DISCUSSION PAPER SERIES

DP15235

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Joël Peress, Xi Dong and NAMHO KANG

FINANCIAL ECONOMICS

ISSN 0265-8003

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Discussion Paper DP15235
Published 31 August 2020
Submitted 31 August 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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Abstract

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JEL Classification: N/A

Keywords: pricing anomalies, Market Efficiency, return persistence and cyclicality/seasonality, Mutual funds, Hedge Funds, Slow-moving capital, transaction costs, Limits to Arbitrage, Spectral analysis

Joël Peress - joel.peress@insead.edu
INSEAD and CEPR

Xi Dong - xi.dong@baruch.cuny.edu
Baruch College, City University of New York

NAMHO KANG - nkang@bentley.edu
Bentley University

Fast and Slow Arbitrage:
Fund Flows and Mispricing in the Frequency Domain

Xi Dong

Namho Kang

Joel Peress*

August 2020

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*Dong: Department of Economics and Finance, Baruch College, City University of New York. Email: xi.dong@baruch.cuny.edu. Kang: Finance Department, Bentley University. Email: nkang@bentley.edu. Peress: INSEAD, Boulevard de Constance, 77300 Fontainebleau, France. Email: joel.peress@insead.edu. For helpful comments and suggestions, we thank Li An, Adrian Buss, Ian Dew-Becker, Vincent Bogousslavsky, Stefano Giglio, Sergei Glebkin, David Hirshleifer, Yicheng Kang, Min Kim (discussant), Dong Lou (discussant), Lin Peng, Avanidhar (Subra) Subrahmanyam, Andrea Tamoni, Yajun Wang, Wei Xiong, Hongjun Yan (discussant), Jing Zhao (discussant), and Marius Zoican (discussant) and seminar participants at Baruch College, Bentley University, Bristol University, the Chinese University of Hong Kong, City University of New York, Edinburgh Business School, INSEAD, London School of Economics, PanAgora Asset Management, Vienna University of Economics and Business, the 2019 SFS Cavalcade Conference, the 2019 Conference on Mutual Funds, Hedge Funds and Factor Investing, the 2019 China International Conference in Finance, Paris December 2019 Finance Meeting, and the AFA 2020 Annual Meeting.

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Fund Flows and Mispricing in the Frequency Domain

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Abstract

Using spectral analysis, we document that hedge fund and mutual fund flows explain much of the persistence and cyclicality of anomaly returns. Indeed, they correct and amplify mispricing *slowly*, 24 and 4 times more, respectively, over horizons longer than one year compared with shorter horizons. Passive fund flows, in contrast, have no effect on mispricing. Over long horizons, hedge fund flows are most influential among fund types on a per-dollar basis. Hedge fund managers, rather than investors, helm this "slow-moving" effect, and frictions explain their behavior. We propose a model highlighting the horizon-dependent effects of capital on market efficiency.

Keywords: pricing anomalies; market efficiency; return persistence and cyclicality/seasonality; mutual funds; hedge funds; slow-moving capital; transaction costs; limits to arbitrage; spectral analysis

1. Introduction

We use spectral analysis to study how anomaly returns and fund flows are related. Our analysis sheds light on two important aspects of market efficiency that are difficult to tackle in the traditional time domain. First, most anomaly returns, both in the United States and globally, are autocorrelated (e.g., there is factor momentum) and driven by components with different serial correlations.[1] Relatedly, individual stock returns display seasonalities or appear cyclical, which our findings suggest is also true of factor returns.[2] These patterns are puzzling as they are at odds with the weakest forms of market efficiency. Second, casual observation, as well as theory, suggests that investors specialize in specific investment horizons (e.g., pension funds over the long term vs. quant funds over the short term) (Crouzet, Dew-Becker, and Nathanson 2020). This raises the possibility that the relationship between capital flows and anomaly returns might vary across horizons.

Separately, a large body of evidence indicates that capital flows to hedge and mutual funds affect mispricing. In particular, Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) show that hedge (respectively, mutual) fund flows are positively (respectively, negatively) related to anomaly returns, suggesting that they correct (respectively, exacerbate) mispricing.[3] Evidence also indicates that fund flows contain autocorrelated and cyclical components.[4] These observations naturally lead to two (related) conjectures: first, that the dynamic properties of market efficiency, as reflected in the serial correlation and cyclicality of anomaly returns, are connected to those of flows to financial institutions (hedge and mutual funds), and, second, that the role of flows in market efficiency, as reflected in the sensitivity of anomaly returns to flows, varies across horizons. In this paper, we investigate these conjectures.

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[1] For evidence on the serial correlation of factor returns, see, for example, McLean and Pontiff (2016), Avramov, Cheng, Schreiber, and Shemer (2017), Ehsani and Linnainmaa (2019), Arnott, Clements, Kalesnik, and Linnainmaa (2019), Gupta and Kelly (2019), and Alti and Titman (2019). See also the evidence reported in Section 5.

[2] For evidence on the seasonality or cyclicality of individual stock or anomaly returns, see, for example, Kamstra et al. (2003), Heston and Sadka (2008), Hartzmark and Solomon (2013), Lou, Yan, and Zhang (2013), Novy-Marx (2014), Dew-Becker and Giglio (2016), Gao, Han, Li, and Zhou (2018), Cieslak et al. (2019), Linnainmaa and Zhang (2019), Etula, Rinne, Suominen, and Vaittinen (2020), and Pitkäjärvi, Suominen, and Vaittinen (2020). Keloharju, Linnainmaa, and Nyberg (2016, 2020) document seasonal momentum and reversal patterns in anomaly returns, which, together, lead to cycles. Our study does not distinguish between seasonality and cyclicality, and, for simplicity, we refer to cyclicality throughout. Bogousslavsky (2016) shows that serial correlation and seasonality are linked to one another. Furthermore, as spectral analysis establishes (see Section 4), more persistent time series contain components with longer cycles.

[3] To be concise, we use the words "mispricing," "anomalies," and "factors" interchangeably throughout the paper. In doing so, we follow the flow return literature, which interprets anomalies as mispricing rather than as compensation for risk. This literature provides evidence that funds' capital affects mispricing. In addition to Akbas et al. 2015), Kokkonen and Suominen (2015) find that hedge funds constitute "smart money" in that their flows correct the mispricing identified by anomaly signals (for trades-based evidence, see also Dong et al. 2018). In contrast to hedge funds, mutual funds amplify mispricing and thus behave as "dumb money" (see also Frazzini and Lamont 2008).

[4] For evidence on the serial correlation and/or cyclicality of fund flows, see Kamstra et al. (2017), among others, and the evidence reported in Section 5.

In a nutshell, we find that both hedge and mutual fund capital flows play a large part in the autocorrelation and cyclicality of anomaly returns, especially over long horizons (one year and longer), and thus contribute to factor persistence. That's because they, respectively, correct and amplify mispricing over all horizons, but their effect on returns is "slow," that is, up to 24 and 4 times stronger over horizons longer than one year than over shorter horizons. Furthermore, as these numbers suggest, the tilt toward low frequency is more pronounced for hedge funds than for mutual funds: over long horizons, a one-standard-deviation (1-SD) increase in hedge (respectively, mutual) fund flows is associated with a 1.3% (respectively, 1.7%) increase (respectively, decrease) in monthly anomaly return, implying that hedge fund flows can correct 80% of the mispricing induced by mutual fund flows; over short horizons, this figure drops to 12%. As a result, hedge funds deploy capital toward improving market efficiency seven times more slowly than do mutual funds toward reducing efficiency. The sharp contrasts between fund types can be retraced to fund managers: unlike mutual fund managers, hedge fund managers generate returns that are far more persistent than the flows they receive, a behavior we dub "slowing down" flows. Put differently, arbitrage capital does not move slowly (Duffie 2010) from hedge fund investors to hedge fund managers, but rather it is deployed by managers to slowly correct pricing anomalies. The reasons for such a behavior are, we document and rationalize in theory, related to frictions that limit arbitrage activity.

To come to these conclusions, we decompose fund flows and anomaly returns in the frequency domain using Fourier analysis and then study how flows and returns are related frequency by frequency. Fourier analysis enables one to decompose any (stationary) time series into a combination of uncorrelated random waves (or sinusoids). Each wave is characterized by a cycle length (aka 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).[5] We refer to periods of one year or more as "low frequency" and to periods of less than one year as "high frequency."

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 strategy is rebalanced (aka turnover) and also from the closely related notion of a holding horizon. 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 the returns of a strategy accrue and at which capital flows, that is, on their serial correlation and cycle length.[6] Our approach allows us to examine,

[5] The physical sciences and engineering widely use this approach, which is analogous to using a prism to separate white light into its component colors, where each color corresponds to a different frequency. The resultant 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).
[6] See Section 4.3 for a detailed discussion of the differences between these notions.

frequency by frequency, how flows relate to returns, in terms of explanatory power, direction, and magnitude. Furthermore, it captures aspects of these series, namely, the serial correlation and length of the cycles composing these series, not easily represented by 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) (e.g., Dew-Becker and Giglio 2016), firm/fund annual and quarterly fiscal and reporting cycles, the one-year asset allocation cycle (Kamstra et al. 2003, 2017), and seasonal momentum and reversal (Heston and Sadka 2008, 2010; Keloharju, Linnainmaa, and Nyberg 2020).

In our analysis, we loosely interpret a group of funds as a *filter* that receives capital (flows) over a range of frequencies and selects the frequencies of its profit (returns) through active management. In other words, fund investors supply capital over various frequencies, and fund managers select which to pass on to the equity markets and which to attenuate. Our goal is to assess how closely the serial correlation and cyclicality of anomaly returns relate to those of fund flows, and the extent to which they derive from those of investor flows themselves, which are simply passed through, versus from the "filtering" behavior of fund managers.

Our proxy for mispricing is the returns on the long-minus-short strategy based on the 11 anomalies documented by Stambaugh, Yu, and Yuan (2012, 2015), or the "SYY anomalies." We also consider a subset of seven anomalies unrelated to real investment—the so-called "non-investment (NINV) anomalies"—because they are more closely related to mutual and hedge fund flows (Akbas et al. 2015). We measure flows as aggregate net flows to hedge and mutual funds.

We derive three sets of results. The first concerns the serial correlation of anomaly returns and comprises three findings. First, the serial correlation of anomaly returns is tightly related to that of fund flows. Intuitively, we show that the tightness of that relationship is determined by the explanatory power (R^2) of flows for anomaly returns in contemporaneous time-series regressions.[7] At low frequency (below one cycle per year), mutual and hedge fund flows, together, explain 20% to 24% of the variations in anomaly returns; they account for the majority of the total R^2 and far more than does any factor in prominent factor models. At high frequency, their explanatory power drops to 2.3% but nonetheless represents from one-tenth to one-fifth of the total R^2. Second, the contrast between low- and high-frequency regressions is striking. For mutual funds, the R^2 is five times larger at low frequency than it is at high frequency; for hedge funds, it is 40 to 325 times larger. This finding is a manifestation of the slow movement of capital toward mispricing, a phenomenon we refer to as the "slow-moving effect." Third, as these numbers suggest,

[7] Suppose a time series, X_t, follows a first-order autoregressive process with coefficient ρ, and a second time series, Y_t, is related to X_t through $Y_t = \alpha + \beta X_t + \varepsilon_t$ with ε_t i.i.d. Then the first-order autocorrelation coefficient of Y_t equals ρR^2, where R^2 is the R-squared of a least squares regression of Y_t on X_t. See Section 3 for more details.

differences across fund types are also very pronounced. Flows' explanatory power is tilted toward low frequency 8 to 60 times more for hedge funds than it is for mutual funds. Taken together, these three results imply that the serial correlation of anomaly returns is related to the serial correlation of fund flows, especially at low frequency and for hedge funds.

Our second set of results concerns the direction and magnitude of mispricing changes in response to flows. It also consists of three findings. First, in the aforementioned regressions of anomaly returns on flows, the coefficient estimates are positive for hedge funds and negative for mutual funds, regardless of the frequency considered. Thus, hedge and mutual funds behave as, respectively, smart and dumb monies over the entire spectrum. Second, consistent with our findings for R^2, the economic magnitudes of these effects are larger at low frequency, by factors of 24 and 4 for hedge and mutual funds, respectively. Hedge funds' tilt toward low frequency is considerably more pronounced: at low frequency, a 1-SD increase in hedge (respectively, mutual) fund flows is associated with a 1.3% (respectively, 1.7%) increase (respectively, decrease) in monthly anomaly return, implying that hedge fund flows could correct 80% of the mispricing induced by mutual fund flows; at high frequency, this figure drops to 12%. Stated differently, hedge funds deploy capital toward improving market efficiency 7 times more slowly than do mutual funds toward reducing efficiency.

Third, we investigate whether fund managers receive capital predominantly at low frequency (i.e., receive slow capital) or instead actively tilt flows toward low-frequency mispricing (i.e., slowing down capital). Or, put in the language of filtering, we investigate whether they merely pass through the signals they receive or rather actively filter them. We find that capital flows (the filter's input) are slow for mutual funds, in that low-frequency flows explain one-third more of the total variations in flows than do high-frequency flows, but not for hedge funds, whose variations are equally driven by low- and high-frequency flows. Turning to managers (i.e., the filter itself), we find that both types of funds behave, in aggregate, as a *low-pass filter*: regressions of anomaly returns on flows yield coefficient estimates that are larger in magnitude at low frequency than they are at high frequency. In other words, managers appear to attenuate the effect of high-frequency flows such that the effect of flows on mispricing is mainly observed at low frequency. This low-pass filtering is most pronounced for hedge fund managers, who correct mispricing at low frequency 4–13 times more than they do at high frequency. Thus, managers, rather than investors, are the main drivers of the slow-moving effect for hedge funds. For mutual funds, in contrast, managers' tendency to amplify mispricing at low frequency is comparable with their investors' tendency to supply capital at low frequency, so that the slow-moving effect is split equally between managers and investors.

In a sharp contrast, flows to passive funds have no effect on mispricing—consistent with their role as benchmarks—and are actually associated with a stronger effect at high frequency on the returns of passive benchmark portfolios (e.g., the S&P 500), possibly because of more limited liquidity provision at that frequency. To summarize our second set of results, hedge and mutual funds, respectively, correct and amplify mispricing in each frequency. Both types of fund managers actively slow down the flow of capital toward mispriced stocks, but hedge fund managers do it far more than mutual fund managers.

Overall, our first two sets of results suggest that capital allocated to correct and exacerbate mispricing is slow moving. Managers' low-pass filtering plays an important role in this process, particularly in hedge funds. As our spectral analysis demonstrates, hedge and mutual fund flows move in (non-offsetting) cycles, so cycles in anomaly returns can arise. In particular, anomaly return cycles may emerge from flows of smart and dumb monies because they alternately correct and exacerbate mispricing (Pontiff 2006; Akbas et al. 2015).

Our analysis so far does not explicitly deal with the endogeneity of flows with respect to mispricing. Rather, we rely on prior research lending support to a causal effect of flows on mispricing.[8] Endogeneity might arise because of an omitted variable affecting fund flows and anomaly returns simultaneously (e.g., investment opportunities) or through reverse causality. Neither seems likely given the contrasting patterns we report across fund types. Indeed, an omitted variable would need to have opposite influences on hedge and mutual fund flows and no influence on passive fund flows. Likewise, reverse causality requires mispricing to affect hedge and mutual fund flows in opposite directions, while not affecting passive fund flows. Notwithstanding, we conduct two formal endogeneity tests, namely, the omitted variable test of Oster (2019) and Granger causality tests, and find little support for endogeneity, especially for hedge funds. Finally, we propose a theory in which exogenous flows cause the low-pass filtering behavior of managers (and which makes several ancillary predictions that match well with the data).

Remarkably, although hedge funds manage only one-tenth of mutual funds' assets, the impact of their flows on mispricing at low frequency is comparable to that of mutual funds'. Thus, on a per-dollar basis, their flows are the most influential. Accordingly, our final set of results illuminate the determinants of hedge funds' behavior, especially managers'. Specifically, the results shed light on whether their behavior is related to frictions that limit arbitrage activity over specific frequency bands. After all, if there were no limits to arbitrage, mispricing corrections would be instantaneous rather than slow moving. We consider three types of frictions: fundamental risk, limited arbitrage capital, and implementation costs.[9]

[8] Akbas et al. (2015) document that hedge fund flows correct mispricing contemporaneously and, moreover, display no predictive power for future anomaly returns; that is, once mispricing is corrected, the correction is maintained. Exploiting detailed trading records, Dong et al. (2018) show that an increase in hedge funds' capital leads to an increase in the intensity with which they trade on anomalies; Kokkonen and Suominen (2015) show that their trades correct mispricing. Likewise, several studies document that flow-induced mutual funds' trades cause an exacerbation of mispricing (see, e.g., Wermers 1999; Coval and Stafford 2007; Frazzini and Lamont 2008; Greenwood and Thesmar 2011; Lou 2012; Shive and Yun 2013).

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

Exploiting variations in 14 proxies for these frictions—over time, in the cross section, and with two exogenous shocks to sharpen causal interpretations—we report evidence consistent with all three frictions hindering hedge fund activity in important ways. However, we find limited 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 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. 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 derive six 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 as a result of the flows they receive. The next two predictions state that the regression coefficient and R^2 are larger for the slower-decaying asset. These predictions reflect two factors: (1) arbitrageurs are exposed for longer to the slower asset and so they demand a larger risk premium, and (2) they trade that asset more slowly and so incur lower transaction costs. Both factors drive a wedge between the prices of the two assets, a wedge that results in the slower asset being more mispriced and hence more responsive to fluctuations in arbitrage capital. In theory, two mechanisms underlie managers' low-pass filtering. The first is that lower-frequency mispricing requires managers to commit capital for longer spells of time and so is more sensitive to fluctuations in arbitrage capital. The second is that managers invest more aggressively flows that they deem less likely to reverse, that is, lower-frequency flows. An alternative version of the latter mechanism is that managers convert high-frequency flows into low-frequency flows by holding on to those flows and investing them gradually in mispriced assets. All of these mechanisms make managers appear to "slow down flows."

Our final three predictions concern the three frictions we empirically examined. That is, 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 demonstrates that our diverse empirical findings can be rationalized within a unified framework featuring limited risk bearing and transaction costs.

Collectively, our findings indicate that capital flows to financial institutions contribute to explaining anomaly returns mainly at low frequency; that is, these two series are most closely related through their components with high serial correlation and long cycles. Furthermore, anomaly returns respond to hedge and mutual fund flows in opposite directions over the full spectrum, but both responses, especially hedge funds', are stronger at low frequencies. Thus, hedge and mutual fund capital moves slowly toward mispricing, a process in which hedge fund managers play a prominent role, thereby contributing to factor persistence. These findings can be viewed as a mixed blessing for market efficiency. On the one hand, that hedge fund managers prioritize low-frequency anomalies suggests that they improve the efficiency of financial markets over long horizons, over which, presumably, it matters most for most investors and policy makers.[10] On the other hand, that dumb money also moves slowly suggests that arbitrageurs need to maintain open positions for long spells of time.

The rest of our paper proceeds as follows. Section 2 reviews the related literature and discusses our contribution. Section 3 describes the data and variables. Section 4 presents the methodology employed for the spectral analysis, and then Section 5 applies it to fund flows and mispricing. Section 6 discusses how their frequency structures are related. Section 7 investigates the role of frictions. Section 8 presents our theoretical model. Section 9 concludes with a brief summary.

2. Related literature and contribution

The starting point of our analysis is the evidence in the literature that flows to asset managers affect market efficiency. In particular, Akbas et al. (2015, 2016) and Kokkonen and Suominen (2015) report that flows to hedge funds and mutual funds are associated with, respectively, correcting and worsening mispricing. We combine spectral analysis with the regression approach of Akbas et al. (2015) to understand how this flow-mispricing relationship varies across frequencies and why it does. This novel spectral perspective sheds light on four important aspects of market efficiency.

First, we contribute to the recent literature that documents that anomaly returns are serially correlated. Notably, Ehsani and Linnainmaa (2019) report pervasive "factor momentum," which can last for more than a year and is driven by factor return autocorrelations.[11] We describe how hedge and mutual

[10] High-frequency traders are credited with improving market efficiency over fractions of a second, leading critics to question their social value (e.g., Biais, Foucault, and Moinas 2015; Budish, Cramton, and Shim 2015).

[11] McLean and Pontiff (2016), Avramov et al. (2017), Arnott et al. (2019), Gupta and Kelly (2019), and Alti and Titman (2019), among others, report various degrees of persistence in anomaly returns. In addition, although they do not directly examine serial correlations, Daniel, Hirshleifer, and Sun (2020) show that two factors—capturing long- (one year or longer) and short-horizon (less than one year) mispricing—suffice to span a large set of anomalies.

fund flows contribute to explaining the serial correlation of anomaly returns. As a matter of fact, no factor from recent prominent models exhibits as much explanatory power as fund flows at low frequency (below one cycle per year), that is, for the persistent component of anomaly returns. At high frequency, that is, for the transient component of anomaly returns, in contrast, we find a limited role for flows, despite anomaly returns displaying large variations, suggesting that forces unrelated to flows explain those variations. Moreover, that hedge funds persistently correct mispricing has implications that go beyond cross-sectional anomalies; it illuminates more general forms of long-run predictability, where returns that identify mispricing corrections in one asset predict those in other assets (e.g., the cross-asset autocorrelation reported in Pitkäjärvi, Suominen, and Vaittinen 2020 and Dong, Li, Rapach, and Zhou 2020).[12] Theoretically, we present a mechanism that ties together arbitrage activity, the serial correlation of anomaly returns, and frictions.

With serial correlation and cycle length uniquely linked in the frequency domain, our findings also relate to the studies documenting cycles in stock or anomaly returns (reviewed in Section 5.1). Moreover, Pontiff (2006) and Akbas et al. (2015) argue that mispricing follows exacerbation and correction cycles. Our findings suggest that capital flow cycles are closely related to anomaly return cycles over long horizons (one year or longer), but not over short horizons (less than one year).

Second, our findings are also relevant to research on slow-moving capital (e.g., Duffie 2010) in three ways. First, we suggest that, in addition to smart money moving slowly to correct mispricing, which is the focus of existing work, dumb money too moves slowly to exacerbate mispricing. Second, we differentiate, in the slow movement of capital, the provision of capital (by investors) from the processing of capital (by managers). Our finding suggests that such a distinction is especially important for hedge funds, where managers do most of the "slowing down." Finally, and closely related to our first contribution on the dynamic properties of anomalies, prior studies take for granted that the slow movement of capital amplifies return predictability. But they fail to condition on whether capital moves gradually (i.e., persistently) or in delayed but sudden bursts as a result of, for example, capital lumpiness, limited attention, or infrequent portfolio rebalancing (Chen, Cole, and Lustig 2012). This distinction matters, because such bursts make returns less, not more, predictable. Our findings do not support this alternative view and instead suggest that capital to financial institutions changes mispricing not only slowly but also persistently.

Third, we document that the flow-anomaly return relationship varies across frequencies depending on the type of institution. In other words, how market efficiency is shaped by institutions is not only frequency specific but also institution specific. This finding is consistent with the theory of Crouzet, Dew-

[12] For example, Pitkäjärvi, Suominen, and Vaittinen (2020) document long-horizon (around one year) predictability between equity and bond market returns. Dong, Li, Rapach, and Zhou (2020) show that mispricing corrections identified by anomaly returns predict mispricing corrections manifested in aggregate market returns.

Becker, and Nathanson (2020) demonstrating that, in equilibrium, investors endogenously specialize in specific frequencies. Our study also answers the call from recent work (Koijen et al. 2019; Koijen and Yogo 2019) to understand the roles played by different types of institutions in asset pricing. Consistent with these authors' finding that hedge funds are the most influential institutions per dollar of assets under management, we report that hedge funds' flows are slowed down more than are mutual funds, and that, despite their smaller size, their effect on mispricing *at low frequency* is comparable to mutual funds'.

Fourth, we analyze the effects of frictions on mispricing. In contrast to theoretical work, the empirical literature has not yet reached a consensus on how important frictions actually are and on which ones matter.[13] We confirm the relevance of three categories of frictions (risk, limited access to capital, and implementation costs) by documenting, for hedge funds, a stronger (respectively, weaker) flow effect on persistent (respectively, transient) mispricing in periods of elevated frictions. This evidence indicates not only that these frictions matter but also that frictions affect the persistence of mispricing corrections.

Our final contribution is methodological. Our work is part of a growing stream that exploits new tools (e.g., statistical and machine learning) in finance. Much like other techniques, such as principal component analysis or partial least squares, spectral analysis is essentially a way of understanding the covariance structure of variables. Here, we apply spectral analysis to explain persistent and cyclical variations. With persistent cycles at the heart of so many economic variables, including capital flows and returns, spectral analysis is a promising approach. In fact, a nascent literature examines investments and asset returns through the lens of frequencies.[14]

3. Data and variable construction

We employ three main variables in our analyses: (1) anomaly returns, which proxy for aggregate cross-sectional mispricing; (2) aggregate mutual fund flows; and (3) aggregate hedge fund flows. In this section, we describe all three variables and the control variables used in our tests.

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[13] Consider, for example, our results for implementation costs. Their role in hampering arbitrage has been hotly debated in the literature. Contrary views reflect differences in samples and methodologies used across various studies. One strand of papers uses broad data sets to 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 those managers' costs are low and so arbitrage profits are sizable. 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. (2020). Among the second are Keim and Madhavan (1997), Engle, Ferstenberg, and Russell (2012), and Frazzini, Israel, and Moskowitz (2018). 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.

[14] From a theoretical perspective, models work out the implications of frequency profiles for asset pricing (Dew-Becker and Giglio 2016; Crouzet et al. 2020). On the empirical front, studies conduct frequency analyses of concepts, such as news (Calvet and Fisher 2007), consumption risk (Ortu, Tamoni, and Tebaldi 2013), risk prices (Dew-Becker and Giglio 2016), investment strategies' alphas and betas (Chaudhuri and Lo 2019; Bandi, Chaudhuri, Lo, and Tamoni forthcoming), market return (Schneider 2019), and state vectors (Neuhierl and Varneskov forthcoming).

3.1. Anomalies and mispricing

3.1.1. Mispricing proxies

Following Stambaugh et al. (2012, 2015), we use a set of 11 prominent cross-sectional return anomalies to measure aggregate cross-sectional 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 non-investment anomalies (the first seven of those listed), not anomalies related to real investments (the last four), drive the relation between fund flows and SYY anomaly returns. Accordingly, we also proxy for aggregate mispricing using NINV anomalies only.

Assuming that, at least, part of an anomaly's return predictability is due to mispricing, 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 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 anomalies individually, we follow Stambaugh et al. (2015) and construct an aggregate mispricing measure to identify overvalued and undervalued stocks at the end of each calendar month (we report the results for each individual anomaly in Table A2 of the appendix). Using the 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 explains a set of 73 anomalies well.

To construct this aggregate mispricing measure, we proceed in three steps. First, in each month, we assign all sample stocks to deciles that reflect degrees of mispricing, based on their next-month expected returns as predicted by each of the individual 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 based on the average of the decile ranks. If a stock is mispriced in the current month, then we expect the mispricing to be corrected the next month, on average. This means that undervalued (respectively, overvalued) stocks are expected to realize high (respectively, low) returns in the subsequent month. Scoring is performed in such a way that stocks with higher scores are expected to earn higher average returns over the next month. 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).

3.1.2. Mispricing correction versus exacerbation

That mispricing is corrected on average over time does not imply that it is corrected every month. At times, mispricing can be indeed exacerbated. By tracking the returns of the long-short strategy, as well as the long and short legs of that strategy, during the post-ranking calendar month, we can determine whether mispricing is corrected or exacerbated. Specifically, stocks in the short leg are overvalued at the end of month t. So a positive return on the short leg during month $t+1$ indicates that these overvalued stocks continue to appreciate and become even more overvalued. Analogously, stocks in the long leg are undervalued at the end of month t. Hence a negative return on the long leg in month $t+1$ indicates an exacerbation of undervaluation. In 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.[15]

3.2. Flows to mutual funds and hedge funds

Following the literature, we compute the monthly aggregate fund flows to actively managed mutual funds (MF) and to hedge funds (HF) as

$$\mathrm{MF}_t \text{ (or } \mathrm{HF}_t) = \frac{\sum_{i=1}^{N} \mathrm{TNA}_{i,t} - \mathrm{TNA}_{i,t-1}\left(1 + R_{i,t}\right)}{\sum_{i=1}^{N} \mathrm{TNA}_{i,t-1}}, \tag{10}$$

where $\mathrm{TNA}_{i,t}$ represents the total net assets of fund i in month t and $R_{i,t}$ 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 U.S. 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 U.S. 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).

To construct HF, we obtain monthly hedge fund returns and net asset value from the Lipper TASS database. As with our mutual fund sample, we focus on hedge funds that mostly trade in the U.S. equity

[15] The data reveal that, on average, monthly returns to the long leg, the short leg, and the long-short strategy are positive, negative, and positive, respectively. This means that, consistent with the mispricing-based interpretation in the anomaly literature, 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.

market. Hence, we only include funds denominated in U.S. dollars and exclude funds whose strategies are emerging market, fixed income, fund of funds, or managed futures. The fund data cover the period from January 1994 to December 2016.[16]

3.3. Control variables and other data

The stock sample includes all common stocks listed on the NYSE, AMEX, and Nasdaq. In our analyses, we follow Akbas et al. (2015) and control for aggregate liquidity and commonly used risk factors. These 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 value and size strategies.

4. Methodology

In this section, we describe our spectral decomposition methodology. Before doing so, we briefly discuss its usefulness in understanding the series of anomalies and fund flows and their relationship. Our frequency approach is motivated by the fact that anomaly returns and flows are made up of serially correlated, seasonal components, that is, of cycles of various frequencies. It is *a priori* unclear how important each component is and how the components of one series relate to those of the other. Indeed, investors differ considerably in their horizons, trading strategies, and performance, and their trades are likely to affect market (in)efficiency only at the frequency at which they operate (Crouzet et al. 2020). For instance, an algorithmic trader might specialize in high-frequency mispricing, while a value investor might focus on low-frequency mispricing. Similarly, capital is supplied to and redeemed from asset managers over various frequencies. On one hand, many mutual fund investors regularly contribute to retirement accounts that offer restricted redemption rights, thus producing low-frequency flows. On the other hand, several mutual fund features, such as open-endedness, liquidity, and mark-to-market, encourage investors to move money at high frequencies. Hedge and mutual funds also differ markedly in their skill sets and clientele. These considerations prompt us to examine, frequency by frequency, how hedge and mutual fund flows relate to anomaly returns.

4.1. Decomposition of mispricing and flows

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

[16] We do not detrend flows since our spectral analysis accounts for trends in the form of a low-frequency component. We confirm that our main findings obtain if we use detrended flows (see Table I1 of the Internet Appendix).

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

here, X_t^L is the slow-moving or persistent (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 or transient (high-frequency) component that captures shorter cycles. Both X_t^L and X_t^H are orthogonal, so $\text{Cov}(X_t^L, X_t^H) = 0$.

Such a decomposition can be performed using a Fourier transformation. Let $\omega_k = 2\pi k/T$ for $k = 0, ..., N$ represent a frequency, where $N = T - 1$ defines the total number of frequencies. Then the Fourier transform of X_t is given by

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

where the absolute value of $J_x(\omega_k)$ is the amplitude of X_t at frequency ω_k. Because ω_k is uniquely defined by k, we slightly abuse notation by referring to frequencies as k (rather than ω_k) when doing so does not cause confusion. The amplitude determines the highest (or lowest) point of a cycle relative to the series' mean. 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 decompose it into distinct time series, each corresponding to a subset of frequencies, or a "frequency band." To do so, we first create a filter F_B, which consists of a vector of size $N + 1$, for frequency band B. Here, $F_B(k)$ is set to one if k belongs to B; otherwise, $F_B(k) = 0$. In the empirical analysis, we focus on two frequency bands, $B=\{L,H\}$: L corresponds to low frequencies, so F_L is a low-pass filter, and H corresponds to high frequencies, so F_H is a high-pass filter. Next, we apply the filter F_B to the series X_t to obtain its component, X_t^B, as follows:

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

X_t^B represents the components of X_t that evolve within the frequency band B.

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

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

in this expression the overline denotes a complex conjugate. The factor $J_x(\omega_k)\overline{J_x(\omega_k)}$ in Equation (5) is known as the series' power (or squared amplitude) at frequency k. Because powers add to the variance of X_t, the ratio of frequency-k power to the sum of all powers measures the contribution of that frequency to the series' total variance. Likewise, $\mathrm{Var}(X_t^B)/\mathrm{Var}(X_t)$ measures the contribution of frequencies in the band B to the total variance of X_t.

Similarly, the covariance between two stationary time series, X_t and Y_t, over the frequency band B is described by their cospectrum:

$$\mathrm{CO}_B = \frac{1}{T}\sum_{t=1}^{T} X_t^B Y_t^B = \sum_{k=0}^{N} F_B(k) J_X(\omega_k)\overline{J_Y(\omega_k)}. \tag{7}$$

When $F_B(k) = 1$ for all frequencies k, CO_B in Equation (7) coincides with the covariance of X_t and Y_t. Essentially, the cospectrum measures the frequency-specific relation between two time series. For example, $\mathrm{CO}_B>0$ (respectively, <0) means that X_t^B and Y_t^B are positively (negatively) related over the frequency band B. Put differently, their cycles tend to move in sync, with their peaks and troughs aligned (respectively, move in opposite directions, with one's peaks aligned with the other's troughs). Importantly, two time series may be positively correlated at some frequencies and yet be negatively correlated at other frequencies. In particular, their cospectrum can be negative over some frequencies even if their covariance is positive.

4.2. A regression approach

An intuitive and straightforward way of evaluating the relation between two time series over a frequency band, $B = \{L,H\}$, is to regress components of one series on the other's:

$$Y_t^B = \alpha + \beta_B X_t^B + \varepsilon_t. \tag{8}$$

In this regression, the coefficient β_B is related to the cospectrum over that frequency band through $\beta_B = \mathrm{CO}_B/\mathrm{Var}(X_t^B)$. Thus, it measures the frequency-specific association between X_t and Y_t . Since each series equals a sum of components that are uncorrelated across frequencies, the regression coefficient for a frequency band reflects the relative contribution of that band to the total covariance between the series.

Moreover, the R^2 of the regression measures the contribution of the serial correlation of X_t^B to that of Y_t^B. As an illustration, suppose a (decomposed) time series, X_t^B, follows a first-order autoregressive (AR1) process with coefficient ρ_B, that is, $X_t^B = \rho_B X_{t-1}^B + \nu_t$, where ν_t is i.i.d. and uncorrelated with X_t^B. Consider a second series, Y_t^B, related to X_t^B through Equation (8), where ε_t is i.i.d. and uncorrelated with X_t^B and ν_t. Then the first-order autocorrelation coefficient of Y_t^B equals

$$\rho_B \frac{Cov(\beta_B X_t^B, Y_t^B)}{Var(Y_t^B)} \equiv \rho_B \times R_B^2, \tag{9}$$

where R_B^2 is the R^2 of Equation (8). Therefore, a higher R_B^2 implies that the serial correlation structure of Y_t^B is more tightly related to that of X_t^B. In a multivariate setting, the R^2 is replaced with a (semi)-partial R^2 (denoted by PR^2), which measures the proportion of the total variation of Y_t^B that is uniquely explained by an explanatory variable. For instance, in the regression of Y_t^B on X_{1t}^B and X_{2t}^B, the partial R^2 of X_{1t}^B is the R^2

of the regression of Y_t^B on the residuals of the regression of X_{1t}^B and X_{2t}^B. Thus, the partial R^2 reflects the extent to which the serial correlation of an explanatory variable is passed on to that of Y_t^B.

Finally, the regression R^2 and coefficient estimate, taken together, are informative about how the cycles composing the variables relate to one another. Each frequency k is associated with a unique cycle length and serial correlation, with more persistent series having longer cycles. A high R^2 in the regression of Y_t^k on X_t^k implies that the serial correlation and the cyclicality of Y_t^k are closely linked to those of X_t^k. Furthermore, the regression coefficient reveals the degree to which the peaks of the two series' cycles are aligned. For example, a high R_B^2 and positive β_B over the frequency band B indicate that the cycles of X_t^B and Y_t^B move up and down together over that frequency band, whereas a high R_B^2 and negative β_B that they move in opposite directions.

4.3. How the frequencies of flows and returns differ from the holding horizon and turnover

Although broadly related, our notion of frequency is distinct from those of a holding period and turnover. Let us start with the frequency of anomaly returns. It represents the frequency at which the returns of an anomaly strategy accrue (those returns typically differ from the returns of the individual stocks composing the strategy) and is closely linked to their serial correlation. To illustrate these differences, consider the following three types of traders. The first is a long-term investor, such as Warren Buffett, who does not adjust his holdings in a stock. Nonetheless, his marked-to-market profits from the stock vary over all frequencies, including the highest, along with fluctuations in the stock's price. The second type of trader is a convergence trader whose strategy requires frequently rotating her portfolio, holding stocks for a few months or less; such a strategy is akin to an anomaly strategy with transient signals that prompt frequent rebalancing. Despite the continuous rotations, the returns to the strategy, not to each stock she holds, might be persistent and evolve at, say, the business-cycle frequency, along with cross-asset return correlations. Finally, consider arbitrageurs who build positions in an underpriced asset by buying shares weekly over a quarter, thereby gradually pushing up the asset's price. The stock's return will likely display low-frequency fluctuations with cycles (e.g., quarterly) longer than those of trading (weekly). Note that if arbitrageurs switched between buying and selling the stock every week, then the stock's return would instead exhibit high-frequency (weekly) movements.

The distinction between these notions is confirmed by the data: we find that anomaly strategies that yield profits over different holding horizons (See Table A1, Panel A, and the discussion in footnote 20) or that require different turnovers (see Table I7 and the discussion in footnote 28) load on *both* low- and high-frequency components of anomaly returns, indicating that the holding horizon and turnover are distinct from the return frequency.

The frequency of capital flows need not relate to turnover either. For example, investors can contribute capital to a fund, either gradually (i.e., at low frequency) as pension investors do or in sudden bursts (i.e., at high frequency) as liquidity traders do, to either a high-frequency trading shop or a buy-and-hold mutual fund.

5. Anomaly returns and flows across frequencies

In this section, we estimate the spectra of anomaly returns and flows; that is, we decompose these series into a sum of frequency-specific components, each associated with a specific autocorrelation and cycle length. We start by connecting these components to cycles of returns and/or flows documented in the literature to illustrate how well our spectral analysis reflects real economic activities. Then we present some descriptive statistics. Finally, we perform a variance decomposition to quantify each frequency's contribution to the series' variability.

5.1. Anomaly returns and flows spectra

Performing a Fourier transformation requires that the time series be stationary. Accordingly, we carry out unit-root tests, which confirm that the anomaly return and flow series are all stationary (Table I2 of the Internet Appendix). 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 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.

In this figure, we link prominent frequencies to cycles in real economic activity and in asset or anomaly returns documented in previous studies (listed below the figure). 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 represents cycles with periods of approximately 8 and 10 years that correspond to the Democratic and Republican presidential anomaly return cycle and to the solar anomaly return cycle reported in Novy-Marx (2014); these cycles are associated with public policy and investors' risk aversion. Point B represents a cycle with a 5-year period that matches the overreaction and underreaction cycle that drives momentum and reversal anomalies (Lee and Swaminathan 2000). Point E represents the frequency of one cycle per year that coincides not only with annual reporting (e.g., to shareholders or fiscal authorities) but also with (a) the seasonal affective disorder (SAD) cycle in returns and asset allocation, which some have argued is related to investors' risk tolerance (Kamstra et al. 2003, 2017) and with (b) a cycle of seasonal momentum and reversal (Heston and Sadka 2008; Keloharju et al. 2020). Point G represents the quarterly frequency that corresponds to return cycles associated with (a) earnings announcements (Linnainmaa and Zhang 2019) and (b) dividend payments (Hartzmark and

Solomon 2013); the latter is also related to inflows induced by investors' preference for dividends (Harris, Hartzmark, and Solomon 2015).

The spectra of anomaly returns and flows display not only commonalities, such as at the quarterly frequency, but also disparities. One example of the latter is point H, which is related to the FOMC return cycle (close to six cycles per year; Cieslak et al. 2019), and 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 it is less than 4% of the NINV total variance.

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

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 or equal to one cycle per year; variables with the "-HIGH" suffix are time series reconstructed 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, these components differ markedly in their persistence. Intuitively, low-frequency (respectively, high-frequency) anomaly returns reflect components that go through long (respectively, short) exacerbation and correction cycles; in other words, they represent the persistent (respectively, transient) component of anomaly returns. Likewise, low-frequency (respectively, high-frequency) fund flows capture components that go through long (respectively, short) high-low flow cycles, that is, persistent (respectively, transient) flows.

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

5.2. Descriptive statistics

Table 1 presents summary statistics (Panel A) and correlations among main variables (Panels B and C). In Panel A of the table, the average monthly returns on the SYY and NINV anomalies are 1.9% and 1.6%, respectively. These average returns are statistically significant, with respective *t*-statistics of 6.52 and 4.36, indicating that a long-minus-short strategy is profitable. Yet over time, anomaly returns widely vary, with standard deviations of 4.8% for SYY and 6.0% for NINV. The monthly average flows to mutual funds and hedge funds are 0.2% and 0.4%, respectively, and their respective standard deviations are 0.5% and 1.7%.

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

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. 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 indicates 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.

5.3. Variance decomposition of fund flows and anomaly returns

Panel D of Table 1 displays the relative contribution of low- and high-frequency bands to the total variance of each series. The table reveals that they differ markedly in their frequency structures. First, the high-frequency components of SYY and NINV anomalies contribute about three times more to their total variance than do their respective low-frequency components. This suggests that the fast-moving mispricing exacerbation and correction cycles drive most of the variation in anomaly returns. Second, the frequency structures of flows differ across fund types. For mutual funds, flows are mostly (66%) driven by low-frequency fluctuations; for hedge funds, they are driven by low- and high-frequency fluctuations to an equal degree; finally, for passive funds, they are mostly driven (54%) by high-frequency fluctuations. Thus, comparatively, mutual fund investors are the slowest in providing capital, and passive fund investors are the fastest. Hedge fund investors, who are neither slow nor fast, lie in between. This ranking is broadly consistent with the characteristics of the clientele that these funds serve.

[[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. 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 two cycles per year), while large spikes for hedge fund flows are concentrated on the low end of the spectrum (fewer than 0.5 cycles per year).

6. Relation between anomaly returns and flows across frequencies

In this section, we evaluate the relation between fund flows and mispricing in the frequency domain. To do so, we estimate regressions of decomposed returns on decomposed flows. We first focus on the coefficient estimates in the regressions and then turn to their explanatory power and economic magnitude. Next, we consider the respective roles of investors and managers. Finally, we examine separately the long and short legs of anomaly portfolios.

6.1. Regressions of anomaly returns on flows

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 constitute smart money that corrects mispricing, whereas mutual fund flows amount to dumb money that exacerbates mispricing. Intuitively, correcting (respectively, exacerbating) mispricing an overvalued stock entails taking a short (respectively, long) position and so, by construction, is associated with a positive (respectively, negative) return on the anomaly portfolio. Therefore, positive net capital flows to hedge (respectively, mutual) funds in a month accompanied by positive (respectively, negative) anomaly returns indicate that those flows are positively associated with a mispricing correction (respectively, exacerbation). We build on this interpretation, as well as on direct evidence obtained from trading records that fund flows affect mispricing.[17] Given that hedge funds and mutual funds may specialize in different frequencies, it is not *a priori* clear how their flows relate to mispricing across frequencies. Our regression sheds light on this question.

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

Table 2 reports the results from regressing long-short anomaly returns on fund flows over low- and high-frequency bands. Panels A, B, and C split, respectively, flows, returns, and both flows and returns, into their low- and high-frequency components. Following Akbas et al. (2015), we control for *Amihud* illiquidity and the aggregate turnover as well as Fama-French three factors.[18] *t*-statistics are calculated based on Newey-West standard errors with 13 lags.

We first reproduce the results of Akbas et al. (2015) in columns (1) and (3) of Panel A, by regressing total anomaly returns on total hedge fund and mutual fund flows. That both SYY and NINV are positively related to hedge fund flows but negatively related to mutual fund flows indicates that hedge fund flows contribute to correcting mispricing, while mutual fund flows contribute to exacerbating it. These results match those reported in Akbas et al. (2015) in both magnitude and significance. Next, in columns (2) and (4), we decompose fund flows into their low- and high-frequency components (HF-LOW, HF-HIGH, MF-LOW, MF-HIGH). Although the coefficient estimates for both HF-LOW and HF-HIGH are positive, the magnitude is much smaller for HF-HIGH (and statistically insignificant), suggesting that mainly low-frequency hedge fund flows correct mispricing. For mutual funds, in contrast, MF-LOW and

[17] See the discussion in footnotes 2 and 7.

[18] In Table A1 of the appendix, we use other factor models and obtain results similar to those in Table 2.

MF-HIGH exhibit coefficients that are (significantly) negative and of comparable magnitudes, suggesting that both low- and high-frequency mutual fund flows tend to aggravate mispricing.

In Panel B, we decompose anomaly returns into their low- and high-frequency components (SYY-LOW, SYY-HIGH, NINV-LOW, NINV-HIGH) and regress each component on total flows. We find that the positive relation between hedge fund flows and anomaly returns is driven by low-frequency anomaly returns (Columns (1) and (2)). At high frequency, the coefficient estimate is positive, but it is much smaller in magnitude and statistically insignificant (Columns (3) and (4)). This finding suggests that hedge fund flows mainly correct low-frequency mispricing. In contrast, a negative relation between mutual fund flows and anomaly returns is observed for both high- and low-frequency returns, with coefficient estimates of comparable magnitude, indicating that mutual fund flows exacerbate both high and low-frequency mispricing.

Finally, in Panel C, we regress decomposed anomaly returns on decomposed flows to examine how each component of flows affects each component of mispricing (as in Equation (8)). The results show that hedge fund flows correct mispricing mainly over low frequencies. For instance, the regression of SYY-LOW on HF-LOW yields a coefficient estimate of 0.796 ($t = 3.56$), whereas the coefficient estimate from regressing SYY-HIGH on HF-HIGH is indistinguishable from zero. In contrast, mutual fund flows exacerbate mispricing over both high and low frequencies. Consider again SYY anomalies: at low frequency, MF-LOW yields a coefficient estimate for SYY-LOW of −2.770 ($t = -3.09$); at high frequency, MF-HIGH yields a coefficient estimate for SYY-HIGH of −2.071 ($t = -3.00$). The magnitudes of these coefficients are more comparable than are those we obtained for hedge funds. We remark that directly comparing coefficients without accounting for the magnitude of the variation in each frequency band may produce misleading results. In Section 6.3, we study these coefficients in depth.

Overall, these results indicate that mutual fund flows constitute dumb money throughout the entire spectrum: they exacerbate mispricing at each frequency. Hedge fund flows amount to smart money, in that they correct mispricing at each frequency. But, in contrast to mutual funds, their smart money effect is concentrated on low frequencies. In the Internet Appendix (Table I3), we examine individual anomalies and confirm that these findings, based on aggregated mispricing measures, are not driven by a subset of anomalies or by differences across anomalies (e.g., by correlations between mispricing and flows in different frequency bands being driven by different sets of anomalies).[19]

[19] Table I3 examines the relation across frequencies between individual anomaly returns and fund flows. For 8 of the 11 SYY anomalies, the coefficient estimates for HF-LOW are positive, and 4 of them are statistically significant. Although we observe 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 for both high- and low-frequency flows. Furthermore, 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.

6.2. *Explanatory power of flow components*

In this section, we examine the explanatory power of fund flows for anomaly returns. Table 2 reports the partial R^2 of each explanatory variable in the regressions. As noted in Section 4.2, the partial R^2 reflects the extent to which the serial correlation of anomaly returns is related to that of the explanatory variable. Columns (1) and (3) of Panel A indicate that HF and MF flows jointly explain 3.0% (respectively, 3.4%) of the variation in SYY (respectively, NINV) anomalies, which represent 13% (respectively, 21%) of the regressors' total explanatory power. These estimates are comparable to those obtained for non-market pricing factors, such as the value factor, HML. Thus, HF and MF flows form two (non-traded) factors that, alongside other prominent factors, contain important information for explaining variations in anomaly returns.

The combined explanatory power for low-frequency returns (Columns (1) and (2) of Panel B) reaches 27% (respectively, 35%) of the regressions' overall explanatory power. On the other hand, the combined explanatory power for high-frequency returns (Columns (3) and (4) of Panel B) accounts for 5% (respectively, 10%), an estimate comparable to (respectively, higher than) the explanatory power achieved by the value factor at 6% (respectively, 2%) but far smaller than that displayed by the market factor at 50% (respectively, 32%) and size factor at 37% (respectively, 52%). These results suggest that flows are related to both the persistent and the transient components of anomaly returns, but that their relation to the persistent component is much stronger.

Panel C of Table 2 shows that decomposing fund flows substantially increases their explanatory power. Low-frequency HF and MF flows, together, explain 20% (respectively, 24%) of the total variation in low-frequency SYY (respectively, NINV). Their explanatory power represents 53% (respectively, 61%) of the regressors' total explanatory power, far more than other factors', the market included. At high frequency, it drops to 2.3% (respectively,2.3%) but nonetheless represents 13% (respectively, 20%) of the regression's total R^2. These results suggest that the serial correlations of the persistent components of anomaly returns and fund flows are closely related to one another. The serial correlations of their transient components are also related, but to a much lesser degree. Table A1 in the appendix re-estimates those partial R^2 using the recent factor models of Daniel, Hirshleifer, and Sun (2020),[20] Fama and French (2015), Stambaugh and Yuan (2017), and Hou, Xue, and Zhang (2015) and reaches similar conclusions: low-

[20] Despite a common emphasis on horizon, our study and Daniel, Hirshleifer, and Sun's (2020) differ in (a) purpose and (b) concept. (a) Our objective is to analyze the relation between flows and mispricing, whereas theirs is to develop (horizon-dependent) asset pricing factors, regardless of flows. (b) We consider distinct notions of horizon: our focus is on the persistence of mispricing's *economic* significance, whereas theirs is on the horizon over which its *statistical* significance sustains. Indeed, as our Table A1 shows, long- and short-horizon factors are significantly related to both low- and high-frequency components of anomaly returns; moreover, for each frequency component, the economic magnitude of the relationship is similar across long- and short-horizon factors.

frequency flow factors have far more explanatory power for low-frequency anomaly returns than any of the factors in those models.

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

Panel A of Table 3 quantifies the difference in flows' explanatory power between the low- and high-frequency regressions and compares it across fund types. It reports, for each fund type, the ratio of the partial R^2 displayed by flows in the low-frequency regression to that displayed in the high-frequency regression (Columns (3) and (6)). For mutual funds, that ratio is around five, whereas for hedge funds, it ranges from 40 to 325. Thus, flows' explanatory power is tilted toward low frequencies, and this tilt is 8 to 60 times more pronounced for hedge funds than for mutual funds. We dub this tilt the *slow-moving effect*.

Overall, these results indicate that fund flows significantly contribute to the serial correlation of anomaly returns, especially at low frequency and for hedge funds. In the next sections, we analyze the direction and magnitude of the slow-moving effect, as well as the contributions of fund investors and managers.

6.3. Direction and magnitude of the slow-moving effect

In this section, we evaluate the slow-moving effect across frequencies in terms of its direction and economic significance. We examine the effect first over the low- and high-frequency bands, then continuously over the entire spectrum, and, finally, separately over the long and short legs of the anomaly portfolios.

6.3.1. The slow-moving effect over low- and high-frequency bands

The direction of the effect of flows on mispricing over the frequency band $B = \{L,H\}$ is given by the sign of the regression coefficient, β_B, and its economic magnitude by the impact on returns (expressed in units of their standard deviation) of a 1-SD increase in flows, $\beta_B \times \sigma_F^B / \sigma_R^B$, where σ_F^B and σ_R^B denote (respectively) the standard deviations of flows and anomaly returns over the band B. Columns (3) to (5) in Panels B and C of Table 3 present estimates of the fund flow effect on SYY and NINV anomaly returns, respectively. The positive (respectively, negative) signs of β_B for hedge (respectively, mutual) fund flows imply that they correct (respectively, exacerbate) mispricing over both low and high frequencies. Consider, for example, hedge fund flows and NINV anomalies (Panel C). The regression coefficient on HF-LOW is 1.107 (Column (1)), which, given the standard deviation of HF-LOW (1.2% in Column (2)), is associated with a 1.3% increase in the NINV-LOW monthly return (Column (3)), that is, a mispricing correction of 1.3% per month. Likewise, a 1-SD increase in MF-LOW exacerbates NINV-LOW mispricing by 1.7% per month. At high frequency, in contrast, a 1-SD increase in flows corrects NINV mispricing by 0.1% per month for hedge funds and exacerbates it by 0.8% per month for mutual funds. In terms of economic magnitude, a 1-SD increase in hedge funds flows corrects mispricing by 46.9% and 1.9% of a SD (Column

(5)) at low and high frequencies, respectively. The corresponding estimates for mutual funds equal -58.9% and -16.2%, respectively.

Next, we compare the effect of flows in a given frequency band across fund types. Taking the ratio of economic magnitudes across funds at low frequency implies that, for NINV (respectively, SYY) anomalies, a 1-SD increase in hedge fund flows corrects 46.9%/58.9%=80% (respectively, 43.1%/54.6% = 79%) of the mispricing entailed by a 1-SD increase in mutual fund flows. Thus, to the extent that hedge funds correct the mispricing generated by mutual funds, their flows can correct most of that mispricing. At high frequency, in contrast, a 1-SD increase in hedge fund flows corrects only 1.90%/16.2% = 12% (5.0%/15.5%=32%) of the NINV (respectively, SYY) mispricing entailed by a 1-SD increase in mutual fund flows.

We then compare the fund flow effect across frequencies for a given fund type. To do so, we report in Column (5) of Panels B and C (row labeled "LOW/HIGH") the *cross-frequency flow-mispricing ratio*, which is defined as the ratio of the magnitudes of the flow effect across frequencies, $(\beta_L \times \sigma_F^L/\sigma_R^L)/(\beta_H \times \sigma_F^H/\sigma_R^H)$. A ratio larger (respectively, smaller) than one indicates that low-frequency flows lead to a larger (respectively, smaller) mispricing correction (or exacerbation) than do high-frequency flows. For hedge funds, the ratio of 24.41 (respectively, 8.62) for NINV (respectively, SYY) anomalies implies that they correct mispricing at low frequency 9 to 24 times more than they do at high frequency. Likewise, the ratio for mutual funds implies that their flows amplify mispricing at low frequency about four times more than they do at high frequency. Remarkably, these high ratios are obtained despite limited liquidity provision magnifying the price impact of high-frequency flows. Indeed, studies in microstructure, both theoretical and empirical, demonstrate that faster trading induces a bigger price impact (e.g., Kyle et al. 2017). Hence, to the extent that higher-frequency flows entail moving in and out of positions faster, they are likely to generate a bigger price impact and, hence, lower cross-frequency ratios.

Finally, a comparison of fund types reveals that these cross-frequency ratios are 2.44 to 6.72 times larger for hedge funds than they are for mutual funds. Thus, the slow-moving effect, that is, fund flows' tendency to affect low-frequency mispricing more than high-frequency mispricing, is considerably stronger for hedge funds than it is for mutual funds. In other words, hedge fund capital improves market efficiency more slowly than mutual fund capital degrades it.

6.3.2. The slow-moving effect over continuously expanding frequency bands

So far, we have relied on a binary breakdown of variables into high- and low-frequency components. We now paint a continuous picture of how the slow-moving effect varies as a function of frequency. Panels A and B of Figure 4 plot the cross-frequency flow-mispricing ratio estimated over expanding frequency bands as follows. First, for each range of frequencies from 0.04 (the lowest frequency generated by our data) to a cutoff c (up to six cycles per year, the highest frequency), 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 [0.04, c] as $\beta_C \times \sigma_F^C/\sigma_R^C$, where σ_F^C and σ_R^C denote, respectively, the standard deviations of flows and mispricing over the frequency band [0.04, c]. Finally, we divide that number by the estimate of the economic magnitude over the high-frequency band, (1, 6] to obtain the cross-frequency flow-mispricing ratio, $(\beta_C \times \sigma_F^C/\sigma_R^C)/(\beta_H \times \sigma_F^H/\sigma_R^H)$. Hence, the ratio at one cycle per year—the frequency at which the expanding band coincides with the low-frequency band—corresponds to the ratio reported in Table 3.

[[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, sharply declines past that threshold. In addition, the decline is more pronounced for hedge funds than for mutual funds. 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 more strongly affect low-frequency mispricing 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.

Furthermore, flow cycles can lead to the appearance of anomaly return cycles. To the extent that flows of smart and dumb monies alternately correct and fuel mispricing, return cycles may emerge (Pontiff 2006; Akbas et al. 2015).[21] Thus, hedge and mutual fund flows can contribute to both the serial correlation and the cyclicality of anomaly returns, especially for cycles longer than one year.

6.3.3. Long versus short legs of anomaly portfolios

Stambaugh et al. (2012, 2015) show that anomalies are mainly driven by overpricing in the short leg of anomaly portfolios. If our findings are driven by correcting or exacerbating mispricing, then they, too, should be driven by the short leg. Table 4 reports the results from regressing long- and short-leg returns separately on fund flows across frequencies.

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

Panel A shows that hedge fund flows are not related to long-leg returns regardless of the frequency band, but, according to Panel B, they 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 is mostly due to the short leg. Observe that, for this leg, a negative coefficient implies that flows correct mispricing. In other words, at low frequency, hedge funds

[21] With a correlation well below one within each frequency band (Table 1), hedge and mutual fund flows' effects on mispricing are unlikely to perfectly offset each other.

correct overvaluation more so than undervaluation. Turning to mutual funds, we find that both 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 slow-moving effect of both fund types operates through the short leg of anomalies.

6.4. *Managers versus investors*

To understand the role of managers and investors in the slow-moving effect, we propose decomposing the effect into one part attributable to fund investors and another part attributable to fund managers. Indeed, that fund flows have a stronger effect on mispricing at low frequency may stem from investors' flows comprising more low-frequency components or from fund managers investing flows in a way that affects mispricing more over low frequencies. Put in the language of filtering, we evaluate the extent to which the properties of returns (output signal) derive from those of investor flows (input signal) or from the investment behavior of fund managers (the filter). Formerly, the cross-frequency flow-mispricing ratio can be written as $\left[\left(\frac{\sigma_F^L}{\sigma_F^H}\right) \times \left(\frac{\beta_L}{\beta_H}\right)\right] / (\sigma_R^L/\sigma_R^H)$. The first term in the numerator of this expression, (σ_F^L/σ_F^H), which we dub the *cross-frequency volatility ratio*, represents the impact of investor flows (or the investor effect for short): a larger such ratio can be interpreted as investors supplying capital more slowly. We already know from the variance decomposition in Section 5.3 that mutual fund and passive fund investors are, respectively, relatively slow and fast in providing capital, while hedge fund investors are neither. The second term in the numerator of the ratio, β_L/β_H, labeled the *cross-frequency beta ratio*, represents the impact of managers' investment strategy (or the manager effect). A larger ratio can be interpreted as the impact of one unit of flows being tilted more toward low frequencies. A ratio larger (respectively, smaller) than one means that flows have a larger (respectively, smaller) effect on returns at low frequency than at high frequency, and so that managers behave as a low (respectively, high)-pass filter.

Returning to Table 3, one sees that Panels B and C present the results from decomposing the slow-moving effect into an investor effect, σ_F^L/σ_F^H, in Column (2), and a manager effect, β_L/β_H, in Column (1). For hedge funds, the estimate of the investor effect (1.03) indicates that investors supply capital equally over low and high frequencies and so do not contribute to the slow-moving effect, whereas estimates of the manager effect (4.42 and 12.98 for SYY and NINV anomalies, respectively) imply that managers play a critical role therein. For mutual funds in contrast, estimates of the investor (1.39) and manager effects (1.34 and 1.43, respectively) imply that investors and managers both contribute, and almost equally so, to the slow-moving effect. Estimates of the manager effect—both above one—indicate that managers, especially at hedge funds, behave as a low-pass filter.

Comparing estimates across fund types suggests that mutual fund investors supply capital one-third more slowly than do hedge fund investors (= 1.39/1.03-1) and that hedge fund managers slow down capital 2 (= 4.42/1.34-1 for SYY) to 8 times (= 12.98/1.43-1 for NINV) more than do mutual fund managers. Panels C and D of Figure 4, which display the investor and manager effects estimated over continuously expanding frequency bands, confirm that these patterns obtain throughout the spectrum. The figure also highlights the prominent role played by hedge fund managers, in comparison to investors and mutual fund managers, in the slow-moving effect.

Several mechanisms can lead fund managers to behave as a low-pass filter. First, these managers might be redirecting high-frequency flows toward low-frequency mispricing. Consider, for example, a fund investor allocating capital to a fund at high frequency, say $1.2 billion in January and zero over the rest of the year. The fund's manager can convert those flows into low-frequency flows by investing them gradually over the course of the year, for example, by investing $100 million every month, and holding the undeployed money in cash or liquid benchmarks. In other words, after the manager spreads those high-frequency flows over time, they are indistinguishable from low-frequency flows.

In the model of Section 8, we propose two alternative mechanisms, based on the equilibrium (mis)pricing of assets. The first is that managers invest more aggressively flows that they deem less likely to reverse, that is, lower-frequency flows (which we refer to as patient capital in our model). In the above example, the manager might invest only 80% of the $1.2 billion received in January and hold the residual in cash or liquid benchmarks to accommodate future redemptions, versus 90% of the $100 million received every month. The second mechanism we propose in our model is based, not on managers investing different amounts over different frequencies, but on mispricing's reaction to the amount invested varying over frequencies. Specifically, lower-frequency mispricing requires longer capital commitments from managers (because it takes more time to correct) and so commands a larger risk premium and hence responds more to fluctuations in arbitrage capital. Returning to our example, we have the manager invest the same amount whether the funds are received all in January or gradually over the year, but each dollar of flows corrects mispricing more at low frequency than it does at high frequency. All three mechanisms (redirecting flows, allowing for more aggressive investing of lower-frequency flows, and lower-frequency mispricing being more responsive to flows) lead to a larger coefficient estimate (beta) at lower frequency and reflect the general idea that managers make optimal decisions given their limited risk-bearing capacity and the presence of market frictions. We therefore loosely refer to all three mechanisms as "slowing down flows."

Taken together, these results indicate that both hedge and mutual fund managers behave as a low-pass filter; however, the importance of managers and investors differ strikingly across fund types. For hedge funds, the slow-moving effect is entirely due to managers slowing down flows, whereas for mutual funds, it is equally driven by investors' flows being slow and managers' slowing them further.

6.5. Passive funds

Passive funds offer some perspective on estimates of the manager effect. Passive fund managers have no discretion in dealing with flows, so comparing beta ratios across passive and active managers provides information on the *active* filtering conducted by managers. We first note that, because passive funds typically track broad indexes rather than take long-short, market-neutral positions in anomaly portfolios, their flows do not affect mispriced assets but the market at large.[22] Accordingly, in Table 5, we estimate the effect of flows, not on anomaly returns, but on two market return proxies: MKT, the value-weighted market returns from CRSP, and S&P 500, the return on the S&P 500 index. Panel A of Table 5 shows that, in sharp contrast to hedge and mutual funds, the effect of passive fund flows is insignificant at low frequency and strong at high frequency. Panel B further estimates that a 1-SD increase in passive flows is associated with a 1.0% increase in the monthly market return (Column (3)) at high frequency—about 0.27 of a SD (Column (5)), and no significant change at low frequency. As a result, the cross-frequency flow-"mispricing" ratio for passive funds is close to zero (Column (5)).

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

Given that passive fund managers have no flexibility for dealing with flows, these results likely reflect the price impact of flows on benchmark stocks due to imperfect liquidity provision. To illustrate, suppose a passive fund receives high-frequency inflows (respectively, outflows) of $1.2 billion in January and zero over the rest of the year. Accommodating those flows upon reception triggers bigger stock price increases (respectively, decreases) than if the fund had received them at low frequency, for example, $100 million in every month of the year. Thus, passive funds flows affect returns at high frequency only.

This interpretation is confirmed by passive funds' cross-frequency beta ratio, which is well below one (ranging from 0.02 for MKT to 0.06 for S&P; see Column (1) in Panel B of Table 5). Since passive managers invest the flows they receive in their designated benchmarks without discretion or delay, this low ratio can only arise from higher-frequency flows triggering a bigger price impact. Indeed, inflows (respectively, outflows) lead to purchases (respectively, sales) that push up (respectively, down) stock prices more if they occur at higher frequency, because market makers require a larger compensation for accommodating orders over a shorter period, consistent with much of the microstructure literature. In other words, because of imperfect liquidity provision, managers who do not actively filter flows, that is, those who behave as a passive pass-through filter, have a cross-frequency beta ratio below one. This suggests that

[22] That passive funds do not affect mispricing is confirmed in Table I4 of the Internet Appendix. The table presents estimates from regressing anomaly returns on passive equity fund flows as in our baseline analysis and shows no significant effect at any frequency.

using as benchmark a ratio of one as in Section 6.4 is likely to understates the true extent of low-pass filtering at hedge and mutual funds.[23]

6.6. Endogeneity

Here, we discuss the endogeneity of flows with respect to mispricing, in the form of reverse causality and an omitted variable. Before proceeding to formal tests, we note that the contrasting patterns we report across fund types should alleviate endogeneity concerns. Indeed, if the flow-return relationship is driven by an omitted variable (e.g., investment opportunities) affecting flows and mispricing simultaneously, then that variable needs to exert (a) opposite influences on hedge and mutual fund flows (given the opposite signs we find in Table 2 for their relationship to mispricing), and (b) no influence on passive fund flows (since, in Table I4 in the Internet Appendix, passive flows have no bearing on mispricing). This seems unlikely given how highly correlated flows are (e.g., in Table 1, the correlations of mutual fund flows with passive and hedge fund flows range from 0.42 to 0.53 at low frequency). Likewise, for reverse causality to hold, mispricing needs to affect hedge and mutual fund flows in opposite directions while not affecting passive fund flows.

Notwithstanding, we conduct two formal endogeneity tests. The first is a Granger causality test that assesses reverse causality. The results, reported in Table A2 of the appendix, indicate that while hedge fund flows Granger cause mispricing corrections at low frequency, the reverse is not true. In contrast, Granger causality is observed in both directions at low frequency for mutual funds. Furthermore, we find no evidence of Granger causality at high frequency for either fund type. Overall, these results are consistent with hedge fund flows correcting mispricing at low frequency, rather than mispricing corrections generating hedge fund flows.

The second endogeneity test is the omitted variable test of Oster (2019).[24] The key parameter of this test, denoted by "delta," measures how important the omitted variable (the unobservable) needs to be (in percentage terms), relative to the controls (the observables), in order to render the parameter of interest (the treatment) insignificant. A delta of one means that the unobservable needs to be 100% as important as the observable controls to overturn the significant finding on the treatment. The higher the absolute value of delta, the smaller the likelihood of an omitted variable having a significant effect. Therefore, an absolute value of delta higher than one suggests that the parameter of interest is unlikely to be biased by an omitted variable. Table A3 of the appendix reports estimates of delta for the coefficients in the regressions of Table

[23] Although anomaly portfolios differ from the market portfolio, liquidity provision at high frequency is likely to be more restricted for anomaly stocks than for the market.

[24] Economics and other social sciences widely use the omitted variable test, which has only started to be applied in finance as of late. See, for example, Mian and Sufi (2014), Michalopoulos and Papaioannou (2016), Gorodnichenko and Weber (2016), Bhagwat, Dam, and Harford (2016), Knüpfer, Rantapuska, and Sarvimäki (2017), Schoenherr (2019), and Heimer et al. (2019).

2. Panel A shows that the deltas for hedge funds are higher than one in absolute value in all regressions, except for NINV-HIGH. For example, for SYY-LOW and HF, the delta estimate of 8.2 suggests that an omitted variable would have to be 820% as important as the controls to render the coefficient on HF insignificant. This is highly unlikely. Panel B confirms this conclusion for HF-LOW and HF-HIGH. Notably, the deltas for hedge fund flows are nontrivially larger than the deltas of traditional asset pricing factors especially at low frequency, suggesting that the hedge fund flow factors is less likely to suffer an omitted variable concern than the prominent factors. Overall, these results alleviate concerns about an omitted variable bias, especially for hedge funds.

We also explicitly model the dependence of flows on lagged market return and turnover. Specifically, using flows orthogonalized with respect to these variables, we find that the baseline results of Table 2 are unchanged (see Table I5 in the Internet Appendix).

Finally, in support of a causal relation from flows to mispricing, we propose in Section 8 a theory in which (exogenous) flows generate the low-pass filtering behavior that we observe in the data. The model makes several additional predictions about the role of frictions in generating the behavior we observe in the data and detail in Section 7.

7. Market frictions and low-pass filtering

We find that the impact of funds, especially hedge funds, on mispricing is tilted toward low frequencies (the slow-moving effect), and that this tilt is mostly due to managers' filtering behavior, again especially for hedge funds. Since flows are measured as a percentage of total net asset and hedge funds manage only a tenth of mutual funds' assets, our finding that hedge funds' flows exert an effect comparable to mutual funds' at low frequency implies that their flows are the most important for mispricing at that frequency on a per-dollar basis.

In this section, we investigate the role of market frictions in inducing managers, especially at hedge funds, to behave as a low-pass filter. Clearly, if there were no frictions to impede arbitrage, then all mispricing, regardless of its frequency profile, would be eliminated instantly. We examine how managers' filtering behavior responds to variations (over time and across funds) in the intensity of three frictions: risk, access to capital, and implementation costs. We then address endogeneity concerns using exogenous shocks to these frictions. Throughout this section, we report results only for the NINV anomaly in the interest of brevity; those based on the SYY anomaly are largely similar and relegated to the Internet Appendix (Table I6).

7.1. Risk

We first examine in Table 6 whether managers' low-pass filtering behavior 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).[25] 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 to one if the economy is in recession during the current month (and set to zero otherwise). For other proxies, D is a quintile score ranging from zero to one; 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 for hedge fund flows interacted with D is significantly positive in the NINV-LOW regressions across all risk proxies (Columns (1), (3), (5), and (7)); for mutual fund flows, instead, the estimates are indistinguishable from zero throughout.

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

In Panel B, the coefficient estimate for HF-LOW × D is significantly positive for low-frequency anomaly returns (Columns (1), (3), (5), and (7)); in contrast, the coefficient estimate for HF-HIGH × D is not significant for high-frequency anomaly returns (Columns (2), (4), (6), and (8)). This result suggests that hedge funds' low-frequency mispricing correction amplifies with risk. The impact of risk as measured in the low-frequency regressions is economically sizable. In Column (1) of Panel B, for example, the coefficient estimate for HF-LOW × D (2.252) is more than three times as large as that on HF-LOW (0.684).

Turning to mutual funds, we observe that none of the regressions yields a significant coefficient estimates for flows interreacted with the risk proxy except for the NBER recession indicator. That set of regressions reveals contrasting findings: the coefficient estimates for MF-LOW × D are negative for low-frequency anomaly returns (Column (1)), indicating that mutual funds' exacerbation of mispricing at low frequency amplifies during recessions, whereas those on MF-HIGH × D are positive for high-frequency anomaly returns (Column (2)), implying that their exacerbation of mispricing at high frequency dampens.

Overall, these results suggest that hedge funds' correction of low-frequency mispricing intensifies in times of heightened aggregate risk. We also find some, albeit weaker, evidence that mutual funds' exacerbation of low-frequency mispricing increases during recessions.

[25] 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-to-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.

7.2. Leverage

In this section, we examine how managers' low-pass filtering behavior relates to leverage, exploiting variations, first in the time series, and then in the cross section.[26] 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 6, the main variables of interest in Table 7 are the low- and high-frequency fund flows interacted with D, now a quintile score scaled from zero to one, where a higher score indicates a wider TED spread or greater risk aversion.

[[INSERT **Table 7** 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 rises (Columns (1), (2), (5), and (6)). The effects are economically significant. In column (2) of Panel B, for example, the coefficient for HF-LOW × D (1.184) is three 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 mispricing corrections to be more pronounced for unlevered funds. In Table 8, 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. 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 (Column (1)). When 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 8** about Here]]

[26] A growing literature studies the influence of intermediaries, such as broker-dealers and banks (through their balance sheets), on asset prices. Intermediaries act as middlemen between capital providers (households) and end users (e.g., hedge and mutual funds). Our paper differs by focusing on end users and not on middlemen.

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

7.3. Liquidity and transaction costs

We explore how managers' low-pass filtering behavior depends on aggregate liquidity, again starting with the time series, and then turning to the cross section. We employ four measures of illiquidity that track variations in marketwide liquidity over time: (1) Amihud illiquidity, (2) the aggregate illiquidity described by Pastor and Stambaugh (2003), (3) the "permanent variable factor" proposed in Sadka (2006), and (4) 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 (2019) show that the permanent variable factor is an especially relevant component of transaction costs for both hedge funds and mutual funds. Finally, the noise measure of Hu et al. (2013) 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.[27]

For our analyses, the illiquidity variables (denoted by ILLIQ) are constructed as follows. First, if the original variable measures market liquidity, then we convert it to an illiquidity measure by multiplying it by negative one. Next, we detrend the measure and sort monthly (detrended) illiquidity values into quintiles. Finally, we standardize quintile scores from zero to one 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.

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

Table 9 presents results from regressing anomaly returns on flows interacted with ILLIQ. For hedge funds, the effect at low frequency strengthens considerably when liquidity worsens: all coefficient estimates for HF × ILLIQ (Panel A) and HF-LOW × ILLIQ (Panel B) are significantly positive. The effect is economically sizable; in Column (1) of Panel B, for instance, the magnitude of the effect of HF-LOW on NINV-LOW triples, from 0.349 when ILLIQ = 0 (lowermost illiquidity quintile) to 1.505 (1.156 + 0.349) when ILLIQ = 1 (uppermost illiquidity quintile). The coefficient estimates for HF-HIGH × ILLIQ are insignificant throughout, except in Panel B, where the coefficient for the Pastor-Stambaugh measure is significant. For mutual funds in contrast, the slow-moving effect is not sensitive to the level of liquidity

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

(the coefficient estimates for MF × ILLIQ, MF-LOW × ILLIQ, and MF-HIGH × ILLIQ are indistinguishable from zero).

As we discussed for the case of passive flows (Sections 6.3.2 and 6.4), flows may affect returns because of limited liquidity provision. One may therefore wonder whether heightened price impact in periods of low liquidity mechanically leads to higher coefficient estimates for hedge funds. We find this interpretation implausible because it implies a stronger flow-induced price effect (1) at high frequency and (2) particularly for mutual funds (since the mutual fund industry is more than 10 times larger than the hedge fund industry), neither of which is consistent with our results. Rather, our results indicate 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 lockup, redemption notice, and payout periods. This measure is widely used in the hedge fund literature to capture fund-level 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.

In each month, we divide hedge funds into two groups, denoted by HFBelow and HFAbove, based on the median value of share restrictions; we then estimate fund flows and their frequency components separately for each group. The results, which are presented in Table 10, 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' low-pass filtering.

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

Note that these findings do not imply that arbitrageurs trade fewer shares or less frequently because of transaction costs. Indeed, for a given target portfolio, arbitrageurs may simply spread their trades over a longer period, a behavior that would result in more persistent rebalancing and trading (e.g., gradually building a stake in an underpriced stock) and hence in a more persistent correction of mispricing. That is, to the extent that trades are consistently in the direction of correcting mispricing, then high-frequency rebalancing and trading in a stock can result in low-frequency mispricing correction. Thus, our tests speak to how transaction costs might alter the persistence of mispricing corrections by hedge funds, but not to how those costs affect the turnover or profitability of their strategies.[28] This viewpoint differentiates our liquidity tests from those presented in other studies of transaction costs.[29]

7.4. Exogenous shocks

To sharpen the identification of the effect of frictions on the low-pass filtering behavior of hedge fund managers, we exploit two quasi-natural experiments associated with shifts in the intensity 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 by U.S. stock exchanges. It considerably improved liquidity (Bessembinder 2003; Furfine 2003) and is used as an exogenous shock to liquidity (e.g., Chordia, Roll, and Subrahmanyam 2008; Fang, Noe, and Tice 2009). Table 11 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 one if the month *t* is included in the period of the shocks and to zero otherwise.

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

The results presented in Table 11 reveal that low-pass filtering strengthened for hedge funds during the financial crisis but weakened during decimalization: in the low-frequency returns regressions of Panels A (total flows) and B (decomposed flows), the coefficient estimate for hedge fund flows interacted with the SHOCK indicator is significantly positive during the former (Column (1)) and negative during the latter (Column (3)). For decimalization, there was also an amplification of hedge funds' mispricing corrections at high frequency, as evidenced by the significantly positive coefficient estimate for HF-HIGH × SHOCK (Column (4)). This result suggests that improved liquidity induces a shift in hedge funds' mispricing corrections from low to high frequency, that is, a weakening of their low-pass filtering. It also speaks against our findings being mechanically driven by limited liquidity provision since the high-frequency flow effect on mispricing corrections strengthens when liquidity improves.

[28] As further evidence, we compute the average returns on low- and high-turnover anomalies separately. Viewing them as two factors, we then perform the same test used in Table A1. The results, which are reported in Table I7 of the Internet Appendix, indicate that both low- and high-turnover anomalies load significantly on low- and high-frequency anomaly returns, supporting our claim that frequency and turnover are distinct notions. In that test, the low turnover anomalies are based on the Novy-Marx and Velikov (2016) low turnover anomalies, which require rebalancing less than once per year; the high-turnover anomalies, consistent with our one-year cutoff, are based on a combination of their medium and high-turnover anomalies, which require rebalancing on average, one to five times per year and more than five times per year, respectively.

[29] See, for example, Keim and Madhavan (1997), Korajczyk and Sadka (2004), Lesmond et al. (2004), Engle et al. (2012), Novy-Marx and Velikov (2016), DeMiguel et al. (2020), Frazzini et al. (2018), and Patton and Weller (2020).

Mutual funds exhibit largely similar patterns, namely, a strengthening of low-pass filtering during the financial crisis and a weakening during decimalization. In Panel B, for example, the coefficient estimate for MF-LOW × SHOCK is significantly negative in Column (1) and positive in Column (3). Again, decimalization, through improved liquidity, induces a shift in mutual funds' exacerbation of mispricing from low to high frequency (negative coefficient estimate for MF-LOW × SHOCK in Column (4)). Overall, the evidence from these two experiments indicates that frictions cause fund managers, especially at hedge funds, to behave as low-pass filters.

8. 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 stymieing arbitrage activity: risk, transaction costs, and the limited availability of capital. We build on two papers by Garleanu and Pedersen (2013, 2016; denoted by 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. The third ingredient—limited capital— is incorporated into the model by assuming arbitrageurs' risk-bearing capacity to be finite and increasing in the funds they receive.

8.1. The economy

Our model helps explain the dynamics of asset returns given the dynamics of mispricing. We start with an (exogenous) shock to the demand for assets that causes them to be mispriced; 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.[30]

Hedge funds accommodate variations in demand. How aggressively they trade depends on two features: their risk tolerance (a function of their capital) and transaction costs. Two comments on our modeling strategy are in order. First, we view hedge funds' finite risk tolerance (i.e., that they are not risk neutral) 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:

[30] 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.

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).

8.1.1. Assets

A riskless asset and two risky assets, which are labeled "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 $\mathrm{Var}_t(du_t^s) = \Sigma dt$. 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 $r_t^s \equiv dQ_t^s / p_t^s$.[31] 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 $\lambda \geq 0$ parameterizes the trading costs.[32] There are no restrictions on short selling or borrowing.

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

8.1.2. 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, which is represented by holdings x_t^s of asset s ($s = \{S, F\}$)

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[31] 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 decay rate of percentage returns is a function of the asset's mispricing and therefore of the severity of frictions. Therefore, the percentage returns allow us to link together decay rates, mispricing, and frictions.

[32] 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, $\Sigma {\Delta x_t^s}^2$, 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 resultant price, when multiplied by the trade size Δx_t^s, yields a total trading cost given by the previous expression.

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 and τ is the arbitrageur's risk tolerance coefficient. The first term in brackets represents the portfolio's expected excess return; the second term represents its variance scaled by the arbitrageur's risk tolerance; and the last term represents the penalty for transaction costs. This objective corresponds to equation (5) in GP2016. We replace (to facilitate the presentation) the coefficient γ of absolute risk aversion with its inverse, that is, 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. We assume that the residual demand for asset s in period t, denoted by 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, in accordance with

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

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, $\Phi^S < \Phi^F$. The top panel of Figure 5 illustrates these dynamics. We refer to f_t^s (≥ 0) as a factor because of its role (as we will 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.

8.1.3. 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 markets are initially in equilibrium, that is, $x_0^s = -f_0^s$.

8.2. Equilibrium characterization

Given our assumptions (i.i.d. dividends and deterministic residual demand), asset prices evolve deterministically over time. Hence, the dividend remains the sole source of risk. It is then natural to suppose, as we will 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

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

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.

See the appendix for all proofs.

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 only partially rebalance toward this portfolio. Specifically, this is achieved by a fraction a/λ (which is infinite only in the absence of transaction costs), which 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.

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

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

and the price is given by

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

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, $(\Sigma dt) \times (-\frac{f_t^s}{\tau})$, 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 (a) the risk per share, Σdt, is identical across assets and (b) the current *level* of the factor f_t^s, regardless 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 : 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. The residual supply of the slower asset decays more slowly, thereby exposing the arbitrageur in every period to more fundamental risk. To compensate the arbitrageur for this higher risk, the slower asset offers a higher return.

The second component of the expected return is compensation for trading costs, $\Sigma\lambda\Phi^s(\Phi^s + \rho)f_t^s dt$. The compensation 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 the asset must offer a higher expected return. 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). If the arbitrageur were risk neutral (i.e., had an infinite risk tolerance) and there were no transaction costs, then the price simply would be equal to the 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.[33] The former increases the price (so a short position earns a positive premium), whereas the latter reduces 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.[34] In equilibrium, then, the price strikes a balance: it is high enough to compensatefor 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.[35]

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. Put differently, the arbitrageur needs to maintain open positions in asset F for a shorter spell of time and so is less exposed to the asset's fundamental risk. This leads 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. Thus, *the slow asset is more overvalued than the fast asset*. The bottom panel of Figure 5 illustrates this.

[33] The relation between an asset's price and its expected return is 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 $y \geq \underline{t}$. Therefore, $P_t^S = \int_{+\infty}^{t} E_t(dQ_y^S)\, dy$.

[34] In terms of the optimal trading strategy described in Proposition 1, market clearing requires that the arbitrageur's aim portfolio loads 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.

[35] 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.

The next lemma describes how the decay rates of prices and returns relate to the decay rates of the factor, 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 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 (exogenous) 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 undergird 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 rebalancing frequency and portfolio turnover. 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, our framework sheds light on how the severity of market inefficiency (i.e., the size of the mispricing) and the frequency of market inefficiency (i.e., the persistence of mispriced assets' returns) relate to one another: the more overvalued an asset, the more slowly its return decays. This connection further motivates our study of market efficiency in the frequency domain.

Taking stock, two forces make returns persistent (slow-moving) in equilibrium. The first is that noise traders are slow to reduce their demand for the stock, and the second is that arbitrageurs are slow to correct mispricing; that is, they fail to correct it fully and immediately. In our empirical analysis, these two forces correspond to mutual funds persistently exacerbating mispricing and to hedge funds persistently correcting mispricing. Given the prominence of hedge funds in our empirical findings, we endogenize arbitrageurs in our model and make noise trading exogenous. In the next section, we introduce capital flows to arbitrageurs and analyze their effect on returns.

8.3. Flow return regressions

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

8.3.1. 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 adjusts her holdings of the riskless asset. To account for the behavior of hedge funds, which typically buy (respectively, sell) shares in response to capital inflows (respectively, 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. These flows have mean $E_t(NetFlows_t) = \Pi dt$ and variance $\mathrm{Var}_t(NetFlows_t) = \Psi dt$. As in our empirical analysis, we further decompose flows into two orthogonal components: one persistent (labeled 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 arbitrageurs' risk tolerance by $k(1+\omega)$, whereas a dollar's worth of impatient flows increases their 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 equally affect risk tolerance regardless of their persistence; if $\omega = 1$, then only patient flows matter for risk tolerance. For simplicity, the variances of patient and impatient net flows are assumed equal. This assumption eliminates any investor effect from the model and implies that the total effect of flows coincides with the manager effect.

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 arbitrageurs' actual 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.

8.3.2. Linking flows to returns

To evaluate the impact of flows on return, we proceed as follows. Starting from 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 (respectively, outflows) render an arbitrageur more (respectively, less) risk tolerant, the effect of which is to lower (respectively, raise) the price toward (respectively, away from) the fundamental value. As a result, the price displays a tendency to decline toward the fundamental value, while being 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 $r_t^s = (dp_t^s + du_t^s - r^f p_t^s dt)/p_t^s$.

8.3.3. 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 ($NetFlows_t^P, NetFlows_t^I$). β^s, $\beta^{s,P}$, and $\beta^{s,I}$ ($s = \{S, F\}$) denote the corresponding regression coefficients. The beta ratio, $\beta^{S,P}/\beta^{F,I}$, 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.[36] Our main prediction is Prediction 2; the other predictions describe its sensitivity to model parameters.

Prediction 1 (Sign of regression coefficient). *The regression coefficient of the excess return on total flows,* β^S ($s = \{S, F\}$), *is positive.*

Prediction 1 states that the arbitrageur corrects mispricing to a greater (respectively, lesser) extent when she gains (respectively, 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. In addition, the negative regression coefficient we report for mutual funds can be rationalized by interpreting flows to mutual funds as shocks to the noise trader's demand f_t^s for assets.[37]

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

Prediction 2 (Impact of speed of decay on the regression coefficient). *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 beta ratio exceeds unity:* $\beta^{S,P}/\beta^{F,I} > 1$.

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 the 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 $\beta^S > \beta^F$. The bottom panel of Figure 5 illustrates this effect. 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 ($\lambda = 0$).[38]

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

[37] An inflow of capital to mutual funds (noise traders) 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.

[38] Moreover, no such restriction is required when the regressions are based on dollar returns, dQ_t^s, rather than relative returns, $r_t^s \equiv dQ_t^s/p_t^s$, or on relative returns normalized by their standard deviation.

Two mechanisms contribute to making the beta ratio greater than one, which we interpret as managers slowing down flows as explained in Section 6.4. 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 is that patient flows trigger a greater increase in risk tolerance than do impatient flows: $d\tau_t/dNetFlows_t^P = k(1+\omega) > d\tau_t/dNetFlows_t^I = k(1-\omega)$. An alternative version of this second mechanism is that the arbitrageur, rather than investing patient flows more aggressively than impatient flows, "converts" impatient flows into patient flows (see Section 6.4). Specifically, assume that flows, whether they are patient or impatient, increase risk tolerance by the same amount. Assume further that the arbitrageur possesses a technology for turning impatient flows into patient flows, that is, in the data, for transforming high-frequency flows into low-frequency flows. In practice, this might be achieved by parking high-frequency flows into cash or the market and then gradually reallocating the funds in mispriced assets. Then, to the econometrician, high (respectively, low)-frequency flows appear to have a small (big) effect on anomaly returns since there are in fact few (respectively, many) such flows after the arbitrageur has converted them.

Prediction 3 (Impact of speed of decay on the regression R^2). *The R^2 from regressing the excess return on total flows is larger for assets that decay more slowly*.

Prediction 3 states that flows have more explanatory power for the returns of the slower-decaying asset. This is a consequence of this asset having a larger regression coefficient (which amplifies the impact of flows on returns), as well as a higher price (which dampens the impact of the dividend on returns). Note that no restriction on parameter values is required for the prediction to obtain.

We remark that, when 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 the regression coefficients' sensitivity to the speed of decay varies with the economy's three characteristics: fundamental risk, risk tolerance, and transaction costs. Given that flows trigger larger price adjustments for more overvalued assets, the effect of a characteristic will be determined by its differential effect on overvaluation (across assets' speed of decay), that is, by whether it widens or narrows the gap between the slow and fast asset's prices.

Prediction 4 (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 4 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 assets than for fast-decaying assets. This is because the arbitrageur's compensations for risk and for transaction costs both increase, pushing prices in opposite directions (see the discussion after Proposition 2), but the former increases more than the latter (by Assumption 3). On the one hand, 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. On the other hand, 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.[39]

Prediction 5 (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*): $\frac{d(\beta^S - \beta^F)}{d\tau_t} \leq 0$.[40]

Prediction 5 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, not on the *changes* that we associate with flows. We interpret the level of risk tolerance to represent 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, widens. As before, no restriction on parameter

[39] No restriction on parameter values is required for the prediction to obtain when our regressions are based on dollar, rather than relative, returns or on relative returns normalized by their standard deviation.

[40] 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.

values is required for this prediction to obtain provided that we use dollar (rather than relative) returns in the regressions.

Prediction 6 (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 6 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.[41]

Predictions 4 to 6 for the effect of frictions zero in on the arbitrageur, who is the only optimizing agent in the model. These predictions are likely to extend to mutual funds (noise traders) if they, too, are modeled as optimizing agents who are concerned with risk and transaction costs. Such an extension is consistent with the findings of Section 7, which documents that the intensity of frictions affects mutual funds' behavior.

This section demonstrates that our diverse empirical findings can be rationalized within a unified framework featuring frictions related to the limited availability of arbitrageur capital (modeled as finite risk tolerance) and transaction costs. The model focuses on our main empirical findings, namely, the relation between the various components of flows and returns. We have derived an array of predictions consistent with the data, provided the transaction cost is not too high relative to risk aversion (Assumption 1) and that the asset is not too mispriced (Assumptions 2–5 concerning f_0's magnitude).[42] 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 feature prominently in any such model.

9. Conclusion

We examine the frequency structure of fund flows, anomaly returns, and their relationship. Through spectral analysis, we show that hedge fund and mutual fund flows are major determinants of the persistence and cyclicality of anomaly returns. This is because capital supplied by hedge fund investors slowly correct

[41] Assumption 5 implies Assumption 2.

[42] Furthermore, because mispricing approaches zero over time, Assumptions 2–5 must all hold after some date.

mispricing, while capital supplied by mutual fund investors slowly exacerbate it. Specifically, both types of flows are more influential (respectively, 24 and 4 times more) over frequencies below one cycle per year, which we refer to as low frequencies. In other words, both types of funds behave, in aggregate, as low-pass filters, slowing down the effect of flows on mispricing. In contrast, passive fund flows have no effect on mispricing. As these numbers suggest, hedge funds are the most selective low-pass filter. Their flows are also the most influential of all fund types at low frequency. We show that hedge fund managers, rather than hedge fund investors, are responsible for this slow-moving effect, and market frictions explain much of their behavior. We propose a simple model that ties together our evidence and illustrates the frequency-dependent effects of capital on the dynamics of market efficiency.

Our study sheds light on the persistence and cyclicality of anomaly returns by linking them to capital flows. We introduce two capital flow factors and demonstrate their importance in explaining the dynamics of market efficiency, especially at low frequency. In so doing, our analysis deepens the understanding of the nature of "slow capital" and of its market efficiency implications. Furthermore, it reveals that funds have heterogeneous effects across frequencies, and that frictions play a central role in driving those effects. 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.

More generally, with many forces in finance exhibiting serial correlation and moving in cycles or waves (e.g., trading activity, volatility, liquidity, corporate cash flows, innovation), the frequency approach we take can be fruitfully employed to explain how such dynamic properties are linked across variables.

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Appendix. 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 $c_0^s = \frac{D}{rf}$ and $c^s = \frac{\Sigma[1/\tau-\lambda\Phi^s(\Phi^s+\rho)]}{\Phi^s+r^f}$ and thus confirms 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 beta ratio, $\frac{\beta^{S,P}}{\beta^{F,I}} = \frac{1+\omega}{1-\omega}\frac{\beta^S}{\beta^F}$, is positive.

Proof of Prediction 2

Differentiating the regression coefficient with respect to the speed of decay yields $\frac{d\beta^s}{d\Phi^s} = \frac{\partial\beta^s}{\partial\Phi^s}\Big|_{f_t^s} + \frac{\partial\beta^s}{\partial f_t^s}\Big|_{\Phi^s}\frac{df_t^s}{d\Phi^s}$. The first term captures the direct effect of speed on β^s; the second, captures the indirect effect via factor decay. We show that both terms are negative. Starting with the first term, we write $\frac{\partial\beta^s}{\partial\Phi^s}\Big|_{f_t^s} = \frac{\partial}{\partial\Phi^s}\left(\frac{k}{p_t^s}\frac{\Sigma}{\tau_t^2(\Phi^s+r^f)}f_t^s\right)\Big|_{f_t^s} = \frac{k\Sigma f_t^s}{\tau_t^2}\frac{\partial}{\partial\Phi^s}\left(\frac{1}{p_t^s(\Phi^s+r^f)}\right) = -\frac{k\Sigma f_t^s}{\tau_t^2}\frac{\frac{D}{rf}-\Sigma\lambda(2\Phi^s+\rho)f_t^s}{p_t^{s2}(\Phi^s+r^f)^2}$; here, we use 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, $\frac{\partial\beta^s}{\partial\Phi^s}\Big|_{f_t^s} \leq 0$ if $f_t^s \leq D/[r^f\Sigma\lambda(2\Phi^s+\rho)]$. This condition holds if $f_0^s < D/[r^f\Sigma\lambda(2\Phi^s+\rho)]$ since $f_t^s \leq f_0^s$. 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, one of which 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 beta ratio $\frac{\beta^{S,P}}{\beta^{F,I}} = \frac{1+\omega}{1-\omega}\frac{\beta^S}{\beta^F} > 1$.

Proof of Prediction 3

The R^2 from regressing the excess return on total flows is given by $R^{s2} = \frac{\beta^{s2}\mathrm{Var}(NetFlows_t)}{\mathrm{Var}(r_t^s)} = \frac{\beta^{s2}\Psi dt}{\beta^{s2}\Psi dt+\Sigma dt/p_t^{s2}}$, where we dropped the terms of order dt^2 in $\mathrm{Var}_t(r_t^s)$. Rearranging yields and substituting in the expression for β^S yields $R^{s2} = \left(1+\frac{\Sigma}{\Psi(\beta^s p_t^s)^2}\right)^{-1} = \left(1+\frac{1}{\Sigma\Psi}\left(\frac{\tau_t^2(\Phi^s+r^f)}{\mathrm{k}f_t^s}\right)^2\right)^{-1}$. Since f_t^s is positive and decreasing in Φ^s, R^{s2} is decreasing in Φ^s.

Proof of Prediction 4

Differentiating $\frac{\partial\beta^s}{\partial\Phi^s}$ with respect to Σ, we obtain the equality $\frac{\partial^2\beta^s}{\partial\Phi^s\partial\Sigma} = -\frac{kf_t^s D/r^f\{D/r^f(D/r^f+r^f)-2\Sigma f_t^s[\lambda(\Phi^s(\Phi^s+2r^f)+\rho r^f)+1/\tau_t]\}}{\tau_t^2 p_t^{s3}(\Phi^s+r^f)^3}$. This expression is negative if the numerator is positive, which Assumption 3 ensures since $f_t^s \le f_0^s$ 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 5

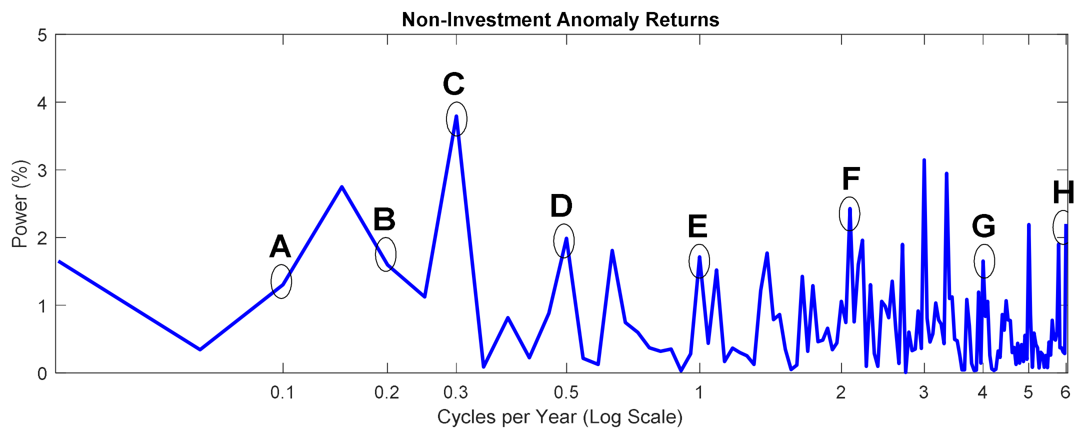
The expression $\frac{\partial\beta^s}{\partial\Phi^s} = -\frac{k\Sigma f_t^s}{\tau_t^2}\frac{D/r^f-\Sigma\lambda(2\Phi^s+\rho)f_t^s}{p_t^{s2}(\Phi^s+r^f)^2}$ (see the proof of Prediction 2) implies that $\frac{\partial\beta^s}{\partial\Phi^s}$ increases with τ_t if also $\tau_t p_t^s(\Phi^s+r^f)$ increases 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 $f_t^s \le f_0^s$. Finally, observe that the right-hand side of this inequality is decreasing in Φ^S. Hence, Assumption 4 suffices to show that $\frac{\partial^2\beta^s}{\partial\Phi^s\partial\tau_t} \ge 0$. 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: $\frac{d(\beta^S-\beta^F)}{d\tau_t} \le 0$. 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.

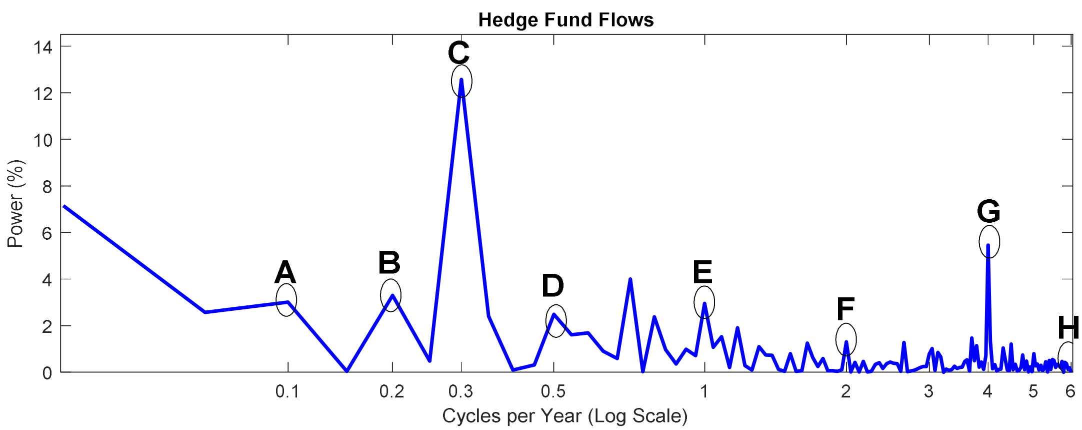
Proof of Prediction 6

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. 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 anomaly 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): 5-year overreaction/underreaction anomaly return cycle (Lee and Swaminathan 2000), 5-year El Niño weather related anomaly return cycle (Novy-Marx 2014), 4-year presidential cycle (Hirsch 1968; Allvine and O'Neill 1980), 4-year Mars-Vesta anomaly return 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 (Heston and Sadka 2008).

D. 0.5 c/y (2-year period): 2-year return seasonality (Heston and Sadka 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 2016, 2020).

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

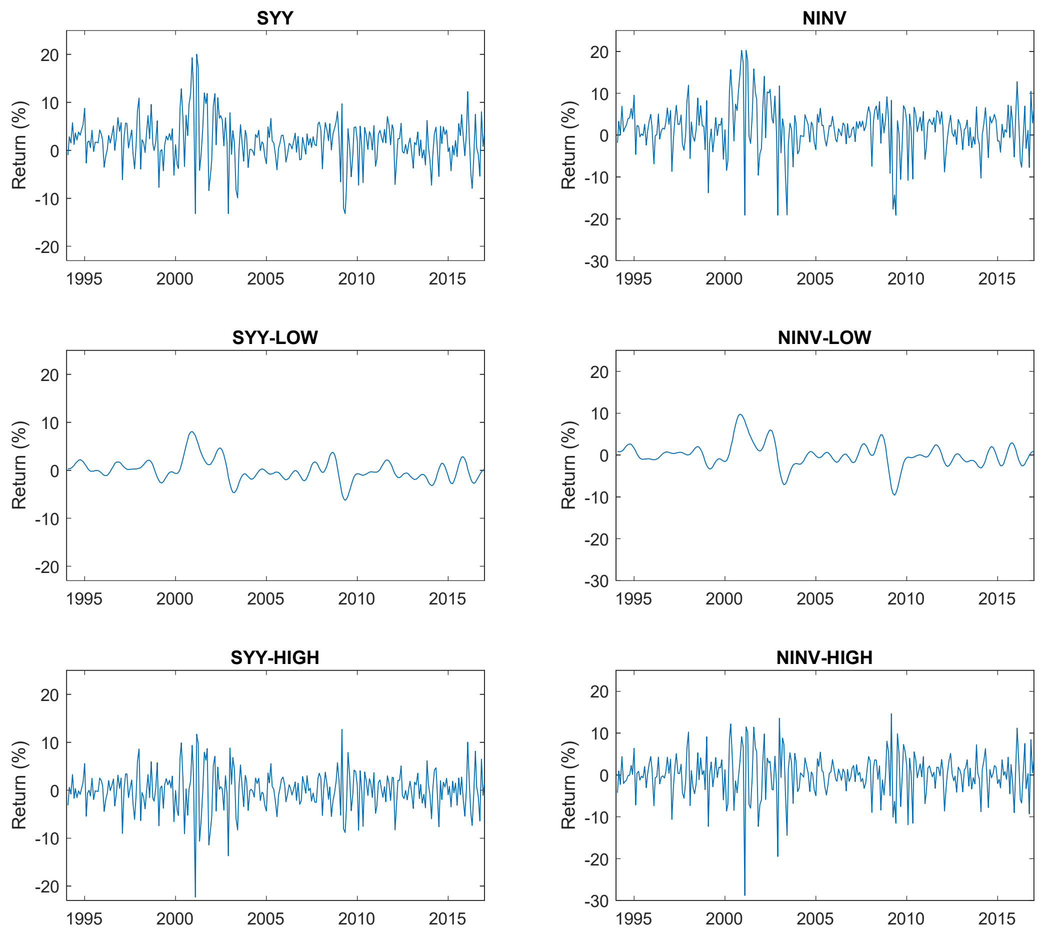
G. 4 c/y (quarterly period): Quarterly rebalancing/reporting period of funds; Earnings-announcement return cycle (Linnainmaa and Zhang 2019); Dividend return cycle (Hartzmark and Solomon 2013).

H. 6 c/y (2-month period): FOMC return cycle (Cieslak, Morse, and Vissing-Jorgensen 2019); Monthly payment cycle (Etula, Rinne, Suominen, and Vaittinen 2020).

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

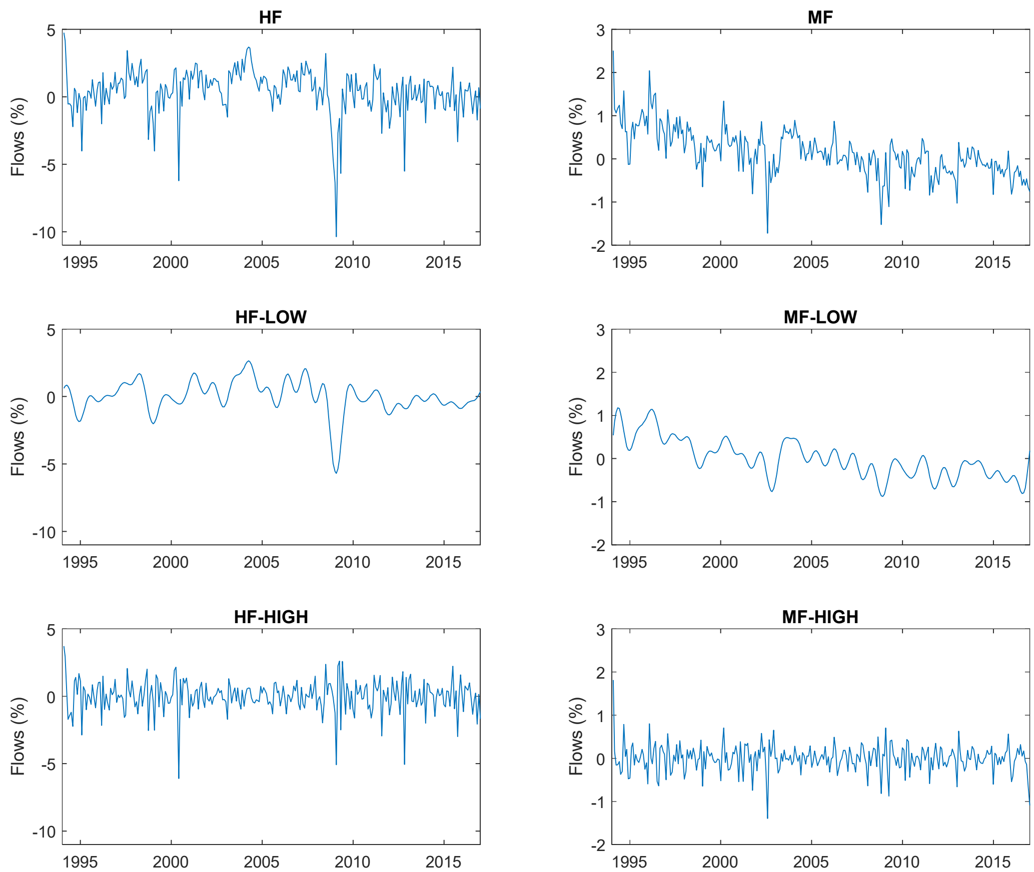


Figure 3: Relative Contribution of Frequencies to Total Variance

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.

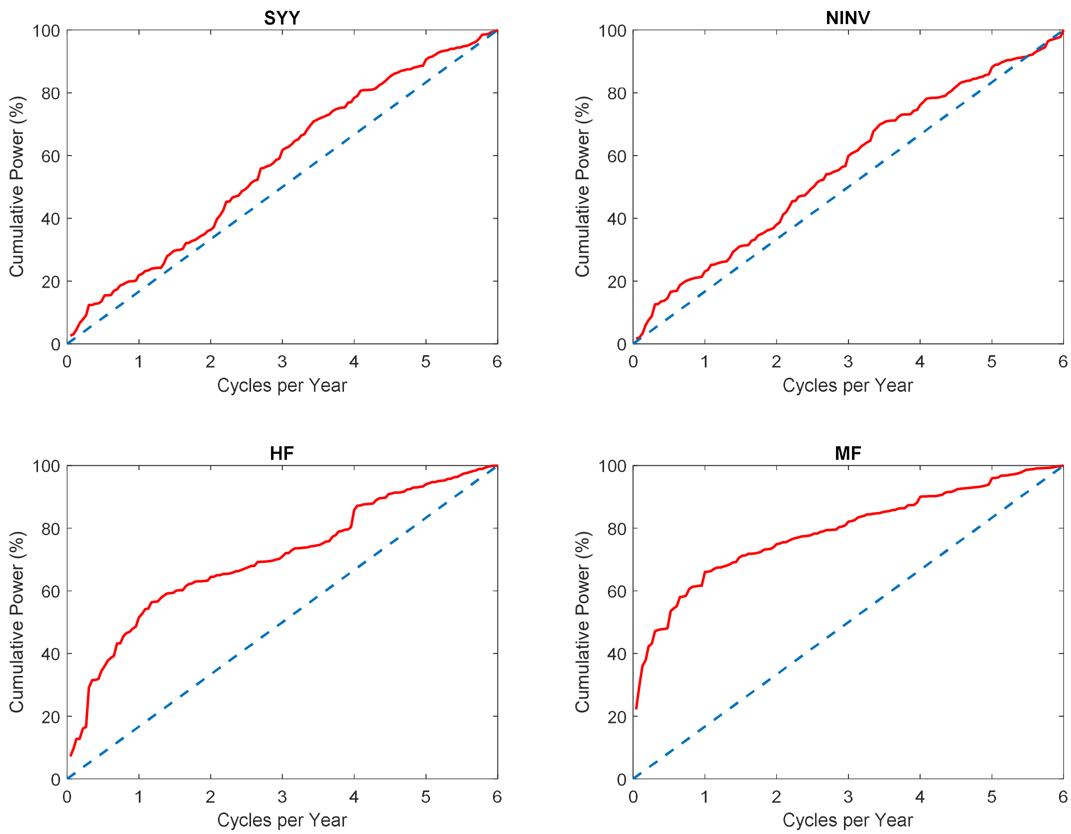
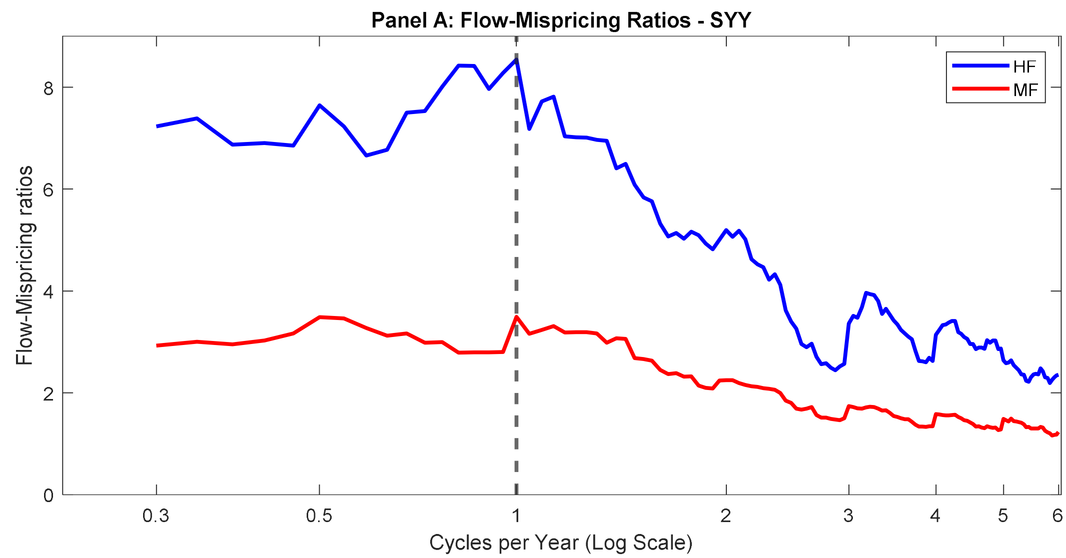
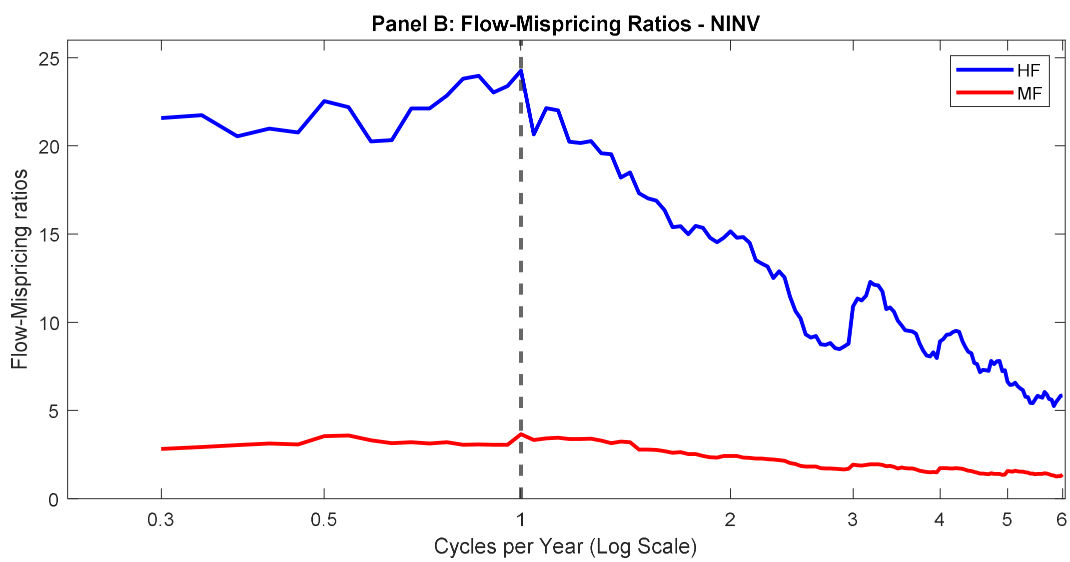
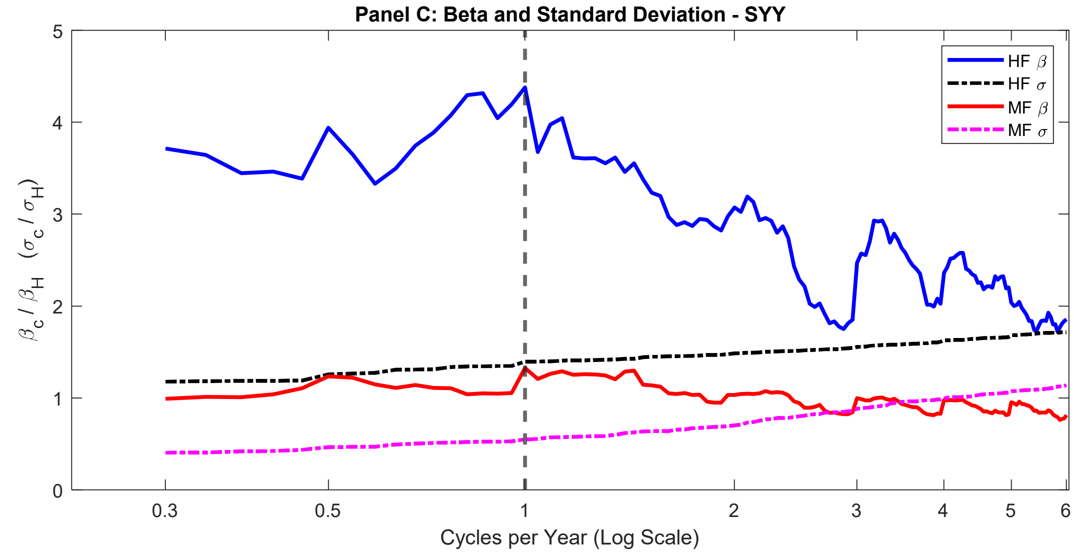


Figure 4: Economic Significance over Expanding Frequency Bands

The figure plots measures for economic significance of the effect of fund flows on mispricing across frequency bands. Panels A and B plot the cross-frequency flow-mispricing ratios (flow-mispricing ratio) over expanding frequency bands, and Panels C and D show the ratio of the beta (standard deviation) that corresponds to an expanding frequency band to the beta (standard deviation) that corresponds to the high-frequency band. The cross-frequency flow-mispricing ratio for an expanding window is calculated as follows. 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 and obtain β_c and σ_F^c. Then, we estimate the economic magnitude of the fund-flow effect over the frequency band (0, *c*] as $\beta_c \times \sigma_F^c / \sigma_R^c$, where σ_F^c and σ_R^c denote, respectively, the standard deviations of flows and mispricing over the frequency band (0, *c*]. Finally, we divide that estimate by the economic magnitude over the high-frequency band (1, 6] to obtain the cross-frequency flow-mispricing ratio. For Panels C and D, we divide β_c and σ_F^c by the estimates for the high-frequency band (1, 6] to calculate the ratios, β_c / β_H and σ_F^c / σ_F^H. 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.






Panel C: Beta and Standard Deviation - SYY
HF β
HF σ
MF β
MF σ
β_c / β_H (σ_c / σ_H)
Cycles per Year (Log Scale)

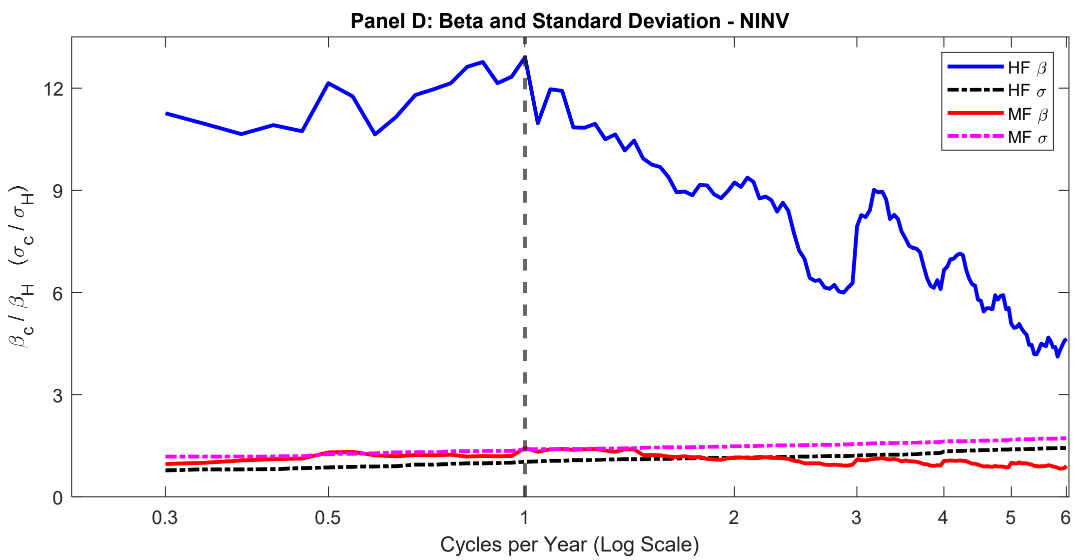

Panel D: Beta and Standard Deviation - NINV
HF β
HF σ
MF β
MF σ
β_c / β_H (σ_c / σ_H)
Cycles per Year (Log Scale)

Figure 5: Model of frictions and arbitrage

This figure illustrates the model presented in Section 8. The top panel displays the excess demands for the slow and fast assets, f_t^s for $s = \{S, F\}$, which evolves over time according to $df_t^s = -\Phi^s f_t^s dt$ starting from $f_0^S = f_0^F$, and where $\Phi^S < \Phi^F$ controls the speed of decay. The bottom panel displays the prices of the slow and fast assets, p_t^s, which equal $p_t^s = \frac{D}{r^f} + \frac{\Sigma[1/\tau - \lambda\Phi^s(\Phi^s+\rho)]}{\Phi^s + r^f} f_t^s$ in equilibrium. The panel also indicates the impact of an inflow of funds on the two assets' prices. The inflow, labelled "\$ Inflow", increases arbitrageurs' risk tolerance, and leads to a price correction (negative return) marked by an arrow labeled r_t^s. The correction is larger for the slow asset than for the fast asset. The parameters of the model are as follows: $\Phi^S = 0.1$, $\Phi^F = 0.2$, $f_0^S = f_0^F = 1, \rho = 0.01, D = 0.005, r^f = 0.05, \Sigma = 0.1$, $\lambda = 0.5, \tau = 0.4$ before the inflow and 1 after.

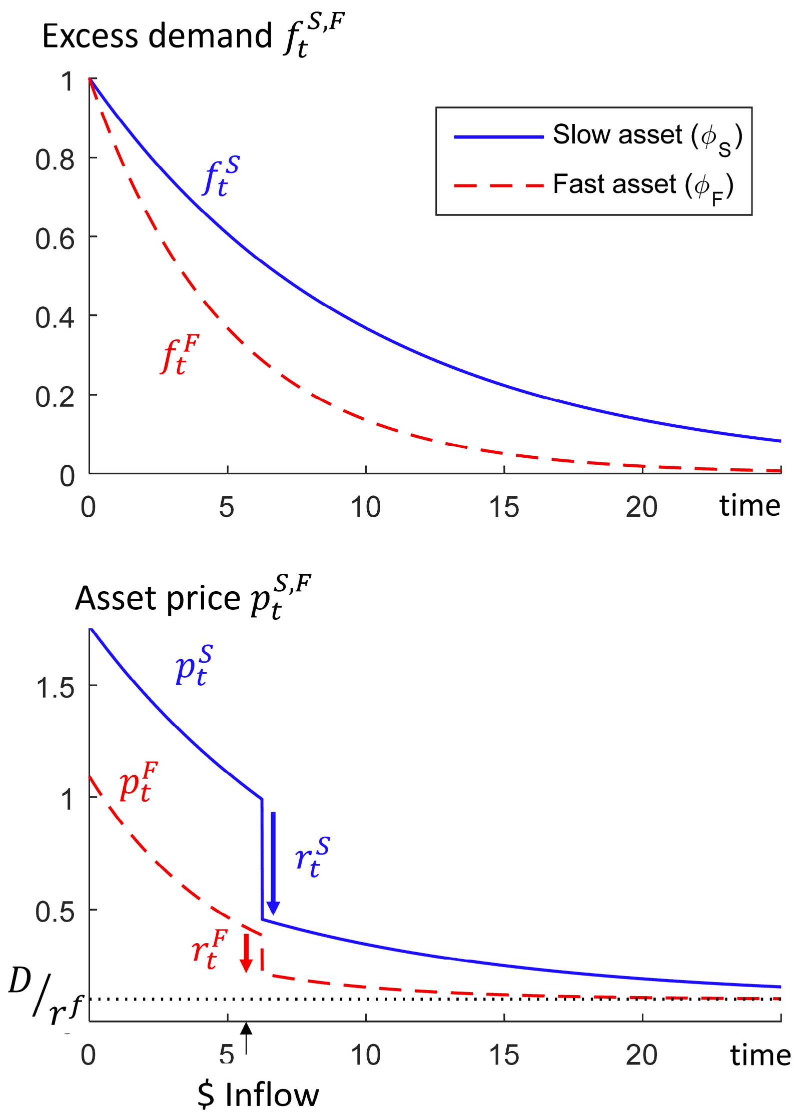


Table 1: Summary Statistics

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. 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	t Value	Std Dev	P10	Q1	Median	Q3	P90
SYY	276	1.88	[6.52]	4.80	-3.87	-0.39	1.81	4.34	7.24
SYY-LOW	276	0.00	[0.00]	2.24	-2.38	-1.27	-0.31	1.15	2.35
SYY-HIGH	276	0.00	[0.00]	4.25	-5.39	-2.06	0.25	2.36	4.82
NINV	276	1.56	[4.36]	5.97	-5.37	-0.96	2.11	4.51	7.46
NINV-LOW	276	0.00	[0.00]	2.87	-2.58	-1.37	-0.05	1.16	2.85
NINV-HIGH	276	0.00	[0.00]	5.23	-6.88	-2.45	0.38	3.01	5.54
MF (Active)	276	0.15	[4.58]	0.54	-0.46	-0.18	0.13	0.47	0.82
MF-LOW	276	0.00	[0.00]	0.44	-0.54	-0.32	-0.06	0.29	0.54
MF-HIGH	276	0.00	[0.00]	0.32	-0.39	-0.15	0.02	0.18	0.32
HF	276	0.42	[4.11]	1.69	-1.23	-0.24	0.60	1.42	2.00
HF-LOW	276	0.00	[0.00]	1.22	-1.10	-0.50	0.03	0.72	1.49
HF-HIGH	276	0.00	[0.00]	1.18	-1.34	-0.57	0.10	0.66	1.26
Passive	276	0.96	[14.97]	1.07	-0.22	0.26	0.81	1.57	2.34
Passive-LOW	276	0.00	[0.00]	0.72	-0.75	-0.50	-0.12	0.24	1.10
Passive-HIGH	276	0.00	[0.00]	0.79	-0.92	-0.46	0.02	0.44	0.85
MKTRF	276	0.63	[2.40]	4.37	-5.20	-1.97	1.24	3.47	6.05
Amihud	276	3.74	[25.44]	2.44	1.18	1.65	3.08	5.39	7.22
Turnover	276	15.49	[35.67]	7.21	6.92	8.56	15.01	20.38	24.45
HML	276	0.24	[1.31]	3.09	-2.99	-1.34	0.01	1.76	3.65
SMB	276	0.15	[0.73]	3.34	-3.74	-1.93	0.05	2.05	3.64

Panel B: Pairwise Correlations

Pearson (Upper right) / Spearman (Lower left)	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

Pearson (Upper right) / Spearman (Lower left)	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 variables 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 unrelated 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 returns as dependent variables, while Panels B and C report the results using the low- and high-frequency anomaly returns. The main independent variables are total flows for Panel B and the decomposed flows for Panel C. The first column of each model shows the coefficient of each variable and the corresponding *t* value, and the second column reports the semi-partial R^2 (PR^2) and the ratio of each PR^2 to the sum of all PR^2. The PR^2 is estimated from the difference between a R^2 of the full model that includes all explanatory variables and a R^2 of the reduced model that excludes the variable of interest. *t*-statistics are calculated based on Newey-West standard errors with 13 lags. The sample period is 1994–2016.

Panel A: Total Returns

Anomaly	(1)		(2)		(3)		(4)	
	SYY				NINV			
	Beta	PR^2 / (% of ttl PR^2)	Beta	PR2 / (% of ttl PR2)	Beta	PR2 / (% of ttl PR2)	Beta	PR2 / (% of ttl PR2)
MF	**-1.732**	**1.9%**			**-2.450**	**2.4%**		
	[-2.81]	**(8%)**			**[-3.05]**	**(15%)**		
HF	**0.338**	**1.1%**			**0.399**	**1.0%**		
	[2.61]	**(5%)**			**[2.45]**	**(6%)**		
MF-LOW			**-2.113**	**1.3%**			**-3.447**	**2.3%**
			[-2.12]	**(6%)**			**[-2.60]**	**(13%)**
MF-HIGH			**-1.695**	**1.1%**			**-2.167**	**1.2%**
			[-2.36]	**(5%)**			**[-2.10]**	**(6%)**
HF-LOW			**0.631**	**1.4%**			**0.990**	**2.2%**
			[3.08]	**(6%)**			**[3.13]**	**(12%)**
HF-HIGH			0.165	0.2%			0.068	0.0%
			[0.99]	(1%)			[0.31]	(0%)
MKTRF	-0.416	11.9%	-0.414	11.7%	-0.384	6.6%	-0.383	6.5%
	[-4.19]	(52%)	[-4.20]	(51%)	[-3.04]	(40%)	[-3.06]	(35%)
Amihud	0.258	0.8%	0.361	1.2%	0.202	0.3%	0.418	1.0%
	[1.80]	(4%)	[2.54]	(5%)	[0.87]	(2%)	[2.03]	(6%)
Turnover	-0.105	1.0%	-0.083	0.6%	-0.158	1.5%	-0.120	0.8%
	[-1.83]	(5%)	[-1.45]	(2%)	[-1.63]	(9%)	[-1.39]	(4%)
HML	0.248	2.2%	0.234	1.9%	0.217	1.1%	0.194	0.9%
	[1.37]	(10%)	[1.31]	(8%)	[0.93]	(7%)	[0.84]	(5%)
SMB	-0.305	3.9%	-0.305	3.9%	-0.362	3.5%	-0.362	3.5%
	[-4.86]	(17%)	[-5.01]	(17%)	[-4.70]	(21%)	[-4.90]	(19%)
N	276		276		276		276	
R^2	38.9%	(100%)	39.3%	(100%)	27.2%	(100%)	28.4%	(100%)

Panel B: Decomposed Return – Total Flows

Anomaly	(1)		(2)		(3)		(4)	
	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)
MF	**-0.808**	**1.9%**	**-1.120**	**2.2%**	**-0.923**	**0.7%**	**-1.329**	**0.9%**
	[-2.16]	**(12%)**	**[-2.44]**	**(15%)**	**[-1.66]**	**(4%)**	**[-1.80]**	**(9%)**
HF	**0.227**	**2.3%**	**0.319**	**2.8%**	0.111	0.2%	0.080	0.1%
	[2.36]	**(15%)**	**[2.39]**	**(19%)**	[0.77]	(1%)	[0.45]	(1%)
MKTRF	-0.111	3.8%	-0.146	4.1%	-0.305	8.2%	-0.238	3.3%
	[-2.91]	(25%)	[-2.96]	(29%)	[-3.88]	(50%)	[-2.44]	(32%)
Amihud	0.268	4.0%	0.211	1.5%	-0.010	0.0%	-0.009	0.0%
	[1.64]	(26%)	[0.94]	(11%)	[-0.08]	(0%)	[-0.06]	(0%)
Turnover	-0.053	1.2%	-0.081	1.8%	-0.052	0.3%	-0.076	0.5%
	[-0.80]	(8%)	[-0.84]	(12%)	[-1.29]	(2%)	[-1.56]	(4%)
HML	0.106	1.9%	0.132	1.8%	0.142	0.9%	0.085	0.2%
	[1.54]	(12%)	[1.53]	(12%)	[1.09]	(6%)	[0.49]	(2%)
SMB	0.032	0.2%	0.032	0.1%	-0.338	6.1%	-0.394	5.4%
	[0.63]	(1%)	[0.51]	(1%)	[-6.25]	(37%)	[-5.43]	(52%)
N	276		276		276		276	
R^2	22.7%	(100%)	19.7%	(100%)	27.6%	(100%)	17.0%	(100%)

Panel C: Decomposed Returns – Decomposed Flows

Anomaly	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)
MF-FREQ	**-2.770**	**10.5%**	**-3.825**	**12.2%**	**-2.071**	**2.1%**	**-2.675**	**2.3%**
	[-3.09]	**(27%)**	**[-3.56]**	**(31%)**	**[-3.00]**	**(12%)**	**[-2.73]**	**(20%)**
HF-FREQ	**0.796**	**9.9%**	**1.107**	**11.8%**	0.180	0.2%	0.085	0.0%
	[3.56]	**(26%)**	**[3.71]**	**(30%)**	[1.19]	(1%)	[0.42]	(0%)
MKTRF	-0.115	4.2%	-0.153	4.5%	-0.299	7.8%	-0.230	3.0%
	[-3.33]	(11%)	[-3.40]	(11%)	[-3.65]	(45%)	[-2.29]	(27%)
Amihud	0.517	11.2%	0.554	7.9%	-0.156	0.3%	-0.137	0.1%
	[2.99]	(29%)	[2.61]	(20%)	[-1.14]	(2%)	[-0.80]	(1%)
Turnover	-0.049	0.9%	-0.075	1.3%	-0.034	0.1%	-0.045	0.1%
	[-0.78]	(2%)	[-0.85]	(3%)	[-0.71]	(1%)	[-0.73]	(1%)
HML	0.106	1.8%	0.131	1.7%	0.128	0.7%	0.063	0.1%
	[1.88]	(5%)	[1.88]	(4%)	[0.92]	(4%)	[0.34]	(1%)
SMB	0.031	0.2%	0.030	0.1%	-0.336	6.0%	-0.392	5.4%
	[0.73]	(0%)	[0.57]	(0%)	[-6.34]	(34%)	[-5.49]	(48%)
N	276		276		276		276	
R^2	34.3%	(100%)	33.2%	(100%)	29.4%	(100%)	18.5%	(100%)

Table 3: Economic Significance across Frequency Bands and Fund Types

The table estimates the economic significance of the effect of low- and high-frequency flows on returns at their respective frequency. Panel A summarizes the semi-partial R^2s (PR^2) of low- and high-frequency flows, while Panels B and C calculate cross-frequency flow-mispricing ratios for SYY and NINV anomalies. The PR^2 is estimated from the difference between a R^2 of the full model that includes all explanatory variables and a R^2 of the reduced model that excludes the variable of interest. The economic magnitude of the fund-flow effect at frequency band *B=(L, H)* is calculated as $\beta_B \times \sigma_F^B / \sigma_R^B$, where σ_F^B and σ_R^B denote, respectively, the standard deviations of flows and mispricing at frequency band *B*, and β_B is the coefficient estimate from regressing mispricing on flows, at frequency band *B*, as reported in Table 2. Then, the cross-frequency flow-mispricing ratio (flow-mispricing ratio) 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: Semi-Partial R^2 of Low- and High-Frequencies

	(1)	(2)	(3)	(4)	(5)	(6)
	SYY			NINV		
Flows	FREQ=LOW	FREQ=HIGH	LOW/HIGH	FREQ=LOW	FREQ=HIGH	LOW/HIGH
MF-FREQ	10.5%	2.1%	**5.05**	12.2%	2.3%	**5.36**
HF-FREQ	9.9%	0.2%	**40.41**	11.8%	0.0%	**324.62**
Ratio HF/MF	0.95	0.12	**8.01**	0.96	0.02	**60.62**

Panel B: Cross-Frequency Flow-Mispricing Ratio – SYY Anomaly

Fund Type	Frequency	(1)	(2)	(3)	(4)	(5)	(6)
		Beta-FREQ	STD(Flows)-FREQ	Effect of One σ_F^B on Ret	STD(Ret)-FREQ	Econ. Magnitude (Flow-Misp. Ratio)	Manager vs. Investor
		β_B	σ_F^B	$\beta_B \times \sigma_F^B$	σ_R^B	$\beta_B \times \sigma_F^B / \sigma_R^B$	(1)/(2)
MF	FREQ=LOW	-2.770	0.4%	**-1.2%**	2.2%	**-54.6%**	
	FREQ=HIGH	-2.071	0.3%	**-0.7%**	4.2%	**-15.5%**	
	LOW / HIGH	**1.34**	**1.39**	**1.87**		**3.53**	**0.96**
HF	FREQ=LOW	0.796	1.2%	**1.0%**	2.2%	**43.1%**	
	FREQ=HIGH	0.180	1.2%	0.2%	4.2%	5.0%	
	LOW / HIGH	**4.42**	**1.03**	**4.56**		**8.62**	**4.28**
Ratio HF/MF		**3.30**	**0.74**	**2.44**		**2.44**	**4.47**

Panel C: Cross-Frequency Flow-Mispricing Ratio – NINV Anomaly

Fund Type	Frequency	(1)	(2)	(3)	(4)	(5)	(6)
		Beta-FREQ	STD(Flows)-FREQ	Effect of One σ_F^B on Ret	STD(Ret)-FREQ	Econ. Magnitude (Flow-Misp. Ratio)	Manager vs. Investor
		β_B	σ_F^B	$\beta_B \times \sigma_F^B$	σ_R^B	$\beta_B \times \sigma_F^B / \sigma_R^B$	(1)/(2)
MF	FREQ=LOW	-3.825	0.4%	**-1.7%**	2.9%	**-58.9%**	
	FREQ=HIGH	-2.675	0.3%	**-0.8%**	5.2%	**-16.2%**	
	LOW / HIGH	**1.43**	**1.39**	**1.99**		**3.63**	**1.03**
HF	FREQ=LOW	1.107	1.2%	**1.3%**	2.9%	**46.9%**	
	FREQ=HIGH	0.085	1.2%	0.1%	5.2%	1.9%	
	LOW / HIGH	**12.98**	**1.03**	**13.39**		**24.41**	**12.59**
Ratio HF/MF		**9.08**	**0.74**	**6.72**		**6.72**	**12.28**

Table 4: 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 the low- and high-frequency components of value weighted market return (MKT) and returns to S&P500 index (S&P) as dependent variables. Panel B calculates cross-frequency flow-return ratios for both MKT and S&P. The economic magnitude of the fund-flow effect at frequency band *B=(L, H)* is calculated as $\beta_B \times \sigma_F^B / \sigma_R^B$, where σ_F^B and σ_R^B denote, respectively, the standard deviations of flows and market returns at frequency band *B*, and β_B is the coefficient estimate from regressing market returns on flows, at frequency band *B*, as reported in Panel A. Then, the cross-frequency flow-return ratio (flow-return ratio) is defined as the ratio of the economic magnitude of the fund-flow effect at low frequency to its magnitude at high frequency. The control variables include the aggregate Amihud measure, the aggregate turnover, HML and SMB. *t*-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2016.

Panel A: Regressions

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Variables	MKT-LOW		S&P-LOW		MKT-HIGH		S&P-HIGH	
Passive-FREQ	0.029	[0.05]	0.074	[0.12]	**1.313**	**[3.97]**	**1.300**	**[3.90]**
Controls	Yes		Yes		Yes		Yes	
N	276		276		276		276	
R^2	9.2%		10.1%		8.8%		12.9%	

Panel B: Economic Significance

Returns	Frequency	(1) Beta-FREQ	(2) STD(Flows)-FREQ	(3) Effect of One σ_F^B on Ret	(4) STD(Ret)-FREQ	(5) Econ. Magnitude (Flow-Ret. Ratio)	(6) Manager vs. Investor
		β_B	σ_F^B	$\beta_B \times \sigma_F^B$	σ_R^B	$\beta_B \times \sigma_F^B / \sigma_R^B$	(1)/(2)
MKT	FREQ=LOW	0.029	0.7%	0.0%	1.9%	1.1%	
	FREQ=HIGH	1.300	0.8%	**1.0%**	3.9%	26.1%	
	LOW / HIGH	**0.02**	**0.92**	**0.02**		**0.04**	**0.02**
S&P	FREQ=LOW	0.074	0.7%	0.1%	1.9%	2.8%	
	FREQ=HIGH	1.313	0.8%	**1.0%**	3.8%	27.3%	
	LOW / HIGH	**0.06**	**0.92**	**0.05**		**0.10**	**0.06**

Table 5: 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 variables are the low- and high-frequency components of long (decile 10) and short (decile 1) returns in month *t* on two composite anomalies, SYY and NINV. 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 shows 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. The control variables include MKTRF, aggregate Amihud measure, aggregate turnover, HML and SMB. *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)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF-FREQ	**2.553**	**[4.13]**	**2.399**	**[4.26]**	**1.962**	**[5.44]**	**1.578**	**[4.06]**
HF-FREQ	-0.102	[-0.48]	-0.126	[-0.59]	-0.101	[-1.35]	-0.044	[-0.51]
Controls	Yes		Yes		Yes		Yes	
N	276		276		276		276	
R^2	35.6%		35.2%		80.4%		80.4%	

Panel B: Short-Leg Returns

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
MF-FREQ	**5.323**	**[4.69]**	**6.224**	**[4.53]**	**4.033**	**[5.05]**	**4.253**	**[4.35]**
HF-FREQ	**-0.898**	**[-2.64]**	**-1.233**	**[-3.24]**	-0.281	[-1.77]	-0.129	[-0.67]
Controls	Yes		Yes		Yes		Yes	
N	276		276		276		276	
R^2	31.5%		30.9%		68.1%		60.8%	

Table 6: Aggregate Risk

The table examines whether the flow-return relation is affected by aggregate risk. The dependent variables are the low- and high-frequency components of NINV anomaly. The main independent variables are the total fund flows, 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. The control variables include MKTRF, aggregate Amihud measure, aggregate turnover, HML and SMB. *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)
	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH
MF	-0.867	-1.567	-1.152	-1.430	-0.528	-1.135	-0.766	-1.541
	[-1.69]	[-1.92]	[-1.40]	[-1.80]	[-0.70]	[-1.46]	[-0.89]	[-1.42]
MF × D	0.825	1.663	0.315	-0.168	0.054	-0.887	-0.398	-0.132
	[0.54]	[0.79]	[0.25]	[-0.09]	[0.04]	[-0.48]	[-0.30]	[-0.06]
HF	0.087	0.181	-0.108	0.205	-0.148	0.170	-0.168	0.481
	[0.54]	[0.87]	[-0.56]	[0.61]	[-0.79]	[0.66]	[-1.31]	[1.40]
HF × D	**0.708**	-0.371	**0.630**	-0.179	**0.719**	-0.143	**0.799**	-0.512
	[3.58]	[-1.48]	**[2.62]**	[-0.42]	**[3.29]**	[-0.46]	**[3.62]**	[-1.17]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	254	254
Adj R^2	20.7%	14.5%	18.7%	14.0%	21.2%	14.1%	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)
	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH
MF-FREQ	-2.989	-3.283	-3.725	-2.165	-2.325	-2.012	-3.030	-2.321
	[-2.94]	[-3.10]	[-2.58]	[-2.16]	[-1.75]	[-1.81]	[-1.86]	[-1.35]
MF-FREQ × D	**-16.145**	**4.558**	-0.546	-1.237	-1.687	-1.415	-2.183	-0.936
	[-12.30]	**[2.05]**	[-0.24]	[-0.47]	[-0.60]	[-0.53]	[-0.78]	[-0.26]
HF-FREQ	0.684	0.170	0.188	0.230	0.142	0.180	0.154	0.614
	[1.64]	[0.74]	[0.57]	[0.50]	[0.37]	[0.57]	[0.44]	[1.40]
HF-FREQ × D	**2.252**	0.026	**1.475**	-0.285	**1.466**	-0.215	**1.470**	-0.717
	[5.53]	[0.06]	**[4.18]**	[-0.42]	**[3.53]**	[-0.49]	**[3.65]**	[-1.04]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	254	254
Adj R^2	40.7%	15.3%	36.6%	14.3%	34.1%	14.3%	36.8%	13.4%

Table 7: 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 the low- and high-frequency components of NINV anomaly. The main independent variables are the total fund flows, 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)
	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH
MF	-1.525	-0.686	-1.422	-1.635
	[-2.82]	[-0.62]	[-1.52]	[-2.18]
MF × D	1.125	-1.508	0.430	0.235
	[1.21]	[-0.93]	[0.34]	[0.13]
HF	-0.207	0.316	0.031	0.107
	[-1.34]	[0.96]	[0.13]	[0.31]
HF × D	**0.858**	-0.404	**0.486**	0.053
	[4.12]	[-0.98]	**[1.65]**	[0.12]
Controls	Yes	Yes	Yes	Yes
N	276	276	254	254
Adj R^2	23.4%	14.8%	19.9%	13.1%

Panel B: Decomposed Flows

	TED Spread		Risk Aversion (BEX)	
	(1)	(2)	(3)	(4)
	FREQ = LOW	FREQ = HIGH	FREQ = LOW	FREQ = HIGH
MF-FREQ	-4.098	-1.749	-4.533	-2.541
	[-3.09]	[-1.09]	[-2.79]	[-2.18]
MF-FREQ × D	0.909	-2.163	-0.120	-0.321
	[0.38]	[-0.74]	[-0.05]	[-0.12]
HF-FREQ	0.351	0.387	0.415	0.350
	[0.81]	[0.94]	[1.00]	[0.84]
HF-FREQ × D	**1.184**	-0.562	**1.255**	-0.256
	[2.34]	[-1.02]	**[3.08]**	[-0.40]
Controls	Yes	Yes	Yes	Yes
N	276	276	254	254
Adj R^2	37.7%	15.2%	39.7%	13.0%

Table 8: 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 the low- and high-frequency components of NINV anomaly. 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

	(1)		(2)	
	NINV-LOW		NINV-HIGH	
MF	-1.196	[-2.56]	-1.310	[-1.76]
HFUnLev	**0.340**	**[3.36]**	-0.102	[-0.40]
HFLev	0.074	[0.64]	0.168	[0.83]
Controls	Yes		Yes	
N	276		276	
Adj R^2	18.9%		14.6%	

Panel B: Decomposed Flows

	(1)		(2)	
	FREQ = LOW		FREQ = HIGH	
MF-FREQ	-3.860	[-3.66]	-2.700	[-2.75]
HFUnLev-FREQ	**1.328**	**[3.26]**	-0.167	[-0.52]
HFLev-FREQ	-0.115	[-0.23]	0.235	[0.96]
Controls	Yes		Yes	
N	276		276	
Adj R^2	36.2%		15.3%	

Table 9: 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 the low- and high-frequency components of NINV anomaly. The main independent variables are the total fund flows, 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 obtain the detrended illiquidity measures from the residuals of regressions of the illiquidity measures on a linear deterministic trend. Finally, we sort the detrended illiquidity measures into quintiles and 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)
	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH
MF	-1.446	-0.254	-0.867	-1.849	-1.455	-1.981	-0.891	-1.566
	[-2.22]	[-0.21]	[-1.05]	[-2.12]	[-1.65]	[-2.22]	[-0.97]	[-1.62]
MF × ILLIQ	0.955	-1.932	-0.304	0.879	0.997	-0.059	0.088	0.351
	[0.91]	[-1.10]	[-0.29]	[0.60]	[0.88]	[-0.03]	[0.09]	[0.20]
HF	-0.065	0.134	0.000	0.268	-0.157	0.450	-0.194	0.182
	[-0.25]	[0.40]	[0.00]	[0.82]	[-0.93]	[1.41]	[-0.80]	[0.75]
HF × ILLIQ	**0.576**	-0.080	**0.558**	-0.327	**0.728**	-0.448	**0.763**	-0.150
	[1.82]	[-0.21]	**[2.74]**	[-0.75]	**[2.71]**	[-1.02]	**[2.82]**	[-0.52]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	228	228	276	276
Adj R^2	18.9%	14.3%	18.4%	14.1%	19.9%	14.0%	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)
	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH
MF-FREQ	-4.118	-1.166	-3.295	-4.285	-3.164	-1.313	-2.551	-3.284
	[-3.45]	[-0.56]	[-2.66]	[-3.69]	[-2.20]	[-0.74]	[-1.63]	[-1.80]
MF-FREQ × ILLIQ	0.847	-2.551	-0.851	2.250	-0.724	-2.912	-1.602	0.952
	[0.64]	[-0.78]	[-0.59]	[0.90]	[-0.29]	[-0.82]	[-0.74]	[0.31]
HF-FREQ	0.349	-0.063	0.739	0.755	0.148	0.488	0.235	0.076
	[0.86]	[-0.17]	[2.31]	[2.30]	[0.42]	[1.20]	[0.47]	[0.25]
HF-FREQ × ILLIQ	**1.156**	0.245	**0.591**	-1.226	**1.371**	-0.447	**1.243**	0.051
	[2.58]	[0.48]	**[2.01]**	[-2.55]	**[2.98]**	[-0.79]	**[2.52]**	[0.12]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	228	228	276	276
Adj R^2	34.1%	14.7%	31.3%	15.6%	34.1%	14.5%	32.4%	14.3%

Table 10: 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 variables are the high- and low-frequency components of the long-minus-short returns of NINV anomaly. 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

	(1)		(2)	
	NINV-LOW		NINV-HIGH	
MF	-1.433	[-2.99]	-1.276	[-1.65]
HFBelow	-0.060	[-0.65]	0.105	[0.47]
HFAbove	**0.392**	**[2.94]**	-0.024	[-0.17]
Controls	Yes		Yes	
N	276		276	
Adj R^2	20.2%		14.5%	

Panel B: Decomposed Flows

	(1)		(2)	
	FREQ = LOW		FREQ = HIGH	
MF-FREQ	-4.168	[-4.22]	-2.749	[-2.65]
HFBelow-FREQ	-0.464	[-2.13]	0.028	[0.10]
HFAbove-FREQ	**1.647**	**[4.53]**	0.083	[0.53]
Controls	Yes		Yes	
N	276		276	
Adj R^2	44.1%		15.3%	

Table 11: 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 the high- and low-components of NINV anomaly. The main independent variables are the total fund flows, 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)
	NINV-LOW	NINV-HIGH	NINV-LOW	NINV-HIGH
MF	-0.786	-1.777	-0.814	-1.068
	[-1.58]	[-2.11]	[-1.99]	[-1.46]
MF × SHOCK	-0.747	3.398	**6.145**	**-21.277**
	[-0.50]	[1.50]	**[6.16]**	**[-6.37]**
HF	0.105	0.215	0.211	0.160
	[0.60]	[0.99]	[1.55]	[0.96]
HF × SHOCK	**0.625**	-0.394	**-2.706**	0.073
	[2.88]	[-1.60]	**[-8.24]**	[0.07]
Controls	Yes	Yes	Yes	Yes
N	276	276	276	276
Adj R^2	19.6%	14.9%	36.0%	20.3%

Panel B: Decomposed Flows

	Financial Crisis		Decimalization	
	(1)	(2)	(3)	(4)
	FREQ = LOW	FREQ = HIGH	FREQ = LOW	FREQ = HIGH
MF-FREQ	-2.900	-3.456	-2.963	-2.069
	[-2.96]	[-3.26]	[-3.24]	[-2.10]
MF-FREQ × SHOCK	**-17.642**	4.988	**9.849**	**-33.607**
	[-12.12]	[1.46]	**[3.23]**	**[-5.62]**
HF-FREQ	0.769	0.263	0.891	0.149
	[1.83]	[1.16]	[2.89]	[0.74]
HF-FREQ × SHOCK	**2.023**	-0.430	**-2.853**	**5.050**
	[5.46]	[-0.64]	**[-6.90]**	**[2.66]**
Controls	Yes	Yes	Yes	Yes
N	276	276	276	276
Adj R^2	44.7%	15.7%	43.6%	21.7%

Table A1. Robustness to Various Factor Models

This table re-estimates the main results of Table 2 under diverse factor structures. The dependent variables are the low- and high-frequency components of the long-minus-short returns at month *t* of two composite anomalies, SYY and NINV. The main independent variables are the low- and high-frequency fund flows at month *t*. Panel A uses the factors of Daniel, Hirshleifer, and Sun (2020, DHS factors). Panel B uses the factors from Fama and French (2015, FF5 factors). Panel C reports the results using the factors in Stambaugh and Yuan (2017, SY). Panel D reports the factor structure of Hou, Xue, and Zhang (2015, HXZ factors). The first column of each model shows the coefficients and the corresponding *t* values, and the second column report the semi-partial R^2 (PR^2). The PR^2 is estimated from the difference between a R^2 of the full model that includes all explanatory variables and a R^2 of the reduced model that excludes the variable of interest. *t*-statistics are calculated based on Newey-West standard errors with 13 lags. The sample period is 1994–2016.

Panel A: DHS Factors

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2	Beta	PR^2	Beta	PR^2	Beta	PR^2
MF-FREQ	**-2.631**	**9.5%**	**-3.674**	**11.3%**	-1.949	1.8%	**-2.477**	**2.0%**
	[-3.12]		**[-3.57]**		[-2.80]		**[-2.51]**	
HF-FREQ	**0.815**	**10.6%**	**1.136**	**12.6%**	0.138	0.1%	0.039	0.0%
	[3.37]		**[3.60]**		[1.00]		[0.20]	
MKTRF	-0.053	0.7%	-0.089	1.1%	-0.053	0.2%	0.055	0.1%
	[-1.85]		[-2.36]		[-0.78]		[0.59]	
Amihud	0.506	10.8%	0.542	7.6%	-0.116	0.2%	-0.087	0.1%
	[3.06]		[2.64]		[-0.81]		[-0.51]	
Turnover	-0.037	0.5%	-0.064	0.9%	0.011	0.0%	0.006	0.0%
	[-0.59]		[-0.72]		[0.26]		[0.11]	
Short(PEAD)	0.117	1.1%	0.114	0.6%	0.464	4.8%	0.522	4.0%
	[2.33]		[1.86]		[4.86]		[4.30]	
Long(FIN)	0.111	3.3%	0.120	2.4%	0.497	18.8%	0.562	15.8%
	[3.52]		[3.04]		[6.15]		[5.65]	
N	276		276		276		276	
R^2	36.2%		34.2%		41.1%		29.1%	

Panel B: FF5 Factors

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2	Beta	PR^2	Beta	PR^2	Beta	PR^2
MF-FREQ	**-2.688**	**9.8%**	**-3.743**	**11.6%**	**-2.527**	**3.1%**	**-3.243**	**3.3%**
	[-3.23]		**[-3.74]**		**[-3.54]**		**[-3.13]**	
HF-FREQ	**0.744**	**8.6%**	**1.046**	**10.4%**	0.209	0.3%	0.144	0.1%
	[3.43]		**[3.55]**		[1.22]		[0.75]	
MKTRF	-0.063	0.9%	-0.099	1.3%	-0.037	0.1%	0.119	0.6%
	[-1.81]		[-2.18]		[-0.63]		[1.47]	
Amihud	0.477	9.2%	0.513	6.5%	-0.356	1.4%	-0.403	1.2%
	[2.85]		[2.48]		[-2.47]		[-2.31]	
Turnover	-0.057	1.2%	-0.085	1.6%	-0.064	0.4%	-0.089	0.5%
	[-0.91]		[-0.96]		[-1.62]		[-1.79]	
SMB	0.100	1.5%	0.116	1.2%	-0.117	0.6%	-0.044	0.1%
	[2.04]		[1.91]		[-1.80]		[-0.42]	
HML	0.044	0.2%	0.083	0.4%	-0.333	2.6%	-0.488	3.6%
	[0.79]		[1.13]		[-3.72]		[-3.15]	
RMW	0.206	3.1%	0.244	2.7%	0.758	11.7%	1.131	17.2%
	[5.97]		[5.51]		[5.46]		[5.77]	
CMA	0.030	0.0%	-0.021	0.0%	0.629	4.9%	0.632	3.2%
	[0.42]		[-0.23]		[3.35]		[2.20]	
N	276		276		276		276	
R^2	37.4%		36.0%		44.5%		37.4%	

Panel C: SY Factors

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2	Beta	PR^2	Beta	PR^2	Beta	PR^2
MF-FREQ	**-2.444**	**8.0%**	**-3.455**	**9.8%**	**-1.568**	**1.2%**	**-2.275**	**1.6%**
	[-2.82]		**[-3.33]**		**[-2.28]**		**[-2.50]**	
HF-FREQ	**0.794**	**10.0%**	**1.112**	**12.0%**	0.091	0.1%	-0.052	0.0%
	[3.39]		**[3.66]**		[0.79]		[-0.28]	
MKTRF	-0.037	0.3%	-0.067	0.6%	0.075	0.3%	0.229	2.1%
	[-1.39]		[-2.11]		[1.33]		[2.87]	
Amihud	0.482	9.7%	0.515	6.8%	-0.253	0.7%	-0.224	0.4%
	[2.84]		[2.46]		[-1.86]		[-1.37]	
Turnover	-0.033	0.4%	-0.058	0.8%	0.032	0.1%	0.034	0.1%
	[-0.57]		[-0.70]		[0.57]		[0.47]	
SMB	0.047	0.4%	0.044	0.2%	-0.242	3.0%	-0.301	3.0%
	[1.37]		[0.96]		[-3.28]		[-2.66]	
MGMT	0.162	3.1%	0.176	2.2%	0.470	7.3%	0.397	3.4%
	[3.20]		[2.75]		[7.19]		[4.10]	
PERF	0.091	2.7%	0.103	2.1%	0.525	24.6%	0.711	29.7%
	[2.76]		[2.53]		[13.29]		[12.76]	
N	276		276		276		276	
R^2	37.8%		35.5%		58.6%		50.1%	

Panel D: HXZ Factors

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2	Beta	PR^2	Beta	PR^2	Beta	PR^2
MF-FREQ	**-2.719**	**10.1%**	**-3.743**	**11.7%**	**-1.357**	**0.9%**	-1.597	0.8%
	[-3.31]		**[-3.84]**		**[-1.88]**		[-1.60]	
HF-FREQ	**0.813**	**10.6%**	**1.130**	**12.5%**	-0.009	0.0%	-0.177	0.2%
	[3.49]		**[3.79]**		[-0.07]		[-0.91]	
MKTRF	-0.049	0.6%	-0.073	0.8%	-0.024	0.0%	0.133	0.8%
	[-2.37]		[-2.85]		[-0.47]		[2.09]	
Amihud	0.517	11.2%	0.555	7.9%	-0.133	0.2%	-0.096	0.1%
	[3.15]		[2.76]		[-0.92]		[-0.56]	
Turnover	-0.036	0.5%	-0.059	0.8%	0.017	0.0%	0.025	0.0%
	[-0.63]		[-0.74]		[0.30]		[0.37]	
SMB	0.087	1.2%	0.098	1.0%	-0.047	0.1%	0.016	0.0%
	[2.72]		[2.34]		[-0.77]		[0.21]	
IA	0.110	0.9%	0.092	0.4%	0.389	3.0%	0.293	1.1%
	[2.18]		[1.48]		[3.14]		[1.77]	
ROE	0.220	4.7%	0.287	4.9%	0.868	20.4%	1.227	26.9%
	[4.70]		[4.79]		[12.63]		[12.04]	
N	276		276		276		276	
R^2	38.0%		36.8%		51.9%		46.2%	

Table A2: Granger Causality Test

The table provides the results of Granger causality tests of our main variables. Panel A examines whether the high- and low-frequency components of fund flows Granger-cause mispricing in the respective frequency. We use two composite anomalies, SYY and NINV, as proxies for mispricing. Panel B investigates whether mispricing proxies Granger-cause fund flows. We use the following specification for the Granger causality tests: $Y_t = Y_{t-1} + \Delta X_{t-1} + \text{Controls} + e_t$. *t*-statistics of the regression coefficients are calculated based on Newey-West standard errors with 13 lags, and are reported in brackets. *p*-values for Granger causality tests are reported in parentheses. The sample period is 1994–2016.

Panel A: Granger Causality of Mispricing

Y Variable	SYY-LOW				NINV-LOW				SYY-HIGH				NINV-HIGH			
X Variable	Restricted	HF-LOW	MF-LOW	Both	Restricted	HF-LOW	MF-LOW	Both	Restricted	HF-HIGH	MF-HIGH	Both	Restricted	HF-HIGH	MF-HIGH	Both
Lagged Y	0.960	1.004	0.931	0.966	0.963	1.013	0.931	0.972	-0.016	-0.015	0.009	0.011	-0.076	-0.072	-0.073	-0.067
	[42.06]	[25.16]	[36.84]	[27.24]	[40.06]	[24.43]	[32.88]	[25.55]	[-0.44]	[-0.40]	[0.22]	[0.28]	[-1.93]	[-1.79]	[-1.70]	[-1.59]
Lagged HF		0.708		1.104		0.983		1.510		0.086		0.097		0.185		0.188
		[3.49]		[5.90]		[3.04]		[5.25]		[0.75]		[0.85]		[1.19]		[1.23]
Lagged MF			-1.423	-3.114			-2.029	-4.258			0.675	0.701			0.151	0.206
			[-2.41]	[-4.05]			[-2.75]	[-4.47]			[1.43]	[1.50]			[0.22]	[0.31]
Adj RSQ	93%	94%	94%	95%	94%	94%	94%	95%	25%	25%	25%	25%	15%	15%	14%	15%
Granger Test																
F		31.48	9.82	85.05		38.25	12.52	106.75		0.45	1.52	2.10		1.19	0.05	1.28
(p value)		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)		(0.50)	(0.22)	(0.15)		(0.28)	(0.83)	(0.26)
X^2		31.82	9.92	85.99		38.67	12.66	107.93		0.46	1.54	2.12		1.21	0.05	1.29
(p value)		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)		(0.50)	(0.21)	(0.15)		(0.27)	(0.83)	(0.26)

Panel B: Granger Causality of Fund Flows

Y Variable	HF-LOW			MF-LOW			HF-HIGH			MF-HIGH		
X Variable	Restricted	SYY-LOW	NINV-LOW	Restricted	SYY-LOW	NINV-LOW	Restricted	SYY-HIGH	NINV-HIGH	Restricted	SYY-HIGH	NINV-HIGH
Lagged Y	0.932	0.937	0.936	0.941	0.994	1.006	-0.140	-0.141	-0.140	0.014	0.003	0.007
	[54.58]	[40.90]	[35.71]	[52.62]	[41.56]	[39.92]	[-2.61]	[-2.45]	[-2.50]	[0.24]	[0.05]	[0.13]
Lagged X		-0.019	-0.012		-0.066	-0.061		0.001	-0.001		-0.004	-0.002
		[-0.43]	[-0.27]		[-3.82]	[-4.87]		[0.09]	[-0.07]		[-1.40]	[-1.05]
Adj RSQ	94%	94%	94%	96%	97%	97%	0%	0%	0%	10%	10%	10%
Granger Test												
F		0.34	0.21		56.21	78.35		0.01	0.00		2.55	1.20
(p value)		(0.56)	(0.65)		(0.00)	(0.00)		(0.92)	(0.95)		(0.11)	(0.27)
X^2		0.34	0.21		56.83	79.21		0.01	0.00		2.58	1.22
(p value)		(0.56)	(0.65)		(0.00)	(0.00)		(0.92)	(0.95)		(0.11)	(0.27)

Table A3: Omitted Variable Test

The table reports the results of test for unobservable selection, using δ of Oster (2019). Oster's δ measures the degree of selection on unobservables relative to observables that would be required to make the estimated beta zero. δ is calculated based on the assumptions that the maximum R^2—the R^2 value that can be obtained if all unobserved variables are included—is one and the true beta is zero. Panel A uses the total fund flows, while Panel B reports the results using the low- and high-frequency fund flows. The sample period is 1994–2016.

Panel A: Total Flows

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
MF	**1.6**	**-0.2**	0.2	**1.4**	**-0.2**	0.2
HF	**-5.7**	**8.2**	**-1.0**	**-3.2**	**1.5**	**-0.2**
MKTRF	0.7	0.5	0.4	0.4	0.4	0.2
Amihud	0.4	0.2	0.0	0.2	0.2	0.0
Turnover	0.8	0.1	-0.4	1.0	0.1	-0.2
SMB	0.5	-0.1	0.4	0.3	-0.1	0.3
HML	0.5	0.5	0.2	0.2	0.3	0.1

Panel B: Decomposed Flows

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	SYY	SYY-LOW	SYY-HIGH	NINV	NINV-LOW	NINV-HIGH
MF-LOW	**-0.4**	**-0.2**	-0.4	**-0.4**	**-0.3**	-0.2
MF-HIGH	0.4	-0.5	0.3	0.3	-0.5	0.2
HF-LOW	**12.0**	**-1.9**	-0.4	**9.0**	**-3.9**	-0.2
HF-HIGH	**-2.0**	-0.5	**-1.1**	**-0.3**	-0.5	**-0.2**
MKTRF	0.7	0.9	0.4	0.4	0.9	0.2
Amihud	0.4	0.6	-0.2	0.4	2.0	-0.1
Turnover	0.4	0.1	-0.4	0.3	0.2	-0.3
SMB	0.5	-0.2	0.5	0.4	-0.1	0.3
HML	0.4	0.8	0.2	0.2	0.7	0.1

Table I1. Detrended Flows

The table reproduces our main results using detrended fund flows. We obtain the detrended MF and HF from the residuals of regressions of MF and HF on a linear deterministic trend. Then, we decompose the detrended flows into low- and high-frequency components. Panel A corresponds to Panel C of Table 2, and Panels B and C correspond to Panels B and C of Table 3. *t*-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2016.

Panel A: Regressions of Anomaly Returns on Detrended Flows

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)
MF-FREQ	**-2.934**	**10.5%**	**-3.800**	**10.7%**	**-2.166**	**2.0%**	**-2.721**	**2.1%**
	[-3.52]	**(34%)**	**[-3.81]**	**(36%)**	**[-2.87]**	**(11%)**	**[-2.51]**	**(19%)**
HF-FREQ	**0.733**	**8.7%**	**1.011**	**10.2%**	0.162	0.2%	0.061	0.0%
	[3.37]	**(29%)**	**[3.29]**	**(34%)**	[1.07]	(1%)	[0.31]	(0%)
MKTRF	-0.111	3.8%	-0.150	4.2%	-0.305	7.9%	-0.237	3.2%
	[-3.59]	(12%)	[-3.65]	(14%)	[-3.63]	(45%)	[-2.28]	(28%)
Amihud	0.331	5.1%	0.304	2.6%	-0.106	0.1%	-0.107	0.1%
	[2.17]	(17%)	[1.49]	(9%)	[-0.83]	(1%)	[-0.67]	(1%)
Turnover	-0.006	0.0%	-0.015	0.1%	-0.041	0.2%	-0.046	0.2%
	[-0.11]	(0%)	[-0.20]	(0%)	[-0.92]	(1%)	[-0.81]	(1%)
HML	0.108	1.9%	0.131	1.7%	0.126	0.7%	0.062	0.1%
	[1.84]	(6%)	[1.79]	(6%)	[0.90]	(4%)	[0.33]	(1%)
SMB	0.021	0.1%	0.016	0.0%	-0.334	5.9%	-0.391	5.4%
	[0.51]	(0%)	[0.30]	(0%)	[-6.46]	(33%)	[-5.58]	(47%)
N	276		276		276		276	
R^2	34.6%	(100%)	32.3%	(100%)	29.8%	(100%)	18.6%	(100%)

Panel B: Cross-Frequency Flow-Mispricing Ratio using Detrended Flows – SYY Anomaly

Fund Type	Frequency	(1)	(2)	(3)	(4)	(5)	(6)
		Beta	STD of Flows	Effect of One σ_F^B on Ret	STD of Ret	Econ. Magnitude (Flow-Misp. Ratio)	Manager vs. Investor
		β_B	σ_F^B	$\beta_B \times \sigma_F^B$	σ_R^B	β_B x σ_F^B / σ_R^B	(1)/(2)
MF	FREQ=LOW	-2.934	0.3%	**-0.8%**	2.2%	**-37.0%**	
	FREQ=HIGH	-2.166	0.3%	**-0.7%**	4.2%	**-15.3%**	
	LOW / HIGH	**1.35**	**0.94**	**1.28**		**2.41**	**1.44**
HF	FREQ=LOW	0.733	1.2%	**0.9%**	2.2%	**39.0%**	
	FREQ=HIGH	0.162	1.2%	**0.2%**	4.2%	**4.5%**	
	LOW / HIGH	**4.54**	**1.02**	**4.63**		**8.76**	**4.44**
Ratio HF/MF		**3.35**	**1.09**	**3.63**		**3.63**	**3.09**

Panel C: Cross-Frequency Flow-Mispricing Ratio using Detrended Flows – NINV Anomaly

Fund Type	Frequency	(1)	(2)	(3)	(4)	(5)	(6)
		Beta	STD of Flows	Effect of One σ_F^B on Ret	STD of Ret	Econ. Magnitude (Flow-Misp. Ratio)	Manager vs. Investor
		β_B	σ_F^B	$\beta_B \times \sigma_F^B$	σ_R^B	β_B x σ_F^B / σ_R^B	(1)/(2)
MF	FREQ=LOW	-3.800	0.3%	**-1.1%**	2.9%	**-37.4%**	
	FREQ=HIGH	-2.721	0.3%	**-0.8%**	5.2%	**-15.6%**	
	LOW / HIGH	**1.40**	**0.94**	**1.31**		**2.40**	**1.48**
HF	FREQ=LOW	1.011	1.2%	**1.2%**	2.9%	**42.1%**	
	FREQ=HIGH	0.061	1.2%	**0.1%**	5.2%	**1.4%**	
	LOW / HIGH	**16.47**	**1.02**	**16.83**		**30.68**	**16.13**
Ratio HF/MF		**11.80**	**1.09**	**12.80**		**12.80**	**10.87**

Table I2. Stationarity Tests

The table provides the results of Phillips–Perron unit-root tests. For each variable, we report the test results based on the models with zero mean, a single mean, and a deterministic trend. Each test provides the rho (ρ) and tau (τ) statistics, and their respective *p*-values, which are reported in the parenthesis. The sample period is 1994–2016.

	MF		HF		SYY		NINV	
Type\Test stats	ρ	τ	ρ	τ	ρ	τ	ρ	τ
Zero Mean	-86.58	-7.75	-158.95	-10.33	-210.29	-12.66	-232.95	-13.66
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Single Mean	-94.17	-8.00	-169.95	-10.71	-223.70	-14.03	-238.63	-14.33
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trend	-176.28	-11.36	-174.74	-10.85	-223.79	-14.20	-238.81	-14.40
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table I3: 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%

Table I4: Passive Fund Flows and Mispricing

The table examines the flow-return relation between passive funds and two composite anomalies, SYY and NINV. 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 unrelated to corporate investments. Passive funds are identified by names, following Appel, Gormley, and Keim (2016). *t*-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2016.

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Variables	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
Passive-FREQ	0.268	[0.53]	0.214	[0.31]	-0.176	[-0.63]	-0.290	[-0.96]
Active-FREQ	-2.945	[-3.37]	-3.960	[-3.60]	-2.050	[-3.05]	-2.636	[-2.73]
HF-FREQ	0.836	[3.86]	1.138	[3.63]	0.174	[1.15]	0.075	[0.38]
Controls	Yes		Yes		Yes		Yes	
N	276		276		276		276	
Adj R^2	32.3%		31.0%		26.8%		15.4%	

Table I5: Fund Flows Controlling Past Returns and Turnover

This table re-estimates the main results of Table 2, using fund flows orthogonalized from past market returns and turnover. Both MF and HF at month *t*, the percentage flows of active mutual funds and hedge funds, are regressed on MKTRF at *t*-1 and Turnover at *t*-1. Then, the residuals of the regressions are decomposed into low- and high-frequency components. The dependent variables 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 unrelated to corporate investments. The first column of each model shows the coefficient of each variable and the corresponding *t* value, and the second column reports the semi-partial R^2 (PR^2) and the ratio of each PR^2 to the sum of all PR^2. The PR^2 is estimated from the difference between a R^2 of the full model that includes all explanatory variables and a R^2 of the reduced model that excludes the variable of interest. *t*-statistics are calculated based on Newey-West standard errors with 13 lags. The sample period is 1994–2016.

Anomaly	(1) SYY-LOW		(2) NINV-LOW		(3) SYY-HIGH		(4) NINV-HIGH	
	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)	Beta	PR^2 / (% of ttl PR^2)
MF-FREQ	-2.657	8.7%	-3.692	10.3%	-1.342	0.9%	-1.435	0.7%
	[-2.90]	(23%)	[-3.32]	(27%)	[-2.05]	(5%)	[-1.49]	(6%)
HF-REQ	0.810	10.3%	1.123	12.1%	0.277	0.6%	0.234	0.3%
	[3.65]	(28%)	[3.87]	(32%)	[1.80]	(3%)	[1.20]	(2%)
MKTRF	-0.122	4.6%	-0.162	5.0%	-0.311	8.3%	-0.252	3.6%
	[-3.32]	(12%)	[-3.43]	(13%)	[-3.69]	(46%)	[-2.40]	(32%)
Amihud	0.509	11.0%	0.543	7.7%	-0.170	0.3%	-0.161	0.2%
	[3.05]	(29%)	[2.65]	(20%)	[-1.21]	(2%)	[-0.90]	(2%)
Turnover	0.020	0.2%	0.019	0.1%	-0.053	0.4%	-0.055	0.3%
	[0.41]	(1%)	[0.28]	(0%)	[-1.14]	(2%)	[-0.94]	(2%)
HML	0.104	1.7%	0.129	1.6%	0.131	0.8%	0.066	0.1%
	[1.85]	(5%)	[1.87]	(4%)	[0.95]	(4%)	[0.36]	(1%)
SMB	0.031	0.2%	0.030	0.1%	-0.349	6.5%	-0.413	6.0%
	[0.74]	(0%)	[0.59]	(0%)	[-6.57]	(36%)	[-5.75]	(53%)
N	276		276		276		276	
R^2	34.3%	(100%)	33.3%	(100%)	28.6%	(100%)	17.1%	(100%)

Table I6: The Impact of Frictions Using SYY Anomaly Returns

This table re-estimates the results of Tables 6 to 11, using SYY anomaly. The dependent variables are the low- and high-frequency components of SYY anomaly, and the main independent variables are the low- and high-frequency fund flows, and their interaction with various friction variables. SYY is the return of the long-minus-short strategy based on eleven anomalies documented in Stambaugh, Yu, and Yuan (2012). Each panel corresponds to Panel B of Tables 6–11. *t*-statistics are calculated based on Newey-West standard errors. The sample period is 1994–2016.

Panel A: Aggregate Risk (Table 6)

	NBER Recession		VIX		Financial Uncertainty Index (JLN)		Economic Uncertainty Index (BEX)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH
MF-FREQ	-2.348	-2.222	-2.415	-1.321	-1.162	-1.170	-2.193	-1.848
	[-2.59]	[-2.84]	[-2.13]	[-1.47]	[-1.13]	[-1.23]	[-1.75]	[-1.35]
MF-FREQ × D	**-11.625**	2.168	-0.469	-1.538	-1.444	-1.800	-1.328	-0.927
	[-10.17]	[1.09]	[-0.27]	[-0.77]	[-0.76]	[-0.90]	[-0.63]	[-0.35]
HF-FREQ	0.621	0.160	0.151	0.162	0.073	0.216	0.227	0.601
	[1.87]	[0.86]	[0.55]	[0.41]	[0.23]	[0.82]	[0.76]	[1.91]
HF-FREQ × D	**1.358**	0.316	**0.985**	-0.025	**1.033**	-0.132	**0.881**	-0.534
	[4.11]	[0.70]	**[3.10]**	[-0.05]	**[2.96]**	[-0.40]	**[2.75]**	[-1.06]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	276	276	254	254
Adj R^2	39.0%	26.5%	34.3%	25.9%	36.2%	26.1%	36.6%	26.4%

Panel B: Leverage (Table 7)

	TED Spread		Risk Aversion (BEX)	
	(1)	(2)	(3)	(4)
	FREQ = LOW	FREQ = HIGH	FREQ = LOW	FREQ = HIGH
MF-FREQ	-2.813	-1.048	-3.161	-1.938
	[-2.70]	[-0.91]	[-2.39]	[-2.12]
MF-FREQ × D	0.096	-2.254	0.180	-0.546
	[0.05]	[-1.11]	[0.10]	[-0.30]
HF-FREQ	0.436	0.371	0.352	0.362
	[1.15]	[1.15]	[1.00]	[1.16]
HF-FREQ × D	0.619	-0.378	**0.775**	-0.128
	[1.43]	[-0.88]	**[2.15]**	[-0.30]
Controls	Yes	Yes	Yes	Yes
N	276	276	254	254
Adj R^2	36.4%	26.9%	37.4%	26.2%

Panel C: Fund Leverage (Table 8)

	(1)		(2)	
	FREQ = LOW		FREQ = HIGH	
MF-FREQ	-2.767	[-3.26]	-2.106	[-3.04]
HFUnLev-FREQ	**1.071**	**[3.34]**	-0.075	[-0.33]
HFLev-FREQ	-0.228	[-0.57]	0.265	[1.29]
Controls	Yes		Yes	
N	276		276	
Adj R^2	36.9%		26.7%	

Panel D: Market Liquidity (Table 9)

	Amihud		Aggregate Liquidity (PS)		PV-Level (Sadka)		Noise (HPW)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH	FREQ=LOW	FREQ=HIGH
MF-FREQ	-2.551	-0.981	-2.341	-3.183	-2.061	-1.177	-1.411	-2.329
	[-3.25]	[-0.63]	[-2.29]	[-3.09]	[-1.95]	[-0.80]	[-1.11]	[-1.47]
MF-FREQ × ILLIQ	-0.253	-1.719	-0.691	1.628	-0.723	-2.333	-1.900	0.389
	[-0.28]	[-0.73]	[-0.63]	[0.81]	[-0.41]	[-0.82]	[-1.18]	[0.16]
HF-FREQ	0.319	-0.167	0.551	0.568	0.098	0.395	0.181	0.159
	[1.03]	[-0.59]	[2.05]	[2.25]	[0.36]	[1.22]	[0.50]	[0.62]
HF-FREQ × ILLIQ	**0.728**	0.532	**0.393**	-0.697	**0.989**	-0.163	**0.861**	0.062
	[2.16]	[1.55]	**[1.90]**	[-1.96]	**[3.03]**	[-0.38]	**[2.48]**	[0.20]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276	276	276	276	228	228	276	276
Adj R^2	33.1%	26.3%	31.8%	26.6%	34.3%	27.6%	33.2%	25.9%

Panel E: Hedge-Fund Liquidity (Table 10)

	(1)		(2)	
	FREQ = LOW		FREQ = HIGH	
MF-FREQ	-2.977	[-3.49]	-2.243	[-3.14]
HFBelow-FREQ	**-0.481**	**[-3.13]**	0.018	[0.08]
HFAbove-FREQ	**1.286**	**[4.90]**	0.176	[1.67]
Controls	Yes		Yes	
N	276		276	
Adj R^2	45.3%		27.0%	

Panel F: Exogenous Shocks to Frictions (Table 11)

	Financial Crisis		Decimalization	
	(1)	(2)	(3)	(4)
	FREQ = LOW	FREQ = HIGH	FREQ = LOW	FREQ = HIGH
MF-FREQ	-2.298	-2.492	-2.007	-1.555
	[-2.61]	[-3.18]	[-2.89]	[-2.21]
MF-FREQ × SHOCK	**-12.583**	**3.926**	**7.717**	**-26.695**
	[-12.39]	**[2.19]**	**[2.55]**	**[-6.70]**
HF-FREQ	0.690	0.213	0.597	0.239
	[2.03]	[1.15]	[2.97]	[1.61]
HF-FREQ × SHOCK	**1.166**	0.173	**-1.934**	**4.267**
	[3.98]	[0.43]	**[-7.04]**	**[2.86]**
Controls	Yes	Yes	Yes	Yes
N	276	276	276	276
Adj R^2	42.1%	27.0%	46.6%	33.3%

Table I7: Anomaly Turnover, Mispricing, and Fund Flows

This table re-estimates the main results of Table 2 controlling for anomalies in Novy-Marx and Velikov (2016). The dependent variables are the low- and high-frequency components of the long-minus-short returns at month *t* of two composite anomalies, SYY and NINV. The main independent variables are the low- and high-frequency fund flows at month *t*. Low TO is the average anomaly returns of the low-turnover anomaly strategies of Novy-Marx and Velikov (2016), which require rebalancing less than once per year. High TO is the average anomaly returns across their medium- and high-turnover strategies, which require rebalancing one or more per year. The first column of each model shows the coefficients and the corresponding *t* values, and the second column report the semi-partial R^2 (PR^2). The PR^2 is estimated from the difference between a R^2 of the full model that includes all explanatory variables and a R^2 of the reduced model that excludes the variable of interest. *t*-statistics are calculated based on Newey-West standard errors with 13 lags. The sample period is 1994–2016.

	(1)		(2)		(3)		(4)	
	FREQ = LOW				FREQ = HIGH			
Anomaly	SYY-LOW		NINV-LOW		SYY-HIGH		NINV-HIGH	
	Beta	PR^2	Beta	PR^2	Beta	PR^2	Beta	PR^2
MF-FREQ	-2.445	8.0%	-3.411	9.6%	-2.275	2.5%	-2.791	2.5%
	[-2.91]		[-3.34]		[-4.17]		[-3.93]	
HF-FREQ	0.771	9.4%	1.079	11.3%	0.271	0.6%	0.199	0.2%
	[3.32]		[3.48]		[1.84]		[1.18]	
MKTRF	-0.038	0.3%	-0.063	0.6%	-0.016	0.0%	0.140	0.8%
	[-1.72]		[-2.24]		[-0.30]		[1.99]	
Amihud	0.468	9.1%	0.503	6.4%	-0.233	0.6%	-0.226	0.4%
	[2.93]		[2.51]		[-1.55]		[-1.41]	
Turnover	-0.035	0.4%	-0.055	0.6%	0.047	0.2%	0.066	0.3%
	[-0.59]		[-0.65]		[0.95]		[1.15]	
Low TO	**0.062**	0.9%	0.048	0.3%	**0.085**	0.5%	0.061	0.2%
	[2.41]		[1.32]		**[2.21]**		[1.12]	
High TO	**0.046**	2.1%	**0.065**	2.6%	**0.256**	18.6%	**0.340**	21.6%
	[2.87]		**[2.76]**		**[8.25]**		**[7.95]**	
N	276		276		276		276	
R^2	37.9%		36.3%		48.4%		41.7%	