the domestic equity market; in this way we eliminate balanced, bond, money market, and international funds. We also exclude passive funds identified using the procedure described in Appel, Gormley, and Keim (2016).

We obtain hedge fund returns and net asset value from the Lipper TASS database. As with our mutual fund sample, we focus on hedge funds that trade mostly in the US equity market. Hence we include only funds denominated in US dollars and exclude funds whose strategies are emerging market, fixed income, fund of funds, or 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 2016. The sample period starts in 1994 because that is when monthly hedge fund flow data became available.

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

5. Relation between mispricing and fund flows across frequencies

5.1. Descriptive statistics

We first estimate the spectra of anomaly returns and flows; that is, we decompose these series into a continuum of orthogonal components using the methodology outlined in Section 3.[10] We connect these components to cycles of returns and/or flows documented in the literature to illustrate how well our spectral analysis reflects real economic activities.

Figure 1 displays the spectra of NINV anomaly returns and hedge fund flows. The *x*-axis corresponds to a variable's frequency, and the *y*-axis represents the *power* (i.e., the squared amplitude) of each frequency scaled by the sum of powers over the full spectrum—that is, the relative contribution of each frequency to the variable's total variance. The figure also links prominent frequencies to cycles in real economic activity and asset returns that previous research has documented and that are listed beneath the graphs. For instance, business cycles have periods of 2–8 years (i.e., points A, B, C, and D with frequencies from 0.1 to 0.5 cycles per year); see Dew-Becker and Giglio (2016). Point A marks cycles with periods of approximately 8 and 10 years, which correspond to the Democratic/Republican presidential return cycle and to the solar return cycle reported in Novy-Marx (2013); these cycles are associated with (respectively) public policy and investors' risk aversion. Point B marks a cycle with a 5-year period, which matches the overreaction and underreaction cycle that drive the momentum and reversal anomalies (Lee and Swaminathan 2000). Point E marks the frequency of one cycle per year, which coincides not only with annual reporting (e.g., to shareholders or fiscal authorities) but also with (i) the seasonal affective disorder (SAD) cycle in returns and asset allocation, which some have argued are related to investors' risk tolerance (Kamstra et al. 2003, 2017), and (ii) a cycle of seasonal momentum and reversal (Heston and Sadka 2008; Keloharju et al. 2019). The spectra of anomaly returns and flows display some commonalities, such as the quarterly earnings announcement cycle (Point G) that affects both, and some disparities. One example is that of the FOMC cycle (close to six cycles per year), which is an important contributor to the variance of anomaly returns but not to that of hedge fund flows. Another is that, whereas the business cycle peak at 0.3 cycle per year stands out for both variables, its contribution exceeds 12% of the total variance in hedge fund flows yet is less than 4% of the NINV total variance.

[[INSERT **Figure 1** about Here]]

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[10] Performing a Fourier transformation requires that the time series be stationary. We run unit-root tests on the mispricing and flow series; a unit root is strongly rejected.

For most of the analysis, we group frequencies into two bands representing the low- and high-frequency components of the series. Variables with the "-LOW" suffix represent those time series that are reconstructed from frequencies lower than one cycle per year; variables with the "-HIGH" suffix are reconstructed time series from frequencies higher than one cycle per year. The -LOW and -HIGH variables are orthogonal to one another. Because flow variables are measured monthly, our highest frequency is six cycles per year. Figure 2 plots the time-series of anomaly returns and fund flows together with their high- and low-frequency components. As expected, the low- and high-frequency components differ markedly in their persistence.

[[INSERT **Figure 2** about Here]]

Table 1 presents summary statistics (Panel A), correlations among main variables (Panels B and C), and variance decompositions (Panel D). In Panel A of the table, the average monthly returns on the SYY and NINV anomalies are (respectively) 1.9% and 1.6%. These average returns are statistically significant, with respective *t*-statistics of 6.52 and 4.36, indicating that a long-minus-short strategy would be profitable. Yet there is wide variation over time in anomaly returns, with standard deviations of 4.8% for SYY and 6.0% for NINV. The monthly average flows to mutual funds and hedge funds are 0.1% and 0.4%, respectively, while their respective standard deviations are 0.5% and 1.7%.

[[INSERT **Table 1** about Here]]

Panel A also presents descriptive statistics for decomposed time series. We can see that anomaly returns are more volatile at high than at low frequencies. For example, the standard deviation of SYY-LOW is 2.2% versus 4.2% for SYY-HIGH. In contrast, for flows the low-frequency component contributes as much as (for hedge funds) or more than (for mutual funds) the high-frequency component: HF-LOW and HF-HIGH have identical standard deviations (1.2%), and the standard deviation of MF-LOW (0.4%) is higher than that of MF-HIGH (0.3%). For passive funds, high-frequency flows contribute most: the standard deviations of Passive-HIGH (0.8%) exceeds that of Passive-LOW (0.7%).

The values reported in Panel B of Table 1 establish that anomaly returns are positively related to hedge fund flows, negatively related to mutual fund flows, and unrelated to passive fund flows. These correlations are in accordance with the notion that hedge funds constitute smart money whereas mutual funds amount to dumb money (see e.g. Akbas et al. 2015). The results suggest also that passive funds, whose performance is based on tracking the benchmarks, are neither dumb nor smart money.

Panel C of Table 1 reports correlations calculated between the low- and high-frequency components of returns and fund flows. Whereas Panel B indicated that the correlations between HF flows and anomaly returns are positive but statistically insignificant, Panel C shows that correlations at low frequency are significantly positive. In contrast, the correlations between HF-HIGH and high-frequency anomaly returns are indistinguishable from zero.

5.2. *Variance decomposition of fund flows and mispricing*

Our spectral decomposition allows for estimating the relative contribution of low- and high-frequency bands to the total variance of a series, since, by Equation (1) and the orthogonality of the components, we have $\mathrm{Var}(X_t) = \mathrm{Var}(X_t^L) + \mathrm{Var}(X_t^H)$. The variance decomposition results displayed in Panel D of Table 1 reveal that our main variables differ markedly in their frequency structures. The variances of anomaly returns are driven mostly by the variance of their high-frequency components. Indeed, the high-frequency components of SYY and NINV anomalies contribute about 3 times more to their total variance than do their respective low-frequency components. In contrast, for hedge fund and mutual fund flows, most of the variance stems from low-frequency components. Moreover, the slow-moving component plays a larger role in explaining variations in mutual fund flows than those in hedge fund flows.

[[INSERT **Figure 3** about Here]]

Figure 3 offers a visual representation of the variance decomposition by displaying the cumulative contribution of frequencies. Thus the figure plots $\mathrm{Var}(\sum_{k=0}^{K} X_t^k)/\mathrm{Var}(X_t)$ for each frequency *K*. Again, cycles of frequency less than or equal to one per year are part of the low-frequency band while those of frequency greater than one per year belong to the high-frequency band. The figure illustrates a major difference between anomaly returns and fund flows: whereas the cumulative contribution of frequencies to the total variance in anomaly returns is close to the 45° line, which corresponds to an equal contribution benchmark, it is located well above that line for fund flows—especially for mutual funds. For example, the lowest frequency for mutual fund flows is the most important contributor to their variance, which suggests that many mutual fund investors are long-term investors. This observation is consistent with the observation that a substantial portion of mutual fund assets under management are tied to retirement accounts and so are restricted from redemption. The contrast between anomaly returns and fund flows was already evident in Figure 1, where NINV exhibits large spikes at high frequencies (i.e., at more than 2 cycles per year) while large spikes for hedge fund flows are concentrated at the low end of the spectrum (fewer than 0.5 cycles per year).

5.3. *Relation between fund flows and mispricing across frequencies*

We now present our main results on the relation between fund flows and mispricing in the frequency domain. We regress decomposed returns on decomposed flows and various controls, as in Equation (8). Akbas et al. (2015) show that the coefficient estimate from regressing (total) anomaly returns on (total) flows is positive for hedge funds but negative for mutual funds. Their interpretation is that hedge fund flows correct mispricing whereas mutual fund flows exacerbate mispricing. Intuitively, capital inflows (resp. outflows) in a month accompanied by positive anomaly returns are an indication that inflows (resp. outflows) are positively associated with a mispricing correction (resp. worsening). For example, correcting (resp. worsening) mispricing of an overvalued stock entails taking a short (resp. long) position and so, by construction, is associated with a positive (resp. negative) return on the anomaly portfolio.[11] We build on this interpretation and examine the relation, across frequencies, between flows and anomaly returns.

[[INSERT **Table 2** about Here]]

Table 2 reports the results from regressing long–short anomaly returns on fund flows over the low- and high-frequency bands. Panel A is based on total fund flows, whereas Panel B splits them into low- and high-frequency flows. The *t*-statistics are calculated based on Newey–West standard errors with 13 lags. We start by reproducing the results of Akbas et al. (2015). Thus we regress total anomaly returns on total hedge fund and mutual fund flows; the results are reported in columns (1) and (4) of Panel A. Both SYY and NINV are significantly and negatively related to mutual fund flows but positively related to hedge fund flows, which indicates that mutual funds exacerbate mispricing while hedge funds correct it. These results match those reported in Akbas et al. (2015) in both magnitude and significance.

Next, we decompose anomaly returns into their low- and high-frequency components (SYY-LOW, SYY-HIGH, NINV-LOW, NINV-HIGH) and regress each component on flows (columns (2) and (3) and columns (5) and (6)). We find that the positive relation between hedge fund flows and anomaly returns is driven by low-frequency anomaly returns. At high frequency, the coefficient estimate is positive, but it is much smaller in magnitude and statistically insignificant. This finding suggests that hedge fund flows mainly correct mispricing at low frequencies. In contrast, a negative relation between mutual fund flows and anomaly returns is observed for both high- and low-frequency returns, with coefficients of comparable magnitude.

In Panel B of Table 2, we further decompose fund flows into their low- and high-frequency components (HF-LOW, HF-HIGH, MF-LOW, MF-HIGH). Columns (1) and (4) in this panel use total anomaly returns as the dependent variables. Although the coefficient estimates for both HF-LOW and HF-HIGH are positive, the magnitude is much weaker for HF-HIGH (in fact, it is not statistically distinguishable from zero). For mutual funds, in contrast, MF-LOW and MF-HIGH exhibit coefficients that are (significantly) negative and of comparable magnitudes—indicating that both types of flows tend to aggravate mispricing.

The rest of Panel B decomposes mispricing into low- and high-frequency components, which allows us to examine how each component of flows affects each component of mispricing. The results

[11] Confirming this interpretation, Akbas et al. (2015) report that hedge fund flows have no predictive power for future anomaly returns; indeed, once mispricing is corrected, it remains so. Analyses of funds' trading patterns further support this interpretation. Dong et al. (2018) establish that capital supplied to hedge funds is positively related to the intensity of hedge funds' trading on anomalies and also to the correction of mispricing. Many other studies likewise document that flow-induced mutual funds' trades exacerbate mispricing (see e.g. Coval and Stafford 2007; Frazzini and Lamont 2008; Greenwood and Thesmar 2011; Shive and Yun 2013).

confirm that the mispricing correction effect of hedge fund flows occur mainly in the low-frequency band. This difference is more pronounced for NINV anomalies. Our regression of NINV-LOW on HF-LOW yields a coefficient estimate of 1.107 (t = 3.71), whereas the coefficient estimates for our regressions of NINV-LOW on HF-HIGH, of NINV- HIGH on HF- LOW, and of NINV-HIGH on HF-HIGH are all indistinguishable from zero. A similar pattern is observed for the SYY anomaly, where the HF-LOW component yields a coefficient estimate of 0.796 for SYY-LOW versus statistically insignificant estimates for the other three pairs of components.

Unlike hedge fund flows, both low- and high-frequency mutual fund flows exacerbate mispricing. Consider SYY, for example: at low frequency, MF-LOW yields a coefficient estimate of −2.770 (t = −3.09); at high frequency, however MF-HIGH yields a coefficient estimate of −2.071 (t = −3.00). The magnitudes of these coefficients are more comparable than are those of hedge funds. We remark that directly comparing coefficients without accounting for the magnitude of the variation in each frequency band could produce misleading results. In the next section, we formally evaluate the economic magnitude of those coefficients.

5.4. Attenuation factor

Here we interpret the Table 2 results and evaluate the economic relevance of fund flow effects. In doing so, we account for the proportion of low- and high-frequency variation in the total variance of mispricing. More specifically, we define the *attenuation factor* as the ratio of the economic magnitude of the low-frequency fund flow effect to its magnitude at high frequency. The economic magnitude of this 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 of the change in mispricing's standard deviation is associated with a 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 we interpret it as the extent of attenuation of high-frequency flows relative to that of low-frequency flows.

In essence, 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 1 indicates that changes in low- and high-frequency flows of identical magnitudes (with respect to standard deviations) result in changes in low- and high-frequency anomaly returns of identical magnitudes (again with respect to standard deviations). A value greater than 1 means that, all else equal, low-frequency flows lead to a larger mispricing correction (or exacerbation) than do high-frequency flows. This outcome arises provided that fund managers behave as low-pass filters.

A fund behaving as a low-pass filter implies that, in response to receiving high-frequency flows, managers "slow them down" by redirecting some of those flows toward low-frequency mispricing—which is to say, managers convert these high-frequency flows into low-frequency flows. It follows that, for regressions in which we do not observe how managers deploy their capital, mispricing appears to respond more strongly to low-frequency flows than it would if managers applied low-frequency flows only to low-frequency mispricing. Similarly, the mispricing reaction to high-frequency flows appears weaker than it would if all high-frequency flows were used to trade on high-frequency mispricing. These results imply further that, ceteris paribus, the beta of low-frequency anomaly returns on low-frequency flows is larger in (absolute value of) economic magnitude than is the beta of high-frequency anomaly returns on high-frequency flows; in other words, the attenuation factor is larger than 1.

Table 3 shows how the attenuation factors are calculated. Take NINV, for example; the beta on HF-LOW is 1.107 and that on HF-HIGH is 0.085. On the one hand, a 1-SD increase (1.2%) in HF-LOW is associated with a 1.3% increase in the return of NINV-LOW, which corresponds to 46.9% of its standard deviation (2.9%). On the other hand, a 1-SD increase (1.2%) in HF-HIGH is associated with 0.1% increase in the return of NINV-HIGH, or 1.9% of its standard deviation. The attenuation factor is 24.41, indicating that the effect of a 1-SD change to low-frequency flows on low-frequency mispricing is more than 24 times the size of the effect of a 1-SD change to high-frequency flows on high-frequency mispricing.

[[INSERT **Table 3** about Here]]

Overall, the results in Table 3 establish that both hedge and mutual funds behave as low-pass filters. Hedge funds have an attenuation factor of 8.62 for SYY anomalies and of 24.41 for NINV anomalies, meaning that they correct mispricing at low frequency 9 to 24 times more than they do at high frequency. Likewise, mutual funds amplify mispricing at low frequency about 4 times more than they do at high frequency.

Moreover, the estimates reported in the table's last column indicate that the attenuation factors are 2.44 to 6.72 times larger for hedge funds than for mutual funds. This observation suggests that hedge funds are a more selective (low-pass) filter than are mutual funds. It is worth noting that the difference in the attenuation factors is not an artefact of differences in the frequency structures of smart and dumb money, since we control for any such difference when calculating the attenuation factor. Instead, this result reflects how managers filter frequency-specific flows. Furthermore, our calculation of the attenuation factor does not account for statistical significance; if it did, then we might treat as zero the effect of hedge fund flows on mispricing at high frequency ($t = 1.19$) and obtain an even more striking difference between hedge funds and mutual funds.

Table 3 offers an alternative way of gauging the differential effect of hedge and mutual funds on market efficiency. Consider the NINV anomaly and low frequency. A 1-SD increase in MF-LOW results in a −1.7% return; this implies that the increase in mutual fund flows exacerbates NINV-LOW mispricing by 1.7% per month. For hedge funds, in contrast, a 1-SD increase in HF-LOW corrects NINV-LOW mispricing by 1.3% per month. So at low frequency, a 1-SD increase in hedge fund flows corrects

1.3% / 1.7% = 76% of the mispricing entailed by a 1-SD increase in mutual fund flows. For SYY anomalies, this figure rises to 1.0% / 1.2% = 83%. Such estimates suggest that, at low frequency, hedge funds can correct most of the mispricing that mutual funds generate. At high frequency however, a 1-SD increase in flows exacerbates NINV mispricing by 0.8% per month for mutual funds—versus a correction of 0.1% per month for hedge funds—which leads to a ratio of 0.1% / 0.8% = 13%. This ratio rises to 29% for SYY anomalies but remains well below the estimate obtained in the low-frequency case.

In short, both hedge funds and mutual funds behave as low-pass filters, but the former are a more selective filter: hedge fund managers' deployment of capital toward improving market efficiency proceeds more slowly than does mutual fund managers' directing capital in a way that degrades efficiency.

5.5. A spectrum of economic magnitudes

So far, we have relied on a binary breakdown of variables into a high- and a low-frequency component. We now provide a continuous picture of how the flow–return effect varies as a function of frequency. The frequencies generated by the flows and returns data range from about 0.04 cycles per year to 6 cycles per year. Figure 4 compares the economic magnitudes estimated over expanding frequency bands to the economic magnitudes estimated over the high-frequency band (one or more cycles per year). We proceed as follows. First, for each range of frequencies from 0 to a cutoff c, we regress SYY or NINV on mutual fund flows, hedge fund flows, and control variables. Then, just as in our calculation of the attenuation factor, we multiply the regression coefficient by the standard deviation σ_X of the flow component over the frequency band $[0, c]$ and divide it by the standard deviation σ_Y of the mispricing component over $[0, c]$. This operation yields an estimate of the economic magnitude of the flow–return effect over that frequency band. Finally, we divide that number by the estimate of the economic magnitude over the high-frequency band, which occupies the frequency range [1, 6]. Hence the ratio at one cycle per year—the frequency at which the expanding band coincides with the low-frequency band—corresponds to the attenuation factor reported in Section 5.4 (e.g., 8.62 for SYY anomalies and 24.41 for NINV anomalies in the case of hedge fund flows).

[[INSERT **Figure 4** about Here]]

Figure 4 reveals that, for all frequencies lower than one cycle per year, the ratio remains elevated for both fund types and then, as the band expands to include higher frequencies, declines precipitously past that threshold—a pattern that reflects low-pass filtering. In addition, the decline is more pronounced for hedge funds than for mutual funds, in line with the former being a more selective low-pass filter. The break in the flow–return relation around one cycle per year indicates that one year is an important cutoff for the influence of both hedge funds and mutual funds on mispricing. Yet as the figure shows, our finding that mutual and hedge funds operate as low-pass filters is *not* sensitive to the choice of this cutoff for defining the low-frequency band; rather, it reflects their broad behavior over the entire spectrum.

Taken as a whole, our frequency analysis is a rich description of the dynamics of anomaly returns, fund flows, and their relationship; in particular, it delivers both qualitative and quantitative insights. Qualitatively, the analysis suggests that the effect of financial institutions on mispricing depends on both the frequency and the institution being considered: at low frequencies, the dynamics of mispricing are driven both by hedge fund flows and by mutual fund flows; at high frequencies, though, these dynamics are mostly related to mutual fund flows.

Quantitatively, our analysis sheds light on several empirical regularities. First, at the most general level, it helps explain why mispricing is driven by components that evolve over multiple frequencies. Daniel, Hirshleifer, and Sun (forthcoming) demonstrate that many anomalies are driven by the mispricing of different "horizons"; for these authors, a horizon corresponds to how long after portfolio formation an anomaly's return remains *statistically* significant (i.e., whether an anomaly earns statistically significant positive return for less or more than one year). Our notion of frequency, which is based on the persistence in the *economic* magnitude of anomaly returns, is distinct from their notion of horizon.[12] Nevertheless, the two notions are broadly related in that both capture the idea that mispricing is shaped by economic forces moving at various speeds. Our findings suggest that hedge funds are a critical force that drives mispricing for frequencies in excess of one cycle per year, whereas mutual funds operate over the entire frequency spectrum.

The second quantitative implication is that anomaly returns persist (e.g., factor momentum continues over horizons longer than one year) because fund flows have a more pronounced effect on anomalies for frequencies up to one year and for hedge funds (Ehsani and Linnainmaa 2019). Indeed, our finding suggests that this pattern is at least partly caused by arbitrageurs repeatedly trading on anomalies, which results in persistent mispricing corrections; it could also be caused, in part, by dumb money

[12] Our study and Daniel, Hirshleifer, and Sun's (forthcoming) differ in (i) purpose, (ii) concept, and (iii) methodology. (i) Our objective is to analyze the relation between flows and mispricing, whereas theirs is to develop (horizon-dependent) asset-pricing factors (irrespective of flows). (ii) Conceptually, the persistence of mispricing's economic significance and of its statistical significance represent distinct notions though they are related. For example, an anomaly's return can remain statistically significant for a long time, because the signal on which it is based maintains a high precision in every period, while its economic magnitude deteriorates. Conversely, anomaly returns might have a persistently significant economic magnitude caused by, e.g., the slow incorporation of material information into prices, but a statistical significance that fades quickly due to noise. (iii) In terms of methodologies, our low- and high-frequency mispricing components are extracted from a large set of anomalies in such a way to maximize information about these components with no component corresponds to a specific anomaly. In contrast, the long- and short- horizon factors in Daniel, Hirshleifer, and Sun are each based on a single anomaly (share issuance and post earnings announcement drift, respectively), each comprising a mix of low- and high-frequency components. Our approach better suits our purpose of differentiating low- and high-frequency relationships. Consistent with this view, qualitatively similar but statistically weaker results (unreported) obtain when we use long- and short-horizon factors in place of our low- and high-frequency mispricing components in Table 2.

continuously fueling mispricing at lower frequency, which results in a persistent exacerbation of mispricing. Our evidence of mispricing being corrected by hedge funds and being exacerbated by mutual funds suggests that the two events occur during different periods; therefore, they do not cancel each other out during a given month. This observation might also explain why infrequently reported holdings of hedge funds forecast stock returns many months ahead (e.g., Agarwal et al. 2013; Aragon, Hertzel, and Shi 2013).

5.6. Long and short legs

Stambaugh et al. (2012, 2015) show that anomalies are driven mainly by overpricing in the short leg of anomaly portfolios. If our findings are driven by the correction or exacerbation of mispricing then they, too, should be driven by the short leg. Table 4 reports the results from our investigation of this claim; for that purpose, we regress long- and short-leg returns separately on fund flows across frequencies.

[[INSERT **Table 4** about Here]]

Panel A of the table shows that hedge fund flows are not related to long-leg returns irrespective of the frequency band: neither HF-LOW nor HF-HIGH have any explanatory power for high- or low-frequency returns. Yet according to the estimates presented in Panel B, these flows are significantly and negatively related to short-leg returns at low frequency. Comparing the magnitude of the coefficient estimates, we conclude that the positive relation between flows and returns exhibited in Table 2 and Table 3 is mostly due to the short leg. Observe that, for this leg, a negative coefficient implies that flows correct mispricing. In sum, at low frequency, hedge funds correct overvaluation more so than undervaluation.

Turning to mutual funds, both the long and short legs yield positive coefficient estimates at low and high frequencies; these results imply that mutual funds correct underpricing and exacerbate overpricing. But a comparison of the magnitudes of the coefficient estimates reveals that the effect on the short leg is far greater. Hence we conclude that the frequency-specific effects of both fund types operate through the short leg of anomalies.

5.7. Individual anomalies and flows

Our analysis so far has relied on aggregated mispricing measures. In Table A1 of the Online Appendix, we examine the relation—across frequencies—between individual anomaly returns and fund flows. Panel A uses the total anomaly returns as the dependent variables; it documents that, in line with previous results, the positive relation between hedge fund flows and anomaly returns is stronger for low-frequency flows than for high-frequency flows. For 8 of the 11 SYY anomalies, the coefficient estimates for HF-LOW are positive, and four of them are statistically significant. Although there are also some positive coefficients for HF-HIGH, their magnitude is (on average) smaller; and only two of them are significant. For mutual funds, the negative relation prevails both for high- and low-frequency flows.

Panels B and C of Table A1 present the results for (respectively) low-frequency and high-frequency anomaly returns. The mispricing correction by hedge funds at low frequency is observed to be robust for the individual SYY anomalies: HF-LOW is positively related to eight low-frequency anomaly returns, six of which are statistically significant; HF-HIGH is positively related to four high-frequency anomaly returns, none of which is significant. Taken together, these outcomes suggest that our findings are not driven by any particular anomaly.

6. Market frictions and low-pass filtering

We hypothesize that hedge funds behave as a low-pass filter because of market frictions. Clearly, if there were no frictions impeding arbitrage then all mispricing would be eliminated instantly. In this section we test this hypothesis directly, exploiting variations in friction proxies over time and across funds. The frictions we consider are risk, access to capital, and implementation costs.

6.1. Risk

We first examine whether the frequency-specific relation between fund flows and mispricing depends on aggregate risk. We use various proxies, including the NBER recession indicator, the VIX, the financial uncertainty index of Jurado et al. (2015), and the economic uncertainty index of Bekaert et al. (2019).[13] Table 5 reports the results. The variables of interest are the low- and high-frequency flows interacted with a dummy variable, D, that represents a risk proxy. For the NBER indicator, D is a dummy variable set equal to 1 if the economy is in recession during the current month (and set equal to 0 otherwise). For other proxies, D is a quintile score ranging from 0 to 1; here higher scores indicate greater uncertainty. Panel A uses total flows as independent variables, while Panel B uses low- and high-frequency flows. In Panel A, the coefficient estimates on flows interacted with D is significantly positive in the SYY-LOW and NINV-LOW regressions across all risk proxies for hedge funds (e.g., columns (2) and (5)); for mutual funds, however, the estimates are indistinguishable from zero throughout.

[[INSERT **Table 5** about Here]]

In Panel B, the coefficient estimate on HF-LOW × D is significantly positive for low-frequency anomaly returns (e.g., Columns (2) and (5)); in contrast, the coefficient estimate on HF-HIGH × D is not significant for the high-frequency anomaly returns (e.g., Columns (3) and (6)). This result suggests that hedge funds' low-frequency mispricing correction amplifies with risk. The impact of risk as measured in

[13] Jurado et al. (2015) estimate a financial uncertainty index from the conditional volatility of prediction errors; these errors are calculated based on various macroeconomic (e.g., real output and employment) and financial (e.g., earnings/price ratio, default and term spreads) time series. Bekaert et al. (2019) jointly estimate time-varying risk aversion and economic uncertainty from a dynamic model of asset prices; their estimation also makes use of macroeconomic (e.g., consumption and industrial production) and financial (e.g., stock returns and the VIX) variables.

the low-frequency regressions is economically sizable. In Column (2) of Panel B for example, the coefficient estimate on HF-LOW × D (1.358) is more than twice as large as that on HF-LOW (0.621).

Turning to mutual funds, none of regressions yields a significant coefficient estimates on flows interreacted with the risk proxy except for the NBER recession indicator. In that set of regressions, the coefficient estimates on MF-LOW × D are negative for low-frequency and total mispricing (Columns (1), (2), (4) and (5)), indicating an amplification of the (negative) flow-return relation during recessions, whereas those on MF-HIGH × D are positive for high-frequency and total mispricing (Columns (1), (3), (4) and (6)), implying a dampening of the relation.

Overall, these results suggest that hedge funds' correction of low-frequency mispricing intensifies in times of heightened aggregate risk. We also find evidence that mutual funds' exacerbation of low-frequency mispricing increases during recessions, but this effect seems less robust across risk proxies.

6.2. Leverage

In Table 6 we examine how the frequency-dependent relation between fund flows and anomalies relates to leverage.[14] We consider two determinants of hedge funds' leverage: funding costs (which makes leverage more expensive), and risk aversion (which makes leverage less desirable). We proxy for the former with the TED spread and for the latter with the measure developed by Bekaert et al. (2019). As in Table 5, the main variables of interest in Table 6 are the low- and high-frequency fund flows interacted with D, now a quintile score scaled from 0 to 1, where a higher score indicates a wider TED spread or greater risk aversion.

[[INSERT **Table 6** about Here]]

The coefficient estimates for HF × D and HF-LOW × D are generally positive and significant for low-frequency anomaly returns, suggesting that the low-frequency mispricing correction by hedge funds strengthens when either funding costs or risk aversion rise (columns (2), (5), (8), and (11)). The effects are economically significant. In column (5) of Table 6's Panel B, for example, the coefficient for HF-LOW × D (1.184) is 3 times as large as the coefficient for HF-LOW (0.351). These values imply that an increase in the TED spread from the lowest to the highest quintile is associated with a quadrupling of the flow–return relation at low frequency ((1.184 + 0.351) / 0.351 = 4.37).

We then examine leverage in the cross section of hedge funds. Because leverage is chosen by funds, unlevered funds are likely to be more risk averse or to face more restrictions on borrowing than are levered funds. As Adrian and Shin (2013) show, risk-bearing capacity is positively related to leverage. So to the extent that frictions are the reason why funds behave as low-pass filters, we expect low-frequency

[14] A growing literature studies the role of intermediaries, such as broker-dealers and banks (and their balance sheets), in asset pricing. These intermediaries act as middlemen between capital's providers (households) and its end users (investors, such as hedge and mutual funds). Our paper differs in focusing on the end users and not on the middlemen.

mispricing corrections to be more pronounced for unlevered funds. In Table 7, we examine whether the flow–return relationship is affected by funds' use of leverage. For each month, we classify hedge funds into two groups: those that use leverage (HFLev) and those that do not (HFUnLev). Then we calculate flows separately for each group and decompose these flows in the frequency domain. Panel A of the table shows that, for total flows, the positive relation between hedge funds and mispricing is significant only for unlevered funds and for low-frequency mispricing. In Panel B, where we decompose the flows in the frequency domain, only HFUnLev-LOW exhibits a significant coefficient estimate, which is positive with low-frequency mispricing. This result suggests that more risk-averse funds—or funds with less access to borrowing—are more likely to pursue low-frequency arbitrage.

[[INSERT **Table 7** about Here]]

Altogether, our findings indicate that limitations on hedge funds' risk-bearing capacity leads them to behave as more selective low-pass filters.

6.3. Liquidity and transaction costs

In this section we explore how low-frequency mispricing corrections depend on aggregate liquidity. We employ four measures of illiquidity that track variations in marketwide liquidity over time: (i) Amihud illiquidity, (ii) the aggregate illiquidity described by Pastor and Stambaugh (2003), (iii) the "permanent variable factor" proposed in Sadka (2006), and (iv) Hu et al.'s (2013) noise measure. Each of these measures captures a different aspect of illiquidity. The Amihud illiquidity proxy computes volume-induced price impact, and the Pastor–Stambaugh measure tracks return reversals post-trading, which reflect the compensation paid to liquidity providers (Nagel, 2012). The Sadka measure calculates the permanent variable component of price impact, which is extracted from bid–ask spreads. Sadka (2010) and Dong, Feng, and Sadka (2017) show that the permanent variable factor is an especially relevant component of transaction costs for both hedge funds and mutual funds. Finally, the Hu et al. noise measure reflects the shortage of arbitrage capital and helps to explain the cross section of hedge fund returns. Following the liquidity literature, we obtain aggregate illiquidity measures by averaging individual illiquidity measures over all stocks.[15]

For our analyses, the liquidity variables (denoted ILLIQ) are constructed as follows. First, if the original variable measures market liquidity, then we convert it to an illiquidity measure via multiplying all values by −1. Next, we detrend the measure and sort monthly illiquidity values into quintiles. Finally, we standardize quintile scores from 0 to 1 to obtain ILLIQ. Thus the coefficient estimates for the interaction between flows and ILLIQ can be interpreted as the difference in the effect between the lowest and highest illiquidity periods.

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

[[INSERT **Table 8** about Here]]

Table 8 presents results from regressing anomaly returns on flows interacted with ILLIQ. Panel A focuses on total flows and reveals that the effect of mutual funds is not sensitive to the level of liquidity (coefficient estimates for the MF × ILLIQ are indistinguishable from zero); in contrast, hedge fund flows more strongly correct low-frequency mispricing when liquidity worsens (coefficient estimates for HF × ILLIQ in the SYY-LOW and NINV-LOW regressions are almost all significantly positive). These patterns are confirmed in Panel B, where the regressors are the decomposed flows. In this panel, the coefficient estimates for MF-LOW × ILLIQ and MF-HIGH × ILLIQ are statistically insignificant throughout, whereas those for HF-LOW × ILLIQ and HF-HIGH × ILLIQ are (respectively) statistically significant and positive in all the low-frequency mispricing regressions (e.g., columns (2) and (5)) but statistically insignificant in all the high-frequency mispricing regressions (e.g., columns (3) and (6)). The effect of liquidity on the hedge fund flow–return relationship is economically sizable. In column (2) of Table 8's Panel B, for instance, the magnitude of the effect of HF-LOW on SYY-LOW is 1.047 (0.728 + 0.319) when ILLIQ = 1 (uppermost illiquidity quintile), a threefold increase relative to when ILLIQ = 0 (lowermost illiquidity quintile, where the magnitude of the effect is 0.319.

The contrast between hedge and mutual funds makes it unlikely that heightened price impact in periods of low liquidity "mechanically" gives hedge fund flows more influence on mispricing. Our findings rather indicate that only flows to hedge funds affect mispricing—and that they do so in a certain direction (i.e., by correcting it) and at a particular (i.e., low) frequency. Thus, we conclude that hedge fund managers choose to filter flows more selectively when transactions are more costly.

Next, we explore illiquidity differences in the cross section of funds. More specifically: we examine share restriction provisions, which are measured as the sum of the number of days in the lock-up, redemption notice, and payout periods. This measure is widely used in the hedge fund literature to capture hedge fund illiquidity, since funds whose underlying assets are more illiquid set higher share restrictions (Aragon 2007; Sadka 2010; Teo 2011). We expect such funds to engage in more low-pass filtering given that transaction costs are a greater concern with illiquid assets.

For each month we divide hedge funds into two groups, denoted HFBelow and HFAbove, based on the median value of share restrictions; we then estimate fund flows and their components separately for each group. The results, presented in Table 9, show that the positive relation between mispricing and hedge fund flows is confined to funds with high share restrictions (HFAbove). This outcome indicates that illiquidity is a driver of hedge funds' frequency filtering.

[[INSERT **Table 9** about Here]]

Note that our findings do not imply that arbitrageurs trade less or less frequently because of transaction costs. Indeed, for a given target portfolio, arbitrageurs may simply spread their trades over a longer period—resulting in more persistent rebalancing/trading (e.g., gradually building a stake in an underpriced stock) and hence in a more persistent correction of mispricing. That is, if trading is consistently in the direction of correcting mispricing, then high-frequency rebalancing/trading in a stock results in low-frequency mispricing correction. Thus our test speaks to how transaction costs might alter the persistence of hedge funds' trading to correct mispricing. In other words, we are silent about whether transaction costs affect the quantity, turnover, or profitability of arbitrageurs. This viewpoint differentiates our work from studies that focus on these topics (e.g., Keim and Madhavan 1997; Korajczyk and Sadka 2004; Lesmond et al. 2004; Engle et al. 2012; Novy-Marx and Velikov 2016; DeMiguel et al. 2019; Frazzini et al. 2018; Patton and Weller, forthcoming).

6.4. Exogenous shocks

To sharpen identification of the effect of frictions on hedge funds, we exploit two quasi-natural experiments associated with shifts in the level of frictions. The first is the 2007-2009 financial crisis. Many studies use this event as an adverse shock to economic uncertainty (i.e., risk), funding access (i.e., risk-bearing capacity; Aragon and Strahan, 2012), and market liquidity (Sadka, 2010). Following Akbas et al. (2015), we consider the crisis to have unfolded from July 2007 to December 2009. The second experiment is the adoption of decimalization, which was implemented between August 2000 and May 2001 on US stock exchanges and considerably improved liquidity (Chordia et al. 2008; Fang et al. 2009). Table 10 examines how the relation between flows and mispricing changed in response to these two shocks. The main variables of interest are the low- and high-frequency fund flows interacted with SHOCK, an indicator variable set equal to 1 if the month t is included in the period of the shocks and is otherwise set to 0.

[[INSERT **Table 10** about Here]]

The results for total flows, presented in Panel A of the table, establishes that the effect of hedge fund flows on low-frequency mispricing strengthens significantly during the financial crisis, as evidenced by the significantly positive coefficient estimate for HF × SHOCK in the low-frequency returns regression (columns (2) and (5)). In contrast, but consistently with the notion that frictions magnify the flow–return relation, the coefficient estimate is significantly negative during decimalization, which implies that hedge funds' low-frequency filtering weakens when liquidity improves. The Panel B results are based on decomposed flows; they confirm our findings for hedge funds—namely, a stronger (resp. weaker) relation between HF-LOW and low-frequency returns during the financial crisis (resp. decimalization). For decimalization only, there is also an amplification of the effect at high frequency: the coefficient estimates for HF-HIGH × SHOCK are significantly positive in columns (9) and (12). This result suggests that improved liquidity leads hedge funds to shift from correcting mispricing at low frequency to correcting it at high frequency.

With regard to mutual funds, Panel A reveals no change in the effect of total flows on mispricing during the financial crisis yet evidences a marked amplification during decimalization. Panel B offers some nuance to these findings. During the financial crisis, the effect of flows on mispricing was indeed larger at low frequency (a negative coefficient estimate for MF-LOW × SHOCK) but was smaller at high frequency (a positive coefficient estimate for MF-HIGH × SHOCK). Likewise, during decimalization, the effect was smaller at low frequency (positive coefficient estimate for MF-LOW × SHOCK) but larger at high frequency (negative coefficient estimate for MF-HIGH × SHOCK). In other words, it seems that mutual funds shift part of their exacerbation of mispricing from high to low frequency when frictions are more severe. Thus mutual funds' filtering behavior is also caused by market frictions.

In addition, the opposite patterns observed for hedge funds and mutual funds renders it unlikely that our results are driven mechanically by variations in the price impact of flows correlated with market liquidity. Overall, the evidence from these two natural experiments indicates that frictions cause mutual funds—and especially hedge funds—to behave as low-pass filters.

6.5. Additional analysis: Passive and skilled mutual funds

We perform two additional investigations to check that the filterlike behavior we report is linked to investment decisions of active managers. First, we examine whether passive funds behave like the hedge and mutual funds considered so far. If so, then this would imply that the filtering behavior we observe reflects the nature of the flows received by funds more so than it reflects managers' investment strategy. Therefore, in Table 11, we replicate our baseline analysis (from Panel B of Table 2) after adding passive equity fund flows to the set of regressors. Panel A uses the composite anomalies, SYY and NINV, and their low- and high-frequency components, as dependent variables. Panel B uses two proxies for market returns as dependent variables. MKT is value-weighted market returns from CRSP, while S&P500 is returns to S&P500 index. Following Appel et al. (2016), we identify passive funds by their names.

We find that passive fund flows do not have significant effects on mispricing at any frequency. In fact, Panel A reports that the coefficient estimates are similar (and insignificant) in regressions of low-frequency anomaly returns on low-frequency flows to those in regressions of high-frequency anomaly returns on high-frequency flows. These outcomes indicate that passive funds perform as a passthrough filter. We conclude that the low-pass filtering behavior observed for both mutual funds and hedge funds is attributable to the active investment decisions of managers.

[[INSERT **Table 11** about Here]]

Next, in Table 12 we examine how the skill of mutual funds affects the flow–return relationship. Toward that end, we assign mutual funds to two groups (denoted MF-UnSkilled and MF-Skilled) according to their skill measured at $t-1$; we then calculate the fund flows separately for each group. We use four common measures of skill: the return gap (Kacperczyk et al. 2006), $1 - R^2$ (Amihud and Goyenko, 2013), past alpha (Carhart, 1997), and active share (Cremers and Petajisto, 2009). The literature shows that such skilled funds likely constitute but a small subset of all the mutual funds (e.g., Fama and French 2010). So for each measure, we classify as skilled only those funds that are in the top decile of performance.

[[INSERT **Table 12** about Here]]

We find that skilled fund flows generate, on average, positive coefficient estimates for mispricing. It follows that unskilled funds are those that exacerbate mispricing over both high and low frequencies whereas skilled funds behave more like hedge funds. Thus the low-frequency mispricing correction we find for hedge funds is likely to be driven by their smart investment decisions, rather than by structural or institutional differences between hedge funds and mutual funds.

7. Modeling frictions and arbitrage in the frequency domain

This section presents a model that ties together the pieces of evidence that we have reported. The model describes the dynamics of asset returns when the factors driving those returns decay at different speeds. It features three ingredients that, as indicated by the data, play a central role in hindering arbitrage activity: risk, transaction costs, and the limited availability of capital. The last of these is incorporated into the model in that we assume arbitrageurs' risk-bearing capacity to be finite and to increase with the funds they receive. We build on two papers by Garleanu and Pedersen (2013, 2016; denoted GP2013 and GP2016 henceforth), who describe the optimal dynamic trading strategy of a mean-variance investor in the presence of transaction costs when stock returns can be predicted by signals, or factors, decaying at different speeds. Here we develop a (continuous-time) equilibrium model that speaks to the notion of market efficiency.

7.1. The economy

The purpose of our model is to help explain the dynamics of asset returns given the dynamics of mispricing. We start from an (exogenous) shock to the demand for assets, which causes them to be mispriced; the demand then gradually reverts to its initial level. The speed of reversion is the model's key parameter. We interpret the shock and its reversion as being caused by noise trading—for example, mutual funds trading in response to flows.[16]

Variations in demand are accommodated by hedge funds. How aggressively they trade depends on two features: their risk tolerance (a function of their capital) and transaction costs. Two comments on our

[16] This model is a version of the equilibrium model analyzed in the last section of GP2016 and streamlined along two dimensions. The first is that a single factor, rather than two, drives mispricing; the second is that the dynamics of mispricing are deterministic rather than stochastic. These simplifications allow us to characterize the dynamics of returns in closed form and to derive sharp predictions.

modeling strategy are in order. First, we view hedge funds' finite risk tolerance (i.e., that they are not neutral to risk) as a tractable and intuitive way of capturing frictions—such as asymmetric information or limited contract enforceability—that hinder their ability to share risk by, say, borrowing or issuing claims contingent on future trading profits. Second, asset demand in our setup is exogenous, whereas prices are endogenous: prices reflect the compensation required by hedge funds for accommodating demand shocks. This equilibrium approach contrasts with, though is closely related to, a dual one in which prices are exogenously given but trades are endogenously determined (e.g., GP2013).

7.1.1. Assets

A riskless asset and two risky assets, labelled "slow" and "fast" (respectively, S and F for short) for reasons that will become clear shortly, trade competitively. The riskless rate equals an exogenous constant r^f. Risky asset s ($s = \{S, F\}$) pays a stochastic dividend du_t^s, between times t and $t + dt$, with mean $E_t(du_t^s) = Ddt$ and variance $\text{Var}_t(du_t^s) = \Sigma dt$. Here Σ denotes risk, and dividends are independent and identically distributed (i.i.d.) across assets and over time.

Both the price p_t^s of asset s and the return on that asset are determined endogenously. The return (in excess of the risk-free return) on one share of asset s between times t and $t + dt$, to which we refer as the "dollar excess return", is given by

$$dQ_t^s \equiv dp_t^s + du_t^s - r^f p_t^s dt.$$

The excess return is defined as $r_t^s \equiv dQ_t^s / p_t^s$.[17] Trading risky assets is subject to transaction costs. We maintain GP2016's Assumption A.2 that these costs are proportional to the amount of risk. Specifically, consider an agent trading with intensity $h_t^s \in \mathbb{R}$, which represents the rate of change of her holdings x_t^s of asset s; that is, $dx_t^s \equiv h_t^s dt$. The transaction costs incurred per unit of time come to $\frac{1}{2}\lambda\Sigma(h_t^s)^2$, where λ is a positive parameter.[18] There are no restrictions on short-selling or borrowing.

The slow and fast assets represent the low- and high-frequency components of anomalies in our empirical analysis. Because our evidence derives mostly from the short leg of the long–short portfolio, the analysis focuses on the case of overvalued assets. Symmetric predictions obtain for undervalued assets.

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[17] In the model, we analyze both dollar and percentage returns. Although mean-variance models typically focus on dollar returns, our tests are based on percentage returns. Also, as Lemma 3 shows, the frequency of percentage return changes with the mispricing of an asset, where mispricing is affected by frictions. Therefore, percentage returns provide us a way to link frequency, mispricing, and frictions together. That being said, all our predictions hold for both dollar and percentage returns.

[18] One interpretation of this expression is that it follows from an investor trading with a risk-averse dealer. The compensation demanded by this dealer for bearing the risk that the asset price might fluctuate over a period of time dt is given by the dealer's risk aversion λ multiplied by the size (variance) of the risk, $\Sigma\Delta x_t^{s2}$, where Δx_t^s represents the number of shares traded. Therefore, trading Δx_t^s shares moves the (average) price by $\frac{1}{2}\lambda\Sigma\Delta x_t^s$; the resulting price, when multiplied by the trade size Δx_t^s, yields a total trading cost given by the previous expression.

7.1.2. Agents

The economy is populated by two representative agents. The first, and the focus of our study, is a hedge fund (or *arbitrageur*; for ease of exposition, hereafter we use a feminine pronoun for the arbitrageur). This arbitrageur chooses a dynamic trading strategy—represented by holdings x_t^s of asset *s* ($s = \{S, F\}$) and an associated trading intensity $h_t^s \equiv dx_t^s/dt$—to maximize a mean-variance objective that includes the cost of trading. Specifically, she maximizes the present value of future expected excess returns, penalized for risks and trading costs, as follows:

$$\max_{x_0^S, x_1^S, \ldots} E_0 \int_0^\infty e^{-\rho t} \left[(x_t^S r_t^S + x_t^F r_t^F) - \frac{1}{2}\frac{\Sigma}{\tau}\left({x_t^S}^2 + {x_t^F}^2\right) - \frac{(1-\rho)^t}{2} \lambda \Sigma \left({h_t^S}^2 + {h_t^F}^2\right)\right] dt;$$

here $\rho > 0$ is a discount rate, τ is the arbitrageur's risk tolerance coefficient, and λ parameterizes the trading costs. The first term in brackets represents the portfolio's expected excess return; the second, its variance scaled by the arbitrageur's risk tolerance; and the last, the penalty for transaction costs. This objective corresponds to Equation (5) in GP2016, in which we replace (to facilitate the presentation) the coefficient γ of absolute risk aversion with its inverse, the coefficient of absolute risk tolerance, $\tau \equiv 1/\gamma$.

The second agent is a *noise trader* (to which we refer hereafter with a masculine pronoun). He might be a mutual fund responding to flows or any trader subject to shocks (such as to liquidity needs, perceived investment opportunities or sentiment) unrelated to asset fundamentals. This interpretation is consistent with the evidence reported in Tables 2 and 4 and in the literature (e.g., Akbas et al. 2015). The behavior of the noise trader is not explicitly modeled; instead, we represent it by the residual demand for the assets (i.e., his demand minus the number of shares outstanding), which is price-inelastic. Any such excess demand causes assets to be overvalued. We assume that the residual demand for asset *s* in period *t*, denoted f_t^s, is positive and gradually declines to zero. Specifically, starting from $f_0^s \geq 0$, the demand f_t^s evolves deterministically over time according to

$$df_t^s = -\Phi^s f_t^s dt \quad \text{for } t \geq 0,$$

where $\Phi^S \geq 0$ is a parameter that controls the speed at which f_t^s decays to zero. We assume that the shocks are initially identical across assets ($f_0^S = f_0^F$) but that they decay at different speeds: asset *S*, the "slow" asset, is associated with a smaller mean-reversion speed than asset *F*, the "fast" asset; that is, $\Phi^S < \Phi^F$. We refer to f_t^s (≥ 0) as a factor because of its role (as we shall describe) in driving returns. In short, the two risky assets are each associated with distinct predicting factors that differ only in the speed at which they decay (i.e., in the mean-reversion parameter Φ^S).

Finally, we assume that the model's parameters satisfy the following restriction.

<u>Assumption 1</u> (Upper bound on the magnitude of transactions costs): $\lambda < \frac{1}{\tau \Phi^F(\Phi^F + \rho)}$.

Assumption 1 ensures that the cost of trading assets is not too large relative to their risk premium, a scenario that most closely matches our evidence.

7.1.3. Equilibrium

The equilibrium price process is such that the optimal holdings of the arbitrageur and the noise trader clear the asset market; that is, $x_t^s + f_t^s = 0$ for all periods $t \geq 0$ and assets $s = \{S, F\}$. We assume that $x_0^s = -f_0^s$.

7.2. *Equilibrium characterization*

Given our assumptions (i.i.d. dividends and deterministic residual demand), asset prices evolve deterministically over time. Hence the dividend remains as the sole source of risk. It is then natural to suppose, as we confirm later, that asset prices are driven by the factors (f_t^S, f_t^F). Thus we write $p_t^s = c_0^s + c^s f_t^s$, where c_0^s and c^s are constants. The mean and variance of excess returns over dt are, accordingly, given by

$$E_t(dQ_t^s) = dp_t^s + E_t(du_t^s) - r^f p_t^s dt = (-c^s(\Phi^s + r^f) f_t^s + D - r^f c_0^s)dt$$

$$\text{and} \quad \mathrm{Var}_t(dQ_t^s) = \mathrm{Var}_t(du_t^s) = \Sigma dt.$$

Since these factors have the structure assumed by GP2016, the arbitrageur's optimal strategy is given by their Proposition 1, which we restate next.

<u>Proposition 1</u> (Optimal trading strategy). *The arbitrageur tracks a moving "aim portfolio",* aim_t^s, *toward which she rebalances her holdings by a fraction* a/λ. *That is, her optimal trading intensity* h_t^s *is given by*

$$h_t^s \equiv \frac{dx_t^s}{dt} = \frac{a}{\lambda}(\mathrm{aim}_t^s - x_t^s),$$

where

$$\mathrm{aim}_t^s = \frac{\tau}{1+\Phi^s a\tau} \frac{E_t(dQ_t^s)}{\Sigma dt} \text{ for } s = \{S, F\}) \quad \text{and} \quad a \equiv \frac{\lambda}{2}\left(\sqrt{\rho^2 + \frac{4}{\lambda\tau}} - \rho\right).$$

The rebalancing fraction a/λ *is positive, decreasing in the transaction cost* λ *and in risk tolerance* τ, *and independent of assets' mean reversion speeds* Φ^S.

The proofs of our two propositions (and of the five predictions to follow in Section 7.3.3) are all given in Appendix 1.

According to Proposition 1, the arbitrageur's optimal trading strategy can be broken down into two parts. The first, called the "aim portfolio", is the position the arbitrageur seeks to achieve. This aim portfolio is a scaled-down version of the "Markowitz portfolio", $(\tau/(\Sigma dt))E_t(dQ_t^s, dQ_t^s)^{\mathrm{T}}$, which is the optimal portfolio in the absence of transaction costs. The aim portfolio places less weight on an asset whose factor decays more rapidly (higher Φ^S). The reason is that any holdings of such an asset must be rebalanced more frequently, which is more costly. The second part of the optimal trading strategy consists of the extent to which the arbitrageur rebalances toward her aim portfolio. Transaction costs dictate that the arbitrageur rebalance only partially toward this portfolio—specifically, by a fraction a/λ (which is infinite only in the absence of transaction costs). This fraction does not depend on the decay speed of the factor underlying an asset's price. Equilibrium expected returns and prices are given by Proposition 2.

<u>Proposition 2</u> (Equilibrium expected returns and prices). *The expected dollar excess return over dt is*

$$E_t(dQ_t^s) = -\Sigma[1/\tau - \lambda\Phi^s(\Phi^s + \rho)]f_t^s dt \quad for\ s = \{S, F\},$$

and the price is given by

$$p_t^s = \frac{D}{rf} + \frac{\Sigma[1/\tau - \lambda\Phi^s(\Phi^s + \rho)]}{\Phi^s + rf} f_t^s \quad for\ \ s = \{S, F\}.$$

Proposition 2 establishes that the expected return consists of two components. The first is a reward that compensates the arbitrageur for taking "the other side" of noise trades. It is equal to the amount of risk that she must bear, $(\Sigma dt) \times (-f_t^s)$, where the product's first term is the risk per share and the second is the number of shares she must hold in equilibrium, divided by her risk-bearing capacity τ. This risk reward is negative because the arbitrageur is short the asset in equilibrium ($f_t^s \geq 0$). Note that, *for a given* f_t^s, the speed of decay Φ^S has no bearing on the risk reward because: (i) the risk per share, Σdt, is identical across assets; and (ii) the current *level* of the factor f_t^s, irrespective of its change df_t^s, determines how many shares the arbitrageur holds in equilibrium. However, Φ^S matters owing to its influence on f_t^s: in any period $t > 0$, the residual supply of shares $(-f_t^s)$ is greater for asset *S* than for asset *F*, which implies a larger (i.e., more negative) risk reward for the former ($f_t^S > f_t^F$). In sum, the arbitrageur must maintain a larger short position in the slower asset because its residual supply decays more slowly, which exposes her—in every period—to more fundamental risk. To compensate for this higher risk, the slower asset offers a higher return and so is more overvalued.

The second component of the expected return is a compensation for trading costs, $\Sigma\lambda\Phi^s(\Phi^s + \rho)f_t^s dt$. It is positive (so the arbitrageur expects a positive return from buying shares) and increases with risk Σ, with the transaction cost parameter λ, and with the size of the arbitrageur's trade over the interval *dt*, $\Phi^s f_t^s dt$. Unlike the risk component, the trading-cost component increases with the speed of decay. The reason is that, when the factor decays faster, the arbitrageur must adjust her holdings of the asset more rapidly in equilibrium (i.e., she has less time to close her short positions), which entails higher transaction costs (recall that such costs are convex in the rate of change in the arbitrageur's holdings). The fast-decaying asset is therefore less attractive to a short-seller, from which it follows that asset *F* must offer a higher expected return than asset *S*. Assumption 1 implies that the compensation for risk dominates the compensation for transaction costs and thus the expected return is negative (but less so for the faster-decaying asset). Since the arbitrageur is short the asset, she expects to earn a positive return. This expected return gradually vanishes as the demand shock reverts to zero.

The price is the sum of two terms. The first is a constant, D/r^f, which equals the present value of expected dividends (i.e., the asset's fundamental value). The second term is a transitory component, $\frac{\Sigma[1/\tau-\lambda\Phi^S(\Phi^S+\rho)]}{\Phi^S+r^f} f_t^S$, which is positive by Assumption 1, implying that the asset is overvalued. Initially (i.e., at $t = 0$), the asset's price exceeds its fundamental value—as a result of noise traders' excess demand—and the arbitrageur is short the asset. Then (at $t > 0$), as excess demand fades, the arbitrageur closes her short positions and the price converges to the fundamental value. The price is shaped by the same forces as the expected return: compensations for risk and transaction cost.[19] The former increases the price (so a short position earns a higher premium) whereas the latter reduce it. Intuitively, transaction costs discourage the arbitrageur from buying back shares (as illustrated by the smaller rebalancing fraction a/λ in Proposition 1). So for the market to clear at a time when the noise trader offloads shares, the price must be sufficiently low to compensate the arbitrageur for transaction costs.[20] In equilibrium, then, the price strikes a balance: it is high enough to compensate for risk (thereby enticing the arbitrageur to short the asset) yet low enough to compensate for transaction costs (thus encouraging her to close her short positions later). By Assumption 1, the former channel dominates the latter so the asset's price exceeds its fundamental value.[21]

We turn now to discussing the impact of the decay rate on the extent of overvaluation. A faster decay reduces the price through the two channels just described. The first is that, at any date $t > 0$, asset *F* has a lower residual demand ($f_t^F < f_t^S$)—leading to less risk compensation and so to a lower price. Second, for markets to clear, the arbitrageur must buy back more shares of asset *F* than of asset *S* over any period *dt*; thus she incurs higher transaction costs. She is compensated for these more rapid buys of asset *F* through a lower price.

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[19] The relation between an asset's price and its expected return is perhaps most easily seen by setting both the riskless rate and the expected dividend to zero; in that case, the expected dollar excess return coincides with the price change: $E_t(dQ_y^S) = dP_y^S$ for any date $y \geq t$. Therefore, $P_t^S = \frac{D}{rf} + \int_{+\infty}^{t} E_t(dQ_y^S)\, dy$.

[20] In terms of the optimal trading strategy described in Proposition 1, market clearing requires that the arbitrageur's aim portfolio load more positively on a risky asset, the higher its speed of decay and the higher the transaction cost: $\text{aim}_t^S = -f_t^S - \frac{\lambda}{a}\frac{df_t^S}{dt} = (-1 + \frac{\lambda\Phi^S}{a}) f_t^S$. This, in turn, implies that the asset has: (a) a higher expected return, given Proposition 1's definition of the aim portfolio; and (b) a lower price, since its price in the long-term (i.e., as $t \to \infty$) is pinned down by the fundamental value.

[21] Relaxing Assumption 1 implies that, if transaction costs are high enough, then the asset is undervalued (i.e., its price at $t = 0$ is below its fundamental value, then rises) despite the noise trader's excess demand. Again, this is because the market can clear in periods $t > 0$ only if the price is sufficiently low to yield a buyer a return high enough to offset the transaction costs.

A useful benchmark is when the arbitrageur is risk neutral (i.e., has an infinite risk tolerance). In that case, there is no risk compensation and the price is below the fundamental value due only to the transaction costs ($p_t^s = \frac{D}{rf} - \frac{\Sigma\lambda\Phi^s(\Phi^s+\rho)}{\Phi^s+rf} f_t^s$). If in this benchmark there were also no transaction costs, then the price would be equal to the fundamental value.

The next lemma describes how the decay rates of prices and returns relate to the decay rates of factors Φ^S.

Lemma 3 (Rates of decay). *The decay rates for asset* ($s = \{S, F\}$) *are given by the following expressions:*

(i) *for the holdings,* $-\frac{1}{x_t^s}\frac{dx_t^s}{dt} = \Phi^s$;

(ii) *for the price,* $-\frac{1}{p_t^s}\frac{dp_t^s}{dt} = (1 - \frac{D/r^f}{p_t^s})\Phi^s$;

(iii) *for the expected excess return,* $-\frac{1}{E_t(r_t^s)}\frac{dE_t(r_t^s)}{dt} = \frac{D/r^f}{p_t^s}\Phi^s$.

Part (i) of Lemma 3 characterizes the speed of trading as measured by the percentage change in the arbitrageur's holdings, $-\frac{1}{x_t^s}\frac{dx_t^s}{dt}$. Since market clearing requires that the arbitrageur's and noise trader's holdings sum to zero in every period (i.e., that $x_t^s = -f_t^s$ and $dx_t^s = -df_t^s$), it follows that—in equilibrium—the trading rate equals the factor's decay rate: $-\frac{1}{x_t^s}\frac{dx_t^s}{dt} = -\frac{1}{f_t^s}\frac{df_t^s}{dt} = \Phi^s$.

Two implications of Lemma 3 underlie our empirical analysis. The first is that returns decay at rates that differ across assets, since those rates are themselves functions of the decay rate of the assets' underlying factors. Thus the lemma supports our use of Fourier transforms in the empirical analysis for extracting, from a portfolio's returns, components that decay at distinct rates. The lemma's second implication is that the decay rate of returns differs from that of their underlying factors. Given that the factor's decay rate coincides with the trading rate, it must be that returns decay at some rate other than the trading rate. This observation underscores how our approach, which is based on the frequency of returns, differs from those that focus on the frequency of trading (i.e., portfolio turnover; see e.g. Novy-Marx and Velikov, 2016). Furthermore, the decay rate of returns depends on the extent of mispricing as measured by the ratio of the fundamental value to the price, $(D/r^f)/p_t^s$. Thus the persistence of returns, or their frequency, is associated with market inefficiency: the more overvalued an asset, the more slowly its return decays. This connection further motivates our study of market efficiency in the frequency domain. In the next section, we introduce capital flows and analyze their effect on returns.

7.3. Flow-return regressions

We analyze how the relation between returns and flows varies with the speed at which the underlying factor decays.

7.3.1. Modeling flows

So far, we have described the behavior of an unconstrained mean-variance investor characterized by a constant coefficient of absolute risk tolerance. As is well known, there are no wealth effects under such preferences: as wealth fluctuates, the investor holds the same number of shares but simply adjust her holdings of the riskless asset. To account for the behavior of hedge funds, which typically buy (resp. sell) shares in response to capital inflows (resp. outflows), we assume that net flows increase risk tolerance (as in, e.g., Merton 1987) and furthermore, that this increase is greater for flows that the arbitrageur deems more persistent. Thus we assume that the change in an arbitrageur's coefficient of absolute risk tolerance over the interval *dt* is given by

$$d\tau_t = k \times NetFlows_t,$$

where $NetFlows_t$ denotes net capital flows over the interval *dt* and where k is a positive constant. As in our empirical analysis, we further decompose flows into two orthogonal components: one persistent (the "patient" component) and the other transitory (the "impatient" component). We then write the flow-induced change in absolute risk tolerance as

$$d\tau_t = k \times [(1+\omega)NetFlows_t^P + (1-\omega)NetFlows_t^I];$$

here $NetFlows_t^P$ and $NetFlows_t^I$ denote (respectively) patient and impatient net flows, and $\omega \in [0,1]$ is a constant. Thus a dollar's worth of patient flows increases risk tolerance by $k(1+\omega)$ whereas a dollar's worth of impatient flows increases risk tolerance by the smaller amount $k(1-\omega)$. This parameterization offers an intuitive and tractable way of representing the observed behavior of arbitrageurs: as capital flows in, risk tolerance increases; this leads the arbitrageur to scale up her risky portfolio, and more so for flows that she believes will not reverse soon (and that are therefore less likely to force her to liquidate positions). The parameter ω controls the impact of flow persistence on risk tolerance. The larger is ω, the greater is this impact. If $\omega = 0$, then flows have an equal effect on risk tolerance regardless of their persistence; if $\omega = 1$, then only patient flows matter for risk tolerance.

We assume that the arbitrageur does not anticipate flows and that she views shifts in risk tolerance as permanent so that we can apply the results of GP2016 (our Proposition 1). Finally, we assume that flows (and thus also shocks to risk tolerance) are independent of dividends, du_t^s $(s = \{S, F\})$.

Although we acknowledge that this representation of the effects of flows is somewhat ad hoc and not fully consistent with investor rationality, we believe that it offers a realistic and tractable account of actual arbitrageurs' behavior. Developing a full-fledged model of dynamic trading under general investor preferences is a task that goes beyond the scope of this paper. More importantly, we see no reason to believe that fluctuations in risk tolerance will *differentially* affect an arbitrageur's portfolio allocation to the fast- and slow-decaying assets, which is the focus of our study. The ability to anticipate flows might well affect the choice of liquid (e.g., cash) versus illiquid assets but not—*for a given level of liquidity*—the choice of fast- versus slow-decaying stocks.

7.3.2. Linking flows to returns

To evaluate the impact of flows on return, we proceed as follows. Starting from an equilibrium for a given risk tolerance coefficient, we consider a flow-induced shock to risk tolerance and then solve for the equilibrium under the new risk tolerance coefficient. Finally, we analyze how prices and returns adjust from one equilibrium to the other. In that setting, price dynamics are determined by two forces: the mean reversion of the demand shock (i.e. the factor's decay), which results in the price also reverting to the mean; and the flow-induced fluctuation in risk tolerance. Inflows (resp., outflows) render an arbitrageur more (resp., less) risk tolerant, the effect of which is to lower (resp., raise) the price toward (resp., away from) the fundamental value. As a result, the price displays a tendency to decline toward the fundamental value whilst perturbed by flows. Formally, the price change over *dt* can be written as

$$dp_t^s = \left.\frac{\partial p_t^s}{\partial f_t^s}\right|_{\tau_t} df_t^s + \left.\frac{\partial p_t^s}{\partial \tau}\right|_{f_t^s} d\tau_t = \left.\frac{\partial p_t^s}{\partial f_t^s}\right|_{\tau_t} (-\Phi^s f_t^s dt) + \left.\frac{\partial p_t^s}{\partial \tau}\right|_{f_t^s} kNetFlows_t,$$

where the first term captures the downward trend and the second term represents the variations due to flows. The excess return follows from $r_t^s = (dp_t^s + du_t^s - r^f p_t^s dt)/p_t^s$.

7.3.3. Predictions

In line with the empirical investigation, our predictions pertain to the least-squares coefficient from regressing returns on flows. The dependent variable is the negative of the excess return, $-r_t^s$, since the arbitrageur takes a short position in the overvalued asset (which corresponds to the short leg of the anomaly portfolio in our empirical analysis). For the independent variable, we consider both total flows, $NetFlows_t$, and decomposed flows $(NetFlows_t^P, NetFlows_t^I)$. We use β^s, $\beta^{s,P}$, and $\beta^{s,I}$ ($s = \{S, F\}$) to denote the corresponding regression coefficients. The attenuation factor is defined as $A \equiv \beta^{S,P}/\beta^{F,I}$.[22] It measures the extent to which the arbitrageur's correction of mispricing in the slow asset in response to patient flows exceeds her correction in the fast asset in response to impatient flows—that is, her tendency to correct slow rather than fast mispricing. Our main prediction is Prediction 2; the other predictions describe its sensitivity to model parameters.

<u>Prediction 1</u> (Sign of regression coefficient).

- *The regression coefficient of the excess return on total flows,* β^S ($s = \{S, F\}$), *is positive.*

[22] By assumption, both assets have identical return volatility, which is determined by the volatility of dividends and flows.

- *Moreover, the coefficient $\beta^{s,P}$ for the regression on patient flows is larger than the coefficient $\beta^{s,I}$ for the regression on impatient flows: $\beta^{s,P} - \beta^{s,I} > 0$.*

Prediction 1 states that the arbitrageur corrects mispricing to a greater (resp. lesser) extent when she gains (resp. loses) capital. This outcome reflects that inflows expand her risk-bearing capacity and so she requires a smaller premium to accommodate the demand shock. Prediction 1 is consistent with the positive coefficients we generally find in the data for the regressions of anomaly returns on hedge fund flows. It also states that patient flows lead to a bigger return adjustment than do impatient flows. We can rationalize the negative regression coefficient we report for mutual funds by interpreting flows to mutual funds as shocks to the noise trader's demand f_t^s for assets: an inflow of capital to mutual funds in period *t* increases f_t^S and f_t^F, thereby magnifying asset overvaluation and leading to negative returns on the arbitrageur's short position.

Our main prediction follows. It describes how the flow–return relation varies with factors' speed of decay.

Prediction 2 (Speed of decay). *Assume that $f_0^s < \frac{D/r^f}{\Sigma\lambda(2\Phi^F+\rho)}$ (Assumption 2).*

- *The coefficient from regressing the excess return on total flows is larger for assets that decay more slowly: $\beta^S - \beta^F > 0$.*
- *The attenuation factor exceeds unity: $A \equiv \beta^{S,P}/\beta^{F,I} > 1$.*

Prediction 2 states that mispricing whose decay is slower is associated with a larger regression coefficient. Intuitively, the arbitrageur has more risk exposure to the slower-decaying asset (per our discussion following Proposition 2), so an increase in risk tolerance—due to inflows—leads to a larger reduction in the risk compensation and price of that asset. Put differently, because asset *S* is more overvalued than asset *F*, its price has farther to decline to reach its fundamental value. As a result, flows trigger larger price adjustments and returns for asset *S* and so $\beta^S > \beta^F$. Note that our restriction on parameter values (Assumption 2) is sufficient but not necessary for the prediction to hold. That assumption is satisfied, in particular, when there is no transaction cost ($\lambda = 0$). Moreover, no such restriction is required when the regressions are based on dollar returns, dQ_t^s, rather than relative returns, $r_t^s \equiv dQ_t^s/p_t^s$.

Two effects contribute to making the attenuation factor greater than 1. The first is that, for a given level of persistence of flows, the slow asset is associated with a larger regression coefficient ($\beta^S > \beta^F$). The second effect is that patient flows trigger a greater increase in risk tolerance than do impatient flows: $d\tau_t/dNetFlows_t^P = k(1+\omega) > d\tau_t/dNetFlows_t^I = k(1-\omega)$.

We remark that, for the benchmark case in which the arbitrageur is risk neutral (i.e., has infinite risk tolerance), the regression coefficient equals zero regardless of the factor's decay rate and of transaction costs. This observation confirms that the arbitrageur's limited risk-bearing capacity is a predominant driver of our predictions.

Next, we present three auxiliary predictions that describe how regression coefficients' sensitivity to the speed of decay varies with the economy's three characteristics: fundamental risk, risk tolerance, and transaction costs.

Prediction 3 (Fundamental risk). *Assume that* $f_0^s < \frac{D(D/r^f + r^f)}{2r^f\Sigma[1/\tau + \lambda(\Phi^F(\Phi^F + 2r^f) + r^f\rho)]}$ *(Assumption 3). Then the coefficients from regressing the excess return on total, patient, and impatient flows are all more sensitive to the speed of decay when fundamentals are riskier* (*i.e., when* Σ *is larger*). *Thus, we have* $\frac{d(\beta^S - \beta^F)}{d\Sigma} \geq 0$ *and* $\frac{d(\beta^{S,P} - \beta^{F,I})}{d\Sigma} \geq 0$.

Prediction 3 states that assets are more sensitive to the speed of factor decay when fundamental risk is higher. Intuitively, when risk rises, asset prices move farther away from their fundamental values—and to a greater extent for slow-decaying than for fast-decaying assets. That's because the arbitrageur's compensations for risk and for transaction costs both increase, but the former increases more than the latter (by Assumption 3). The reason is as follows (see the discussion after Proposition 2). The compensation for risk, and hence the asset's price, increases because each share is now riskier; this effect is more pronounced for the slow asset because the arbitrageur's exposure to that asset is greater. The compensation for transaction costs also increases—because such costs are (by assumption) proportional to fundamental risk, yet that increase reduces the asset's price; this effect is stronger for the fast-decaying asset, the arbitrageur's holding of which must be adjusted more rapidly. By Assumption 3, the effect of risk dominates that of transaction costs; hence an increase in risk has a greater effect on the slower-decaying asset. This increase widens the gap between the two asset's prices and thus also between their sensitivities to the speed of decay of their underlying factor. Observe that no restriction on parameter values is required for the prediction to obtain when our regressions are based on dollar rather than relative returns.

Prediction 4 (Risk tolerance). *Assume that* $f_0^S < \frac{D/r^f(\Phi^F+r^f)}{\Sigma\lambda\Phi^F(\Phi^F+\rho)}$ *(Assumption 4). Then the coefficients from regressing the excess return on total, patient, and impatient flows are more sensitive to the speed of decay when the arbitrageur is less risk tolerant* (*i.e., when* τ_t *is smaller*): $\frac{d(\beta^S-\beta^F)}{d\tau_t} \leq 0$.[23]

Prediction 4 describes how the sensitivity of the regression coefficient to the speed of factor decay depends on the level of risk tolerance. Note that it focuses on the *level* of risk tolerance and not on the *changes* that we associate with flows. We interpret the level of risk tolerance as representing the ease with which the arbitrageur can increase her leverage. We predict that assets are more sensitive to the speed of factor decay when the arbitrageur is less risk tolerant. Intuitively, when there is less tolerance for risk, asset prices move away from their fundamental values—and more so for the slower-decaying asset (once again, the result of the arbitrageur's greater risk exposure to that asset). Therefore, the gap between the two assets' prices, and hence between their sensitivities to the speed of factor decay, becomes wider. As before, no restriction on parameter values is required for this prediction to obtain provided that we use dollar (rather than relative) returns in the regressions.

Prediction 5 (Transaction costs). *Assume that* $f_0^S < \frac{D(\Phi^F\rho-r^f\rho-2r^f\Phi^F)}{r^f\Sigma(2\Phi^F+\rho)[1/\tau+\lambda\Phi^F(\Phi^F+\rho)]}$ *(Assumption 5). Then the coefficients from regressing the excess return on total, patient, and impatient flows are more sensitive to the speed of decay when transaction costs* λ *are higher*: $\frac{d(\beta^S-\beta^F)}{d\lambda} \geq 0$ *and* $\frac{d(\beta^{S,P}-\beta^{F,I})}{d\lambda} \geq 0$.

Prediction 5 states that transaction costs magnify the gap between the slow- and fast-decaying assets' regression coefficients. Intuitively, when transaction costs rise, an asset's price moves closer to its fundamental value in compensation for the (future) cost of buying shares; that price's movement is greater for the asset requiring faster trading—namely, the faster-decaying asset (see Proposition 2 and the subsequent discussion). Hence the gap widens between the two assets' prices and therefore between their respective sensitivities to the speed at which their underlying factor decays.[24]

This section demonstrates that our diverse empirical findings can be rationalized within a unified framework featuring two frictions: the limited availability of arbitrageur capital (modeled as finite risk tolerance) and transaction costs. We have derived an array of predictions that are consistent with the data—that is, provided the transaction is not too large relative to risk (Assumption 1) and that the asset is not too

[23] The sign of $\frac{d(\beta^{S,P}-\beta^{F,I})}{d\tau_t}$ is ambiguous because of a conflict between two effects. On the one hand, for a given level of flows' persistence, the regression coefficient is less sensitive to risk tolerance for the slow asset than for the fast asset. On the other hand, patient flows induce a larger increase in risk tolerance than do impatient flows.

[24] Assumption 5 implies Assumption 2.

mispriced (Assumptions 2–5 concerning f_0's magnitude). We point out that, because mispricing approaches zero over time, there must exist a date after which Assumptions 2–5 all hold. More general models could, perhaps, deliver similar predictions; yet we believe that, in light of the empirical evidence presented here, capital scarcity and transaction costs will need to figure prominently in any such model.

8. Conclusion

We examine the frequency structure of fund flows and mispricing. Applying spectral analysis, we show that capital supplied by mutual fund investors moves more slowly than does capital supplied by hedge fund investors. Both types of funds behave, in aggregate, as low-pass filters—suggesting that fund managers allocate their capital mainly either to correct or to 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 greater extent. Finally, we present evidence consistent with market frictions driving hedge funds behavior as low-pass filters. In the time series, hedge funds' attenuation factor is high when uncertainty is high, when aggregate liquidity low, and when market conditions are adverse. In the cross section, correction of low-frequency mispricing is attributable primarily to hedge funds with no leverage and with high share restrictions; the implication is that risk aversion and liquidity provisions are important consideration when determining the speed of arbitrage.

In light of the debate over the social value of hedge funds, our work suggests that hedge fund managers improve the efficiency of financial markets at low frequencies, where such efficiency is presumably more socially useful. More work is needed to shed light on this important question. The frequency approach we take to explaining the relation between market efficiency and flows can also be applied in many areas of finance to explore relationships between economic forces in the frequency domain.

References

Acharya, V.V. and Pedersen, L.H., 2005, Asset pricing with liquidity risk. Journal of Financial Economics 77, 375-410.

Adrian, T. and Shin, H.S., 2013, Procyclical leverage and value-at-risk. Review of Financial Studies 27, 373-403.

Agarwal,V., Jiang, W., Tang, Y., and Yang, B., 2013, Uncovering hedge fund skills from the portfolio holdings they hide. Journal of Finance 68, 739–783.

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.

Akbas, F., Armstrong, W.J., Sorescu, S. and Subrahmanyam, A., 2016. Capital market efficiency and arbitrage efficacy. Journal of Financial and Quantitative Analysis, 51(2), pp.387-413.

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Market 5, 31-56.

Amihud, Y. and Goyenko, R., 2013, Mutual fund's R^2 as predictor of performance. Review of Financial Studies 26, 667-694.

Appel, I.R., Gormley, T.A., and Keim, D.B, 2016, Passive investors, not passive owners. Journal of Financial Economics 121, 111-141.

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

Aragon, G.O., Hertzel, M., and Shi, Z., 2013, Why do hedge funds avoid disclosure? Evidence from confidential 13F filings. Journal of Financial and Quantitative Analysis 48, 1499–1518.

Aragon, G.O. and Strahan, P.E., 2012. Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. Journal of Financial Economics, 103(3), pp.570-587.

Arnott, R., Clements, M., Kalesnik, V., and Linnainmaa, J.T., 2019, Factor momentum, Working paper.

Avramov, D., Cheng, S., Schreiber, A., and Shemer, K., 2017, Scaling up market anomalies, Journal of Investing 26, 89-105.

Bandi, F.M, 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., 2017, Business-cycle consumption risk and asset prices. Working paper, London School of Economics.

Bekaert, G., Engstrom, E.C, and Xu, N.R., 2019, The Time Variation in Risk Appetite and Uncertainty. Working paper, Columbia University.

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

Biais, Bruno, Thierry Foucault, and Sophie Moinas (2015), Equilibrium Fast Trading, Journal of Financial Economics, 116 (2015), 292-313

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

Brunnermeier, M.K. and Pedersen, L.H., 2005. Predatory trading. The Journal of Finance, 60(4), pp.1825-1863.

Budish, Eric, Peter Cramton, and John Shim, 2015. The high-frequency trading arms race: Frequent batch auctions as a market design response, Quarterly Journal of Economics, 30, 1547-1621

Calvet, L.E. and Fisher, A.J., 2007, Multifrequency news and stock returns. Journal of Financial Economics 86, 178-212.

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

Carhart, M.M, 1997, On Persistence in Mutual Fund Performance. Journal of Finance 52, 57-82.

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

Chen, J., Hanson, S., Hong, H. and Stein, J.C., 2008. Do hedge funds profit from mutual-fund distress? (No. w13786). National Bureau of Economic Research.
Chen, L., Novy-Marx, R., and Zhang, L., 2010, An alternative three-factor model. Working paper.
Chordia, T., Roll, R., and Subrahmanyam, A., 2008, Liquidity and market efficiency. Journal of Financial Economics 87, 249-268.
Cieslak, A., Morse, A. and Vissing-Jorgensen, A., 2018, Stock returns over the FOMC cycle. Journal of Finance, Forthcoming.
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.
Coval, J. and Stafford, E., 2007, Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479-512.
Cremers, K.M. and Petajisto, A., 2009, How active is your fund manager? A new measure that predicts performance. Review of Financial Studies 22, 3329-3365.
Crouzet, N., Dew-Becker, I., and Nathanson, C.G., 2019, On the effects of restricting short-term investment. Review of Financial Studies, Forthcoming.
Daniel, K., Hirshleifer, D. and Sun, L., 2019, Short-and Long-Horizon Behavioral Factors. Review of Financial Studies, Forthcoming.
Daniel, K.D. and Titman, S., 2006, Market reactions to tangible and intangible information. Journal of Finance 61, 1605-1643.
DeMiguel, V., Martin-Utrera, A., Nogales, F.J., and Uppal, R., 2019, A transaction-cost perspective on the multitude of firm characteristics. Working paper.
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.
Ehsani, S. and Linnainmaa, J.T., 2019, Factor momentum and the momentum factor. Working paper, National Bureau of Economic Research.
Engle, R., Ferstenberg, R., and Russell, J., 2012, Measuring and Modeling Execution Cost and Risk. Journal of Portfolio Management, Winter.
Etula, E., Rinne, K., Suominen, M. and Vaittinen, L., 2019, Dash for cash: Monthly market impact of institutional liquidity needs, Review of Financial Studies, Forthcoming.
Fama, E.F. and French, K.R., 2010, Luck versus Skill in the Cross-Section of Mutual Fund Returns. Journal of Finance 65, 1915-1947.
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.
Heston, S.L. and Sadka, R., 2008, Seasonality in the cross-section of stock returns. Journal of Financial Economics 87, 418-445
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.
Hu, G.X., Pan, J., and Wang, J., 2013, Noise as Information for Illiquidity. Journal of Finance 68, 2341-2382.
Huang, D., Jiang, F., Tu, J. and Zhou, G., 2015, Investor sentiment aligned: A powerful predictor of stock returns. Review of Financial Studies 28, 791-837.
Huang, J., Sialm, C., and Zhang, H., 2011, Risk shifting and mutual fund performance. Review of Financial Studies 24, 2575-2616.
Jegadeesh, N., and Titman, S., 1993, Returns to buying winners and selling losers: Implications for market efficiency. Journal of Finance 48, 65-91.
Jurado, K., Ludvigson, S.C., and Ng, S., 2015, Measuring uncertainty. American Economic Review 105, 1177-1216.
Kacperczyk, M., Sialm, C. and Zheng, L., 2006, Unobserved actions of mutual funds. Review of Financial Studies 21, 2379-2416.
Kamstra, M.J., Kramer, L.A., and Levi, M.D., 2003, Winter Blues: A SAD Stock Market Cycle. American Economic Review 93, 324-343.
Kamstra, M.J., Kramer, L.A., Levi, M.D., and Wermers, R., 2017, Seasonal Asset Allocation: Evidence from Mutual Fund Flows. Journal of Financial and Quantitative Analysis 52, 71-109.
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.
Kelly, B.T., Pruitt, S., and Su, Y., 2019, Characteristics are covariances: A unified model of risk and return. Journal of Financial Economics, Forthcoming.
Keloharju, M., Linnainmaa, J.T., and Nyberg, P., 2019, Long-Term Discount Rates Do Not Vary Across Firms. Working paper, NBER.
Koijen, R.S., Richmond, R.J. and Yogo, M., 2019. Which Investors Matter for Global Equity Valuations and Expected Returns?. Available at SSRN.
Koijen, R.S. and Yogo, M., 2019. A demand system approach to asset pricing. Journal of Political Economy, 127(4), pp.1475-1515.
Kokkonen, J. and Suominen, M., 2015, Hedge funds and stock market efficiency. Management Science 61, 2825-3096.
Korajczyk, R.A. and Sadka, R., 2004, Are Momentum Profits Robust to Trading Costs? Journal of Finance 59, 1039-1082.
Lee, C.M.C. and Swaminathan, B., 2000, Price Momentum and Trading Volume. Journal of Finance 55, 2017-2069.
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., 2019, 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.
Lou, D., Yan, H. and Zhang, J., 2013, Anticipated and repeated shocks in liquid markets. Review of Financial Studies 26, 1891-1912.
Loughran, T., and Ritter, J.R., 1995, The new puzzle. Journal of Finance 50, 23-51.
McLean, R.D., and Pontiff, J., 2016, Does academic research destroy stock return predictability? Journal of Finance 71, 5–32.
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.
Pastor, L., and Stambaugh, R.F., 2003, Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111, 642-685.
Patton, A.J., and Weller, B.M., 2019, What You See is Not What You Get: The Costs of Trading Market Anomalies. Journal of Financial Economics, Forthcoming.
Pitkäjärvi, A., Suominen, M. and Vaittinen, L., 2019. Cross-Asset Signals and Time Series Momentum. Journal of Financial Economics, Forthcoming.
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.
Schneider, P., 2019, An anatomy of the market return. Journal of Financial Economics 132, 325-350.
Shive, S., and Yun, H., 2013, Are mutual funds sitting ducks? Journal of Financial Economics 107, 220-237.
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.
Stock, J. H., and Watson, M. W., 1999, Business cycle fluctuations in US macroeconomic time series. Handbook of macroeconomics, *1*, 3-64.
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.

Appendix 1: Proof of Propositions and Predictions

Proof of Proposition 1

See GP2016's Proposition 1 and observe that $E_t(dQ_t^s)$ is an affine function of the factor f_t^s (in the GP2016 notation, $E_t(dQ_t^s) = Bf_t^s$).

Proof of Proposition 2

The equilibrium price process is such that the optimal holdings of the arbitrageur and the noise trader clear the asset market at every instant; formally, $x_t^s + f_t^s = 0$ and $dx_t^s + df_t^s = 0$. Substituting our conjectured price function, $p_t^s = c_0^s + c^s f_t^s$, into the expression for the mean expected excess return, $E_t(dQ_t^s)$, yields $\text{aim}_t^s = \frac{\tau}{\Sigma}\frac{-c^s(\Phi^s+r^f)f_t^s+D-r^f c_0^s}{1+\Phi^s a\tau}$. Market clearing in period *t* implies that $dx_t^s = \frac{a}{\lambda}(\text{aim}_t^s + f_t^s)dt$ (Proposition 1). Equating this expression to the change in the residual asset supply, $-df_t^s$, leads to $c_0^s = \frac{D}{r^f}$ and $c^s = \frac{\Sigma[1/\tau-\lambda\Phi^s(\Phi^s+\rho)]}{\Phi^s+r^f}$, thus confirming the price conjecture. Note that, by Assumption 1, $c^s > 0$.

Proof of Prediction 1

Given Section 7.3.2's expression for dp_t^s, the excess return equals $r_t^s = \frac{1}{p_t^s}\frac{\partial p_t^s}{\partial f_t^s}\Big|_{\tau_t} df_t^s - r^f dt + \frac{1}{p_t^s}\frac{\partial p_t^s}{\partial \tau}\Big|_{f_t^s} kNetFlows_t + \frac{1}{p_t^s}du_t^s$, where the first two terms capture a deterministic trend and the last term represents a dividend shock that is uncorrelated with flows. Hence the least-squares coefficient for our regression of r_t^s on total flows, $NetFlows_t$, equals $\beta^s = \frac{k}{p_t^s}\frac{\partial p_t^s}{\partial \tau}\Big|_{f_t^s} = \frac{k}{p_t^s}\frac{\Sigma}{\tau_t^2(\Phi^s+r^f)}f_t^s$; this coefficient is positive because all terms are positive. Likewise, the regression coefficients of r_t^S on patient and impatient flows are equal to (respectively) $\beta^{s,P} = \frac{k(1+\omega)}{p_t^s}\frac{\partial p_t^s}{\partial \tau}\Big|_{f_t^s} = (1+\omega)\beta^s$ and $\beta^{s,I} = \frac{k(1-\omega)}{p_t^s}\frac{\partial p_t^s}{\partial \tau}\Big|_{f_t^s} = (1-\omega)\beta^s$. As a result, $\beta^{s,P} - \beta^{s,I} = 2\omega\beta^s > 0$. Moreover, the attenuation factor $A = \frac{1+\omega}{1-\omega}\frac{\beta^S}{\beta^F}$ is positive.

Proof of Prediction 2

Differentiating the regression coefficient with respect to the speed of decay yields $\frac{d\beta^s}{d\Phi^s} = \frac{\partial \beta^s}{\partial \Phi^s}\Big|_{f_t^s} + \frac{\partial \beta^s}{\partial f_t^s}\Big|_{\Phi^s}\frac{df_t^s}{d\Phi^s} > 0$. The first term captures the direct effect of speed on β^s; the second, the indirect effect via the factor decay. We show that both terms are negative. Starting with the first term, we write $\frac{\partial \beta^s}{\partial \Phi^s}\Big|_{f_t^s} = \frac{\partial}{\partial \Phi^s}\left(\frac{k}{p_t^s}\frac{\Sigma}{\tau_t^2(\Phi^s+r^f)}f_t^s\right)\Big|_{f_t^s} = \frac{k\Sigma f_t^s}{\tau_t^2}\frac{\partial}{\partial \Phi^s}\left(\frac{1}{p_t^s(\Phi^s+r^f)}\right) = -\frac{k\Sigma f_t^s}{\tau_t^2}\frac{\frac{D}{r^f}-\Sigma\lambda(2\Phi^s+\rho)f_t^s}{p_t^{s2}(\Phi^s+r^f)^2}$; here we have used that $(\Phi^s + r^f)p_t^s = D(\Phi^s + r^f)/r^f + \Sigma[1/\tau - \lambda\Phi^s(\Phi^s+\rho)]f_t^s$ (see Proposition 2). Hence $\frac{\partial \beta^s}{\partial \Phi^s}\Big|_{f_t^s} \le 0$ if $f_t^s \le D/[r^f\Sigma\lambda(2\Phi^s+\rho)]$. This condition holds if $f_0^s < D/[r^f\Sigma\lambda(2\Phi^s+\rho)]$ since $f_t^s \le f_0^s$. Finally note that $D/[r^f\Sigma\lambda(2\Phi^F+\rho)] < D/[r^f\Sigma\lambda(2\Phi^S+\rho)]$ because $\Phi^S < \Phi^F$. As for the second term, $\frac{d\beta^s}{d\Phi^s}$ is also negative because it is the product of two terms of which one is positive, $\left.\frac{\partial \beta^s}{\partial f_t^s}\right|_{\Phi^s} = \frac{k}{p_t^s} \frac{\Sigma}{\tau_t^2(\Phi^s + r^f)}$, and the other is negative, $\frac{df_t^s}{d\Phi^s} = -tf_t^s$. The ranking of regression coefficients for patient and impatient flows now follows given that $\beta^{S,P} = (1+\omega)\beta^S$ and $\beta^{F,P} = (1+\omega)\beta^F$. Finally, the attenuation factor $A = \frac{1+\omega}{1-\omega}\frac{\beta^S}{\beta^F} > 1$

Proof of Prediction 3

Differentiating $\frac{\partial \beta^s}{\partial \Phi^s}$ with respect to Σ, we obtain the equality $\frac{\partial^2 \beta^s}{\partial \Phi^s \partial \Sigma} = -\frac{k f_t^s D/r^f\{D/r^f(D/r^f + r^f) - 2\Sigma f_t^s[\lambda(\Phi^s(\Phi^s + 2r^f) + \rho r^f) + 1/\tau_t]\}}{\tau_t^2 p_t^{s3}(\Phi^s + r^f)^3}$. This expression is negative if the numerator is positive, which Assumption 3 ensures since $f_t^s \leq f_0^s$ and $\Phi^S < \Phi^F$. The relations for patient and impatient flows follow from the expressions $\beta^{S,P} = (1+\omega)\beta^S$ and $\beta^{F,I} = (1-\omega)\beta^F$, which in turn imply that $\frac{d\beta^{S,P}}{d\Sigma} = (1+\omega)\frac{d\beta^S}{d\Sigma}$ and $\frac{d\beta^{F,I}}{d\Sigma} = (1-\omega)\frac{d\beta^F}{d\Sigma}$.

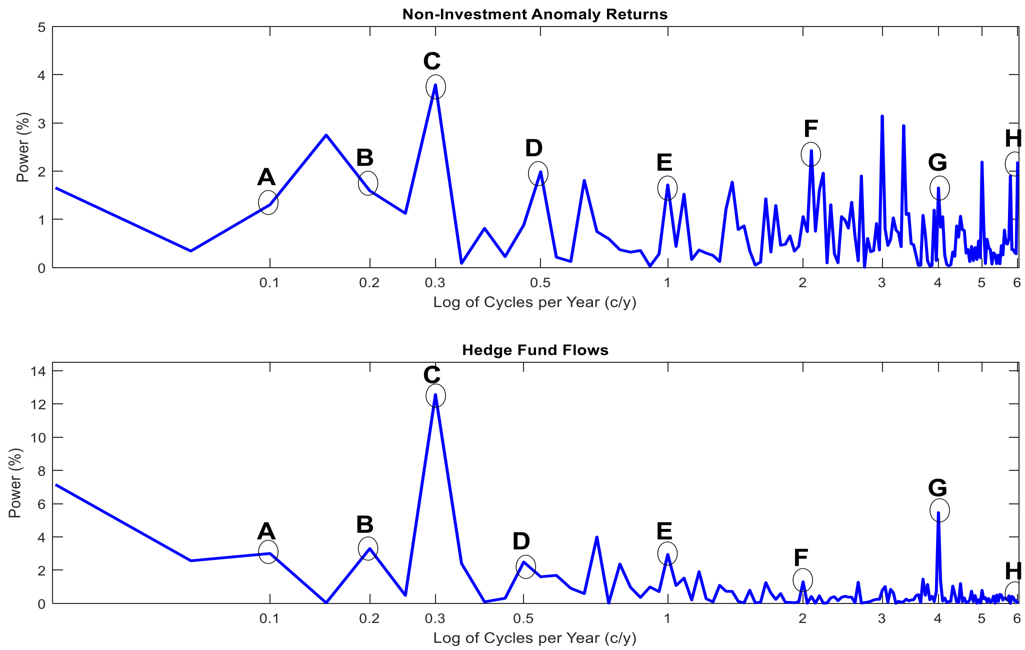
Proof of Prediction 4

The expression $\frac{\partial \beta^s}{\partial \Phi^s} = -\frac{k\Sigma f_t^s}{\tau_t^2}\frac{D/r^f - \Sigma\lambda(2\Phi^s + \rho)f_t^s}{p_t^{s2}(\Phi^s + r^f)^2}$ (see the proof of Prediction 2) implies that $\frac{\partial \beta^s}{\partial \Phi^s}$ increases with τ_t if also $\tau_t p_t^s(\Phi^s + r^f)$ increases with τ_t. Plugging in our expression for p_t^s reveals that this condition is satisfied if $f_t^s < \frac{D/r^f(\Phi^s + r^f)}{\Sigma\lambda\Phi^s(\Phi^s + \rho)}$, an inequality that holds if $f_0^s < \frac{D/r^f(\Phi^s + r^f)}{\Sigma\lambda\Phi^s(\Phi^s + \rho)}$ since $f_t^s \leq f_0^s$. Finally, observe that the right-hand side of this inequality is decreasing in Φ^S. Hence Assumption 4 suffices to show that $\frac{\partial^2 \beta^s}{\partial \Phi^s \partial \tau_t} \geq 0$. To establish the relations for patient and impatient flows, we proceed as in the proof of Prediction 3 but with one difference: we cannot determine the sign of $\frac{d(\beta^{S,P} - \beta^{F,I})}{d\tau_t}$ because the two effects that control this term's sign work in opposite directions. On the one hand, for a given level of persistence of flows, the regression coefficient is less sensitive to τ_t for the slow asset than for the fast asset: $\frac{d(\beta^S - \beta^F)}{d\tau_t} \leq 0$. On the other hand, patient flows induce a larger increase in risk tolerance than do impatient flows: $k(1+\omega) > k(1-\omega)$. It follows that the sign of $\frac{d(\beta^{S,P} - \beta^{F,I})}{d\tau_t} = \frac{d((1+\omega)\beta^S - (1-\omega)\beta^F)}{d\tau_t}$ is ambiguous.

Proof of Prediction 5

Differentiating $\frac{\partial \beta^s}{\partial \Phi^s}$ with respect to λ yields $\frac{\partial^2 \beta^s}{\partial \Phi^s \partial \lambda} = -\frac{k\Sigma^2 f_t^{s2}\{D/r^f(\rho r^f + 2r^f\Phi^s - \Phi^s\rho) + \Sigma(2\Phi^s + \rho)f_t^s[\lambda\Phi^s(\Phi^s + \rho) + 1/\tau_t]\}}{\tau_t^2 p_t^{s3}(\Phi^s + r^f)^3}$. This expression is negative if the numerator is positive, a condition ensured by Assumption 5 because $f_t^s \leq f_0^s$ and $\Phi^S < \Phi^F$. To establish the predicted relations for patient and impatient flows, we simply proceed as in the proof of Prediction 3.

Figure 1. Economic Cycles and Seasonality in the Frequency Domain. This figure shows the relation between the frequency decomposition of time series variables (non-investment anomaly return, NINV, in the top panel; hedge fund flows in the bottom panel) and the corresponding cycles of asset returns or economic activity. Circles represent frequencies that correspond to prominent cycles in asset returns/economic activity documented in the literature. The x-axis shows the natural log of frequency of the time-series variables, and the y-axis shows the power (squared amplitude) of each frequency scaled by the sum of powers over the full spectrum. Therefore, it shows the relative contribution (in percentage points) of each frequency to the total variance of the time series variable. Non-Investment anomaly (NINV) return is the return of the long-minus-short strategy based on seven anomalies, reported in Stambaugh, Yu, and Yuan (2012), which are not related to corporate investments. Hedge fund flows are the monthly net aggregate percentage flows to equity hedge funds. The sample period is 1994–2016.



A. 0.1 c/y (Approximately 8 to 10-year period): 10-year solar cycle and 8-year democratic/republican presidential cycle in stock returns (Novy-Marx 2014). Business cycle (Stock and Watson 1999; Dew-Becker and Giglio 2016).

B. 0.2 c/y (Approximately 4 to 5-year period): Multiple stock return cycles including 5-year overreaction/underreaction cycle (Lee and Swaminathan 2000), 5-year El Niño weather cycle (Novy-Marx 2014), 4-year presidential cycle (Hirsch 1968; Allvine and O'Neill (1980), 4-year Mars-Vesta cycle (Novy-Marx 2014), and 4-year return seasonality (Heston and Sadka 2008). Business cycle (Stock and Watson 1999, Dew-Becker and Giglio 2016)

C. 0.3 c/y (3-year period): Business cycle (Stock and Watson 1999; Dew-Becker and Giglio 2016); 3-year return seasonality (Sadka and Heston 2008).

D. 0.5 c/y (2-year period): 2-year return seasonality (Sadka and Heston 2008); Long-run uncertainty periodicity (Barrero, Bloom, and Wright 2018). Business cycle (Stock and Watson 1999; Dew-Becker and Giglio 2016).

E. 1 c/y (1-year period): Annual firm/fund fiscal and reporting cycles; SAD cycle and seasonal asset allocation cycle (Kamstra et al. 2003, 2017); Momentum and reversal seasonality (Heston and Sadka 2008; Keloharju, Linnainmaa, Nyberg 2019).

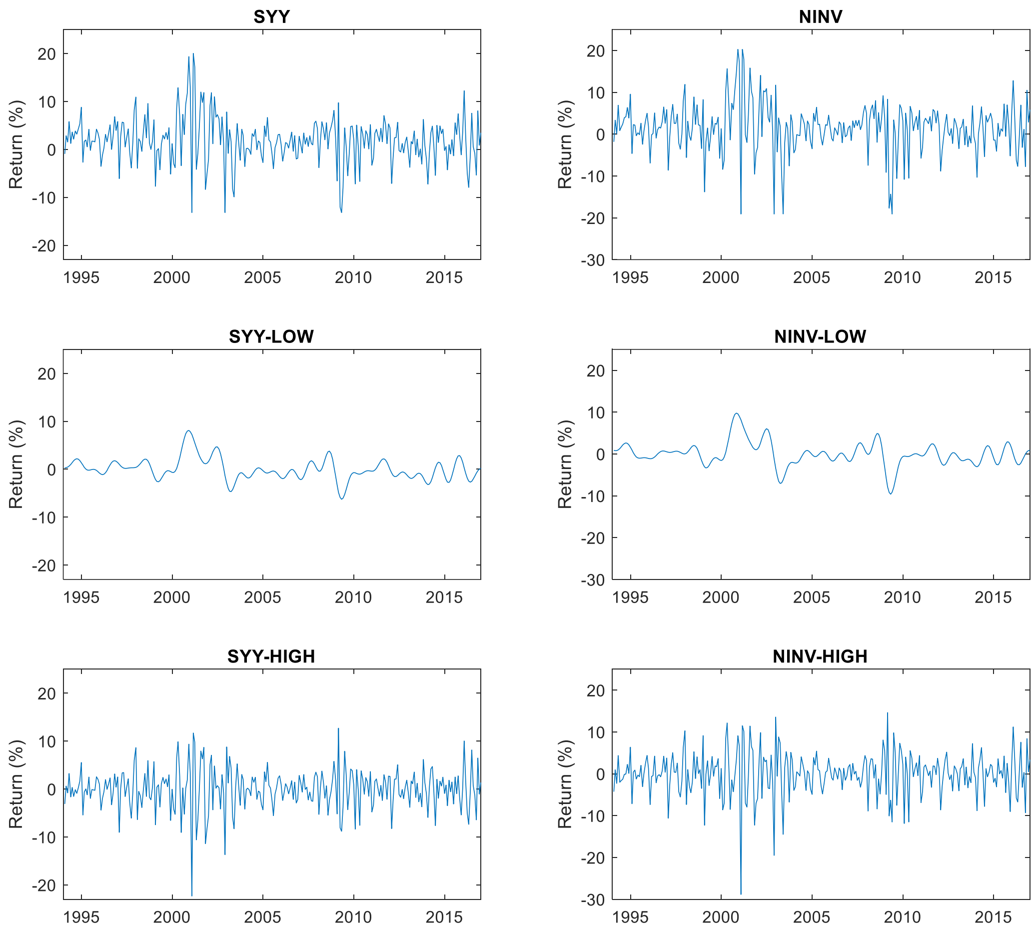
F. 2 c/y (semi-annual period): Low-frequency interest rate periodicity (Hanson, Lucca, and Wright 2018).

G. 4 c/y (quarterly period): Quarterly rebalancing and reporting period of mutual/hedge funds; Earnings-announcement return cycle (Linnainmaa and Zhang 2019).

H. 6 c/y (2-month period): FOMC return cycle (Cieslak, Morse, and Vissing-Jorgensen 2018); Monthly payment cycle (Etula et al. 2019).

Figure 2. Time Series of Decomposed Anomaly Returns and Fund Flows. This figure plots the time series of decomposed variables. Panel A shows the decomposed anomaly returns, while Panel B displays decomposed fund flows. 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 and fund flows to obtain the frequency components. Then, the time series of LOW (HIGH) frequency anomaly returns and fund flows 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. MF and HF are the monthly aggregate percentage flow of equity mutual funds and equity hedge funds, respectively. The sample period is 1994–2016.

Panel A: Decomposed Time Series of Anomaly Returns.



Panel B: Decomposed Time Series of Fund Flows.

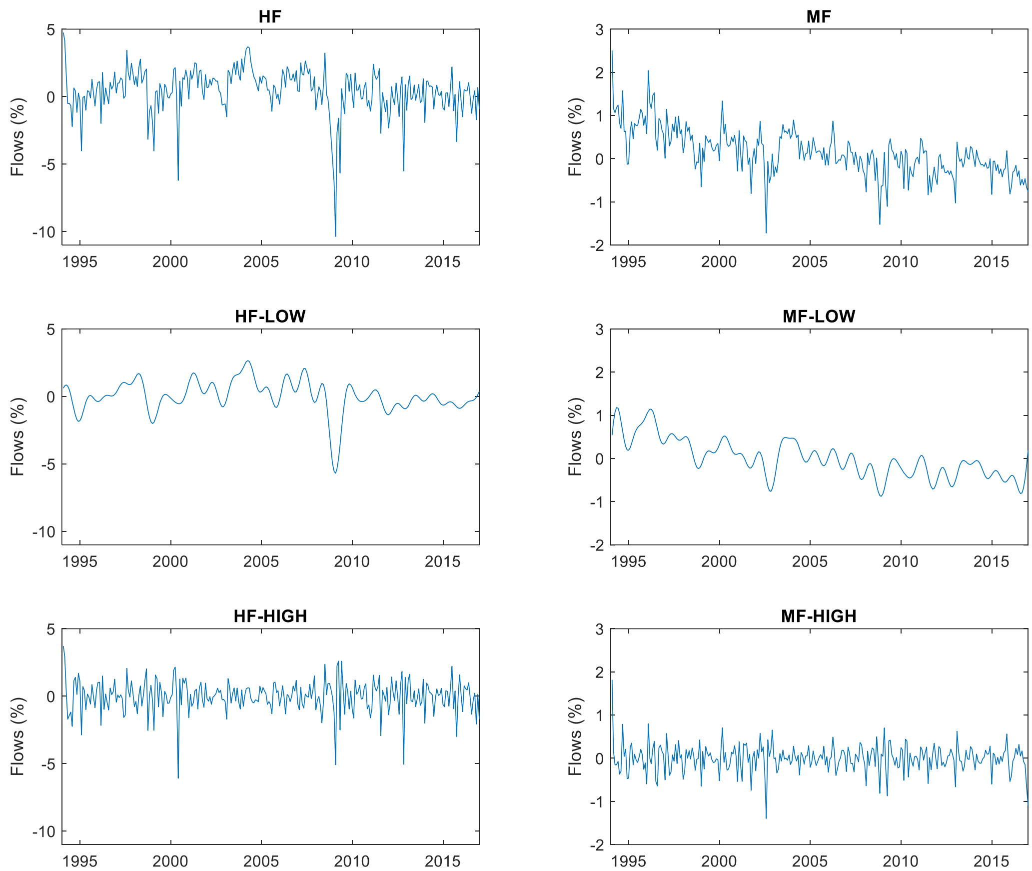


Figure 3. Relative Contribution of Frequencies to Total Variance. This figure shows the relative contribution of each frequency to the total variance of anomaly returns and fund flows. Specifically, we first calculate the cumulative power (squared amplitude) in a frequency band from 0 to a cutoff *c* as the sum of powers in the band. Then, we divide this number by the sum of powers over the full spectrum, and plot that ratio as a function of the cutoff *c*. Therefore, the figures show the cumulative contribution (in percentage points) of expanding frequency bands to the total variance of the variables. The dashed lines represent the equal-contribution benchmark. 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 active equity mutual funds and equity hedge funds, respectively. The sample period is 1994–2016.

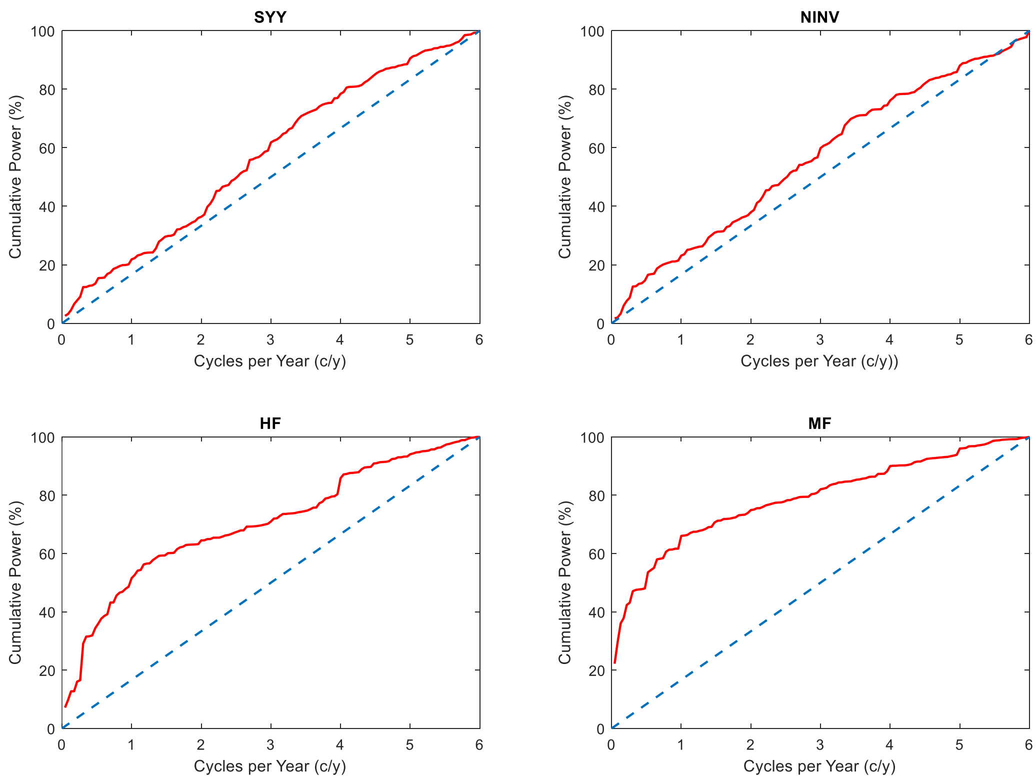


Figure 4. Attenuation Factor over Expanding Frequency Bands. The figure plots the attenuation factor corresponding to expanding frequency bands. The attenuation factor over a frequency band is defined as the ratio of the economic magnitude of the fund-flow effect over that frequency band to its magnitude over the high-frequency band (frequencies larger than one cycle per year). Specifically, for each frequency range from 0 to a cutoff *c*, we regress SYY (or NINV) on mutual fund flows, hedge fund flows, and control variables. Then, we estimate the economic magnitude of the fund-flow effect over the frequency band [0, *c*] as $\beta_c \times \sigma_X^c / \sigma_Y^c$, where σ_X^c and σ_Y^c denote, respectively, the standard deviations of flows and mispricing over the frequency band [0, *c*]. Finally, we divide that estimate by the estimate of the economic magnitude over the high-frequency band [1, 6]. The x-axis shows the natural log of frequency cutoff *c*. The vertical dashed line marks the frequency of one cycle per year, to which the results in Tables 2 and 3 correspond. The sample period is 1994–2016.

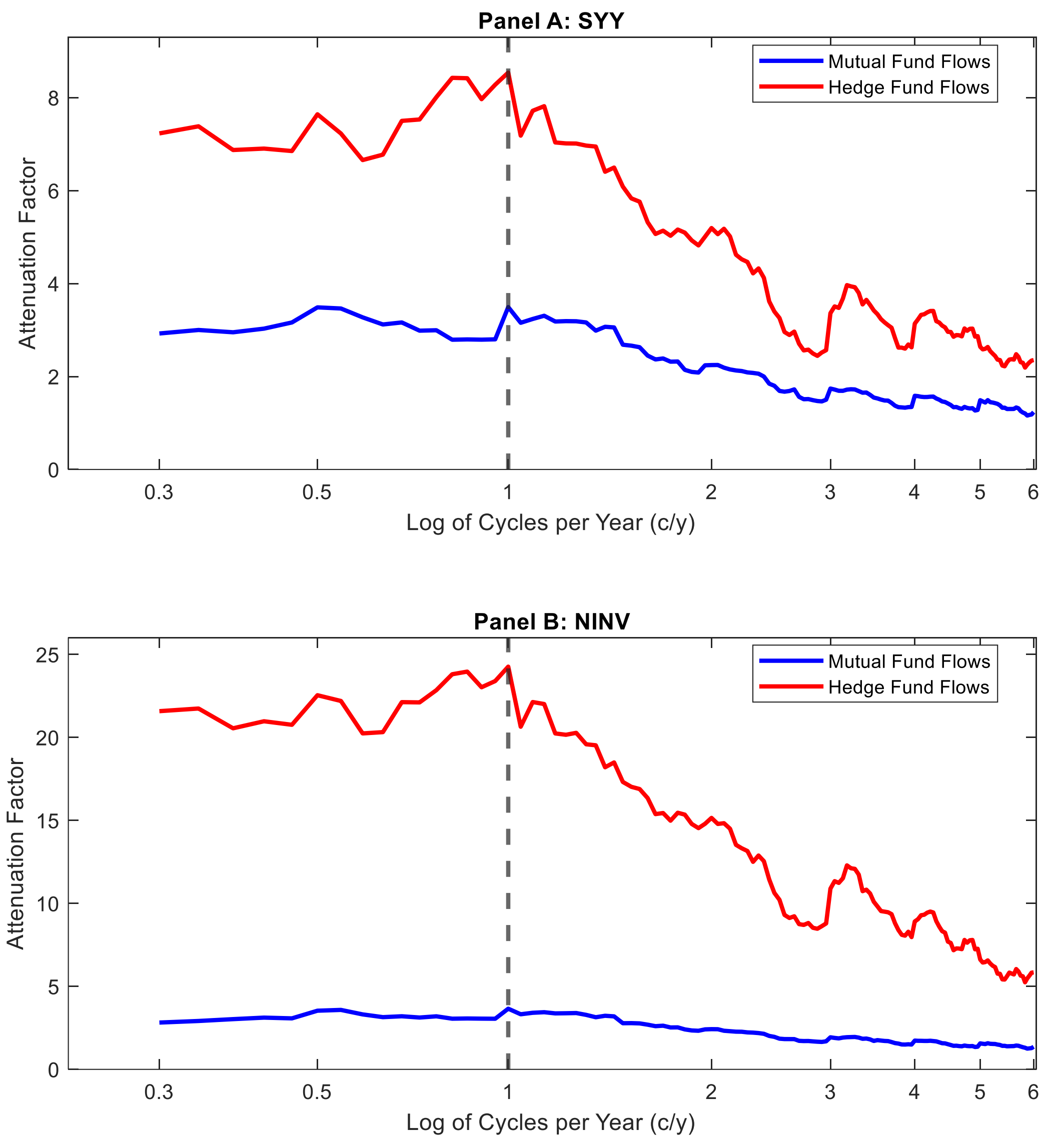


Table 1. Summary Statistics

Panel A shows descriptive statistics for main variables, and Panel B reports their 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 shows 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 flows of US-equity oriented active mutual funds and hedge funds, respectively. Passive is the monthly aggregate percentage flow of US-equity oriented passive mutual funds. 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 1994–2016.

Panel A: Descriptive Statistics

Variable	N	Mean	Std Dev	P10	Q1	Median	Q3	P90	t Value
SYY	276	0.019	0.048	-0.039	-0.004	0.018	0.043	0.072	6.52
SYY-LOW	276	0.000	0.022	-0.024	-0.013	-0.003	0.012	0.024	0.00
SYY-HIGH	276	0.000	0.042	-0.054	-0.021	0.002	0.024	0.048	0.00
NINV	276	0.016	0.060	-0.054	-0.010	0.021	0.045	0.075	4.36
NINV-LOW	276	0.000	0.029	-0.026	-0.014	-0.001	0.012	0.029	0.00
NINV-HIGH	276	0.000	0.052	-0.069	-0.025	0.004	0.030	0.055	0.00
MF (Active)	276	0.001	0.005	-0.005	-0.002	0.001	0.005	0.008	4.58
MF-LOW	276	0.000	0.004	-0.005	-0.003	-0.001	0.003	0.005	0.00
MF-HIGH	276	0.000	0.003	-0.004	-0.001	0.000	0.002	0.003	0.00
HF	276	0.004	0.017	-0.012	-0.002	0.006	0.014	0.020	4.11
HF-LOW	276	0.000	0.012	-0.011	-0.005	0.000	0.007	0.015	0.00
HF-HIGH	276	0.000	0.012	-0.013	-0.006	0.001	0.007	0.013	0.00
Passive	276	0.010	0.011	-0.002	0.003	0.008	0.016	0.023	14.97
Passive-LOW	276	0.000	0.007	-0.008	-0.005	-0.001	0.002	0.011	0.00
Passive-HIGH	276	0.000	0.008	-0.009	-0.005	0.000	0.004	0.009	0.00
MKTRF	276	0.006	0.044	-0.052	-0.020	0.012	0.035	0.061	2.40
Amihud	276	0.037	0.024	0.012	0.017	0.031	0.054	0.072	25.44
Turnover	276	0.155	0.072	0.069	0.086	0.150	0.204	0.244	35.67
HML	276	0.002	0.031	-0.030	-0.013	0.000	0.018	0.037	1.31
SMB	276	0.001	0.033	-0.037	-0.019	0.000	0.020	0.036	0.73

Panel B: Pairwise Correlations

	SYY	NINV	MF	Passive	HF	MKTRF	Amihud	Turnover	HML	SMB
SYY		0.950	-0.131	-0.066	0.083	-0.490	0.158	-0.120	0.304	-0.374
		[0.00]	[0.03]	[0.28]	[0.17]	[0.00]	[0.01]	[0.05]	[0.00]	[0.00]
NINV	0.929		-0.134	-0.074	0.079	-0.387	0.114	-0.109	0.241	-0.329
	[0.00]		[0.03]	[0.22]	[0.19]	[0.00]	[0.06]	[0.07]	[0.00]	[0.00]
MF	-0.145	-0.174		0.348	0.283	0.287	0.485	-0.633	0.009	0.116
	[0.02]	[0.00]		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.88]	[0.05]
Passive	-0.050	-0.084	0.367		-0.034	0.198	0.333	-0.348	-0.013	0.026
	[0.41]	[0.17]	[0.00]		[0.58]	[0.00]	[0.00]	[0.00]	[0.83]	[0.67]
HF	0.002	0.006	0.310	-0.021		0.040	-0.097	-0.214	0.146	0.044
	[0.97]	[0.92]	[0.00]	[0.72]		[0.51]	[0.11]	[0.00]	[0.02]	[0.46]
MKTRF	-0.431	-0.334	0.261	0.239	-0.040		-0.042	-0.102	-0.147	0.222
	[0.00]	[0.00]	[0.00]	[0.00]	[0.50]		[0.49]	[0.09]	[0.01]	[0.00]
Amihud	0.192	0.135	0.480	0.382	-0.036	-0.019		-0.648	-0.010	-0.081
	[0.00]	[0.02]	[0.00]	[0.00]	[0.55]	[0.75]		[0.00]	[0.86]	[0.18]
Turnover	-0.072	-0.014	-0.661	-0.443	-0.138	-0.066	-0.683		-0.072	0.015
	[0.23]	[0.81]	[0.00]	[0.00]	[0.02]	[0.27]	[0.00]		[0.23]	[0.81]
HML	0.119	0.034	0.061	0.027	0.119	-0.130	-0.013	-0.092		-0.296
	[0.05]	[0.58]	[0.32]	[0.66]	[0.05]	[0.03]	[0.83]	[0.13]		[0.00]
SMB	-0.387	-0.321	0.076	0.055	0.028	0.251	-0.087	0.059	-0.137	1.000
	[0.00]	[0.00]	[0.21]	[0.36]	[0.65]	[0.00]	[0.15]	[0.33]	[0.02]	

Panel C: Correlations - Decomposed Variables

	SYY-LOW	SYY-HIGH	NINV-LOW	NINV-HIGH	MF-LOW	MF-HIGH	Passive-LOW	Passive-HIGH	HF-LOW	HF-HIGH
SYY-LOW		0.000	0.968	0.000	0.057	0.000	0.114	0.000	0.192	0.000
		[1.00]	[0.00]	[1.00]	[0.35]	[1.00]	[0.06]	[1.00]	[0.00]	[1.00]
SYY-HIGH	0.004		0.000	0.945	0.000	-0.296	0.000	-0.157	0.000	0.031
	[0.95]		[1.00]	[0.00]	[1.00]	[0.00]	[1.00]	[0.01]	[1.00]	[0.61]
NINV-LOW	0.949	-0.007		0.000	-0.001	0.000	0.044	0.000	0.233	0.000
	[0.00]	[0.91]		[1.00]	[0.98]	[1.00]	[0.46]	[1.00]	[0.00]	[1.00]
NINV-HIGH	0.003	0.925	-0.009		0.000	-0.261	0.000	-0.137	0.000	-0.003
	[0.97]	[0.00]	[0.88]		[1.00]	[0.00]	[1.00]	[0.02]	[1.00]	[0.96]
MF-LOW	0.080	0.002	-0.028	-0.001		0.000	0.533	0.000	0.415	0.000
	[0.19]	[0.97]	[0.64]	[0.98]		[1.00]	[0.00]	[1.00]	[0.00]	[1.00]
MF-HIGH	0.035	-0.315	0.041	-0.264	-0.056		0.000	0.128	0.000	0.101
	[0.57]	[0.00]	[0.50]	[0.00]	[0.35]		[1.00]	[0.03]	[1.00]	[0.09]
Passive-LOW	0.241	-0.007	0.106	-0.018	0.456	0.012		0.000	-0.006	0.000
	[0.00]	[0.91]	[0.08]	[0.77]	[0.00]	[0.84]		[1.00]	[0.92]	[1.00]
Passive-HIGH	-0.004	-0.207	-0.014	-0.162	0.075	0.147	-0.022		0.000	-0.060
	[0.95]	[0.00]	[0.81]	[0.01]	[0.21]	[0.01]	[0.71]		[1.00]	[0.32]
HF-LOW	0.128	0.021	0.131	0.036	0.474	-0.040	0.094	-0.012		0.000
	[0.03]	[0.73]	[0.03]	[0.55]	[0.00]	[0.51]	[0.12]	[0.85]		[1.00]
HF-HIGH	0.004	-0.003	0.013	-0.023	-0.040	0.110	-0.030	-0.109	-0.139	
	[0.95]	[0.96]	[0.83]	[0.71]	[0.51]	[0.07]	[0.61]	[0.07]	[0.02]	

Panel D: Variance Decomposition

Variable	SYY		NINV		MF (Active)		HF		Passive	
Total Variance (×10000)	23.06	100.0%	35.62	100.0%	0.30	100.0%	2.87	100.0%	1.14	100.0%
Variance-LOW	5.04	21.9%	8.24	23.1%	0.20	66.0%	1.48	51.5%	0.52	45.9%
Variance-HIGH	18.02	78.1%	27.38	76.9%	0.10	34.0%	1.39	48.5%	0.62	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 active 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 with 13 lags. The sample period is 1994–2016.

Panel A: Total Flows

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		SYY-LOW		SYY-HIGH		NINV		NINV-LOW		NINV-HIGH	
MF	**-1.732**	**[-2.81]**	**-0.808**	**[-2.16]**	**-0.923**	**[-1.66]**	**-2.450**	**[-3.05]**	**-1.120**	**[-2.44]**	**-1.329**	**[-1.80]**
HF	**0.338**	**[2.61]**	**0.227**	**[2.36]**	0.111	[0.77]	**0.399**	**[2.45]**	**0.319**	**[2.39]**	0.080	[0.45]
MKTRF	-0.416	[-4.19]	-0.111	[-2.91]	-0.305	[-3.88]	-0.384	[-3.04]	-0.146	[-2.96]	-0.238	[-2.44]
Amihud	0.258	[1.80]	0.268	[1.64]	-0.010	[-0.08]	0.202	[0.87]	0.211	[0.94]	-0.009	[-0.06]
Turnover	-0.105	[-1.83]	-0.053	[-0.80]	-0.052	[-1.29]	-0.158	[-1.63]	-0.081	[-0.84]	-0.076	[-1.56]
HML	0.248	[1.37]	0.106	[1.54]	0.142	[1.09]	0.217	[0.93]	0.132	[1.53]	0.085	[0.49]
SMB	-0.305	[-4.86]	0.032	[0.63]	-0.338	[-6.25]	-0.362	[-4.70]	0.032	[0.51]	-0.394	[-5.43]
Intercept	0.029	[2.23]	-0.001	[-0.09]	0.011	[1.20]	0.037	[1.67]	0.006	[0.27]	0.016	[1.30]
N	276		276		276		276		276		276	
Adj R^2	37.3%		20.6%		25.7%		25.3%		17.6%		14.8%	

Panel B: Decomposed Flows

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		SYY-LOW		SYY-HIGH		NINV		NINV-LOW		NINV-HIGH	
MF-LOW	**-2.113**	**[-2.12]**	**-2.770**	**[-3.09]**	0.657	[1.11]	**-3.447**	**[-2.60]**	**-3.825**	**[-3.56]**	0.378	[0.52]
MF-HIGH	**-1.695**	**[-2.36]**	0.376	[1.18]	**-2.071**	**[-3.00]**	**-2.167**	**[-2.10]**	0.508	[1.23]	**-2.675**	**[-2.73]**
HF-LOW	**0.631**	**[3.08]**	**0.796**	**[3.56]**	-0.165	[-0.80]	**0.990**	**[3.13]**	**1.107**	**[3.71]**	-0.117	[-0.44]
HF-HIGH	0.165	[0.99]	-0.016	[-0.27]	0.180	[1.19]	0.068	[0.31]	-0.018	[-0.26]	0.085	[0.42]
MKTRF	-0.414	[-4.20]	-0.115	[-3.33]	-0.299	[-3.65]	-0.383	[-3.06]	-0.153	[-3.40]	-0.230	[-2.29]
Amihud	0.361	[2.54]	0.517	[2.99]	-0.156	[-1.14]	0.418	[2.03]	0.554	[2.61]	-0.137	[-0.80]
Turnover	-0.083	[-1.45]	-0.049	[-0.78]	-0.034	[-0.71]	-0.120	[-1.39]	-0.075	[-0.85]	-0.045	[-0.73]
HML	0.234	[1.31]	0.106	[1.88]	0.128	[0.92]	0.194	[0.84]	0.131	[1.88]	0.063	[0.34]
SMB	-0.305	[-5.01]	0.031	[0.73]	-0.336	[-6.34]	-0.362	[-4.90]	0.030	[0.57]	-0.392	[-5.49]
Intercept	0.021	[1.75]	-0.011	[-0.88]	0.013	[1.16]	0.021	[1.18]	-0.008	[-0.47]	0.014	[0.95]
N	276		276		276		276		276		276	
Adj R^2	37.3%		32.0%		27.0%		26.0%		31.0%		15.7%	

Table 3: Economic Magnitudes and Attenuation Factors

The table estimates the economic magnitudes of the effect of low- and high-frequency flows on returns at their respective 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*, and β_i is the coefficient estimate from regressing mispricing on flows, both at frequency *i*, as reported in Table 2. Then, the attenuation factor is defined as the ratio of the economic magnitude of the fund-flow effect at low frequency to its magnitude at high frequency. 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 1994–2016.

Panel A: SYY Anomaly

	Beta		STD of	Effect of One σ_X on		STD of	Economic Magnitude	
Flows	SYY-LOW	SYY-HIGH	Flows (σ_X)	SYY-LOW	SYY-HIGH	Returns (σ_Y)	(% of σ_Y)	Attenuation Factor
MF-LOW	-2.770		0.4%	-1.2%		2.2%	-54.6%	
MF-HIGH		-2.071	0.3%		-0.7%	4.2%	-15.5%	3.53
HF-LOW	0.796		1.2%	1.0%		2.2%	43.1%	
HF-HIGH		0.180	1.2%		0.2%	4.2%	5.0%	8.62
						Ratio (HF/MF)		2.44

Panel B: NINV Anomaly

	Beta		STD of	Effect of One σ_X on		STD of	Economic Magnitude	
Flows	NINV-LOW	NINV-HIGH	Flows (σ_X)	NINV-LOW	NINV-HIGH	Returns (σ_Y)	(% of σ_Y)	Attenuation Factor
MF-LOW	-3.825		0.4%	-1.7%		2.9%	-58.9%	
MF-HIGH		-2.675	0.3%		-0.8%	5.2%	-16.2%	3.63
HF-LOW	1.107		1.2%	1.3%		2.9%	46.9%	
HF-HIGH		0.085	1.2%		0.1%	5.2%	1.9%	24.41
						Ratio (HF/MF)		6.72

Table 4: Regressions of 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 in month *t* on 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 for the long-leg returns, and Panel B the results for short-leg returns. The main independent variables are the low- and high-frequency components of fund flows in month *t*, that is, MF-LOW, MF-HIGH, HF-LOW, and HF-HIGH. *t*-statistics are calculated based on Newey-West standard errors with 13 lags. The sample period is 1994–2016.

Panel A: Long-Leg Returns

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		SYY-LOW		SYY-HIGH		NINV		NINV-LOW		NINV-HIGH	
MF-LOW	**0.643**	**[1.72]**	**2.553**	**[4.13]**	-1.910	[-3.29]	0.344	[0.90]	**2.399**	**[4.26]**	-2.055	[-3.32]
MF-HIGH	**1.202**	**[4.77]**	-0.761	[-2.58]	**1.962**	**[5.44]**	**0.803**	**[3.14]**	-0.775	[-2.59]	**1.578**	**[4.06]**
HF-LOW	-0.049	[-0.45]	-0.102	[-0.48]	0.053	[0.24]	0.001	[0.01]	-0.126	[-0.59]	0.127	[0.55]
HF-HIGH	-0.066	[-1.23]	0.035	[0.59]	-0.101	[-1.35]	-0.008	[-0.12]	0.036	[0.63]	-0.044	[-0.51]
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
N	276		276		276		276		276		276	
Adj R^2	91.9%		33.4%		79.8%		92.2%		33.0%		79.8%	

Panel B: Short-Leg Returns

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomaly	SYY		SYY-LOW		SYY-HIGH		NINV		NINV-LOW		NINV-HIGH	
MF-LOW	**2.755**	**[2.57]**	**5.323**	**[4.69]**	-2.568	[-2.58]	**3.790**	**[2.81]**	**6.224**	**[4.53]**	-2.433	[-2.20]
MF-HIGH	**2.897**	**[3.97]**	-1.137	[-1.97]	**4.033**	**[5.05]**	**2.970**	**[3.06]**	-1.283	[-1.90]	**4.253**	**[4.35]**
HF-LOW	**-0.680**	**[-2.74]**	**-0.898**	**[-2.64]**	0.218	[0.61]	**-0.989**	**[-2.97]**	**-1.233**	**[-3.24]**	0.243	[0.63]
HF-HIGH	-0.231	[-1.56]	0.050	[0.51]	-0.281	[-1.77]	-0.076	[-0.39]	0.054	[0.50]	-0.129	[-0.67]
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
N	276		276		276		276		276		276	
Adj R^2	78.4%		29.2%		67.0%		70.8%		28.5%		59.5%	

Table 5: Aggregate Risk

The table examines whether the flow-return relation is affected by aggregate risk. The dependent variables are two composite anomalies, SYY and NINV, and their low- and high-frequency components. The main independent variables are the low- and high-frequency fund flows, and their interactions with D, which measures aggregate risk. We use four variables that measure risk; a NBER Recession Indicator, VIX, the Financial Uncertainty Index of Jurado, Ludvigson, and Ng (2015), and the Economic Uncertainty Index of Bekaert, Engstrom, and Xu (2019). For the NBER indicator, D is a dummy variable that equals one if the current month is in a recessionary period, zero otherwise. For other uncertainty variables, 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 with 13 lags. The sample period is 1994–2016.

Panel A: Total Flows

	NBER Recession						VIX						Financial Uncertainty Index (JLN)						Economic Uncertainty Index (BEX)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
D	-0.007	0.006	-0.012	-0.006	0.003	-0.009	-0.003	0.001	-0.004	-0.013	-0.008	-0.005	0.011	0.015	-0.005	0.007	0.010	-0.003	0.000	0.003	-0.003	-0.003	-0.002	-0.001
	[-0.81]	[0.94]	[-2.01]	[-0.48]	[0.35]	[-1.25]	[-0.40]	[0.11]	[-0.78]	[-1.14]	[-0.86]	[-0.69]	[1.60]	[2.46]	[-0.87]	[0.78]	[1.21]	[-0.48]	[0.03]	[0.44]	[-0.73]	[-0.23]	[-0.17]	[-0.15]
MF	-1.634	-0.689	-0.945	-2.434	-0.867	-1.567	-1.560	-0.693	-0.867	-2.582	-1.152	-1.430	-0.964	-0.142	-0.822	-1.663	-0.528	-1.135	-1.653	-0.493	-1.160	-2.307	-0.766	-1.541
	[-2.38]	[-1.64]	[-1.52]	[-2.80]	[-1.69]	[-1.92]	[-2.34]	[-1.17]	[-1.31]	[-2.77]	[-1.40]	[-1.80]	[-1.62]	[-0.25]	[-1.26]	[-2.09]	[-0.70]	[-1.46]	[-2.24]	[-0.75]	[-1.27]	[-2.23]	[-0.89]	[-1.42]
MF × D	0.682	0.555	0.127	2.488	0.825	1.663	-0.220	0.155	-0.375	0.147	0.315	-0.168	-0.760	-0.083	-0.677	-0.832	0.054	-0.887	-0.436	-0.305	-0.131	-0.529	-0.398	-0.132
	[0.41]	[0.45]	[0.07]	[0.97]	[0.54]	[0.79]	[-0.18]	[0.17]	[-0.28]	[0.08]	[0.25]	[-0.09]	[-0.69]	[-0.09]	[-0.46]	[-0.54]	[0.04]	[-0.48]	[-0.29]	[-0.30]	[-0.08]	[-0.25]	[-0.30]	[-0.06]
HF	0.238	0.104	0.133	0.268	0.087	0.181	0.095	-0.047	0.142	0.097	-0.108	0.205	0.061	-0.102	0.163	0.022	-0.148	0.170	0.350	-0.073	0.423	0.314	-0.168	0.481
	[1.36]	[0.83]	[0.81]	[1.20]	[0.54]	[0.87]	[0.29]	[-0.32]	[0.50]	[0.25]	[-0.56]	[0.61]	[0.26]	[-0.71]	[0.76]	[0.08]	[-0.79]	[0.66]	[1.38]	[-0.67]	[1.64]	[0.98]	[-1.31]	[1.40]
HF × D	0.273	**0.384**	-0.111	0.337	**0.708**	-0.371	0.357	**0.399**	-0.042	0.452	**0.630**	-0.179	0.413	**0.493**	-0.080	**0.576**	**0.719**	-0.143	0.123	**0.501**	-0.378	0.287	**0.799**	-0.512
	[1.06]	**[2.51]**	[-0.49]	[1.18]	**[3.58]**	[-1.48]	[0.95]	**[2.42]**	[-0.13]	[0.94]	**[2.62]**	[-0.42]	[1.53]	**[3.29]**	[-0.31]	**[1.73]**	**[3.29]**	[-0.46]	[0.42]	**[3.02]**	[-1.18]	[0.70]	**[3.62]**	[-1.17]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	254	254	254	254	254	254
Adj R^2	37.0%	22.1%	25.4%	25.2%	20.7%	14.5%	36.8%	20.9%	25.0%	24.9%	18.7%	14.0%	37.3%	27.1%	25.2%	24.9%	21.2%	14.1%	38.1%	23.7%	25.4%	24.8%	20.5%	13.4%

Panel B: Decomposed Flows

	NBER Recession						VIX						Financial Uncertainty Index (JLN)						Economic Uncertainty Index (BEX)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
D	-0.029	-0.019	-0.011	-0.042	-0.029	-0.013	-0.004	-0.003	0.000	-0.015	-0.014	-0.001	0.012	0.013	-0.001	0.008	0.007	0.001	-0.001	-0.002	0.001	-0.007	-0.010	0.003
	[-2.96]	[-4.81]	[-1.09]	[-3.23]	[-5.95]	[-1.05]	[-0.50]	[-0.50]	[-0.10]	[-1.34]	[-1.48]	[-0.23]	[2.32]	[2.23]	[-0.29]	[0.89]	[0.80]	[0.23]	[-0.19]	[-0.30]	[0.18]	[-0.55]	[-0.87]	[0.46]
MF-LOW	-1.769	-2.348	0.580	-2.731	-2.989	0.258	-2.192	-2.415	0.224	-3.887	-3.725	-0.161	-0.824	-1.162	0.338	-1.926	-2.325	0.399	-1.867	-2.193	0.327	-3.121	-3.030	-0.090
	[-1.70]	[-2.59]	[0.94]	[-2.15]	[-2.94]	[0.33]	[-1.97]	[-2.13]	[0.35]	[-2.24]	[-2.58]	[-0.17]	[-1.04]	[-1.13]	[0.50]	[-1.45]	[-1.75]	[0.52]	[-1.78]	[-1.75]	[0.45]	[-1.87]	[-1.86]	[-0.11]
MF-HIGH	-2.048	0.174	-2.222	-2.959	0.323	-3.283	-1.205	0.115	-1.321	-2.083	0.082	-2.165	-0.891	0.279	-1.170	-1.629	0.383	-2.012	-1.010	0.838	-1.848	-1.250	1.071	-2.321
	[-2.71]	[0.57]	[-2.84]	[-2.92]	[0.83]	[-3.10]	[-1.25]	[0.22]	[-1.47]	[-1.84]	[0.13]	[-2.16]	[-0.92]	[0.76]	[-1.23]	[-1.43]	[0.81]	[-1.81]	[-0.72]	[1.91]	[-1.35]	[-0.71]	[2.25]	[-1.35]
MF-LOW × D	**-10.587**	**-11.625**	1.037	**-16.899**	**-16.145**	-0.754	0.414	-0.469	0.884	0.429	-0.546	0.974	-0.555	-1.444	0.889	-1.581	-1.687	0.106	-0.645	-1.328	0.683	-1.524	-2.183	0.659
	[-3.37]	**[-10.17]**	[0.31]	**[-3.74]**	**[-12.30]**	[-0.16]	[0.19]	[-0.27]	[0.71]	[0.14]	[-0.24]	[0.57]	[-0.32]	[-0.76]	[0.68]	[-0.56]	[-0.60]	[0.07]	[-0.29]	[-0.63]	[0.47]	[-0.48]	[-0.78]	[0.36]
MF-HIGH × D	**3.244**	1.076	2.168	**5.718**	1.161	**4.558**	-1.032	0.506	-1.538	-0.459	0.778	-1.237	-1.372	0.428	-1.800	-0.920	0.495	-1.415	-1.504	-0.578	-0.927	-1.529	-0.593	-0.936
	[1.88]	[1.18]	[1.09]	**[2.20]**	[1.02]	**[2.05]**	[-0.59]	[0.60]	[-0.77]	[-0.20]	[0.73]	[-0.47]	[-0.77]	[0.67]	[-0.90]	[-0.37]	[0.59]	[-0.53]	[-0.58]	[-0.79]	[-0.35]	[-0.42]	[-0.65]	[-0.26]
HF-LOW	0.479	0.621	-0.142	0.646	0.684	-0.037	0.093	0.151	-0.058	0.267	0.188	0.079	-0.143	0.073	-0.216	0.030	0.142	-0.112	0.154	0.227	-0.074	0.285	0.154	0.131
	[1.62]	[1.87]	[-0.65]	[1.51]	[1.64]	[-0.13]	[0.32]	[0.55]	[-0.22]	[0.66]	[0.57]	[0.22]	[-0.45]	[0.23]	[-1.05]	[0.07]	[0.37]	[-0.42]	[0.54]	[0.76]	[-0.30]	[0.72]	[0.44]	[0.43]
HF-HIGH	0.157	-0.002	0.160	0.161	-0.008	0.170	0.292	0.130	0.162	0.375	0.145	0.230	0.201	-0.016	0.216	0.144	-0.036	0.180	0.595	-0.005	0.601	0.592	-0.021	0.614
	[0.77]	[-0.03]	[0.86]	[0.65]	[-0.10]	[0.74]	[0.67]	[0.80]	[0.41]	[0.71]	[0.75]	[0.50]	[0.69]	[-0.22]	[0.82]	[0.42]	[-0.45]	[0.57]	[1.74]	[-0.05]	[1.91]	[1.28]	[-0.19]	[1.40]
HF-LOW × D	**1.126**	**1.358**	-0.232	**2.055**	**2.252**	-0.196	**0.800**	**0.985**	-0.185	**1.191**	**1.475**	-0.284	**1.087**	**1.033**	0.053	**1.448**	**1.466**	-0.018	**0.704**	**0.881**	-0.177	**1.105**	**1.470**	-0.365
	[2.66]	**[4.11]**	[-0.64]	**[3.54]**	**[5.53]**	[-0.39]	**[2.01]**	**[3.10]**	[-0.60]	**[2.18]**	**[4.18]**	[-0.66]	**[2.65]**	**[2.96]**	[0.20]	**[2.60]**	**[3.53]**	[-0.05]	**[1.71]**	**[2.75]**	[-0.64]	**[1.76]**	**[3.65]**	[-0.86]
HF-HIGH × D	0.376	0.060	0.316	0.056	0.029	0.026	-0.313	-0.289	-0.025	-0.649	-0.364	-0.285	-0.156	-0.024	-0.132	-0.225	-0.010	-0.215	-0.567	-0.033	-0.534	-0.737	-0.020	-0.717
	[0.81]	[0.67]	[0.70]	[0.11]	[0.27]	[0.06]	[-0.54]	[-1.28]	[-0.05]	[-0.89]	[-1.32]	[-0.42]	[-0.42]	[-0.19]	[-0.40]	[-0.46]	[-0.06]	[-0.49]	[-1.12]	[-0.19]	[-1.06]	[-1.04]	[-0.10]	[-1.04]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	254	254	254	254	254	254
Adj R^2	37.9%	39.0%	26.5%	27.8%	40.7%	15.3%	36.8%	34.3%	25.9%	26.1%	36.6%	14.3%	37.5%	36.2%	26.1%	25.6%	34.1%	14.3%	38.0%	36.6%	26.4%	25.6%	36.8%	13.4%

Table 6: Leverage

The table examines whether the flow-return relation is affected by determinants of fund leverage, namely, the levels of funding cost and risk aversion. The dependent variables are two composite anomalies, SYY and NINV, and their low- and high-frequency components. The main independent variables are the low- and high-frequency fund flows, and their interactions with D, which measures the levels of funding cost and risk aversion in month *t*. We use TED Spread as a funding cost measure and estimate the risk aversion following Bekaert, Engstrom, and Xu (2019). Specifically, monthly TED spreads and risk aversion are ranked into quintiles over the sample period. Then, D is created based on the quintile score, and 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 with 13 lags. The sample period is 1994–2016.

Panel A: Total Flows

	TED Spread						Risk Aversion (BEX)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
D	0.001	0.006	-0.006	0.002	0.007	-0.005	-0.007	-0.001	-0.006	-0.018	-0.012	-0.006
	[0.08]	[0.91]	[-1.16]	[0.17]	[0.70]	[-0.86]	[-1.08]	[-0.17]	[-1.06]	[-1.86]	[-1.17]	[-0.84]
MF	-1.240	-0.897	-0.343	-2.211	-1.525	-0.686	-2.115	-0.955	-1.160	-3.057	-1.422	-1.635
	[-1.46]	[-2.24]	[-0.40]	[-2.04]	[-2.82]	[-0.62]	[-3.09]	[-1.36]	[-1.76]	[-3.07]	[-1.52]	[-2.18]
MF × D	-0.961	0.331	-1.292	-0.383	1.125	-1.508	0.477	0.384	0.093	0.666	0.430	0.235
	[-0.79]	[0.50]	[-1.11]	[-0.22]	[1.21]	[-0.93]	[0.38]	[0.41]	[0.07]	[0.35]	[0.34]	[0.13]
HF	0.102	-0.115	0.218	0.109	-0.207	0.316	0.168	0.063	0.104	0.138	0.031	0.107
	[0.32]	[-0.88]	[0.81]	[0.31]	[-1.34]	[0.96]	[0.63]	[0.32]	[0.38]	[0.40]	[0.13]	[0.31]
HF × D	0.359	**0.567**	-0.208	0.454	**0.858**	-0.404	0.390	0.293	0.097	0.539	**0.486**	0.053
	[0.98]	**[3.42]**	[-0.59]	[1.10]	**[4.12]**	[-0.98]	[1.21]	[1.38]	[0.33]	[1.16]	**[1.65]**	[0.12]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	254	254	254	254	254	254
Adj R^2	36.8%	24.7%	25.7%	24.7%	23.4%	14.8%	38.4%	22.4%	25.1%	25.6%	19.9%	13.1%

Panel B: Decomposed Flows

	TED Spread						Risk Aversion (BEX)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
D	0.001	0.013	-0.012	0.004	0.016	-0.013	-0.006	-0.007	0.001	-0.019	-0.020	0.000
	[0.11]	[1.76]	[-2.07]	[0.41]	[1.61]	[-1.86]	[-1.01]	[-1.03]	[0.13]	[-2.13]	[-2.09]	[0.05]
MF-LOW	-1.304	-2.813	1.509	-2.614	-4.098	1.484	-2.870	-3.161	0.291	-4.682	-4.533	-0.149
	[-0.89]	[-2.70]	[1.24]	[-1.59]	[-3.09]	[1.08]	[-2.44]	[-2.39]	[0.31]	[-3.04]	[-2.79]	[-0.14]
MF-HIGH	-0.552	0.496	-1.048	-0.953	0.796	-1.749	-1.532	0.406	-1.938	-2.071	0.469	-2.541
	[-0.45]	[0.94]	[-0.91]	[-0.62]	[1.17]	[-1.09]	[-1.38]	[0.77]	[-2.12]	[-1.54]	[0.79]	[-2.18]
MF-LOW × D	-1.306	0.096	-1.402	-1.180	0.909	-2.089	1.076	0.180	0.896	0.697	-0.120	0.817
	[-0.56]	[0.05]	[-0.82]	[-0.39]	[0.38]	[-1.01]	[0.43]	[0.10]	[0.57]	[0.22]	[-0.05]	[0.40]
MF-HIGH × D	-2.354	-0.100	-2.254	-2.476	-0.313	-2.163	-0.414	0.132	-0.546	-0.054	0.267	-0.321
	[-1.07]	[-0.12]	[-1.11]	[-0.83]	[-0.27]	[-0.74]	[-0.24]	[0.16]	[-0.30]	[-0.02]	[0.27]	[-0.12]
HF-LOW	0.022	0.436	-0.414	0.101	0.351	-0.250	0.034	0.352	-0.318	0.184	0.415	-0.231
	[0.04]	[1.15]	[-1.03]	[0.18]	[0.81]	[-0.51]	[0.11]	[1.00]	[-0.88]	[0.41]	[1.00]	[-0.51]
HF-HIGH	0.242	-0.129	0.371	0.303	-0.083	0.387	0.406	0.044	0.362	0.381	0.032	0.350
	[0.69]	[-1.16]	[1.15]	[0.70]	[-0.65]	[0.94]	[1.04]	[0.24]	[1.16]	[0.73]	[0.14]	[0.84]
HF-LOW × D	0.871	0.619	0.252	**1.282**	**1.184**	0.099	**0.922**	**0.775**	0.148	**1.393**	**1.255**	0.137
	[1.29]	[1.43]	[0.47]	**[1.62]**	**[2.34]**	[0.15]	**[2.07]**	**[2.15]**	[0.39]	**[2.27]**	**[3.08]**	[0.26]
HF-HIGH × D	-0.166	0.212	-0.378	-0.425	0.138	-0.562	-0.276	-0.148	-0.128	-0.451	-0.195	-0.256
	[-0.37]	[1.39]	[-0.88]	[-0.74]	[0.74]	[-1.02]	[-0.52]	[-0.58]	[-0.30]	[-0.61]	[-0.61]	[-0.40]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	254	254	254	254	254	254
Adj R^2	36.7%	36.4%	26.9%	25.5%	37.7%	15.2%	38.4%	37.4%	26.2%	26.8%	39.7%	13.0%

Table 7: Hedge-Fund Leverage

The table examines, in the cross-section of funds, whether the flow-return relation is affected by hedge funds' use of leverage. Each month, hedge funds are divided into two groups, HFUnLev and HFLev, according to their use of leverage. Then, fund flows are calculated separately for each group of hedge funds. The dependent variables are two composite anomalies, SYY and NINV, and their low- and high-frequency components. *t*-statistics are calculated based on Newey-West standard errors with 13 lags. The sample period is 1994–2016.

	(1)		(2)		(3)		(4)		(5)		(6)	
	SYY		SYY-LOW		SYY-HIGH		NINV		NINV-LOW		NINV-HIGH	
MF	-1.759		-0.852		-0.906		-2.506		-1.196		-1.310	
	[-2.85]		[-2.26]		[-1.61]		[-3.09]		[-2.56]		[-1.76]	
HFUnLev	0.182		**0.258**		-0.075		0.238		**0.340**		-0.102	
	[1.05]		**[3.17]**		[-0.39]		[1.09]		**[3.36]**		[-0.40]	
HFLev	0.204		0.027		0.177		0.243		0.074		0.168	
	[1.04]		[0.29]		[1.11]		[0.99]		[0.64]		[0.83]	
MF-Low		-2.114		-2.767		0.652		-3.475		-3.860		0.385
		[-2.21]		[-3.26]		[1.10]		[-2.70]		[-3.66]		[0.52]
MF-High		-1.709		0.397		-2.106		-2.164		0.536		-2.700
		[-2.35]		[1.22]		[-3.04]		[-2.09]		[1.29]		[-2.75]
HFUnLev-Low		**1.034**		**1.071**		-0.037		**1.345**		**1.328**		0.017
		[3.48]		**[3.34]**		[-0.17]		**[3.48]**		**[3.26]**		[0.06]
HFLev-Low		-0.366		-0.228		-0.138		-0.260		-0.115		-0.144
		[-1.06]		[-0.57]		[-0.58]		[-0.55]		[-0.23]		[-0.53]
HFUnLev-High		-0.148		-0.073		-0.075		-0.258		-0.090		-0.167
		[-0.69]		[-1.22]		[-0.33]		[-0.82]		[-1.26]		[-0.52]
HFLev-High		0.270		0.005		0.265		0.239		0.005		0.235
		[1.27]		[0.08]		[1.29]		[0.96]		[0.06]		[0.96]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	37.1%	38.1%	21.6%	36.9%	25.5%	26.7%	25.2%	26.9%	18.9%	36.2%	14.6%	15.3%

Table 8: Market Liquidity

This table reports the results of regressions of anomaly returns on fund flows and their interaction with liquidity variables. The dependent variables are two composite anomalies, SYY and NINV, and their low- and high-frequency components. The main independent variables are the low- and high-frequency fund flows, and their interaction with ILLIQ, which measures the market illiquidity in month *t*. We use four measures of illiquidity; Amihud illiquidity, the aggregate liquidity proxy of Pastor and Stambaugh (2003), the permanent variable factor of Sadka (2006), and the noise measure of Hu, Pan, and Wang (2013). If the original variable measures 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 1994–2016.

Panel A: Total Flows

	Amihud						Aggregate Liquidity (PS)						PV-Level (Sadka)						Noise (HPW)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
ILLIQ	0.001	-0.001	0.002	0.001	-0.003	0.004	0.000	0.000	0.000	-0.001	-0.002	0.001	-0.010	0.001	-0.012	-0.018	-0.005	-0.013	0.006	0.007	-0.002	0.005	0.005	0.001
	[0.11]	[-0.12]	[0.20]	[0.08]	[-0.23]	[0.27]	[0.06]	[0.11]	[0.00]	[-0.13]	[-0.36]	[0.05]	[-1.16]	[0.15]	[-1.80]	[-1.45]	[-0.40]	[-1.71]	[0.88]	[1.25]	[-0.36]	[0.62]	[0.61]	[0.12]
MF	-0.635	-0.634	-0.002	-1.700	-1.446	-0.254	-1.884	-0.662	-1.222	-2.717	-0.867	-1.849	-2.073	-0.864	-1.210	-3.436	-1.455	-1.981	-1.576	-0.349	-1.227	-2.457	-0.891	-1.566
	[-0.72]	[-1.29]	[0.00]	[-1.57]	[-2.22]	[-0.21]	[-2.68]	[-0.97]	[-1.65]	[-2.94]	[-1.05]	[-2.12]	[-2.77]	[-1.24]	[-1.61]	[-3.46]	[-1.65]	[-2.22]	[-2.04]	[-0.48]	[-1.47]	[-2.48]	[-0.97]	[-1.62]
MF × ILLIQ	-1.594	-0.088	-1.505	-0.977	0.955	-1.932	0.391	-0.143	0.534	0.575	-0.304	0.879	-0.124	0.475	-0.599	0.938	0.997	-0.059	0.063	-0.387	0.450	0.439	0.088	0.351
	[-1.28]	[-0.12]	[-1.22]	[-0.55]	[0.91]	[-1.10]	[0.47]	[-0.17]	[0.49]	[0.45]	[-0.29]	[0.60]	[-0.10]	[0.51]	[-0.41]	[0.56]	[0.88]	[-0.03]	[0.05]	[-0.47]	[0.34]	[0.26]	[0.09]	[0.20]
HF	-0.020	-0.012	-0.008	0.069	-0.065	0.134	0.199	0.031	0.169	0.268	0.000	0.268	0.249	-0.106	0.355	0.293	-0.157	0.450	0.048	-0.128	0.176	-0.011	-0.194	0.182
	[-0.07]	[-0.06]	[-0.03]	[0.18]	[-0.25]	[0.40]	[0.77]	[0.29]	[0.72]	[0.72]	[0.00]	[0.82]	[0.95]	[-0.75]	[1.40]	[0.94]	[-0.93]	[1.41]	[0.19]	[-0.72]	[0.84]	[-0.04]	[-0.80]	[0.75]
HF × ILLIQ	**0.534**	0.356	0.178	0.496	**0.576**	-0.080	0.233	**0.333**	-0.100	0.230	**0.558**	-0.327	0.258	**0.519**	-0.261	0.280	**0.728**	-0.448	0.428	**0.518**	-0.090	**0.613**	**0.763**	-0.150
	[1.80]	[1.49]	[0.72]	[1.15]	**[1.82]**	[-0.21]	[0.65]	**[2.25]**	[-0.30]	[0.46]	**[2.74]**	[-0.75]	[0.81]	**[2.50]**	[-0.80]	[0.67]	**[2.71]**	[-1.02]	[1.47]	**[2.69]**	[-0.36]	**[1.92]**	**[2.82]**	[-0.52]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276	228	228	228	228	228	228	276	276	276	276	276	276
Adj R^2	37.1%	20.6%	25.2%	24.7%	18.9%	14.3%	36.7%	20.8%	24.9%	24.6%	18.4%	14.1%	39.1%	22.1%	26.3%	26.0%	19.9%	14.0%	37.1%	23.0%	24.9%	25.0%	19.9%	13.9%

Panel B: Decomposed Flows

	Amihud						Aggregate Liquidity (PS)						PV-Level (Sadka)						Noise (HPW)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
ILLIQ	0.003	-0.004	0.007	0.003	-0.005	0.008	0.001	0.002	-0.001	0.000	0.001	-0.002	-0.008	0.001	-0.009	-0.015	-0.005	-0.010	0.006	0.003	0.003	0.005	-0.001	0.005
	[0.36]	[-0.49]	[0.72]	[0.27]	[-0.50]	[0.67]	[0.17]	[0.51]	[-0.18]	[-0.05]	[0.18]	[-0.18]	[-1.01]	[0.14]	[-1.48]	[-1.28]	[-0.42]	[-1.40]	[1.00]	[0.51]	[0.69]	[0.51]	[-0.10]	[0.92]
MF-LOW	-1.404	-2.551	1.147	-3.152	-4.118	0.966	-1.147	-2.341	1.194	-2.212	-3.295	1.082	-2.952	-2.061	-0.890	-5.137	-3.164	-1.974	-1.499	-1.411	-0.088	-2.669	-2.551	-0.118
	[-1.69]	[-3.25]	[1.48]	[-2.22]	[-3.45]	[0.98]	[-1.01]	[-2.29]	[1.29]	[-1.41]	[-2.66]	[0.97]	[-2.78]	[-1.95]	[-1.21]	[-3.05]	[-2.20]	[-2.00]	[-1.39]	[-1.11]	[-0.10]	[-1.82]	[-1.63]	[-0.12]
MF-HIGH	0.328	1.309	-0.981	0.301	1.467	-1.166	-2.785	0.398	-3.183	-3.551	0.734	-4.285	-0.023	1.153	-1.177	0.056	1.369	-1.313	-1.483	0.846	-2.329	-2.193	1.091	-3.284
	[0.19]	[2.11]	[-0.63]	[0.13]	[2.04]	[-0.56]	[-2.80]	[0.55]	[-3.09]	[-2.88]	[0.86]	[-3.69]	[-0.02]	[2.36]	[-0.80]	[0.03]	[2.48]	[-0.74]	[-1.00]	[1.65]	[-1.47]	[-1.29]	[1.68]	[-1.80]
MF-LOW × ILLIQ	-0.902	-0.253	-0.650	-0.094	0.847	-0.941	-1.558	-0.691	-0.867	-2.008	-0.851	-1.156	1.344	-0.723	2.067	2.520	-0.724	3.244	-0.246	-1.900	1.653	-0.425	-1.602	1.177
	[-0.56]	[-0.28]	[-0.60]	[-0.04]	[0.64]	[-0.53]	[-1.10]	[-0.63]	[-0.74]	[-0.96]	[-0.59]	[-0.71]	[0.61]	[-0.41]	[1.53]	[0.79]	[-0.29]	[1.72]	[-0.13]	[-1.18]	[1.17]	[-0.16]	[-0.74]	[0.68]
MF-HIGH × ILLIQ	-3.211	-1.492	-1.719	-4.013	-1.461	-2.551	1.760	0.132	1.628	2.092	-0.158	2.250	-3.333	-0.999	-2.333	-3.929	-1.017	-2.912	-0.291	-0.680	0.389	0.088	-0.864	0.952
	[-1.28]	[-1.59]	[-0.73]	[-1.19]	[-1.23]	[-0.78]	[1.13]	[0.10]	[0.81]	[0.98]	[-0.10]	[0.90]	[-1.35]	[-1.30]	[-0.82]	[-1.25]	[-1.03]	[-0.82]	[-0.12]	[-1.00]	[0.16]	[0.03]	[-0.98]	[0.31]
HF-LOW	0.335	0.319	0.016	0.570	0.349	0.220	0.053	0.551	-0.497	0.260	0.739	-0.479	0.277	0.098	0.179	0.498	0.148	0.350	0.033	0.181	-0.148	0.181	0.235	-0.054
	[1.02]	[1.03]	[0.05]	[1.05]	[0.86]	[0.52]	[0.14]	[2.05]	[-1.60]	[0.43]	[2.31]	[-0.99]	[0.86]	[0.36]	[0.81]	[1.12]	[0.42]	[1.14]	[0.09]	[0.50]	[-0.61]	[0.35]	[0.47]	[-0.17]
HF-HIGH	-0.241	-0.075	-0.167	-0.153	-0.089	-0.063	0.408	-0.160	0.568	0.471	-0.284	0.755	0.380	-0.015	0.395	0.447	-0.041	0.488	0.134	-0.025	0.159	0.052	-0.023	0.076
	[-0.72]	[-0.52]	[-0.59]	[-0.34]	[-0.54]	[-0.17]	[1.23]	[-1.14]	[2.25]	[1.00]	[-1.44]	[2.30]	[1.16]	[-0.13]	[1.22]	[1.09]	[-0.33]	[1.20]	[0.45]	[-0.22]	[0.62]	[0.16]	[-0.18]	[0.25]
HF-LOW × ILLIQ	0.464	**0.728**	-0.264	0.652	**1.156**	-0.504	**0.966**	**0.393**	0.573	1.231	**0.591**	0.640	0.423	**0.989**	-0.566	0.599	**1.371**	-0.772	**0.792**	**0.861**	-0.069	**1.102**	**1.243**	-0.141
	[1.07]	**[2.16]**	[-0.66]	[0.92]	**[2.58]**	[-0.79]	**[1.71]**	**[1.90]**	[1.23]	[1.37]	**[2.01]**	[0.89]	[0.85]	**[3.03]**	[-1.52]	[0.84]	**[2.98]**	[-1.48]	**[1.95]**	**[2.48]**	[-0.21]	**[1.87]**	**[2.52]**	[-0.33]
HF-HIGH × ILLIQ	0.574	0.042	0.532	0.283	0.037	0.245	-0.426	0.271	-0.697	-0.718	0.508	-1.226	-0.177	-0.015	-0.163	-0.451	-0.004	-0.447	0.030	-0.031	0.062	-0.004	-0.055	0.051
	[1.39]	[0.18]	[1.55]	[0.43]	[0.14]	[0.48]	[-0.80]	[0.78]	[-1.96]	[-0.85]	[1.03]	[-2.55]	[-0.44]	[-0.10]	[-0.38]	[-0.80]	[-0.02]	[-0.79]	[0.09]	[-0.23]	[0.20]	[-0.01]	[-0.33]	[0.12]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276	228	228	228	228	228	228	276	276	276	276	276	276
Adj R^2	36.9%	33.1%	26.3%	25.3%	34.1%	14.7%	37.1%	31.8%	26.6%	25.6%	31.3%	15.6%	39.1%	34.3%	27.6%	26.8%	34.1%	14.5%	36.7%	33.2%	25.9%	25.1%	32.4%	14.3%

Table 9: Hedge-Fund Liquidity

The table examines, in the cross-section of funds, whether the flow-return relation is affected by restrictions on the redemption of hedge funds' shares. The share restrictions are the sum of the number of days comprising the lock-up period, the redemption notice period, and the payout period. We construct flows of hedge fund based on their share restriction property. Specifically, each month, hedge funds are divided into two groups, HFBelow and HFAbove, based on the median value of the share restrictions. Then, flows are calculated separately for each group of hedge funds. The dependent variable are the long-minus-short returns of two composite anomalies, SYY and NINV, and their respective low- and high-frequency component returns. *t*-statistics are calculated based on Newey-West standard errors with 13 lags. The sample period is 1994–2016.

	(1)		(2)		(3)		(4)		(5)		(6)	
Anomalies	SYY		SYY-LOW		SYY-HIGH		NINV		NINV-LOW		NINV-HIGH	
MF	-1.946		-1.034		-0.912		-2.709		-1.433		-1.276	
	[-2.92]		[-2.60]		[-1.56]		[-3.09]		[-2.99]		[-1.65]	
HFBelow	-0.008		-0.086		0.077		0.045		-0.060		0.105	
	[-0.05]		[-1.26]		[0.44]		[0.22]		[-0.65]		[0.47]	
HFAbove	**0.328**		**0.298**		0.029		**0.368**		**0.392**		-0.024	
	[2.63]		**[2.99]**		[0.27]		**[2.31]**		**[2.94]**		[-0.17]	
MF-Low		-2.248		-2.977		0.730		-3.724		-4.168		0.444
		[-2.16]		[-3.49]		[1.28]		[-2.78]		[-4.22]		[0.60]
MF-High		-1.895		0.349		-2.243		-2.269		0.480		-2.749
		[-2.59]		[1.39]		[-3.14]		[-2.18]		[1.48]		[-2.65]
HFBelow-Low		**-0.332**		**-0.481**		0.149		**-0.345**		**-0.464**		0.120
		[-2.15]		**[-3.13]**		[0.83]		**[-1.69]**		**[-2.13]**		[0.59]
HFAbove-Low		**0.949**		**1.286**		-0.337		**1.389**		**1.647**		-0.258
		[4.01]		**[4.90]**		[-1.52]		**[3.76]**		**[4.53]**		[-1.03]
HFBelow-High		0.009		-0.009		0.018		0.020		-0.008		0.028
		[0.04]		[-0.19]		[0.08]		[0.07]		[-0.14]		[0.10]
HFAbove-High		0.136		-0.040		0.176		0.030		-0.053		0.083
		[1.24]		[-0.91]		[1.67]		[0.19]		[-1.00]		[0.53]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	37.4%	38.3%	23.1%	45.3%	25.4%	27.0%	25.4%	27.5%	20.2%	44.1%	14.5%	15.3%

Table 10: Exogenous Shocks to Frictions

This table examines the relation between anomaly returns and fund flows during period of exogenous shocks to funding and market liquidity. The dependent variables are two composite anomalies, SYY and NINV, and their low- and high-frequency components. 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 the exogenous shock, zero otherwise. We consider two distinct periods of liquidity shocks; Decimalization and Financial Crisis. Decimalization is 08/2000–05/2001, and considered as the period of positive shock to market liquidity. Financial Crisis is 07/2007–12/2009, and considered as the period of negative shock to market and funding liquidity. 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 with 13 lags. The sample period is 1994–2016.

Panel A: Total Flows

	Financial Crisis						Decimalization					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
SHOCK	0.005	-0.002	0.007	0.007	-0.006	0.013	0.098	0.076	0.021	0.134	0.094	0.041
	[0.50]	[-0.14]	[1.04]	[0.37]	[-0.39]	[1.57]	[5.06]	[11.91]	[1.16]	[5.72]	[11.41]	[1.93]
MF	-1.781	-0.641	-1.141	-2.563	-0.786	-1.777	-1.301	-0.542	-0.760	-1.882	-0.814	-1.068
	[-2.67]	[-1.54]	[-1.78]	[-3.07]	[-1.58]	[-2.11]	[-2.48]	[-1.83]	[-1.33]	[-2.84]	[-1.99]	[-1.46]
MF × SHOCK	1.610	-0.721	2.331	2.651	-0.747	3.398	**-13.347**	**3.879**	**-17.226**	**-15.132**	**6.145**	**-21.277**
	[0.83]	[-0.68]	[1.61]	[0.85]	[-0.50]	[1.50]	**[-5.81]**	**[5.82]**	**[-7.45]**	**[-4.27]**	**[6.16]**	**[-6.37]**
HF	0.260	0.121	0.139	0.320	0.105	0.215	0.327	0.138	0.189	0.372	0.211	0.160
	[1.50]	[0.87]	[0.77]	[1.42]	[0.60]	[0.99]	[2.43]	[1.63]	[1.55]	[2.23]	[1.55]	[0.96]
HF × SHOCK	0.231	**0.312**	-0.081	0.232	**0.625**	-0.394	**-1.723**	**-1.937**	0.213	**-2.634**	**-2.706**	0.073
	[1.01]	**[1.87]**	[-0.36]	[0.83]	**[2.88]**	[-1.60]	**[-1.66]**	**[-7.62]**	[0.22]	**[-2.33]**	**[-8.24]**	[0.07]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	37.0%	20.9%	25.5%	25.0%	19.6%	14.9%	41.7%	41.1%	31.9%	30.0%	36.0%	20.3%

Panel B: Decomposed Flows

	Financial Crisis						Decimalization					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
SHOCK	-0.021	-0.035	0.013	-0.038	-0.051	0.014	0.080	0.062	0.018	0.136	0.076	0.060
	[-1.75]	[-5.68]	[1.32]	[-2.22]	[-6.24]	[1.02]	[3.12]	[8.27]	[0.77]	[3.87]	[8.84]	[1.81]
MF-LOW	-1.654	-2.298	0.645	-2.628	-2.900	0.273	-1.603	-2.007	0.405	-2.742	-2.963	0.220
	[-1.76]	[-2.61]	[1.00]	[-2.24]	[-2.96]	[0.34]	[-1.82]	[-2.89]	[0.67]	[-2.33]	[-3.24]	[0.29]
MF-HIGH	-2.283	0.209	-2.492	-3.100	0.356	-3.456	-1.305	0.250	-1.555	-1.734	0.336	-2.069
	[-3.03]	[0.66]	[-3.18]	[-3.07]	[0.91]	[-3.26]	[-1.79]	[0.81]	[-2.21]	[-1.67]	[0.80]	[-2.10]
MF-LOW × SHOCK	**-8.441**	**-12.583**	4.142	**-14.576**	**-17.642**	3.066	-22.446	**7.717**	-30.163	-41.896	**9.849**	-51.745
	[-3.35]	**[-12.39]**	[1.80]	**[-3.60]**	**[-12.12]**	[0.91]	[-1.33]	**[2.55]**	[-1.96]	[-1.77]	**[3.23]**	[-2.28]
MF-HIGH × SHOCK	4.382	0.456	**3.926**	5.555	0.567	4.988	**-23.460**	3.235	**-26.695**	**-29.873**	3.734	**-33.607**
	[2.24]	[0.92]	**[2.19]**	[1.52]	[0.94]	[1.46]	**[-6.38]**	[5.00]	**[-6.70]**	**[-5.31]**	[4.40]	**[-5.62]**
HF-LOW	0.466	0.690	-0.224	0.680	0.769	-0.089	0.554	0.597	-0.043	0.891	0.891	0.000
	[1.68]	[2.03]	[-0.88]	[1.60]	[1.83]	[-0.30]	[2.52]	[2.97]	[-0.27]	[2.66]	[2.89]	[0.00]
HF-HIGH	0.201	-0.013	0.213	0.239	-0.024	0.263	0.192	-0.047	0.239	0.083	-0.066	0.149
	[0.97]	[-0.18]	[1.15]	[0.97]	[-0.28]	[1.16]	[1.17]	[-1.02]	[1.61]	[0.40]	[-1.09]	[0.74]
HF-LOW × SHOCK	**0.986**	**1.166**	-0.181	**1.797**	**2.023**	-0.225	**-2.573**	**-1.934**	-0.639	**-5.029**	**-2.853**	-2.176
	[2.59]	**[3.98]**	[-0.51]	**[3.23]**	**[5.46]**	[-0.45]	**[-2.97]**	**[-7.04]**	[-0.71]	**[-4.17]**	**[-6.90]**	[-1.93]
HF-HIGH × SHOCK	0.153	-0.020	0.173	-0.487	-0.057	-0.430	2.644	-1.623	**4.267**	3.411	-1.638	**5.050**
	[0.35]	[-0.17]	[0.43]	[-0.74]	[-0.35]	[-0.64]	[1.96]	[-8.08]	**[2.86]**	[1.98]	[-6.01]	**[2.66]**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	38.2%	42.1%	27.0%	28.1%	44.7%	15.7%	42.2%	46.6%	33.3%	31.4%	43.6%	21.7%

Table 11: Flows to Passive Funds

The table studies fund flows of passive mutual funds. Passive funds are identified by names, following Appel, Gormley, and Keim (2016). Panel A examines the flow-return relation using two composite anomalies, SYY and NINV, and their low- and high-frequency components, as dependent variables. Panel B uses market returns as dependent variables. MKT is value-weighted market returns, while S&P500 is returns to S&P500 index. *t*-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2016.

Panel A: Anomalies

	(1)		(2)		(3)		(4)		(5)		(6)	
Variables	SYY		SYY-LOW		SYY-HIGH		NINV		NINV-LOW		NINV-HIGH	
Passive-LOW	-0.042	[-0.12]	0.268	[0.53]	-0.310	[-1.16]	-0.154	[-0.26]	0.214	[0.31]	-0.368	[-1.24]
Passive-HIGH	-0.022	[-0.08]	0.154	[1.74]	-0.176	[-0.63]	-0.079	[-0.25]	0.211	[1.75]	-0.290	[-0.96]
Active-LOW	**-2.086**	**[-2.02]**	**-2.945**	**[-3.37]**	0.860	[1.47]	**-3.346**	**[-2.37]**	**-3.960**	**[-3.60]**	0.614	[0.83]
Active-HIGH	**-1.692**	**[-2.38]**	0.357	[1.11]	**-2.050**	**[-3.05]**	**-2.158**	**[-2.10]**	0.478	[1.14]	**-2.636**	**[-2.73]**
HF-LOW	**0.625**	**[2.95]**	**0.836**	**[3.86]**	-0.211	[-1.03]	**0.967**	**[2.89]**	**1.138**	**[3.63]**	-0.171	[-0.64]
HF-HIGH	0.164	[0.98]	-0.011	[-0.18]	0.174	[1.15]	0.065	[0.30]	-0.010	[-0.14]	0.075	[0.38]
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
N	276		276		276		276		276		276	
Adj R^2	36.8%		32.3%		26.8%		25.4%		31.0%		15.4%	

Panel B: Benchmark Returns

	(1)		(2)		(3)		(4)		(5)		(6)	
Variables	MKT		MKT-LOW		MKT-HIGH		S&P500		S&P-LOW		S&P-HIGH	
Passive-LOW	-0.348	[-0.55]	-0.376	[-0.66]	0.028	[0.12]	-0.344	[-0.54]	-0.300	[-0.52]	-0.044	[-0.20]
Passive-HIGH	**1.135**	**[3.61]**	0.009	[0.13]	**1.125**	**[3.74]**	**1.147**	**[3.71]**	0.017	[0.24]	**1.130**	**[3.85]**
Active-LOW	**2.877**	**[2.71]**	**2.932**	**[3.47]**	-0.055	[-0.11]	**2.815**	**[2.68]**	**2.749**	**[3.19]**	0.066	[0.13]
Active-HIGH	**3.241**	**[4.45]**	-0.065	[-0.27]	**3.306**	**[4.21]**	**3.373**	**[4.68]**	-0.036	[-0.15]	**3.409**	**[4.41]**
HF-LOW	-0.352	[-1.61]	-0.360	[-1.43]	0.007	[0.04]	-0.302	[-1.41]	-0.310	[-1.23]	0.008	[0.04]
HF-HIGH	-0.139	[-0.58]	0.014	[0.24]	-0.153	[-0.69]	-0.165	[-0.70]	0.015	[0.28]	-0.180	[-0.83]
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
N	276		276		276		276		276		276	
Adj R^2	18.6%		21.4%		16.5%		15.3%		21.0%		13.2%	

Table 12: Mutual Fund Skill and Flow-Return Relation

This table examines mutual fund skill and the flow-return relation. We use four variables to measure mutual fund managers' skill; Return Gap, (1-R^2), Alpha, and Active Share. Each month *t*, based on the mutual fund skill measures at *t*-1, mutual funds are divided into two groups; MF-UnSkilled and MF-Skilled. A mutual fund is considered as skilled if the fund belongs to the top decile of each skill measure. Then, the fund flows is calculated separately for each group of mutual funds. The dependent variable are the long-minus-short returns of two composite anomalies, SYY and NINV, and their respective low- and high-frequency component returns. *t*-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2016.

Panel A: Total Flows

Skill Measure	Return Gap						(1-R^2)						Alpha						Active Share					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Anomaly	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
MF-UnSkilled	**-2.428**	**-0.920**	**-1.508**	**-3.826**	**-1.657**	**-2.169**	**-1.768**	-0.700	-1.068	**-2.875**	**-1.252**	**-1.623**	**-1.712**	**-0.720**	**-0.992**	**-2.094**	**-0.977**	**-1.117**	**-2.606**	**-1.360**	**-1.246**	**-3.853**	**-1.809**	**-2.044**
	[-3.24]	**[-1.83]**	**[-2.31]**	**[-3.67]**	**[-2.61]**	**[-2.40]**	**[-2.17]**	[-1.58]	[-1.44]	**[-2.64]**	**[-2.31]**	**[-1.66]**	**[-2.81]**	**[-1.89]**	**[-1.94]**	**[-2.49]**	**[-1.84]**	**[-1.64]**	**[-2.97]**	**[-2.42]**	**[-1.76]**	**[-3.28]**	**[-2.63]**	**[-2.15]**
MF-Skilled	**0.376**	0.141	0.234	**0.784**	0.364	0.420	-0.099	-0.096	-0.003	0.164	0.054	0.110	-0.138	-0.007	-0.131	-0.355	-0.049	-0.307	0.322	0.286	0.036	0.547	0.256	0.291
	[1.71]	[0.78]	[0.96]	**[2.61]**	[1.45]	[1.52]	[-0.36]	[-0.48]	[-0.01]	[0.44]	[0.21]	[0.32]	[-0.42]	[-0.03]	[-0.42]	[-0.85]	[-0.18]	[-0.80]	[1.14]	[1.41]	[0.14]	[1.46]	[0.98]	[0.92]
HF	0.338	0.216	0.121	0.402	0.314	0.088	0.360	0.235	0.124	0.411	0.323	0.088	0.360	0.225	0.135	0.423	0.319	0.104	0.301	0.198	0.103	0.343	0.294	0.049
	[2.60]	[2.28]	[0.88]	[2.49]	[2.46]	[0.50]	[2.69]	[2.43]	[0.82]	[2.48]	[2.37]	[0.48]	[2.72]	[2.32]	[0.93]	[2.56]	[2.40]	[0.58]	[2.20]	[2.23]	[0.74]	[2.08]	[2.33]	[0.28]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	38.0%	20.3%	26.2%	27.0%	18.7%	15.4%	37.4%	20.4%	25.6%	25.4%	17.5%	14.7%	37.4%	20.0%	25.9%	25.3%	17.0%	15.0%	38.8%	22.8%	26.0%	27.6%	19.9%	15.4%

Panel B: Decomposed Flows

Skill Measure	Return Gap						(1-R^2)						Alpha						Active Share					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Anomaly	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
MF-Unskilled-Low	**-1.778**	**-2.504**	0.726	**-4.000**	**-4.435**	0.435	**-1.958**	**-2.117**	0.159	**-3.530**	**-3.342**	-0.188	**-2.233**	**-2.137**	-0.096	**-3.204**	**-2.986**	-0.218	**-2.863**	**-3.020**	0.156	**-4.326**	**-4.046**	-0.281
	[-1.61]	**[-2.37]**	[0.96]	**[-2.65]**	**[-3.21]**	[0.47]	**[-2.16]**	**[-2.96]**	[0.21]	**[-3.08]**	**[-3.92]**	[-0.21]	**[-3.13]**	**[-3.31]**	[-0.24]	**[-3.11]**	**[-3.36]**	[-0.44]	**[-2.96]**	**[-2.98]**	[0.19]	**[-3.32]**	**[-3.25]**	[-0.29]
MF-Skilled-Low	-0.109	0.075	-0.184	0.402	0.572	-0.170	-0.355	-0.658	0.302	-0.153	-0.546	0.393	-0.071	-0.453	0.382	-0.391	-0.663	0.272	**0.563**	0.333	0.230	0.531	0.163	0.368
	[-0.40]	[0.24]	[-0.71]	[1.08]	[1.41]	[-0.56]	[-1.11]	[-1.71]	[0.95]	[-0.34]	[-1.02]	[1.05]	[-0.17]	[-1.12]	[1.46]	[-0.70]	[-1.41]	[0.79]	**[2.04]**	[0.97]	[0.80]	[1.27]	[0.35]	[1.15]
MF-Unskilled-High	**-3.029**	0.111	**-3.140**	**-4.015**	0.120	**-4.135**	-1.888	0.580	**-2.467**	-2.655	0.734	**-3.389**	**-1.807**	-0.459	-1.347	-2.168	-0.550	-1.617	**-2.559**	0.124	**-2.683**	**-3.706**	0.197	**-3.903**
	[-3.22]	[0.33]	**[-3.49]**	**[-3.00]**	[0.29]	**[-3.27]**	[-1.28]	[1.43]	**[-1.67]**	[-1.29]	[1.48]	**[-1.68]**	**[-1.68]**	[-1.38]	[-1.33]	[-1.44]	[-1.39]	[-1.14]	**[-2.11]**	[0.43]	**[-2.26]**	**[-2.22]**	[0.55]	**[-2.39]**
MF-Skilled-High	**0.659**	0.186	0.473	**1.000**	**0.244**	**0.756**	0.002	-0.084	0.086	0.154	-0.101	0.255	-0.092	**0.395**	-0.486	-0.175	**0.495**	-0.670	0.103	0.101	0.002	0.465	0.113	0.352
	[1.90]	[1.63]	[1.49]	**[2.53]**	**[1.67]**	**[2.18]**	[0.00]	[-0.51]	[0.14]	[0.19]	[-0.49]	[0.32]	[-0.22]	**[3.62]**	[-1.18]	[-0.34]	**[3.48]**	[-1.36]	[0.23]	[1.03]	[0.01]	[0.79]	[0.95]	[0.62]
HF-Low	0.580	0.728	-0.148	0.953	1.059	-0.106	0.724	0.899	-0.174	1.067	1.206	-0.139	0.712	0.802	-0.090	1.072	1.123	-0.051	0.496	0.627	-0.132	0.843	0.939	-0.096
	[2.74]	[3.17]	[-0.71]	[3.13]	[3.59]	[-0.41]	[3.58]	[3.80]	[-0.78]	[3.33]	[3.71]	[-0.49]	[3.54]	[3.65]	[-0.47]	[3.59]	[3.79]	[-0.20]	[2.46]	[3.22]	[-0.73]	[2.85]	[3.38]	[-0.41]
HF-High	0.162	-0.008	0.170	0.068	-0.004	0.072	0.164	-0.018	0.182	0.065	-0.017	0.083	0.159	-0.049	0.208	0.067	-0.059	0.126	0.145	-0.007	0.153	0.025	-0.005	0.030
	[0.97]	[-0.13]	[1.13]	[0.31]	[-0.06]	[0.35]	[0.97]	[-0.32]	[1.17]	[0.30]	[-0.26]	[0.41]	[0.92]	[-0.91]	[1.31]	[0.30]	[-0.90]	[0.60]	[0.87]	[-0.13]	[0.99]	[0.11]	[-0.08]	[0.15]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	38.2%	29.5%	27.9%	27.6%	31.1%	16.8%	37.3%	33.0%	26.7%	25.9%	31.3%	15.5%	37.3%	32.4%	27.3%	25.9%	31.8%	15.8%	38.7%	32.6%	27.7%	27.9%	32.6%	16.7%

Figure A1. Variance Decomposition. This figure presents the variance decomposition of anomaly returns and fund flows in the frequency domain. Specifically, the x-axis is the natural log of the frequency of the time series variables, and the y-axis shows the power (squared amplitude) of each frequency scaled by the sum of powers over the full spectrum. Therefore, it shows the relative contribution (in percentage term) of each frequency to the total variance. 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 active equity mutual funds and equity hedge funds, respectively. The sample period is 1994–2016.

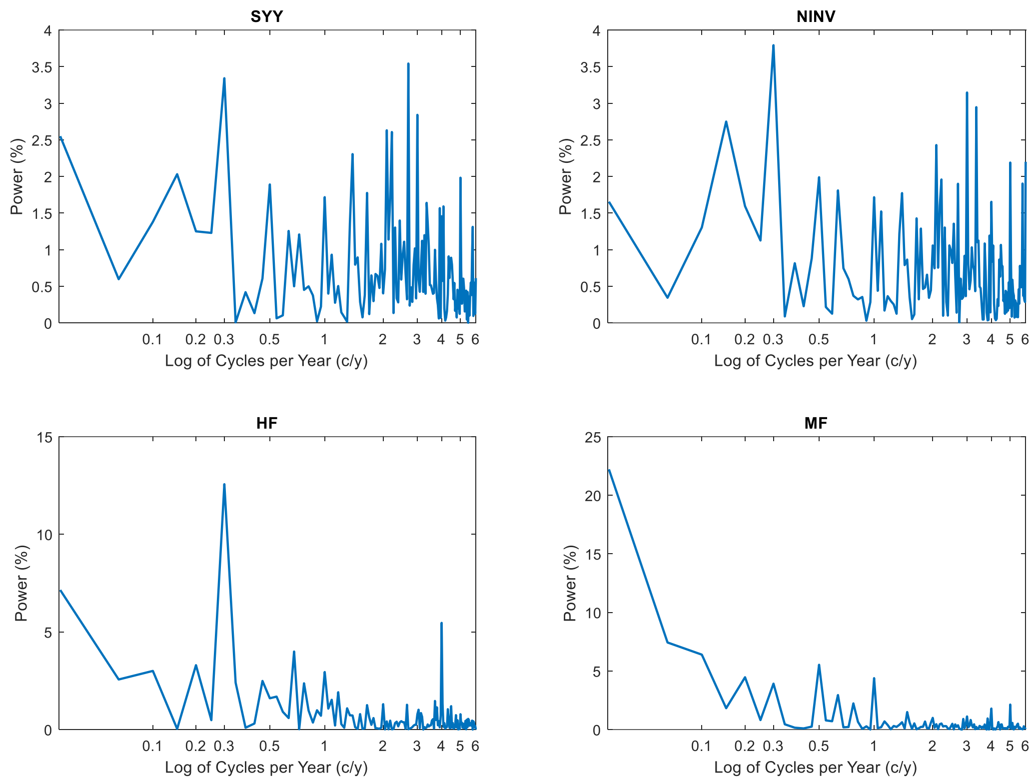


Table A1: Returns of Individual Anomalies and Fund Flows

The table shows the results of time-series regressions of the long-minus-short returns of various anomalies on fund flows. The dependent variables 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 1994–2016.

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	1.186	2.636	-1.054	-0.144	-0.083	-2.667	-2.787	-1.009	-0.598	-1.425	-3.226
	[1.63]	[2.94]	[-3.16]	[-0.31]	[-0.12]	[-3.01]	[-1.23]	[-1.95]	[-1.88]	[-2.90]	[-2.56]
MF-HIGH	1.382	2.698	-0.014	-0.339	-0.677	-1.587	-6.519	-1.639	-0.079	-0.512	-2.567
	[2.87]	[4.21]	[-0.03]	[-0.84]	[-0.90]	[-1.74]	[-3.26]	[-3.88]	[-0.23]	[-0.84]	[-2.44]
HF-LOW	-0.217	-0.636	0.313	0.214	0.149	0.890	0.675	-0.263	0.022	0.434	0.977
	[-1.36]	[-2.07]	[2.42]	[1.42]	[0.48]	[3.94]	[0.83]	[-1.44]	[0.16]	[2.10]	[2.81]
HF-HIGH	0.155	0.086	-0.233	-0.091	0.189	-0.195	0.660	0.417	-0.094	-0.262	-0.144
	[1.32]	[0.57]	[-1.73]	[-0.90]	[1.13]	[-0.80]	[1.81]	[3.55]	[-0.81]	[-1.43]	[-0.64]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	27.3%	17.1%	74.6%	5.9%	29.0%	12.6%	10.9%	19.2%	64.2%	40.7%	37.0%

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	1.464	2.008	-2.217	-0.394	-1.042	-2.815	-3.649	-1.238	-1.570	-1.748	-3.493
	[2.31]	[2.83]	[-3.28]	[-1.06]	[-2.11]	[-3.60]	[-2.06]	[-2.75]	[-3.40]	[-4.14]	[-3.15]
MF-HIGH	-0.416	-0.520	0.405	0.034	0.242	0.234	0.108	-0.216	0.235	0.448	0.765
	[-1.96]	[-1.62]	[1.71]	[0.33]	[0.91]	[0.85]	[0.20]	[-1.13]	[1.40]	[1.66]	[1.51]
HF-LOW	-0.334	-0.426	0.558	0.281	0.284	0.791	1.166	-0.289	0.279	0.256	1.192
	[-2.26]	[-1.86]	[2.58]	[2.06]	[1.35]	[4.39]	[2.13]	[-2.32]	[1.65]	[1.53]	[4.12]
HF-HIGH	0.006	0.003	-0.013	-0.004	-0.015	-0.009	0.023	0.024	-0.008	-0.021	-0.015
	[0.13]	[0.05]	[-0.25]	[-0.16]	[-0.32]	[-0.17]	[0.21]	[0.48]	[-0.22]	[-0.47]	[-0.18]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	17.1%	20.8%	28.3%	13.1%	14.3%	23.6%	23.9%	31.1%	27.3%	23.0%	22.6%

Panel C: High-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	-0.278	0.628	1.164	0.250	0.959	0.147	0.170	0.228	0.973	0.323	0.266
	[-0.57]	[1.07]	[2.09]	[0.83]	[1.73]	[0.34]	[0.13]	[0.53]	[2.30]	[0.74]	[0.28]
MF-HIGH	1.798	3.218	-0.419	-0.373	-0.918	**-1.821**	**-6.303**	**-1.423**	-0.314	**-0.960**	**-3.332**
	[3.71]	[5.43]	[-0.81]	[-1.01]	[-1.29]	**[-2.09]**	**[-3.71]**	**[-3.06]**	[-0.87]	**[-1.64]**	**[-3.12]**
HF-LOW	0.117	-0.210	-0.245	-0.067	-0.135	0.099	-0.140	0.026	-0.256	0.177	-0.216
	[0.81]	[-0.86]	[-1.30]	[-0.91]	[-0.51]	[0.59]	[-0.36]	[0.18]	[-1.77]	[1.11]	[-0.70]
HF-HIGH	0.149	0.083	-0.220	-0.088	0.204	-0.186	**0.631**	**0.393**	-0.086	-0.241	-0.129
	[1.21]	[0.54]	[-1.48]	[-0.90]	[1.21]	[-0.81]	**[2.01]**	**[3.45]**	[-0.74]	[-1.24]	[-0.59]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	276	276	276	276	276
Adj R^2	20.2%	13.8%	63.3%	4.6%	23.4%	8.3%	7.6%	11.2%	55.4%	34.1%	28.3%