Essays in International Macroeconomics and Finance

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Essays in International Macroeconomics and Finance

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Dedication

This is dedicated to my parents, for always supporting and inspiring me throughout my academic pursuits, and especially to Serena, for motivating me to finish this degree.

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Abstract of Dissertation

Essays in International Macroeconomics and Finance

This dissertation examines how decisions and allocations by asset managers affect capital and financial markets. In Chapter 1, I use fund-level data on mutual fund portfolios invested in a broad range of emerging and developed markets to study the behavior of fund managers. Existing literature has shown that mutual fund assets tend to fluctuate procyclically, amplifying the impact of shocks and crises. We may, however, expect these effects to vary across funds depending on how active the fund is. I show that fund strategy affects the amplification channel. Flows through more passive or index funds don't amplify price changes within a country and aren't sensitive to country crises. Active funds display a much wider range of fund strategies, with some amplifying shocks and others behaving in a more contrarian manner. The results suggest less amplification due to manager behavior as the composition of the mutual fund industry changes.

In Chapter 2, I study liquidity management decisions in mutual funds domiciled globally. While we have knowledge on factors that drive investor flows, evidence is scarce on how fund managers react to these flows. Do funds transmit the behavior of investors or do they act as a buffer in any way? To answer these questions, I use fund-level data to estimate how funding shocks from investors affect both cash and country positions in the portfolio. My results are the first to describe liquidity management decisions by mutual funds domiciled globally. I show that funds maintain small cash buffers, accommodating investor flows with cash only to a minimal extent and instead transact more heavily in securities of the underlying portfolio. Notably, this flow-induced trading is stronger in active

funds than we may expect. These results have stability implications in periods of financial stress. To the extent fund managers use cash as a buffer to mitigate investor redemptions, they can either mitigate or amplify fire sales of assets in the portfolio. Finally, I show that in forced asset sales, funds tend to sell allocations in countries with low returns and in countries with higher market liquidity.

Chapter 3 is concerned with risks in hedge funds. The use of leverage is often considered a key potential systemic risk in hedge funds. Yet, data limitations have made empirical analyses of hedge fund leverage difficult. Using new regulatory data on hedge fund activities, we provide the most comprehensive assessment of hedge fund leverage to date. We examine the observable cross-sectional determinants of fund leverage, the relationship between leverage and risk in equilibrium, and the relationship between leverage and fund performance. Our headline finding is that leverage and portfolio risk are weakly negatively correlated. Our findings suggest that the association between leverage and risk in hedge funds is nuanced, and that leverage is in part used to scale the payoffs of low-beta, high-alpha securities, resulting in an essentially flat relationship between leverage and portfolio risk.

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0.1 Introduction

Two salient developments have changed the way we may think about the role of financial intermediaries in financial crises. One is the rising wealth intermediated by asset managers over the past decade. Factors such as search for yield in an environment of low interest rates have contributed to this rise and driven the growth of open-end mutual funds. Coincident with this growth has been an shift by investors out of actively managed funds to more passively managed funds, and rapid growth in index funds and the use of benchmarks as an investment tool. The essays in this dissertation improve our understanding international capital flows and financial crises in light of these developments. In the first two chapters, I focus on the role of mutual funds, and in the third chapter, hedge funds.

In the first two chapters, I study an increasingly important financial intermediary, international mutual funds. The behavior of these funds at a micro-level, driven by the decisions of underlying fund investors and fund managers, is critical to our understanding of what drives capital flows into and out of countries. In Chapter 1, capital flows and retrenchments within a country can be thought of as driven by changes in country weights by fund managers in response to country-specific conditions, whereas in Chapter 2, we can think of flows as driven by investor flows that lead managers to expand or liquidate positions across countries.

Growth in mutual fund assets globally has given rise to concerns of increased procyclicality of capital flows. Principal-agent problems and compensation structures in mutual funds can create incentives for managers to behave in a way that amplifies shocks or crises. In open-end mutual funds, investors can redeem claims at any time, which can create incen-

tives for managers to focus on short-term strategies over longer-term investment opportunities. Funds may follow momentum strategies and chase performance to attract investors, for example, or there can be herding behavior and pressure to follow peers.

In **Chapter 1**, I use a comprehensive set of data on mutual funds domiciled globally to study asset allocation decisions by fund managers. How fund managers respond to shocks and crises within a country-of-investment tell us whether these funds amplify or dampen the transmission of crises. Existing literature suggests that mutual funds tend to behave procyclically, amplifying the impact of shocks. However, we may expect flows through mutual funds to operate through several channels, depending on whether the fund is active or passive. I depart from the existing literature by studying how this amplification channel may vary by fund strategy or how active the fund is. Given the shift from active to passive investing in recent years, understanding these differences is more important.

This first chapter contributes to the literature in three parts. First, my results constitute the first description of how mutual funds respond to local shocks or crises by fund strategy. In active funds, two class of models could persist and we may expect to observe either or both of them. The first class of models would predict that funds follow strategies that lead to procyclical behavior (such as momentum trading or herding) and amplification of shocks (Grinblatt, Titman, and Wermers (1995), Calvo and Mendoza (2000), Lakonishok, Shleifer, and Vishny (1992)). A negative shock to asset prices in a country, for example, may cause outflows that further depress prices. Alternatively, active funds could behave in a more contrarian manner (Hau and Rey (2004), Broner, Gelos, and Reinhart (2006)). Portfolio rebalancing for example, can lead funds to reduce exposure to countries that become overweight and vice versa. Active funds could also just choose to be opportunistic,

taking advantage of longer-term investments and investing in countries when prices are cheap. Flows through index funds, by contrast, with an investment strategy more explicitly tied to a benchmark, shouldnt be sensitive to shocks within a country. I show that while on average, changes in country returns or prices pass through almost fully to country weights, there are significant differences between active and index funds. Active funds as a group appear to behave acyclically, letting valuation changes pass through to country allocations, while index funds are slower to adjust. During crises, active funds become more procyclical, reducing exposure to countries experiencing a crisis while explicit index funds are not sensitive to crises within a country.

Second, I study the distribution of strategies within broad fund type. To fully characterize the range of fund behaviors, I perform estimation at the fund level to uncover significant heterogenity with active funds. I show that the acylical response of active funds on average arises from considerable variation in strategies, with some behaving strongly procyclical and others strongly contrarian. In index funds, by contrast, there is much tighter dispersion in fund strategies.

Finally, I use this heterogeneity in fund strategies to describe the determinants of fund behavior. While the literature has motivated reasons why a fund may behave procyclically versus contrarian, I ask whether observable fund characteristics matter in any systematic way. I find that asset class, investor composition, domicile, and constraints imposed by investors are all relevant factors in fund strategy. My results show that flows to emerging markets and flows from retail funds are associated with more procyclical flows, while flows to developed markets and flows from institutional investors are more stabilizing. Contrarian strategies also tend to be pursued by funds with more financial flexibility, either high

monthly inflows, more stable net flows, or higher realized returns, while funds pursuing more procyclical strategies are those constrained by investor capital. These results help inform what the the distribution of fund types and their changing composition over time implies for financial stability.

In **Chapter 2**, I link the behavior of fund managers with underlying investors, through an important risk channel, investor flows. While Chapter 1 studies how managers allocate the funds available in their portfolio across countries, in this chapter I introduce the underlying fund investor and ask how managers respond to funding shocks from their investor base. Existing literature has documented the drivers of investor behavior and the factors that influence investor flows; for example, investors typically behave procyclically, investing in funds based on past performance, country performance, global crises, and global financial conditions. We dont, however, have knowledge on how managers respond to these shocks from investors. Do managers reinforce the actions of investors or do they provide any buffer? To answer this question, I study liquidity management decisions in international mutual funds. The open-ended structure of mutual funds means that investors can redeem capital at any point, which fund managers can manage by maintaining some level of cash buffer.

My results contribute to the literature in four parts. First, while we have knowledge on factors that drive investor behavior, evidence on how managers react to these investor flows is scarce. To my knowledge, Chernenko and Sunderam (2016) is the only study providing direct evidence on this question and their analysis is limited to U.S. funds. I bring a comprehensive set of data to this question, studying a broad range of funds domiciled globally invested in emerging and developed markets. My model allows me to estimate

how investor flows affect a fund's relative cash to equity position, particularly what portion of new flows is accommodated through cash versus with equities.

Second, I provide the first evidence on how these liquidity management decisions differ between active and passive funds. We might expect active funds to have more capacity to mediate investor flows than index funds. My results show that regardless of fund strategy, funds trade heavily in response to flow-induced pressure and provide little buffer between fund investors and markets. In active funds, this result is stronger than we would expect. While at a short horizon, active funds accommodate a significant portion of flows in cash, at a longer horizon their behavior is similar to index funds.

Third, I consider how the behavior of cash may differ based on the volume or direction of investor flows. I expand my model of cash to test for differences between periods of normal and volatile times. I consider several ways to measure financial stress, including investor outflows, periods of sustained capital outflows, and periods of capital retrenches. I show that the relationship between cash and investor flows weakens in periods of consecutive outflows and periods of capital retrenches. These results are particularly important for periods of financial stress. To the extent cash is used as a buffer, it can be stabilizing and to the extent managers hoard cash, it can amplify fire sales.

Finally, I provide evidence (the first, to my knowledge) on how investor flows affect specific country allocations. The weak relationship between cash and investor flows documented earlier suggests these forced asset sales could be quite significant. Specifically, I test whether local country conditions affect a fund's decision to expand or reduce allocations in a given country. I show that in response to investor flows, funds don't adjust their portfolio in a fixed proportion but rather in a way that depends on conditions in the

country-of-investment, specifically country performance and country liquidity conditions. Funds sell assets in countries with lower performance and countries with higher market liquidity. This is true in both active and index funds, and these considerations become even more significant in periods of forced asset sales (investor outflows).

Chapter 3 focuses on hedge funds.[1] Since the demise of Long Term Capital Management in 1998, leverage has been known as a potential source of systemic risk in hedge funds. High levels of leverage in the financial system often precede financial crises. Leverage establishes interconnections among counterparties and magnifies both the profits and losses of an investment strategy ex ante. Further, excessive leverage may increase the likelihood of default or the failure of a fund. Yet, despite these systemic risk implications, very little is known about the sources, uses, and risks associated with hedge fund leverage. Significant data limitations have precluded even a basic understanding of leverage in hedge fund portfolios. Until recently, little regulatory oversight of hedge funds existed, and existing public hedge fund data services collect data from funds only on a voluntary basis. The few studies that have attempted a systematic analysis of hedge fund leverage suffer from extremely small samples and the potential for severe selection bias (Ang, Gorovyy, and van Inwegen (2011) and Liang and Qiu (2019)) in the public databases.

In addition, alternative theories of capital market equilibrium make different predictions about the associations between leverage and risk. Classical theories (Markowitz (1952), Sharpe (1964), and Lintner (1965)) predict leverage and portfolio risk are positively linearly related. Alternatively, theories of leverage constraints (Garleanu and Ped-

[1] Joint work with Daniel Barth and Phillip Monin, Office of Financial Research, U.S. Department of Treasury

ersen (2011), Frazzini and Pedersen (2014), Boguth and Simutin (2018)) predict leverage and asset risk are negatively correlated, and therefore leverage and portfolio risk may be unrelated or even negatively related.

In this paper, we use new regulatory data on large hedge funds to provide the most comprehensive assessment of hedge fund leverage to date. Our analyses are made possible by the Securities and Exchange Commissions (SEC) Form PF, the first systematic, regulatory collection of data on large private funds. Our results show that theories of leverage constraints explain many empirical features of hedge fund leverage. Consistent with theories of leverage constraints, we find that hedge fund leverage and portfolio risk are weakly negatively correlated. More leveraged funds have lower return volatilities and have a lower probability of experiencing an extreme return. The result that leverage and risk are unrelated is sensible: funds with naturally high-risk (or high-beta), high-reward (or high alpha) strategies employ very little leverage, whereas funds with naturally low-risk, low-reward strategies leverage their strategies to be competitive with their riskier counterparts. This results in an essentially flat relationship between leverage and portfolio risk.

We provide additional results that provide more support to theories of leverage constraints. This includes the finding that leverage and average market beta (the sensitivity of security's return to the market) are strongly related. We find that market beta explains nearly 20% of the variation in hedge fund leverage. Also consistent with these theories, we show that leverage and portfolio alpha are strongly positively related but this relationship is entirely explained by market beta.

We also utilize the richness of our data to provide the first thorough decomposition of the sources and characteristics of hedge fund leverage. We show that cross-sectional

characteristics such as fund strategy, the percentage of borrowing done through repurchase agreements, portfolio liquidity, and investor liquidity are all significant determinants of hedge fund leverage.

Our findings suggest that the association between leverage and risk in hedge funds is nuanced, and that leverage is in part used to scale the payoffs of low-risk, high-reward securities, resulting in an essentially flat relationship between leverage and portfolio risk. Our results also provide the first microfoundational evidence of the leverage-constraint mechanism. To our knowledge, this is the first paper to provide evidence in support of theories of leverage constraints using the actual leverage decisions of investors at the level of the investors portfolio.

Chapter 1: Channels of Crisis Transmission: Does Active Management Matter?

1.1 Introduction

The wealth intermediated by asset managers (mutual funds, hedge funds, pension funds) globally has risen considerably in recent years (See Figure 1.3) and is now estimated to be more than the worldwide holdings of banks.[1] Coincident with overall growth in this industry has been a shift in flows from actively managed funds to more passive funds and exchange-traded funds (ETFs). With these assets comprising a growing share of capital flows, understanding asset allocation decisions by these funds is now more important to our understanding of international capital flows and crises.[2]

The empirical literature on mutual funds in emerging markets has shown fund investors and managers tend to amplify shocks, with assets fluctuating procyclically. For funds that behave procyclically, or chase returns for example, a negative shock to asset prices can generate country outflows that further depress prices. What is less understood is how this amplification may vary by fund strategy. Existing literature has focused only on average effects across funds. Yet we may expect more actively managed funds to respond differently to shocks than an index fund, whose performance or evaluation is more closely tied to a benchmark index. Even among active funds, we may expect variation in strategies, with

[1] See The Financial Stability Board (2018)

[2] Mutual funds should represent a non-trivial fraction of equity flows to emerging markets. See, for example, Broner, Gelos, and Reinhart (2006)

some funds behaving procyclical and some more contrarian.

In this chapter, I provide evidence on how these intermediaries behave in their international investments, how they respond to shocks and crises, and how their response differs by fund strategy. I depart from existing literature by studying how amplification effects from fund managers vary by how active the fund is, that is, the extent to which a fund's country allocations differ from those of their declared benchmark. Are active funds more sensitive to country shocks than funds that track a benchmark? Do active managers chase returns or do they behave in a more contrarian manner? The amplification channel from managers may vary depending on the fund strategy.

In the last several years, active funds have experienced outflows, while passively-managed funds and ETFs - funds that more closely track a benchmark - have experienced considerable growth. Globally, the volume of money held in ETFs has grown from $100 billion in 2000 to to over $6 trillion in 2019. [3] The growth has been even more rapid in recent years, with today's assets under management more than double the amount just under four years ago, and this trajectory is projected to continue. Given these trends, understanding how fund type may affect the channels of investment flows has important financial stability implications.

Previous work has studied how the behavior of mutual fund managers and fund investors can amplify shocks or transmit shocks across countries. In this chapter, I focus on the former, amplification effects .[4] We may expect flows through mutual funds to operate through several channels, depending on whether the fund is an active or passive fund. On

[3] Based on estimates by ETFGI

[4] For evidence on contagion effects in mutual fund trading, see Jotikasthira, Lundblad, and Ramadorai (2012), Kaminsky, Lyons, and Schmukler (2004) Boyer, Kumagai, and Yuan (2006), Frankel and Schmukler (1998)

one end, we may expect the behavior of active funds to amplify shocks. In open-end mutual funds, investors can redeem claims at any time, often monitoring managers based on relative performance. This can create incentives for managers to follow their peers, or focus on short-term returns over long-term opportunities, leading to allocations that increase procyclicality and volatility. For example, funds may follow momentum strategies, investing in past winners to attract additional flows (Grinblatt, Titman, and Wermers (1995)) or follow herding behavior in financial markets (Calvo and Mendoza (2000), Lakonishok, Shleifer, and Vishny (1992)). Raddatz and Schmukler (2012), who focus on aggregate country allocations, show that managers tend to behave procyclically, allowing shocks to country returns to pass through to country weights, and reduce exposure to countries experiencing crises. Other papers providing evidence of procyclical behavior include Kaminsky, Lyons, and Schmukler (2004) who show that both investors and managers are momentum traders, and Borensztein and Gelos (2003), showing that funds withdraw from countries during crises. Managers following these types of strategies would tend to amplify shocks. Further, because mutual fund investors also typically chase performance (see Raddatz and Schmukler (2012), others), funds following these strategies amplify and reinforce shocks from investors.

Active fund managers may also behave in a more contrarian way. Portfolio rebalancing mechanisms, for example, can lead funds to reduce exposure to countries that become overweight, and vice versa (Hau and Rey (2004) and Camanho, Hau, and Rey (2018)). As returns to a country increase, the country becomes overweight in the portfolio and managers sell assets in that country to return to desired weight. Broner, Gelos, and Reinhart (2006) present a model of time-varying risk aversion, which predicts that when fund returns are

relatively low, managers will reduce exposure to countries in which they are "overexposed" and adjust holdings toward the average or benchmark portfolio. Active funds could also just choose to behave more opportunistically, taking advantage of longer-term investments when prices decline. Fund managers managers pursuing these more contrarian strategies would tend to dampen price shocks and have more of a stabilizing role in asset markets.

In truly active funds, we may to expect to observe either of these two class of models: manager behavior that leads to procyclical flows or behavior that leads to contrarian flows. Flows through purely passive or index funds, by contrast, should operate through a different channel. With an investment strategy directly tied to a benchmark index, these funds should not have any amplification effects from managers. To the extent that countries in index funds are weighted by market capitalization, we may expect flows from these funds to move procyclically, moving one-for-one with prices. To the extent index funds maintain fixed weights, however, we may expect flows in these funds to move in a contrarian way. For example, when a country in the portfolio receives a negative shock, the fund may need to increase assets to maintain the desired weight. As growth in mutual funds shifts from active to index funds, and a growing number of funds follow benchmarks to behave more passively, understanding this channel, in addition to the behavior of active funds, is important.

Even among active funds, we can expect benchmark indicies to be a relevant factor in fund strategy. Because managers are usually evaluated against an index, they may choose to stay close to the benchmark. This chapter is also related to a recent literature on how benchmark indexes affect international capital flows. Raddatz, Schmukler, and Williams (2018), for example, show that benchmarks explain on average around 70 percent of coun-

try allocations and have significant effects on international investments and capital flows.[5]

In this chapter, I use fund-level data on country allocations to study how funds react to shocks and valuation changes within a country. I depart from the existing literature by studying how these effects differ by fund strategy. In addition to active and passive funds, I consider closet index funds - funds that declare to be active yet follow an investment strategy that closely tracks their benchmark. I compute a measure of active management for each fund and use this to classify funds as active, closet indexers, or explicit indexers. My contributions to the literature are threefold. First, I provide the first description of how funds behave in their international investments - in particular, how they respond to country shocks - by fund strategy. Second, I study the distribution of strategies within fund type. In addition to identifying differences between active and passive funds, I perform estimation at the fund-level to uncover heterogeneity within fund types and provide a complete typology of fund strategies. Finally, I use the heterogeneity in fund strategies to examine the determinants of fund behavior. While the literature has motivated reasons why a fund may behave procyclically versus contrarian, I ask whether observable fund characteristics matter in any systematic way. If amplification effects vary by fund strategy or fund characteristics, these results inform how the distribution of fund types, and their changing composition over time, affects financial stability.

Country allocations have two components: a passive component, due solely to relative price changes, and an active component, due to manager reallocations. In the absence of active manager reallocations, country weights change by the amount of relative prices. I show that on average, changes in country returns pass through almost fully to country weights.

[5] See also Miyajima and Shim (2014) and Broner, Gelos, and Reinhart (2006)

However, significant differences exist between active funds, closet indexers, and explicit indexers. Flows through explicit index funds pass through less than fully to country weights, with managers undoing the direct impact of country shocks on country weights to maintain a fixed weight at a short horizon. Closet index funds and active funds, with looser investment restrictions, behave acyclically, letting changes in country returns pass through fully to country weights. Thus on average, we don't observe the procyclical behavior predicted by models of momentum trading or herding in active funds. We also don't see evidence of active funds behaving contrarian, taking advantage of value investments. However, I show that the average response for active funds is a result of considerable variation in strategies within the subset of active funds, with some behaving strongly procyclical and some strongly contrarian. About 60 percent of active funds behave in a contrarian manner, 25 percent behave procyclically, and 15 percent behave acyclically, following a buy-and-hold pattern. During crises, active funds and closet indexers become more procyclical, reducing exposure to countries experiencing a crisis, while explicit index funds are not sensitive to crises within a country. Given the growth of index funds and use of benchmarks over the last decade, this suggests less amplification in the industry as a whole.

Finally, I show that certain fund characteristics are relevant for whether an active fund behaves procyclical or contrarian. Asset class, investor composition, domicile, currency, and investor flows are all relevant factors in fund strategy. Funds invested in emerging market assets classes or with retail investors are more likely to behave procyclical. Developed market asset classes and institutional investors are associated with more contrarian strategies. Constraints imposed by investor capital are also significant factors. Contrarian strategies tend to be pursued by funds with more financial flexibility, either high monthly

inflows or stable net flows, and with higher realized returns. Procyclical strategies are associated with more volatile monthly flows, lower monthly flows, and lower fund returns.

The paper is organized as follows: Section 1.2 describes the the data, summary statistics, and classification of fund strategy. Section 1.3 provides a model of country weights and estimates how funds respond to country shocks and crises by broad fund strategy. Section 1.4 performs estimation at the fund-level to uncover heterogeneity within broad fund type. Section 1.5 examines the cross-sectional determinants of fund behavior, and Section 1.6 concludes.

1.2 Data and Summary Statistics

Data on mutual fund portfolios come from Emerging Portfolio Fund Research (EPFR) Global. EPFR covers $30 trillion in total assets domiciled globally, representing a large fraction of U.S., European, and other funds invested in a broad range of emerging markets (EM) and developed markets (DM). EPFR covers about 99% of all EM equity funds, 70-75% of funds in developed European markets, and 90% of U.S. funds. For each fund-month observation, the dataset includes the total net asset value of the fund, the percentage of net assets allocated to each country (country weights), and the percentage held in cash, as well as fund characteristics such as strategy, domicile, geographic focus (global, emerging markets, regional, etc), asset class, investment scope (sector and industry), and the fund's declared benchmark.

Details on the funds used in my the analytic sample are in Table 1.1. Over half of the funds invest in developed markets, 57%, while 43% specialize in emerging markets; in terms of panel observations, the sample is evenly split between developed and emerging

markets. Asset classes are broken out by region, with "Asia Pacific", "Global DM", and "European DM " representing asset in developed markets, and "Middle East and Africa", "Asia", "Europe EM", "Latin America", and "Global EM" representing investments in emerging markets. Within asset classes, funds invested in Global EM equities comprise the largest portion of the sample (20%), followed by Asia Ex-Japan (19%), Global DM (15%), and Western Europe (14.5%). The majority of these funds are actively managed, (82.2%), while passive funds comprise 17.8% of the sample. ETFs, which are also considered passive, make up 15.5% of the sample. The majority of funds are domiciled in European countries, 69.5% of the sample, followed by the U.S., 24.9%.

To classify funds by how active they are, I match the fund-level data to the allocations of their declared benchmark. Data on benchmark indexes come from Morningstar and are available for 279 of the 343 declared benchmarks. Some funds are therefore excluded from the sample due to missing or incomplete benchmark information. These include funds with missing benchmark information, funds with benchmarks that are a weighted average of several benchmarks, and funds for which benchmark weights were unavailable in Morningstar. These exclusions affect less than 4% of the fund-time observations; details on the excluded funds are in Appendix. The excluded funds have characteristics similar to those of the entire sample, so their exclusion is not expected to generate any biases.

I also match the fund-level data with country returns in the countries in which the funds invest. Data on country returns are computed using MSCI Country Indexes; the resulting countries-of-investment included in my main analysis are in Panel C of Table 1.2. I assume throughout the paper that all funds investing in a given country realize the same return to their investments in that country. This assumption follows existing literature (Boren-

sztein and Gelos (2003), Broner, Gelos, and Reinhart (2006), and Raddatz and Schmukler (2012)), and should should be a reasonable approximation given the documented allocations of equity mutual funds invested globally - mutual funds tend to invest in a limited number of stocks but in an allocation that approximates the index (Didier, Rigobon, and Schmukler (2013)).[6] Further, I directly test the extent to which country index returns approximate fund returns by comparing realized fund returns with the predicted return implied by country weights and the MSCI country returns (See Table 1.3). I find the mean deviation in predicted versus actual returns is about 1.4 percentage points (140 basis points), with 90 percent of funds in the sample having a deviation of less than 3.2 percentage points.

The final dataset consists of 1,391 funds and an unbalanced panel of 2,504,194 fund-country allocations. Summary statistics for the main variables used in my analysis - fund returns, country returns, and country weights - are in Table 1.2. Fund returns are computed as the monthly percent change in net asset value (NAV). In the cross-section, funds have average monthly returns of 0.65%, with a median of 0.87%, 90th percentile of 3.19% and standard deviation of 4.26%. There do not appear to be notable differences in fund returns by strategy; active funds, for example have similar returns to index funds.

Funds allocate their portfolio between countries and cash. Funds hold average country allocations equal to 7.2% of total net assets, with a median of 3.48%, 90th percentile of 18.06%, and standard deviation of 10.00%. Within funds, there is also significant variation in country allocation over time. Within fund-country, the average country weight is 5.46% of total net assets and the standard deviation is 1.29% (see Panel B). That country weights

[6]Further, there is synchronicity of returns across assets within countries, especially in developing countries (Morck et al., 2000)

fluctuate substantially within fund highlights the importance of understanding manager reallocations across countries and the impact on capital flows.

1.2.1 Fund Strategy

To classify funds by strategy, I directly compute a measure of how active funds are. This approach also allows me to identify closet indexers - funds that declare to be active but hold a portfolio that closely approximates their benchmark. I adapt a measure of active portfolio management from Cremers and Petajisto (2009)), which represents the share of portfolio holdings that differ from the benchmark index holdings. I compute the following measure for each fund, comparing across countries rather than industries:

$$\text{Active Share} = \left(\tfrac{1}{2}\right) \sum_{j=1}^{N} \mid w_{fund,j} - w_{B,j} \mid$$

where $w_{fund,j}$ and w_B are the portfolio weights of the fund and benchmark in country j, respectively, and the sum is taken over all countries. For each fund, the share is computed each month and averaged across time. The measure can be thought of as the percentage of portfolio holdings invested outside the benchmark. Summary statistics for this measure are presented in Table 1.4. The average active share across all funds in the sample is 15.6; on average, funds have about 85% overlap with the benchmark. For funds that declare to be passive or an ETF, the average active share is lower, 3.2, with a median of 1.6 and 90th percentile of 2.8. For active funds, the average active share is close to 25, with a median of 21.5 and 90th percentile of 38.5. That is, among active funds, the average fund has about 25% of their portfolio invested outside of the benchmark.

Based on these shares, funds are classified as explicit indexers, closet indexers, or active funds. Explicit indexers are those that declare to be passive or an exchange traded

fund (ETF). These funds comprise 25% of the sample. Closet indexers are funds that dont declare to be passive or an ETF but have an active share similar to passive funds (within the 90th percentile of that of explicit indexers) [7] and comprise 5% of the sample. Active funds are all other funds - those that have an active share greater closet indexers and don't declare to be passive or an ETF - and comprise 70% of the sample.

While a static measure of active share for each fund in the analysis, it is interesting to note the average active share among funds over time, which has been declining (see Figure 1.4). The use of benchmarks is rising, as funds are increasingly using these as an investment tool to behave more passively.

Regardless of strategy classification, all funds follow their benchmark to a significant extent. In a simple regression, Table 1.5 regresses country weights on benchmark weights. Across all funds, the estimated coefficient is 71%. For active funds the coefficient is slightly lower, 68%. In explicit index funds, country weights track benchmarks much more closely, with a coefficient of 86%. Closet index funds have a coefficient similar to explicit index funds, 82%. The next section provides a more thorough description of how country weights may fluctuate for different fund types.

1.3 Fund Behavior by Strategy

Fund country weights fluctuate substantially over time. Within fund-country, the mean standard deviation in country weight is 1.29 percentage point. Fund managers face two main shocks or sources of fluctuations in their assets: changes in relative returns and in-

[7] Results using an alternative classification, where closet indexers are defined as having an active share without one standard deviation of that of explicit indexers, are presented in the Appendix

vestor flows. In this chapter, I focus on the first, changes in relative returns. Managers realize the return on their investments and in response decide whether or not to reallocate investments across countries. This response is one of the ultimate determinants of flows into or out of a country in which a fund invests.

Previous work has looked at how funds respond to changes in country returns. Raddatz and Schmukler (2012) show that managers react to valuation changes in the countries in which they invest procyclically, allowing weights to adjust with returns, and moving allocations out of countries experiencing crises. I build on their work by considering how these effects may vary by fund type. While active funds can respond freely to changes in relative prices, we may expect index funds, with an investment strategy closely tied to the benchmark, to respond differently. Passive or index funds, by construction, should not have amplification effects from managers; these funds should respond largely to changes in the benchmark weight and not be sensitive to local country shocks. While some funds dont declare to be passive, such as closet index funds, they may in fact behave similarly to passive funds, changing country allocations only in response to changes in their benchmark's weight. If the benchmark effect is significant, we may expect only truly active funds to respond to economic fundamentals or shocks within a country, in particular, country returns and country crises.

1.3.1 Country Weights

To describe the behavior of fund managers by strategy, this section models a fund's portfolio allocation in a given country. The model builds on Raddatz and Schmukler (2012), who use the following identity to describe a fund's country weight:

$$w_{ijt} = w_{ijt-1}(\frac{R_{ijt}+f_{ijt}}{R_{it}+f_{it}}) \text{ (1)}$$

This identity states that the weight of country j in fund i's portfolio depends on the country weight in the previous period, the return of the fund's investments in that country (R_{ijt}), the overall return of the fund's portfolio (R_{it}), new flows into or out of the country by the fund (f_{ijt}), and net flows to the fund by its underlying investors (f_{it}).

Log-linearizing this around a steady state results in:

$$w_{ijt} = w_{ijt-1} + (r_{jt} - r_{it}) + (f_{ijt} - f_{it}) + \theta_{it} + \varepsilon_{ijt} \text{ (2)}$$

which describes the country weight as a function of relative returns $(r_{jt} - r_{it})$ and relative flows $(f_{ijt} - f_{it})$. In the absence of relative flows to a country - a reallocation of funds into or out of the country - there is complete pass through from relative returns into country weights, to a first order log approximation.

To study differential effects between passive and active funds, I also allow relative flows to depend on the country weight of the fund's declared benchmark. Changes in country weights can also reflect changes in the benchmark's weight. Relative flows are at the discretion of the fund manager and also depend on the lagged weight, relative returns, the incidence of crises in a country. Relative flows to a country then evolve according to the following equation:

$$(f_{ijt} - f_{it}) = \gamma w_{ijt-1} + \lambda(r_{jt} - r_{it}) + \eta w_{ct}^{BM} + \alpha C_{jt} + \theta_{it} + \varepsilon_{ijt} \text{ (3)}$$

The sensitivity of relative flows to changes in the fund's benchmark weight, η, should be higher for index funds than active funds as the investment strategy of index funds is more closely tied to a benchmark. The more pure an indexer a fund is, the higher η will be.

Existing literature has shown that country weights of explicit indexers move almost one-to-one with benchmark weights (Raddatz, Schmukler, and Williams (2018)). The sensitivity of relative flows to relative returns, λ, should be greater than one or less than one for active funds, depending on the strategy pursued. If models of momentum trading are true, for example, we would expect a high λ, amplifying changes in country returns. In index funds, λ should be closer to zero, with more of the variation in country weights driven by changes in the benchmark weight. Active funds have more discretion to respond to changes in relative returns, compared to index funds with a more fixed investment strategy.

Replacing (3) into (2) yields:

$$w_{ict} = \alpha w_{ijt-1} + \beta(r_{jt} - r_{it}) + \eta w_{jt}^{BM} + \alpha C_{jt} + \omega_{ij} + \varepsilon_{ijt} \quad (4)$$

which describes a fund's country weight in terms of it's initial weight, relative country returns, the benchmark weight, and the incidence of a country crisis, C_{jt}.

Finally, we can think of the benchmark weight, w_{jt}^{BM}, as the sum of two components, one that captures exogenous changes in the index and one that moves with changes in relative prices:

$$w_{ijt}^{BM} = w_{ijt}^{BMExog} + w_{ijt-1}^{BM} \frac{R_{J,t}}{R_{BM,t}}$$

The first term accounts for index changes exogenously decided such as changes in underlying securities and upgrades or downgrades of countries. In the absence of any exogenous changes to the benchmark, the benchmark weight follows the second term, a "buy-and-hold" component, where $R_{J,t}$ and $R_{BM,t}$ are the return of country j and the return of the benchmark, respectively.

1.3.2 Shocks to fund managers

To empirically study how funds respond to shocks within a country, I estimate a form of equation (4). Because shocks to relative returns affect both the benchmark weight, through it's buy-and-hold component, and the fund's country weight, I include only the exogenous component of the benchmark weight in estimation. [8] The following panel regressions are run separately for active funds, closet indexers, and explicit indexers, using the classification described in Section 1.2.1:

$$w_{ict} = \beta_1 w_{ict-1} + \beta_2 (r_{ct} - r_{it}) + \beta_3 w_{ict}^{BM,Exog} + \beta_4 C_{ct} + \varepsilon_{ijt} (5)$$

where w_{ict} is the portfolio weight of country c in fund i; relative returns, $(r_{ct} - r_{it})$, are the difference between country net returns and fund net returns expressed as a decimal; and $w_{ict}^{BM,Exog}$ is the exogenous component of the benchmark's weight in the country c. Because stock-level portfolio holdings are unavailable, I assume that funds hold a portfolio within country well proxied by the MSCI country index. This should be a reasonable assumption for the reasons discussed in Section 1.2. Any potential biases that this assumption may introduce are discussed below.

The coefficient on relative prices, β_2, describes how country weights change in response to changes in relative returns. In response to the realized returns of their investments, managers choose whether or not to reallocate or liquidate positions; this is one of the decisions that ultimately determines the net flows to the countries where each fund invests. The total change in country weight, of course, can arise from either changes in prices

[8] w_{ct}^{BM} will be correlated to some extent with the first two terms in equation, more so the more of an indexer the fund is. The lagged benchmark weight will be correlated with lagged country weight, and relative benchmark returns will be correlated with relative fund returns.

or reallocations. For example, in the same way the benchmark was decomposed above, a fund's portfolio weight in any country can be thought of as the sum of a buy-and-hold component and an active manager component:

$$w_{ict} = w^{BH}_{ict-1} + w^{active}_{ict} \quad (6)$$

where the buy-and-hold component, $w^{BH}_{ict-1} = w_{ict-1}\frac{R_{ct}}{R_{it}}$, is the lagged country weight multiplied by the ratio of the gross country return to gross fund return. The estimated β_2 in equation (5) captures the total change in country weight; however, in Section 1.3.3, I isolate changes in country weights due solely to manager reallocations. [9]

Another technical concern relates to the broad country return, r_{ct}. To the extent that r_{ct} differs from the actual returns of a particular fund within that country, this may introduce error in the dependent variable and estimates of β_2, particularly for any fund that invests in a very small number of countries. However, for funds that are diversified across a number of counties, these effects should be small. For example, consider on one extreme, a fund that invests in two countries and in a single stock in one of the countries. If this stock out- or under-performs the country index, the fund could appear to be active when in fact it's following a buy-and-hold pattern. The biases on β_2 could go in either direction.

In equation (5), funds with an estimated β_2 equal to 1 follow a buy-and-hold pattern - any changes in relative returns pass through fully to country weights. Funds with β_2 greater than 1 behave procyclically, amplifying the impact of changes in relative returns. Funds with a β_2 less than one behave in a more contrarian manner. This can include both funds

[9] Ideally we would like to isolate the fund's response exclusive of changes coming from the buy-and-hold component and estimate the following: $w_{ict} = \beta_1 w^{BH}_{ict} + \beta_2(r_{ct} - r_{it}) + \beta_3 w^{BM}_{ict}$. Because changes in $\frac{R_{ct}}{R_{it}}$ could impact all three terms of this equation in the same way, I instead estimate equation (5). However, results are little changed if the buy-and-hold term is included (in unreported results): β_1 is mostly driven by variation in the lagged weight; the multiplicative relative returns contributes little to the overall coefficient.

attempting to maintain a constant country weight and funds behaving in a true contrarian sense; in both cases, country weights move against relative returns. Following equation (6), a β_2 of less than one implies a fund is counteracting the impact of relative returns on country weights, through changes in w_{ict}^{active}. A β_2 less than one, then, does not necessarily imply contrarian behavior in the sense of increasing exposure to underperforming countries. But it suggests these funds don't let let returns pass through fully to desired weight; in this sense, relative flows move in a contrarian way.

The results from equation (5) are in Table 1.6. In the main specification, fund-time and fund-country fixed effects are included to account for time-varying shocks such as injections and fund returns, and standard errors are clustered to allow for correlation at the fund-time level [10] Across all funds, the coefficient on relative returns is 0.94, and statistically different from 1, with a F-statistic of 17. On average, relative returns pass through less than fully to country weights. Significant differences exist by fund type, however. For active funds, the response is 0.99, not statistically different from one. For explicit indexers, β_2 is much lower, 0.79, reflecting an investment strategy tied to a fixed benchmark weight. Closet indexers, by contrast, have a coefficient of 1.07, though not statistically different from one. These funds, with a low active share and generally passive strategy, don't appear restricted in the same way explicit indexers are. Thus in closet and active funds, we don't observe the procyclical behavior predicted by models of momentum trading or herding. We also don't see evidence of active funds behaving contrarian, taking advantage of value investments. These funds appear to let changes in relative prices pass through fully to country weights, at least on average.

[10] For the full set of results including different levels of fixed effects, see Table 1.8

The coefficient for explicit indexers is not what we may immediately expect. In explicit index funds, we would expect β_2 to be close to 1 for funds that follow benchmark weights that are weighted by market capitalization. The result, however, suggests these funds undo, to a significant extent, the impact of relative returns on country weights at a short-horizon. The low average β_2 in explicit index funds could arise from several factors including the frequency of rebalancing, benchmark weights that are equal-weighted rather than market-cap weighted, or differences between the fund and benchmark return. [11] [12] Further inspection reveals that the result appears to be largely driven largely by the frequency with which funds rebalance their weight to match the benchmark. For example, funds with very low active shares have a β_2 close to 1. In unreported results, restricting estimation to funds with an active share less than 1 yields a β_2 equal to 0.92 and not statistically different from one. This suggest that for many explicit index funds, country weights aren't adjusted to benchmarks in real time but rather kept fixed at a short horizon, with small deviations between the country weight and benchmark weight accumulating over time. We therefore observe an overall average β_2 significantly less than one. Nevertheless, the estimated β_2 for explicit index funds reflects funds following an investment strategy that tracks their country weight with the benchmark weight.

Lastly, with regard to explicit index funds, it's worth noting that ETFs, which comprise a large fraction of this group, have a slightly lower β_2 than other passive funds (0.79 for ETFs and 0.82 for non-ETF passive funds). Table 4.3 breaks out the results for explicit

[11] It's possible estimation at a lower frequency would show greater pass through in the long-run

[12] Fund relative returns, $r_{ct} - r_{it}$, could differ from the relative returns contained in the benchmark for a number of reasons, and to the extent this occurs managers offset the impact of these valuation changes on country weights. This is supported by Figure 1.5, which confirms a high correlation between country weights and benchmark weights for explicit indexers - there is little deviation between country and benchmark weights for these funds.

index funds into ETFs versus non-ETFs. Yet excluding ETFs, passive funds still have a β_2 low compared to other fund types and statistically less than 1.

The second column of Table 1.6 adds an indicator variable equal to one if the country-of-investment experienced a crisis in a given year, which can include banking, systemic, currency, or debt crises. [13] [14] On average, funds react procyclically to crises, reducing weights in countries experiencing a crisis, but the response differs by fund type. Active funds respond strongly to a crisis: in response to a country crisis, active funds reduce their weight in the affected country by 1.1%. Closet indexers have an economically larger response, 2.5%, though statistically weaker. Table 1.6 showed closet indexers display the most procyclical behavior among groups during normal times, with β_2 greater than 1. This is also true during crises. Explicit index funds, by contrast, have no response to crises; these funds are not sensitive to local economic conditions. [15] Controlling for country crises, the coefficient on relative returns increases for all groups, though for active and closet funds, the response remains not statistically different from one, and for explicit indexers, statistically less than 1.

Finally, the estimated coefficient on the benchmark weight, β_3, show differences in how funds respond to exogenous changes in the benchmark. Explicit index funds respond strongly changes to these changes, with a coefficient four times that of active funds. Country weights in closet index funds, by contrast, are much less sensitive to exogenous changes

[13] Data are from 2010 forward and thus does not capture the full extent of crises experienced in emerging markets. In a later version, the data will be extended to the 1990s. The current sample contains the following country-year crises observations: 60 banking, 37 systemic, 30 sovereign debt, and 32 currency

[14] Crisis data come from Harvard Business School and Carmen Reinhart, Behavioral Finance and Financial Stability.

[15] In Table 1.9 I distinguish between the type of country crises. Again, the results can be improved by extending the sample period to include more crises.

in the benchmark weight. While the coefficient for closet indexers is insignificant, this group suffer from a relatively smaller sample size, and their point estimate is similar to that of active funds.

These results in this section are robust to alternative ways one may define closet index funds. In Appendix 4.1.3, I consider two additional ways to classify closet indexers, using a higher active share threshold. In Table 4.4, I re-estimate the main results where closet indexers are defined as funds that declare to be active but have an active share of less than 6.9. This increases the number of closet index funds to 126 and more than doubles the number of panel observations. In Table 4.5, I define closet index funds as having an active share within one standard deviation of the mean of that of explicit index funds, as has been done elsewhere in the literature; this increases the number of closet index funds to 218. While these alternative definitions increase the sample size of closet index funds substantially, the results are little changed. In both cases, the β_2 increases slightly for closet index funds (to 1.09 in Table 4.4 and 1.1 in Table 4.5, respectively) but remains not statistically different from one. Under both definitions, closet index funds do not respond to country crises. In active funds, β_2 falls slightly (to 0.98 in Table 4.4 and 0.97 in Table 4.5, respectively) but remains not statistically different from one. Active funds have the same procyclical response to country crises under both definitions. In the main analysis, I use the classification based on the lower active share threshold to ensure that closet indexers are those funds with investment behavior that more closely mirrors that of explicit indexers.

Overall, notable differences between active and index funds exist. Active and closet index funds withdraw from countries experiencing crises, while explicit index funds are insensitive to country crises. Explicit index funds also undo the impact of relative prices

on country weights, at least at a short horizon, and thus exert more of a stabilizing force. In contrast, both active and closet index funds appear to behave acyclically, allowing changes in relative returns to pass through fully to country weights. The overall coefficients for active and closet funds, however, could arise from two cases. All funds couuld behave passively, allowing country weights to change with prices. In this case we should see little dispersion in the strategies of active funds. Or, the average result could be due to variation within the subset of fund type, with some behaving procyclical and some contrarian. This I explore in Section 1.4.

1.3.3 Active Reallocations

The results in Section 1.3.2 are robust to an alternative specification which estimates the active manager component of country weights. As described in equation (6), the country weight can be decomposed into a 'buy-and-hold' component and an active reallocation component. In the absence of new reallocations by the fund manager, the portfolio weight of a country follows the buy-and-hold weight, changing when the country has a return higher or lower than those of other countries in the fund's portfolio.

I replace equation (6) into (5) to yield:

$$w_{ict} - w_{ict}^{BH} = \beta_1(r_{ct} - r_{it}) + \beta_3 w_{ict}^{BMExog} + \varepsilon_{ijt} \quad (7)$$

where the dependent variable measures the country weight less the buy-and-hold weight, or w_{ict}^{active}. In this case, a $\beta_1 > 0$ would indicate procyclical behavior, while $\beta_1 < 0$ indicates contrarian behavior, and $\beta_1 = 0$ indicates a buy-and-hold pattern.

Equation (7) is estimated in Table 4.6. The estimated coefficient on relative returns across all funds is -0.037. For a 1 percentage point decline in relative returns, funds on

average increase their country weight relative to the buy-and-hold by about 0.04 percentage point. In other words, while the buy-and-hold component declines with relative returns, the manager component increases, partially offsetting the effect of relative returns. As in Table 1.6, there is not complete pass through from relative returns to country weights; fund managers offset, to some degree, the impact of changes in relative prices on their country allocations through active reallocations. For explicit index funds, this offsetting behavior is greater, with a β_1 that's strongly negative, -0.094, and statistically less than zero. On average, these funds counteract the impact of changes in relative returns on country allocations at a short horizon, to keep a fixed country weight.

In active funds and closet indexers, the estimated β_1 is not significantly different from zero. As in Table 1.6, these funds appear to follow a buy-and-hold pattern with regard to relative returns. Active reallocations are more useful for informing manager behavior. However, the conclusions from estimating relative flows, rather than country weights, remain unchanged. I therefore focus on the total change in country weight in subsequent analysis, from which we can infer active reallocations.

1.4 Detailed Fund Strategy

Section 1.3 identified differences in how active, closet, and explicit index funds respond to shocks. Variation may exist even within these broad strategy types. Particularly among active funds, with more discretion in strategy, we may expect some funds to behave strongly procyclical and others strongly contrarian. Funds behaving procyclically tend to chase returns, increasing exposure to countries with high relative returns. Because mutual fund investors also typically chase performance, investing in funds with past high returns, shocks

to prices become amplified in procyclical funds. A negative shock to asset prices, for example, may cause outflows that further depress prices. Contrarian funds tend to dampen price shocks and exert more of a stabilizing force. To allow for heterogenous responses to shocks within fund types, I estimate equation (5) for each fund, and provide a complete description of observable fund behaviors.

Figures 1.1 and 1.2 show the distribution of individual fund β_2 by broad fund type. Explicit index funds have the lowest dispersion, with β_2's clustered around the mean of 0.69, and a standard deviation of 0.5 (See Table 1.10). In closet index funds, there is slightly more dispersion around 1.0, with a mean β_2 of 0.79 and standard deviation of 0.62. For active funds, Figure 1.1 shows a much wider band of variation in β_2 and more dispersion around 1.0. The standard deviation in active funds is nearly double that of explicit indexers, 0.96. While the mean β_2's reveal how strategies differ on average between fund types, the standard deviation of β_2 reveals whether there is heterogeneity in strategies. For example, while all fund types have an average β_2 of less than one, the average strategy in active funds reflects a variation in strategies that offset one another. The much wider variation of β_2's in active funds show that some active funds respond quite strongly (positively or negatively) to return differentials, in a way explicit and closet index funds do not. The distributions of active, closet, and explicit index funds are also all statistically different from each other, with p-values from each two-sample test of equality of 0.00. [16]

These findings show the results in Section 1.3 are more nuanced. While active and closet index funds have similar overall β_2's, their distributions are significantly different. While β_2 for active funds as group is not statistically different from 1.0, the group response

[16]The Kolmogorov-Smirnov test was used to test for equality of distributions

reflects a wide range of fund strategies, with some funds responding strongly positive to shocks and some strongly negative. Existing literature that characterizes the nature of fund behavior, therefore, masks these opposing behaviors within fund type.

Figure 1.1: Distribution of β_2 at fund-level

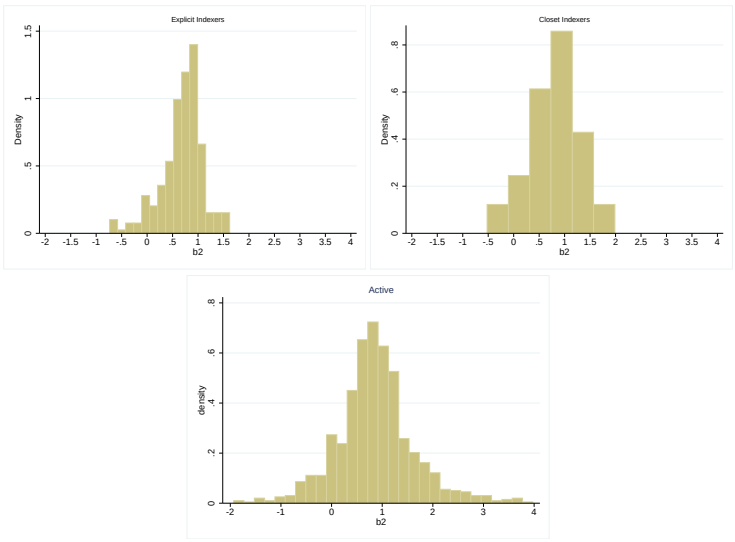
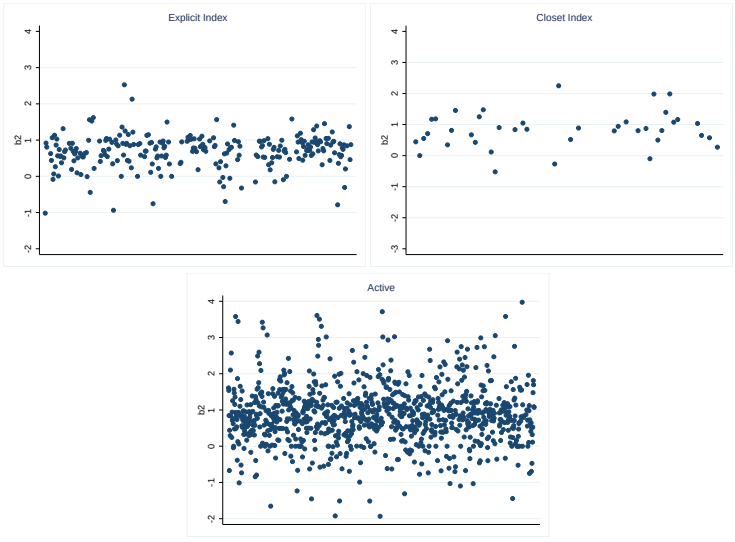


Figure 1.2: Distribution of β_2 at fund-level



Based on the estimated β_2's, active funds can be grouped into three types: acyclical,

procyclical, or contrarian. I define acyclical funds to have a β_2 within 0.1 point of 1.0, or between 0.9 and 1.1. These funds let any changes in prices pass through completely to country weights, with weights changing in response to fundamentals by the amount of the the buy-and-hold component. Procyclical funds have a $\beta_2 > 1.1$. These funds follow momentum strategies, reducing exposure in response to a negative shock and increasing it with a positive shock. Contrarian funds have a $\beta_2 < 0.9$. Country weights in these funds move against relative returns. Within this group, there exists some threshold level of β_2, say β^*, such that a β^2 less than one is necessary to maintain a fixed country weight. Thus contrarian funds with a β_2 between β^* and 1 are reallocating to keep a fixed country weight. Still, these funds are contrarian in the sense they are moving flows against relative prices.

Table 1.11 reports details on these active fund types. Contrarian funds comprise the majority of active funds, 54%. These funds behave strongly contrarian during normal times, with a mean β_2 of 0.29. This group holds the second largest in net assets among the groups, with average total net assets of $841.4 million over the sample period.[17] Contrarian funds invest primarily in developed markets, in Global and European asset classes. Procyclical funds comprise 33% of active funds. These funds behave strongly procyclical, with a mean β_2 of 1.75. These funds have assets of $736.4 million and are more heavily invested in emerging markets, with 56% of funds invested in an EM asset class. Acyclical funds comprise 12% of active funds. These are the largest funds among active funds, with average assets of $1.2 billion. These funds are invested primarily in emerging markets, with 60% of funds invested in an EM asset class.

With active fund types in hand, I re-estimate equation (5) to obtain β_2 for the identified

[17] The reported average AUM by groups have not been weighted by fund size

active fund types (see Table 1.12). In procyclical funds, there is 155% pass through of relative returns to country weights, with a β_2 of 1.55. For a 1 percent increase in relative returns, country weights in these funds rise by 1.5 percent. In contrarian funds, there is just over 50% pass through, with a β_2 of 0.54. Regardless of fund strategy, all active funds respond procyclically to crises, though the response in procyclical funds is twice that of contrarian funds. Procyclical funds reduce country weights by about 1.6% in response to a crisis, while contrarian and acylical funds have smaller responses, 0.8% and 1.0%. While manager allocations tend to move against relative returns in these funds, they react procyclically to crises.

While Table 1.6 showed that active funds as group appear to behave somewhat passively, only a small fraction of active funds behave this way. A larger portion of active funds behave procyclically, amplifying the impact of returns and crises. This is countered by a large number of funds that instead pursue more contrarian strategies. We thus observe behavior that may be motivated by models of momentum strategies and herding behavior discussed earlier, as well as models of portfolio rebalancing and opportunistic investing. The somewhat low presence of amplifying behavior, even among active funds, may reflect growth in the use of benchmarks, as more funds cut costs to behave more passively, and a changing landscape mutual fund flows.

A wide range of strategies exist within active funds. Next, I use this fund-level variation in strategies to describe the determinants of fund behavior.

1.5 The Cross-Section of β_2

Section 1.4 described notable variation in fund strategies among active funds, measured by their sensitivity to changes in relative returns. The majority of active funds behave contrarian in response to relative returns, with β_2's ranging from -0.7 to 0.9. A substantial fraction behave strongly procyclical, with β_2's ranging from 1.1 to 2.93, and a smaller fraction behave acyclical, with a β_2 close to 1.0. This section uses the variation in these fund-level coefficients to ask whether certain fund characteristics are associated with different fund behaviors. The literature has motivated why fund managers may behave a certain way. Information cascades, reputation concerns, and compensation structures can all motivate procyclical behavior in mutual funds. Group pressure or herding behavior are rational behaviors in fund managers concerned about their reputation (Scharfstein and Stein (1990))) and information cascades can lead to investment decisions based on the actions of others (Bikhchandani, Hirshleifer, and Welch (1992))). Compensation based on the performance of others and benchmark-based performance criteria (Ilyina (2007)) can also create similar incentives for herding. At the other end, we may expect funds with more liquidity or higher capital to have greater risk tolerance to pursue longer-term, contrarian investments.

While existing literature has described motivations behind fund behaviors, here I ask if observable fund characteristics or fund constraints matter in any systematic way. Do funds domiciled in different countries or invested in different regions behave differently? Do funds facing constraints such as investor outflows behave differently? Using the estimated fund-level β_2 coefficients from Section 1.4, I regress the β_2 level on cross-sectional characteristics :

$$\beta_{2,i} = \sum_{j=1}^{k} X_{i,j} + \varepsilon_i$$

where $X_{i,j}$ represents features of fund i such as average net assets, investment focus, asset class, investor type, and fund domicile. I also include constraints imposed by investors such as average monthly net flows and volatility of net flows, and average realized returns. I first consider the significance of each of the characteristics separately, in Columns (1) through (8) of Table 1.13, and in Column (9), the joint significance. Table 1.14 estimates a similar specification, where the dependent variable is instead the probability of a fund being procyclical, which I define as having a β_2 greater than 1. [18]

I first consider whether funds invested in different regions pursue different strategies. Asset class is a significant factor in fund strategy. In Column (1) of Table 1.13, funds specialized in an emerging market asset class are more likely to behave procylical or have a higher a β_2 while funds with developed market assets are more likely to be contrarian. A fund invested in emerging markets has a β_2 on average 0.15 higher than a fund invested in developed markets. Investing in EM also increases the probability a fund is strongly procyclical by 11.8% (see Table 1.14). Column (2) includes more granular asset classes. The three asset classes associated with developed markets (Pacific, Global DM, and Europe DM) are all negatively associated with β_2. A fund specialized in Global DM assets, for example, will have a β_2 0.26 lower than a fund invested in MENA (the excluded asset class category from Column (2)). These relationships remain significant controlling for size, investor type, and domicile (Column 9). These relationships also hold in Table 1.14: A fund invested in Global DM assets increases the likelihood the fund is procyclical by 15%.

I next consider investor type. β_2 is regressed on an indicator for whether a fund's in-

[18] Table 1.14 is estimated using OLS, though the same results are obtained using probit estimation.

vestors are primarily institutional or retail. Retail funds have a β_2 about 1.0 point higher on average, while institutional funds have lower β_2. A fund catering to retail investors also increases the probability a fund is procyclical by about 8%. One explanation could be that institutional investors, with a longer investment horizon, exert less pressure on fund managers as a result, accepting short-term volatility; whereas retail investors, on the other hand, are more likely to monitor short-term performance and redeem claims more frequently.

Column (4) includes a fund's average net assets. While fund size is significant, the economic impact on β_2 is negligible. This is consistent with results in Section 1.4, which showed that funds following acyclical strategies (with a β_2 close to 1) have the largest net assets. The relationship between β_2 and fund size thus appears nonlinear. Conditional on a fund having a $\beta_2 > 1$, for example, the relationship between β_2 and net assets becomes strongly negative. As assets grow, funds become more likely to pursue contrarian strategies.

I next consider how funding constraints affect fund behavior. Funds receiving higher investor inflows may have higher liquidity or greater risk tolerance, and thus be more likely to pursue longer-term, riskier strategies. Similarly, funding constraints may create pressure for funds to follow their peers or chase returns. Column (5) regress β_2 on the mean and standard deviation of monthly net flows (scaled by net assets), respectively. The coefficient on net flows is strongly negative, -3.53. Funds with higher net flows are more likely to have lower β_2, or behave more contrarian. A fund with one standard deviation higher average net flows (0.015) will have a β_2 0.06 lower. The volatility of net flows has the opposite effect. Funds facing more volatile flows have higher β_2's and are more likely to behave procyclical. Funds with more capital, thus appear to be more risk tolerant and engage in contrarian, perhaps long-term investment opportunities. Funds with more stable flows over

time are also more likely to pursue a contrarian strategy. These relationships hold within asset class, domicile, investor type, and fund size.

Column (6) asks whether funds with a particular strategy have higher average returns. Mean fund returns are strongly and negatively associated with β_2. A fund with an average fund return one standard deviation higher, or about 4.3%, will have an average beta 0.33 lower. Consistent with the results in column (5), higher returns provide funds with more flexibility to take advantage of contrarian, perhaps longer-term, investments or arbitrage opportunities. It could also be that contrarian strategies turn out to be more profitable. The relationship between fund returns and β_2 becomes insignificant after controlling for investor flows, suggesting that the relevant factor is fund capital. The findings in columns (5) and (6) are also consistent with a performance-based model of arbitrage. In Shleifer and Vishny (1997), arbitrage is conducted by a few, highly specialized investors. Arbitrageurs ability to take advantage of mispricing, however, is limited by investor capital. As prices move away from fundamentals, arbitrageurs experience loses and face fund withdrawals and liquidations, limiting their ability to fully realize opportunities. My results show that funds with more capital and higher returns are those more likely to take advantage of riskier, long-term opportunities.

Finally, I include domicile and fund currency to test whether funds located in different countries behave differently. Funds domiciled in advanced economies appear to have higher β_2's on average. Funds domiciled in European countries (the omitted category from Column 7) and the U.S. have higher β_2's than those in Asian countries, while differences between the U.S., European, and other advanced domiciles are not significant. Similarly, funds dealing in European currencies have similar β_2's to those in USD but higher than

Asian and 'other' currencies (Column 8 of Table 1.13).

Overall, differences in fund strategy exist within asset class, investor composition, and fund domicile. We should expect flows to emerging markets and flows from retail funds to be associated with more procyclical flows, while flows to developed markets and from institutional investors to be stabilizing. Constraints imposed by investor flows are also significant determinants of fund strategy. Contrarian strategies tend to be pursued by funds with more financial flexibility, either high monthly inflows or more stable net flows, and with higher realized returns. This also suggests that funds may behave more procyclically when they become constrained by investor flows or in times of financial stress.

1.6 Conclusion

Growth in mutual fund assets globally has given rise to concerns about increased amplification of shocks or crises and procyclicality of flows. Principal-agent problems and compensation structure in mutual funds can create incentives for funds to chase returns and follow their peers. However, empirical evidence on the composition of fund behaviors and how fund strategy can affect these the amplification channel is limited.

In the last several years, most of the industry growth has been concentrated in index funds, flows through which should operate through a different channel than active funds. My results suggest that as the as the industry shifts from active to passive management, risks arising from manager behavior become attenuated. Recent work has shown that investors in passive funds or ETFs increase volatility, trading in response to crises and global financial conditions. I show that the behavior from fund managers does not mimic this investor behavior; in fact, manager actions tend to dampen such shocks. Flows through

index funds react more contrarian, moving against changes in relative prices. Index funds are also not sensitive to crises within a country, and thus exert more of a stabilizing effect for countries in the portfolio.

In active funds, there is a wide range of fund behaviors, with some managers behaving procyclically, amplifying the impact of shocks, and some behaving contrarian. Procyclical flows, and amplification of shocks, are more likely in investments in emerging market and funds with retail investors, while flows to developed markets and from institutional investors are more stabilizing. Constraints imposed by investor flows are also significant determinants of fund strategy. Contrarian strategies tend to be pursued by funds with more financial flexibility, either high monthly inflows or more stable net flows, and with higher realized returns. My results also highlight the impact of the growing use of benchmarks. Even within active funds, many invest in allocations that closely track the benchmark, or behave acyclically in response to changes in relative prices. As more active funds follow benchmarks, and the composition of assets shifts to passive management, this suggests less amplification from manager behavior.

1.7 Figures and Tables

1.7.1 Figures

Figure 1.3: Assets Under Management

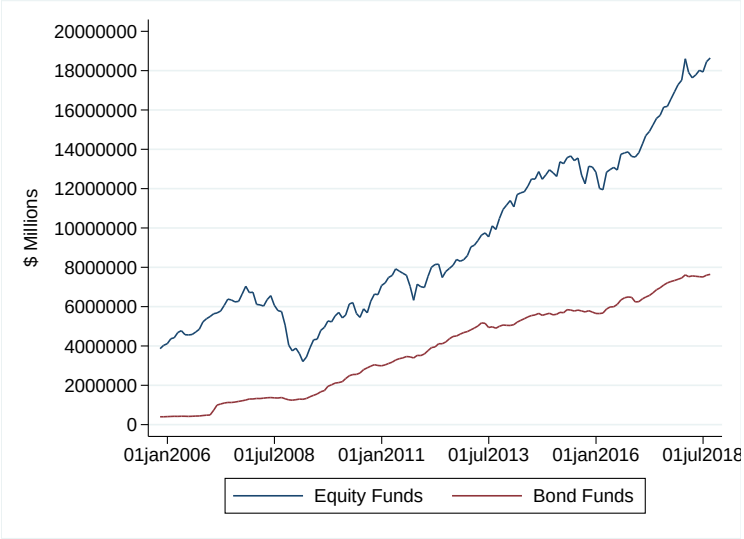


Figure 1.4: Active Share in Equity Funds

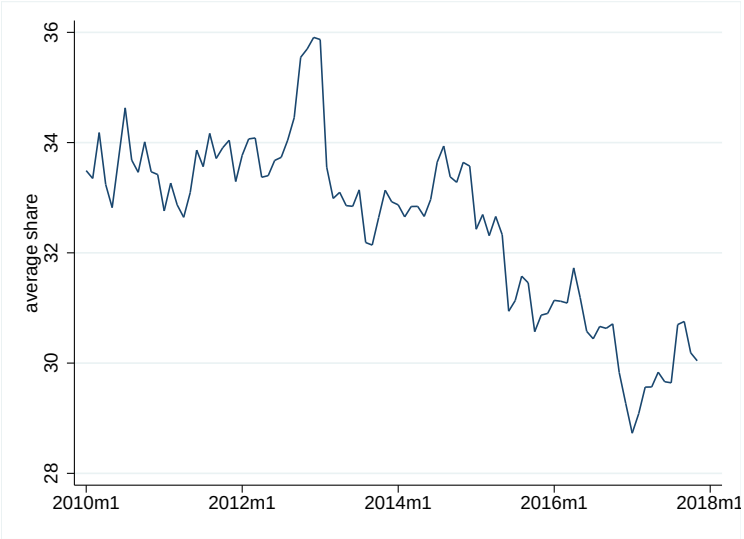
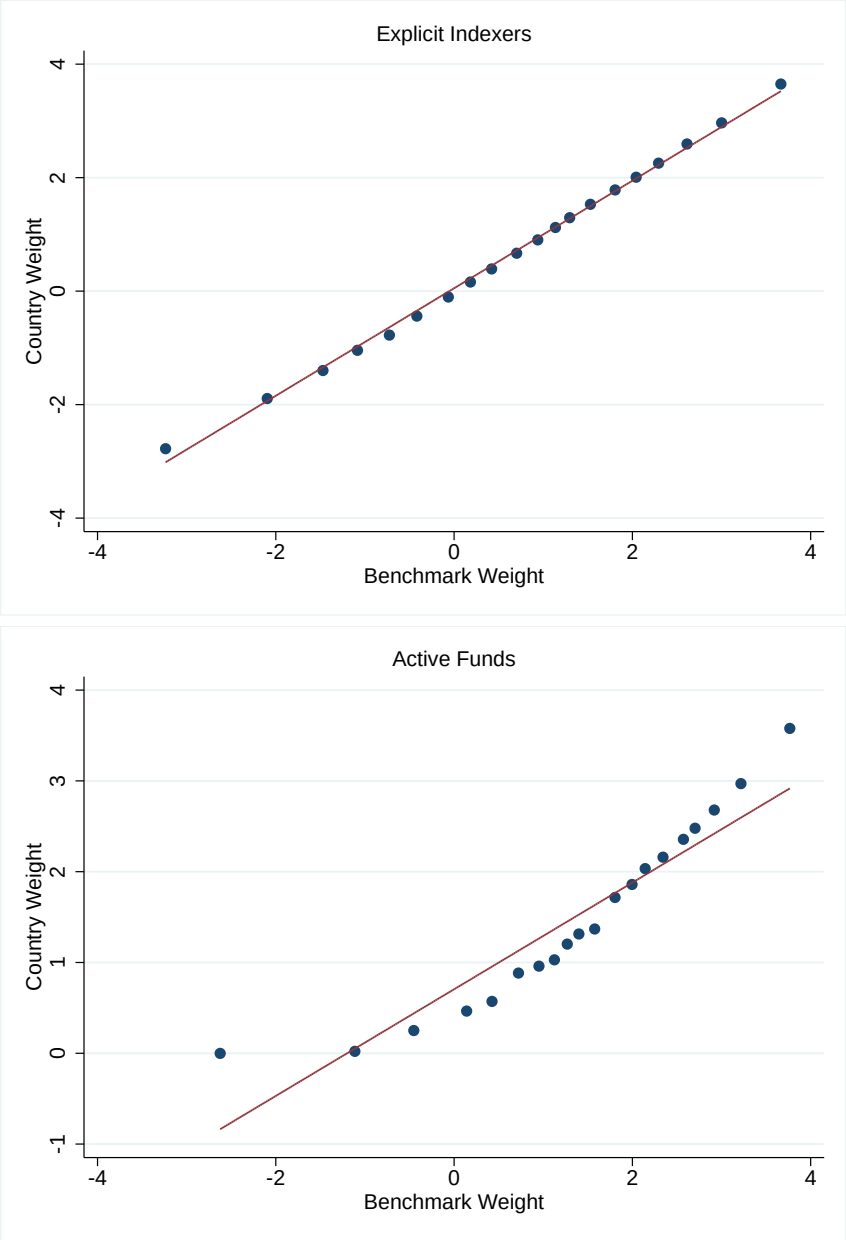


Figure 1.5: Country Weight vs Benchmark Weight



1.7.2 Tables

Table 1.1: Fund characteristics

	Funds	Panel Obs	% of Panel
Strategy			
Passive	319	452,770	17.80
Active	1,072	2,091,251	82.20
ETF			
ETF	271	395,007	15.53
Non-ETF	1,120	2,114,528	84.47
EM or DM			
Emerging Markets	603	1,243,564	49.66
Developed Markets	788	1,260,630	50.34
Asset Class			
Emerging Markets			
Asia ex-Japan	224	468,096	18.69
BRIC	12	34,960	1.40
Emerging Europe	42	96,508	3.85
Global EM	252	492,752	19.68
Latin America	53	124,982	4.99
Middle East and Africa	20	26,266	1.05
Developed			
Global	255	377,798	15.09
Global ex-US	160	239,660	9.57
Western Europe	203	363,906	14.53
Europe ex-UK	142	237,866	9.50
Asia Pacific	28	41,400	1.65
Domicile			
USA	366	623,714	24.91
Europe	913	1,739,628	69.47
Asia	10	11,316	0.45
Other	102	15,594	0.62
Currency			
USD	750	1,328,020	53.03
European	508	988,632	39.48
Other	133	187,542	7.05

Table 1.1 reports statistics for the sample of equity mutual funds by selected characteristics: strategy, asset class, domicile, and currency.

Table 1.2: Summary Statistics

	Mean	Std	p10	p25	p50	p75	p90
Fund Returns (%)	0.65	4.26	-4.69	-1.70	0.87	3.19	5.65
Active	0.65	4.32	-4.74	-1.71	0.86	3.24	5.68
Closet	0.53	4.83	-5.53	-1.89	0.69	3.2	6.13
Explicit	0.65	4.04	-4.42	-1.63	0.92	2.94	5.39
Relative Returns (%)	0.06	4.88	-5.83	-2.78	0.04	2.91	6.00
Country Weight	7.18	10.00	0.38	1.23	3.48	9.0	18.06
Benchmark Weight	5.96	9.77	0.13	0.44	2.24	7.14	15.74
Panel B: Within-Fund Variation							
Country Weights (%)	1.28	1.61	0.07	0.28	0.77	1.70	3.11

Panel C: Countries-of-Investment

Argentina	Australia	Austria	Belgium
Brazil	Canada	Chile	China
Colombia	Czech Republic	Denmark	Estonia
Finland	France	Germany	Greece
Hong Kong	Hungary	India	Indonesia
Ireland	Isreal	Italy	Japan
South Korea	Latvia	Lithuania	Malaysia
Mexico	Netherlands	New Zealand	Pakistan
Peru	Phillipines	Poland	Portugal
Russia	Singapore	Slovakia	South Africa
Spain	Sweden	Switzerland	Taiwan
Thailand	Turkey	U.K.	USA
Venezuela	Vietnam		

Panel A of Table 1.2 reports summary statistics of the full panel sample for fund returns, country returns, the active share measure, country weights, benchmark weights, and relative returns. For country weights and benchmarks, the distribution is on the sample greater than 0. Panel B reports statistics on within-fund variation. The distribution reported is on the standard deviation of country weights within fund-country.

Table 1.3: Predicted vs Actual Fund Returns

	Mean	Std	p10	p25	p50	p75	p90	Min	Max
$\lvert R_{it} - R_{it}^{predicted} \rvert$	0.014	0.014	0.002	0.004	0.010	0.020	0.032	0	0.312
Active	0.015	0.014	0.002	0.005	0.012	0.020	0.032	0.00	0.312
Closet	0.017	0.018	0.002	0.005	0.012	0.023	0.040	0.00	0.156
Explicit	0.011	0.012	0.001	0.003	0.007	0.016	0.027	0.00	0.117

Table 1.3 compares reported fund returns (R_{it}) with the returns implied by country weights and country index returns ((R_{ct})

Table 1.4: Active Share

	Mean	Std	p10	p25	p50	p75	p90
All Funds	15.56	13.26	0	3.03	14.76	23.08	33.0
Passive	2.72	5.51	0	0	1.62	2.76	4.35
ETF	3.38	7.42	0	0	1.45	2.78	5.19
Passive or ETF	3.18	6.86	0	0	1.61	2.79	4.86
Active	24.45	9.6	15.12	17.05	21.49	29.08	38.47

Table 1.4 reports summary statistics for the computed measures of active share - the percentage of the portfolio that is invested outside the benchmark: Active Share = $\left(\frac{1}{2}\right) \sum_{j=1}^{N} \mid w_{fund,j} - w_{B,j} \mid$

Table 1.5: Country Weights vs Benchmark Weights

	Funds	Active	Closet Indexer	Explicit Indexer
Benchmark Weight	0.712***	0.679***	0.817***	0.864***
	(0.002)	(0.003)	(0.007)	(0.002)
Adjusted R^2	0.960	0.948	0.995	0.996
Observations	650381	500580	9503	140298

Table 1.6: Log Country Weights by Strategy

	All Funds		Active		Closet Indexer		Explicit Indexer	
Lagged country weight	0.879***	0.878***	0.882***	0.878***	0.832***	0.904***	0.832***	0.862***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.037)	(0.030)	(0.016)	(0.013)
Relative returns	0.943***	0.964***	0.985***	1.003***	1.070***	1.112***	0.793***	0.819***
	(0.014)	(0.016)	(0.018)	(0.020)	(0.093)	(0.094)	(0.018)	(0.019)
Benchmark weight	0.003***	0.004***	0.002***	0.003***	0.003	0.005***	0.008***	0.007***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Country Crisis		-0.009***		-0.011***		-0.025**		0.001
		(0.002)		(0.002)		(0.012)		(0.002)
Fund FE	No	No	No	No	No	No	No	No
Time FE	No	No	No	No	No	No	No	No
Fund-country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.983	0.982	0.974	0.973	0.994	0.995	0.996	0.997
Observations	261789	194951	200339	155321	3636	2435	57814	37195

Table 1.6 regresses log country weights on the country weight in the previous period, relative returns and the exogenous component of the benchmark weight. Standard errors are clustered at the fund-time level.

Table 1.7: Relative Flows by Strategy

	All Funds	Active	Closet Indexer	Explicit Indexer
Relative returns	-0.037***	-0.016*	0.075	-0.094***
	(0.008)	(0.010)	(0.054)	(0.008)
Benchmark weight	0.001***	0.001**	0.004***	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
Fund FE	No	No	No	No
Time FE	No	No	No	No
Fund-country FE	Yes	Yes	Yes	Yes
Fund-time FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.298	0.241	0.831	0.512
Observations	256370	196292	3595	56657

Table 4.6 regresses log country weights minus log buy-and-hold weights on relative returns and the exogenous component of the benchmark weight. Standard errors are clustered at the fund-time level.

Table 1.8: Log Country Weights, Expanded Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All Funds							
Lagged country weight	0.970***	0.987***	0.989***	0.987***	0.875***	0.988***	0.879***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.005)
Relative returns	0.778***	0.775***	0.781***	0.783***	0.749***	0.977***	0.943***
	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Benchmark weight	0.006***	0.005***	0.005***	0.005***	0.003***	0.005***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund FE	No	Yes	No	Yes	No	No	No
Time FE	No	No	Yes	Yes	No	No	No
Fund-Country FE	No	No	No	No	Yes	No	Yes
Fund-Time FE	No	No	No	No	No	Yes	Yes
Adjusted R^2		0.982	0.982	0.982	0.983	0.982	0.983
Observations	266419	266415	266419	266415	265001	263335	261789
Explicit Indexers							
Lagged country weight	0.983***	0.994***	0.994***	0.994***	0.828***	0.993***	0.832***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)	(0.001)	(0.016)
Relative returns	0.738***	0.732***	0.763***	0.761***	0.680***	0.856***	0.793***
	(0.013)	(0.016)	(0.017)	(0.017)	(0.016)	(0.018)	(0.018)
Benchmark weight	0.005***	0.004***	0.004***	0.004***	0.008***	0.004***	0.008***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fund FE	No	Yes	No	Yes	No	No	No
Time FE	No	No	Yes	Yes	No	No	No
Fund-Country FE	No	No	No	No	Yes	No	Yes
Fund-Time FE	No	No	No	No	No	Yes	Yes
Adjusted R^2		0.995	0.995	0.995	0.996	0.995	0.996
Observations	58465	58464	58465	58464	58090	58196	57814
Closet Indexers							
Lagged country weight	0.970***	0.997***	0.996***	0.997***	0.827***	0.999***	0.832***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.033)	(0.002)	(0.037)
Relative returns	0.826***	0.821***	0.813***	0.818***	0.795***	1.022***	1.070***
	(0.053)	(0.082)	(0.089)	(0.081)	(0.076)	(0.100)	(0.093)
Benchmark weight	0.004***	0.003	0.004**	0.003	0.004*	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fund FE	No	Yes	No	Yes	No	No	No
Time FE	No	No	Yes	Yes	No	No	No
Fund-Country FE	No	No	No	No	Yes	No	Yes
Fund-Time FE	No	No	No	No	No	Yes	Yes
Adjusted R^2		0.993	0.993	0.993	0.994	0.994	0.994
Observations	3862	3861	3862	3861	3839	3664	3636
Active Funds							
Lagged country weight	0.960***	0.983***	0.986***	0.983***	0.879***	0.984***	0.882***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.005)
Relative returns	0.789***	0.787***	0.791***	0.793***	0.764***	1.018***	0.985***
	(0.012)	(0.015)	(0.014)	(0.014)	(0.015)	(0.018)	(0.018)
Benchmark weight	0.006***	0.005***	0.005***	0.005***	0.002***	0.005***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund FE	No	Yes	No	Yes	No	No	No
Time FE	No	No	Yes	Yes	No	No	No
Fund-Country FE	No	No	No	No	Yes	No	Yes
Fund-Time FE	No	No	No	No	No	Yes	Yes
Adjusted R^2		0.972	0.972	0.972	0.974	0.972	0.974
Observations	204092	204090	204092	204090	203072	201475	200339

Table 1.8 regresses log country weights on the country weight in the previous period, relative returns and the exogenous component of the benchmark weight. Standard errors are clustered at the fund-time level.

Table 1.9: Country Weights During Crises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Explicit Indexers				
Lagged country weight	0.862***	0.855***	0.859***	0.862***	0.866***	0.867***	0.868***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Relative returns	0.819***	0.873***	0.856***	0.819***	0.828***	0.832***	0.831***
	(0.015)	(0.019)	(0.018)	(0.015)	(0.015)	(0.015)	(0.015)
Benchmark weight	0.007***	0.007***	0.007***	0.007***	0.008***	0.008***	0.008***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
crisis	0.001						
	(0.002)						
banking		0.000					
		(0.008)					
systemic			-0.021				
			(0.020)				
currency				-0.012***			
				(0.003)			
soverigndebt1						-0.146***	
						(0.018)	
sovereigndebt2							-0.029***
							(0.006)
Adjusted R^2	0.997	0.998	0.997	0.997	0.997	0.997	0.997
Observations	37195	14311	28757	37195	35969	34526	34526
			Closet Indexers				
Lagged country weight	0.904***	0.854***	0.886***	0.903***	0.898***	0.896***	0.895***
	(0.013)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)
Relative returns	1.112***	1.114***	1.139***	1.105***	1.119***	1.100***	1.108***
	(0.071)	(0.084)	(0.079)	(0.071)	(0.072)	(0.073)	(0.073)
Benchmark weight	0.005***	0.004*	0.005**	0.005***	0.005***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
crisis	-0.025**						
	(0.010)						
banking		0.011					
		(0.035)					
systemic			-0.024				
			(0.043)				
currency				-0.040***			
				(0.012)			
soverigndebt1						0.000	
						(.)	
sovereigndebt2							-0.061
							(0.041)
Adjusted R^2	0.995	0.996	0.995	0.995	0.995	0.995	0.995
Observations	2435	1657	2112	2435	2378	2282	2282
			Active Funds				
Lagged country weight	0.878***	0.860***	0.869***	0.878***	0.877***	0.878***	0.878***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Relative returns	1.003***	1.068***	1.047***	1.002***	1.011***	1.026***	1.025***
	(0.017)	(0.022)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)
Benchmark weight	0.003***	0.002***	0.002***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
crisis	-0.011***						
	(0.002)						
banking		-0.012					
		(0.009)					
systemic			-0.008				
			(0.015)				
currency				-0.018***			
				(0.003)			
soverigndebt1						-0.219***	
						(0.028)	
sovereigndebt2							-0.058***
							(0.010)
Adjusted R^2	0.973	0.973	0.973	0.973	0.973	0.973	0.973
Observations	155321	96404	134290	155321	151776	145929	145929

Table 1.9 shows regressions of log country weights on lagged log country weights, relative returns $(r_{ct} - r_{it})$, benchmark weight (w_{ict}^{BMExog}), and an indicator variable for whether a country experienced a crisis. Standard errors are clustered at the fund-time level. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 1.10: Distribution of β_2 at fund-level

	No. of Funds	Mean	p10	p25	p50	p75	p90	Std
Explicit Index	257	0.69	0.05	0.51	0.74	0.95	1.13	0.50
Closet Index	41	0.79	0.00	0.50	0.81	1.1	1.45	0.62
Active	985	0.87	-0.01	0. 45	0.84	1.22	1.81	0.96

Table 1.10 shows the distribution of β_2 from estimating the follow regression at the fund-level: $w_{ict} = \beta_1 w_{ict-1} + \beta_2(r_{ct} - r_{it}) + \beta_3 w_{ict}^{BM} + \beta_4 C_{ct}\alpha_{it}(5)$

Table 1.11: Active Funds

	Contrarian	**Acyclical**	**Procyclical**
Number of Funds	535	127	323
Average Net Assets ($bil)	$0.84	$1.2	$0.74
β_2 Mean	0.29	0.99	1.75
β_2 Median	0.49	0.99	1.49
Emerging Markets (# of funds)	219	77	181)
Developed Markets	316	50	142
Asset Class (# of funds)			
Europe	161	31	88
Global	245	63	144
Latin America	24	7	10
Asia	105	26	81

Table 1.11 shows the characteristics on the composition of active funds by strategy

Table 1.12: Active Funds During Crises

	Contrarian	Acyclical	Procyclical
Lagged country weight	0.890***	0.907***	0.854***
	(0.002)	(0.003)	(0.003)
Relative returns	0.544***	0.994***	1.547***
	(0.024)	(0.034)	(0.031)
Benchmark weight	0.000	0.002*	0.007***
	(0.001)	(0.001)	(0.001)
Country crisis	-0.008***	-0.010**	-0.016***
	(0.003)	(0.004)	(0.004)
Fund FE	No	No	No
Time FE	No	No	No
Fund-country FE	Yes	Yes	Yes
Fund-time FE	Yes	Yes	Yes
Adjusted R^2	0.976	0.983	0.964
Observations	74683	24952	55658

Table 1.12 shows regressions of log country weights on lagged log country weights, relative returns $(r_{ct} - r_{it})$, benchmark weight (w_{ict}^{BMExog}), and an indicator variable for whether a country experienced a crisis. Standard errors are clustered at the fund-time level. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 1.13: Cross-Section of β_2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Em.Mkts	0.147***								0.136***
	(0.041)								(0.041)
Asset Class									
Asia		-0.063							
		(0.090)							
Europe (EM)		-0.067							
		(0.140)							
Lat.Am		-0.141							
		(0.110)							
Global (EM)		-0.003							
		(0.085)							
Pacific		-0.339*							
		(0.174)							
Global (DM)		-0.261***							
		(0.086)							
Europe (DM)		-0.170*							
		(0.095)							
Retail			0.099**						0.101**
			(0.042)						(0.043)
Log TNA				0.032***	0.041***				0.042***
				(0.011)	(0.011)				(0.012)
Average Net Flows					-3.513**				-2.498*
					(1.387)				(1.443)
Volatility of Flows					2.355**				2.534**
					(1.042)				(1.071)
Fund Returns						-7.610**			-5.807
						(3.730)			(3.842)
Domicile									
U.S.							-0.037		0.014
							(0.048)		(0.051)
Other Adv.							-0.182*		-0.102
							(0.098)		(0.094)
Asia							-0.372**		-0.394**
							(0.185)		(0.188)
Offshore							0.177		0.209
							(0.221)		(0.189)
Other							0.008		0.023
							(0.235)		(0.232)
Currency									
USD								-0.023	
								(0.043)	
Asian								-0.353**	
								(0.174)	
Other								-0.182*	
								(0.097)	
Adjusted R^2	0.010	0.018	0.004	0.005	0.015	0.004	0.001	0.002	0.029
Observations	1143	1143	1143	1128	1125	1143	1143	1143	1125

Table 1.13 regresses fund-level β_2 coefficients on the following variables: an indicator whether the fund invests in emerging markets or developed markets, specific asset classes, an indicator for whether the fund's investors are retail or institutional, average total assets, average monthly investor flows, the volatility of investor flows, mean fund returns, and fund domicile. Standard errors are heteroskedasticity-robust.

Table 1.14: Procyclical Funds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Em.Mkts	0.118***							0.117***
	(0.028)							(0.029)
Asset Class								
Asia		-0.007						
		(0.059)						
Europe (EM)		-0.028						
		(0.091)		F				
Lat.Am		-0.138*						
		(0.079)						
Global (EM)		0.039						
		(0.058)						
Pacific		-0.186*						
		(0.101)						
Global (DM)		-0.151***						
		(0.053)						
Europe (DM)		-0.126**						
		(0.059)						
Retail			0.080***					0.065**
			(0.029)					(0.030)
Log TNA				0.016**	0.020**			0.021***
				(0.008)	(0.008)			(0.008)
Average Net Flows					-2.404***			-1.888**
					(0.819)			(0.855)
Volatility of Flows					0.606			0.665
					(0.672)			(0.690)
Fund Returns						-1.497		0.209
						(2.092)		(2.164)
U.S.							-0.061*	-0.023
							(0.032)	(0.034)
Other Adv.							-0.074	-0.029
							(0.066)	(0.065)
Asia							-0.225*	-0.245*
							(0.134)	(0.130)
Offshore							0.132	0.133
							(0.251)	(0.231)
Other							-0.118	-0.121
							(0.218)	(0.215)
Adjusted R^2	0.014	0.022	0.006	0.002	0.009	-0.000	0.001	0.025
Observations	1139	1139	1139	1125	1122	1139	1139	1122

Table 1.14 regresses an indicator equal to one if a fund has a $\beta_2 > 1$ on the following variables: an indicator whether the fund invests in emerging markets or developed markets, specific asset classes, an indicator for whether the fund's investors are retail or institutional, average total assets, average monthly investor flows, the volatility of investor flows, mean fund returns, and fund domicile. Standard errors are heteroskedasticity-robust

Chapter 2: Funding Shocks and Liquidity Management: Evidence from International Mutual Funds

2.1 Introduction

A growing literature focuses on the role financial intermediaries play in the amplification and transmission of crises, and in particular, the behavior of mutual fund investors and managers in understanding these intermediaries. In this chapter, I link the behaviors of these two participants - underlying investors, choosing which funds to invest in and when, and fund managers, deciding where to allocate the assets - through a significant risk channel, investor flows.

Investors in mutual funds tend to respond procyclically to local and international conditions when deciding which funds to invest in and when. They inject money into funds based on past performance and when conditions in their country of origin improve, and they withdraw from funds invested in countries undergoing crises or during periods of global crisis (Raddatz and Schmukler (2012)). Recent work has also shown that investor flows, particularly to exchange traded funds (ETFs), trade in response to global risk factors, increasing volatility and amplifying global financial conditions (Raddatz, Schmukler, and Williams (2018)). While the literature has documented the drivers of investor flows and described investor behavior, we have limited knowledge on how fund managers respond to these flows. Do fund managers provide any buffer from the ultimate investor? Or do they simply buy and sell securities on behalf of investors, perhaps exacerbating the decisions of

fund investors?

Raddatz and Schmukler (2012) estimate how cash weights respond to fund returns and find that cash weights in equity funds respond countercyclically. Funds accumulate extra cash in ”bad times” when fund returns are low and reduce cash in ”good times” when fund returns are high. This doesn't tell us, however, how cash weights respond to investor flows. If we assume that during times when fund returns are low that funds also face pressure from investors, this would imply that funds sell securities in the underlying portfolio to increase cash, rather than draw upon cash holdings to meet investor outflows. Jotikasthira, Lundblad, and Ramadorai (2012) provide evidence to support this claim. They measure the percentage of countries in which a fund increases its holding during a month minus the percentage of countries in which the fund reduces its holding, and show that this net change is strongly related to investor flows. Funds facing the largest inflows expand country positions, while those facing outflows reduce or eliminate positions. This doesn't, however, tell us how flows affect a funds relative cash to equity position and to what extent funds use cash as a buffer to mediate flows before altering country positions.

In this paper, I study the behavior of cash allocations to better understand how investor flows affect a fund's relative cash to equity position. To what extent do funds accommodate new inflows by holding cash versus purchasing equities? The relationship between cash and investors flows also has important implications in periods of financial stress. Open-ended mutual funds can face withdrawals from investors at any time. In response, funds can meet investor redemptions through existing cash reserves or through sales of underlying assets. In the latter case, forced asset sales have been shown to have price impact in equity markets under certain conditions. Particularly in periods of market stress, redemptions from

open-ended funds that force the sale of illiquid assets can depress asset prices, thereby stimulating further redemptions and fire sales. To the extent fund managers use cash as a buffer to meet redemptions, they can mitigate the potential impact on asset markets. Coval and Stafford (2007) show that for U.S. mutual funds, forced sales from investor redemptions significantly impact U.S. domestic equity prices. Jotikasthira et al (2012) show that global funds display this same forced trading behavior as U.S. domestic funds-regardless of their cash holding, they substantially alter portfolio allocations in response to funding shocks from investors, leading to price impact in emerging markets.[1]

Asset managers now control an estimated $160 trillion worldwide, and how they respond to shocks from investors has increasing importance for financial stability considerations. Understanding liquidity management decisions by funds can shed light on this question. In this chapter, I use fund-level data on international mutual funds to ask how managers respond to funding shocks from their investor base. My paper contributes to the literature in four parts. First, while we have evidence on factors that drive investor behavior, evidence is scarce on how managers react to these investor flows. This response is essential for knowing whether managers transmit the behavior of investors, or if they act as a buffer in any way. Do managers anticipate and manage the risk from investors using tools such as cash buffers? To my knowledge, the only paper providing direct empirical evidence on this question is Chernenko and Sunderam (2016). They study cash holdings of U.S. equity and corporate bond funds that report to the SEC. They argue that funds hold a substantial amount of assets in cash and use this cash to accommodate inflows and outflows. The

[1]Other theoretical and empirical literature related to fire sales in debt and equity markets include Shleifer and Vishney (1997), Greenwood and Thesmar (2011), and Merrill et al (2012).

funds I study, in contrast, represent a majority of funds domiciled globally, invested in a wide range of emerging and advanced markets. My results are therefore more reflective of international investor behavior, and show that global mutual funds in fact hold very little in cash and provide little buffer between the ultimate investor and the market.

Second, I study how liquidity management decisions differ by fund strategy. While we may not expect index funds to have much capacity to mediate investor flows, we would expect active funds to. Active funds have more discretion to hold funds in cash and wait for opportune moment to invest. Understanding these differences between fund type are more important in light of the changing landscape of the mutual fund industry. Coincident with growth in the asset management industry as a whole have been large outflows from funds with active investment strategies - those which seek to outperform a benchmark - and a shift to passive or indexing strategies - those that that aim to replicate a benchmark. As seen in Figure 2.1, passive or index funds hold a rising share of the total financial assets in equity mutual funds globally. Since 2009, the share of net assets in equity mutual funds held by passive funds has risen from 23% to 42%. Beginning in January 2008, cumulative flows to active funds turned negative and have declined over 400% since then (as of May 2019). Over the same period, cumulative flows to passive funds have grown more than ninefold (see Figure 2.2). Based on these trends, my analysis considers differences in how active and index funds manage funding shocks. Active funds are more likely to provide investors with liquidity transformation services, and thus we would expect these funds to have greater tendency to accommodate net flows in cash and build cash buffers. Index funds, by contrast, we may expect to act more like a veil, directly buying and selling securities on behalf of investors. As the industry shifts from active to passive management this could imply greater

risks, with funds providing less of buffer between the market and ultimate investor.

Third, I test for a nonlinear relationship between cash and investor flows. I expand my model of cash allocations to capture periods of inflows versus outflows, periods of sustained capital outflows, and periods of capital surges or retrenches. I test whether the relationship between cash and net flows is stronger in good or bad times, and for differences between periods of particularly high inflows and periods of financial stress. During periods of capital surges, do fund managers take additional steps to manage their future liquidity needs? In periods of financial stress, are funds more likely to use cash as a buffer to meet redemptions than during normal times? To measure financial stress, I consider both periods of consecutive outflows as well as periods of severe outflows. Some recent work studying global bond mutual funds has found evidence of cash hoarding (Morris, Shim, and Shin (2017) and Shek, Shim, and Shin (2015)). Rather than use existing cash as a buffer to meet redemptions, bond funds, particularly funds holding more illiquid bonds, sell assets beyond what is needed to meet investor withdrawals through discretionary sales of the underlying asset. This behavior can reflect efforts to maintain a prudent level of cash in the face of market volatility but can also amplify fire sales driven by investor redemptions. Morris, Shim, and Shin (2017) estimate that for every 100 dollars of sales due to investor redemptions in emerging market bond funds, there are an additional 10 dollars in discretionary sales. My results show that during periods of financial stress, even equity mutual funds, which are by comparison more liquid that emerging market bond funds, exhibit this same behavior, though the response differs by fund type.

Finally, I provide evidence on how investor flows affect specific country allocations. The documented relationship between cash and investor flows suggests that flows impact

assets in the underlying portfolio to a significant extent. Specifically, I ask whether local country conditions affect a fund's decision to expand or reduce allocations to a given country. For example, in forced asset sales, which countries are sold? We may expect index funds to liquidate countries in the portfolio proportionally, but for active funds conditions such as country performance and country liquidity may matter. Do active funds use investor flows as an opportunity to reallocate across countries or do they behave similarly to index funds? My results thus provide the first description of how investor flows affect the complete portfolio in global equity funds, both cash and country allocations.

I find that at a short horizon, funds tend to manage investor flows with cash but the impact fades over time and differs by fund strategy. The positive relationship between cash and investor flows is driven the behavior of active funds. In active funds, about 16% of net flows are accommodated through cash in the month they're received. The effect, however, gradually fades, with most of the initial inflow invested across countries within two periods. For index funds, this reallocation of cash to equities happens much quicker.

I also show that the relationship between cash and flows is differs in periods of volatility versus in normal times. On average, cash responds stronger to investor outflows than inflows. However, in periods of more severe financial stress - either consecutive periods of outflows or outflows in the bottom decile of fund flows - the relationship between cash and flow weakens relative to in normal times. This effect is more pronounced in index funds, and in explicit index funds, the relationship between cash and flows becomes negative. That is, cash holdings increase during periods of severe outflows. This result identifies an increased redemption risk in passive funds. In periods of investor outflows, index funds sell assets beyond what is needed to meet outflows, increasing the potential for redemptions to

have a negative price impact in periods of stress. This also increases empirical evidence on the phenomenon of cash hoarding using a broader sample of global funds, invested in equities across the world. Previous literature has focused on a more narrow set of asset classes and linked cash hoarding to the illiquidity of assets.

The behavior of cash weights in these funds implies that investor flows impact securities in the fund portfolio to a significant extent. I show that in response funding pressure, active funds tend to sell allocations in countries with low returns and in countries with higher market liquidity. Overall, the results show that mutual funds invested in global equities transact more heavily in securities in the underlying portfolio than in cash. Index funds provide essentially no buffer between investor flows and equity markets. While at a short horizon, active funds have greater propensity to accommodate flows with cash, in the long-run their behavior is similar to index funds, storing only a small fraction of flows in cash. Even so, given outflows from active funds in recent years and shift to passive investing, this suggests enhanced risk as funds have less capacity to mediate investor flows.

The chapter is organized as follows. Section 2.2 describes the fund-level data, summary statistics, and fund strategy. Sections 2.3 and 2.4 present a model of cash allocations and estimates how they respond to investor flows in normal times and times of crises. Section 2.5 estimates how investor flows impact country allocations and Section 2.6 concludes.

2.2 Data and Summary Statistics

Data on mutual fund portfolios come from Emerging Portfolio Fund Research (EPFR) Global. This dataset represents a large fraction of U.S., European, and other funds invested in a broad range of emerging markets (EM) and developed markets (DM). It covers 99%

of all EM equity funds, 70-75% of funds in developed European markets, and 90% of U.S. funds. For each fund, the data includes net flows to the fund in USD, net asset value, the percentage of net assets held in cash ("cash weights"), and fund characteristics such as strategy, domicile, geographic focus (global, emerging markets, regional, etc), asset class, investment scope (sector and industry), and the fund's benchmark.

To characterize funds by strategy, I match the data to country allocations of the fund's declared benchmark. Data on benchmark indexes come from Morningstar and are available for 249 of the 343 benchmarks. The resulting matched dataset contains 1,444 funds, covering 85% of the original set of funds. The exclusion of these funds is not expected to generate any biases; details on the 264 funds with unavailable benchmark data are available in the Appendix.

The data spans January 2010 through December 2017 and contains 48,189 fund-month observations. Details on the main sample are in Table 2.1. Over half of the funds invest in developed markets, comprising 51% of the sample, with 49% invested in emerging markets. The largest asset class is Global EM, comprising 20.3% of the sample , followed by Asia ex-Japan (18%), Global Developed (15.2%), and Western Europe (14.4). The majority of the funds in the sample self-report as having an active strategy (82%), while 18% of the sample are passive. Exchange traded funds (ETFs), which are also considered passive, make up 16% of the sample. The investor base is primarily European, with 67% of sample domiciled in Europe (primarily developed countries such as Ireland, Luxembourg and the U.K.), 27% domiciled in the U.S. and 6 percent in other countries.

2.2.1 Cash Weights

Cash weights are self-reported by funds, as the percentage of assets held in cash at the end of the month. I restrict my analysis to funds with positive cash weights, which excludes leveraged funds with negative cash weights.[2] Weights are also winsorized at the 1 and 99th percentile to minimize the potential impact of outliers or data errors. Summary statistics for cash weights are in Table 2.2. The average cash weight across all funds is 2.38%, with a median of 1.64% and a standard deviation of 2.42%. Active funds hold a slightly higher percentage in cash, with a mean of 2.77% with a median of 2.06%. Active funds have cash weights in the 90th percentile as high as 5.9% and a standard deviation of 2.49%. Closet index funds hold a similar percentage of cash as active funds, with a mean of 2.19%, median of 1.64%, 90th percentile of 4.77%, and standard deviation of 2.26%. Explicit index funds hold a much lower percentage of assets in cash, with a mean of 0.68% and median of 0.46%. Explicit index funds have a much lower standard deviation, 0.95 %, with weights in the 90th percentile of only 1.31%. Funds in this sample hold a lower percentage of assets in cash relative to that in other literature on cash weights. Chernenko and Sunderam (2016), for example, who focus only on U.S. mutual funds, estimate that actively managed equity and bond funds have average cash weights of 7.48%. My sample is thus more representative of the behavior of funds domiciled globally, invested in a broader range of markets, which I show hold relatively low cash reserves. Particularly surprising is that even among active funds, only a small portion of assets are held in cash.

[2]In the main regression sample, I restrict to funds with non-missing cash weights that are greater than 0 and less than 100 percent, and non-missing monthly fund flows. These restrictions affect about 8.4% of the sample, resulting in 1,215 funds for the main analytic sample.

Figure 2.5 plots the distribution of average cash weights by fund type over time. Explicit index funds have relatively stable weights over the sample period, while active and closet funds have a more volatile average weight. Active funds have higher cash weights on average. We can think of active funds as effectively pooling liquidation costs (the costs associated with selling securities) for investors by holding higher levels of cash. Explicit index funds, in contrast, hold little cash and instead buy and sell securities directly on behalf of investors. Closet index funds, while they hold country allocations that closely track the benchmark, hold levels of cash similar to active funds. This suggests they provide liquidity transformation similar to that of active funds despite displaying more passive trading behavior. Other literature on the determinants and effects of mutual fund cash holdings include Yan (2006), Simutin (2014), Fulkerson and Riely (2015), and Novak Riley and Stahel (2015).

2.2.2 Fund Flows

Fund flows are computed as monthly net flows in USD, as a percentage of total net assets at the end of the month. In the main analysis, I winsorize flows at the 5 and 95th percentile. This level of winsorization is used in existing literature for fund flows; it also produces a range of monthly net flows that seems more reasonable than at the 1st and 99th percentile. In the Appendix Section 4.2.1, I repeat the results using a smaller winsorization of flows.

Summary statistics for net flows, inflows (positive net flows), and outflows (negative net flows) are in Table 2.2. Funds face monthly net flows ranging from -7.8% to 8.3% of total net assets. Across all funds, average monthly flows are -0.22% of total net assets, with

a standard deviation of 2.54%. Explicit index funds have the largest average flows among fund types, 0.53%, and have the highest standard deviation, 2.7%. Explicit index funds also experience the largest monthly inflows by group (2.36%) and the largest outflows (-1.77%).

Average monthly flows to active funds are negative, -0.4%, with a standard deviation of 2.48%. Mean inflows to this group are 0.02%, with a median of 1.24% and 90th percentile of 5.01%. Mean outflows are -1.75%, with a median of -1.23% and 10th percentile of -4.18%. Average net flows to closet indexers fall between the two groups, -0.31%. Average inflows to these funds are closer to that of explicit funds, 1.97% per month. Closet indexers have the smallest average outflows among groups, -1.62%. Thus closet indexers appear to experience higher investor flows, similar to that of explicit indexers, despite declaring an 'active' strategy.

Figure 2.3 plots average investor flows by fund type over time. Active funds have the most stable average flows, while flows to closet and explicit index funds are more volatile. Figure 2.4 plots average flows by group for for periods when net flows are negative. In terms of redemptions, explicit index funds tend to also face the largest outflows, followed by closet indexers. The volume of redemptions in active funds appear more stable over time.

2.2.3 Fund Strategy

In my main analysis, I distinguish between explicit index funds, closet index funds, and active funds. Passively-managed mutual funds - both index funds and exchange-traded funds (ETFs) - offer an investment vehicle that tracks a specified benchmark index. ETFs can be traded continuously throughout the day, offering enhanced liquidity benefits to in-

vestors, while with traditional mutual funds, trading usually only occurs at the close of trading day. Actively-managed funds seek to outperform their benchmark, typically generating higher trading costs and requiring higher compensation as a result.

To classify funds by strategy, I directly compute a measure of how active funds are as in Chapter 1. I calculate the percentage of the portfolio that is invested outside the benchmark is computed following Cremers and Petajisto (2009):

$$\text{Active Share} = \left(\tfrac{1}{2}\right) \sum_{j=1}^{N} \mid w_{fund,j} - w_{B,j} \mid$$

where $w_{fund,j}$ and w_B are the portfolio weights of the fund and benchmark, respectively, in country j and the sum is taken over all countries. For each fund, this share is computed each month and averaged across time as a measure of funds deviation from its benchmark. Based on these shares, funds are classified broadly as explicit indexers, closet indexers, or active funds. Explicit indexers are funds that report to be passive or an ETF. Closet indexers are funds that dont report to be passive yet have an active share similar to passive funds, or within the 90th percentile of passive funds. Active funds are funds that report to be active and have an active share greater than that of closet indexers.

Features of the particular fund strategy can make funds more or less risky from a financial stability perspective. We can also think of risks as stemming from either investor behavior or manager behavior. Investor behavior is transmitted through fund flows, and manager behavior is transmitted through country allocations. Managers, in response to investor flows, decide when and where to allocate based on fund strategy and country-of-investment conditions. The higher liquidity of ETFs can attract investors who are particularly sensitive to global risk factors. Flows to passive funds then may be characterized by high-turnover

investors, pursuing shorter-term investment strategies, and have more volatile flows as a result. In the absence of fund inflows and outflows (investor effects), however, we may expect passive funds to have more of a stabilizing force. As their investment strategy is strictly tied to an index, these funds should only trade in response to investor flows or rebalancing by the fund's benchmark; they should not trade based on market events. Active funds, with less restrictions than index funds, have discretion to adjust portfolio allocations in response to market events. They are free to take advantage of longer-term investment opportunities, chase returns, or buy assets at fire sale prices. In the analysis that follows, I focus on manager behavior but in particular how they respond to risks that may be transmitted by investors.

2.3 Cash Allocations

Investors typically react procyclically to shocks. Raddatz and Schmukler (2012) in particular show that investors withdraw from funds during global crises and withdraw from funds invested in countries experiencing crises. They invest more capital into funds doing well and when conditions in their country of origin improve. Fund managers, in turn, allocate their portfolio in response to these investor flows. How a fund's cash allocation varies with these investor flows can inform whether funds provide any buffer between the decisions of investors and country flows.

To estimate how investor flows affect a fund's portfolio decision, I regress the dollar change in cash holdings on net flows in a given month. A fund's cash holdings in dollars are calculated from the fund's self-reported cash weights and total net assets at the end of the period. The following panel regressions are run:

$$\Delta Cash_{i,t} = \beta_1 Flows_{it} + \beta_2 flows_{i,t-1} + \beta_3 flows_{i,t-2} + \beta_4 flows_{i,t-3} + \alpha_i + \alpha_{tc} + \varepsilon_{i,t} \quad (1)$$

where all variables are scaled by total net assets in period t-1. Time-domicile fixed effects, α_{tc}, are included to control for things such as shocks to monetary policy that may affect flows to a fund and cash weights simultaneously, and standard errors are clustered by time. Fund fixed effects, α_i, are also included. Equation (1) is estimated across the full sample of funds and separately by fund type. In Table 2.3, the dependent variable is the change in the cash over a one-month period, scaled by total net assets in period t-1: $\frac{\Delta Cash_{i,t\rightarrow t-1}}{TNA_{i,t-1}}$. All regressors are also scaled by assets in period t-1, which allows for each coefficient to be interpreted as the fraction of net flows that are accommodated through cash versus equities.

Cash responds procyclically to investor flows at a short time horizon. In the initial month, funds build up cash positions with new inflows to the fund and draw upon cash reserves to meet outflows. On average, for every dollar of inflows, about 13 cents is held in cash; 87 cents, then, flows into country allocations (Column 1). The impact of flows on cash balances lasts for multiple periods but gradually fades over time. The coefficients on flows in period t-1 and t-2 are negative and significant, indicating that this initial increase in cash is gradually reduced, as it's reallocated to country investments. In period t+1, cash declines by 8 cents and in period t+2, by another 1 cents. By the end of period t+2, most of the inflow in period t has been reallocated across countries. The combined effect of β_1, β_2, β_3, and β_4 is statistically different from zero, with a p-value of 0.00. Thus, a small but non-zero portion, about 3 cents, remains in cash.

Columns (2) through (4) show that the positive relationship between cash and net flows is driven primarily by the behavior of active funds. In active funds, about 16% of new flows

are stored in cash initially. Again, the shock lasts for several periods. Within two periods, the effect of the shock has mostly faded, with a small but non-zero amount remaining in cash. For active funds, the combined effect of β_1, β_2, β_3, and β_4 is statistically different from zero, with a p-value of 0.00 and a F-statistic over 30. In index funds, the shock fades quicker. These funds transact more heavily in securities than cash. In closet index funds, the initial impact of flows on cash balances is weaker, with about 10% of flows accommodated through cash in period t. By the next period, the shock has faded. After 1 period, the net effect of the shock on cash is zero - the joint significance of β_1 and β_2 is not statistically different from zero, with a p-value of 0.44. In explicit index funds, this reallocation of cash to equities happens immediately, with just over 1% of flows accommodated through cash initially. By the following period, the total effect is similar to that in closet index funds - all of the flows have been allocated across countries. β_1 and β_2 are jointly insignificant, with a p-value of 0.24.

This adjustment path of cash is evident at a lower frequency, which is examined in Table 2.4. The dependent variable is the change in cash from the previous quarter, with flows aggregated at a quarterly frequency. At a lower frequency with more time to adjust, the initial impact of flows is smaller. Two quarters later, the impact of flows have faded. As in Table 2.3, after two periods the shock has faded for active funds with a small, but non-zero amount remaining in cash (again, the combined effect of $\beta_1+\beta_2+\beta_3$ is statistically different from zero, with a p-value of 0.00). In closet index funds, the net effect of the shock is zero after one quarter (the combined effect of lagged flow coefficients has a p-value of 0.677) . In explicit index funds, the net effect is zero in the initial quarter (the combined effect of $\beta_1+\beta_2$ p-value of 0.16). I also estimate the change in cash over a 6-month period,

to directly compare to the results in Chernenko and Sunderam (2016). In Table 2.5, the change in cash allocation over 6 months is regressed on net flows in the prior 6 periods, with all variables scaled by net assets in period t-6. Relative to the results using the 1-month change in cash, the responses by fund type are similar and become stronger. The coefficient for active funds is slightly higher, 18%. For explicit index funds, the relationship becomes insignificant. Relative to what has been estimated in the literature for U.S. funds, my results suggest cash is less important in international mutual funds domiciled globally. [3] Further, in index funds, which are comprising a growing share of these mutual funds, the role of cash is almost negligible.

These results also have implications for cash during outflows, though I test for asymmetric effects during outflows in the following section. The stronger response of cash in active funds implies these funds are more likely draw upon cash reserves to accommodate outflows. Based on Table 2.3, for a dollar of outflows in period t, about 16 cents of the redemption is met through existing cash reserves; 84 cents of the outflow is met through sales of securities in the portfolio. In the following two periods, cash holdings increase; funds take steps to manage their liquidity needs, increasing cash holdings in anticipation of outflows. In index funds, a smaller fraction of redemptions are met with cash. These funds also increase cash holdings in the following period, suggesting assets in the portfolio are sold beyond the amount needed to meet the redemption.

Increased access to ETFs and other liquid cash-like assets in recent years could affect

[3]Chernenko and Sunderam (2016) find that for each dollar of inflows or outflows in a given month, 23 cents is accommodated by changes in cash rather than securities. The larger coefficient in their paper relative to the results in this paper can be attributed to differences in samples. Their sample is limited to U.S. mutual funds, includes bond funds, and excludes ETFs. For their sample of funds, the median cash-to-assets ratio is much higher, 4.3%, relative to in this paper, 1.8%

funds' use of cash. Estimation of equation (1) by year reveals that β_2 is decreasing over the sample period. On average, β_2 is 0.135 for the first half of the sample period, 2010-2014, and 0.116 for 2015 and later (See Table 4.12). One explanation for a lower β_2 in more recent years is that funds are increasingly holding investments that are highly liquid, reducing the need to transact strictly in cash. By fund type, however, there are not significant differences between the pre- and post-2015 periods.

Overall, the results show that all funds, regardless of strategy, trade heavily in response to flow-induced pressure and provide little buffer between ultimate fund investors and markets. In active funds, this result is stronger than we would expect. Active funds have more capacity to hold new flows in cash and invest when opportunities arise. Active funds can also use these cash buffers to manage future liquidity needs, reducing the costs associated with providing investors with claims more liquid that the underlying investments. While at a short horizon, active funds do accommodate some investor flows through cash, over time, their behavior is similar to index funds. These results are also robust to alternative specifications of cash. In the Appendix, I repeat the analysis using cash weights rather than the computed cash allocations. For the remainder of the paper, I focus on the dollar change in cash allocation rather than cash weights because it provides a more intuitive interpretation.

The somewhat weak relationship between cash and flows documented in this section implies that in periods of outflows, investor withdrawals are met with cash to a minimal extent and instead are raised from sales of underlying assets. The weaker relationship between cash and flows in index funds, and quicker speed of adjustment, suggests enhanced redemption risk in passive funds. Outflows in active funds have a smaller immediate impact, as these funds transact more in cash. To better understand how cash may respond

differently in response to outflows, the next section considers the behavior of cash in periods of stress and crises.

2.4 Cash during crises

2.4.1 Inflows versus outflows

I next consider how the behavior of cash may differ based on the volume or direction of investor flows. Morris, Shim, and Shin (2017), for example, find that the relationship between investor flows and cash in bond funds is stronger during periods of outflows than inflows, and that while bond funds tend to hoard cash during periods of market stress, they don't during normal times. I first test for asymmetric behavior in periods of positive and negative net flows, and later consider other ways in which flows can be constrained.

Section 2.3 included a careful treatment of the timing of funding shocks and lag structure, allowing for the effects of flows on cash last for several periods. In this section, I exclude lagged values of flows and instead focus on the the immediate response of cash in period t. In terms of regulatory and policy implications, this is the response of interest. For comparison to the results in Section 2.3, Table 2.6 shows the specification from that section with no lags.

To test for an asymmetric response in periods of outflows versus inflows, equation (1) is modified to include the interaction of net flows with an indicator for whether flows in a given month were negative:

$$\Delta Cash_{i,t} = \beta_1 Flows_{it} + \beta_2(Outflow_{it}) + \beta_3(Flows_{it})(Outflow_{it}) + \alpha_i + \alpha_{tc} + \varepsilon_{i,t} \quad (2)$$

where $Outflow$ is equal to 1 if net flows in a given month are negative. The results from

equation (2) are in Table 2.7. On average, cash responds slightly stronger during periods of outflows. Across all funds, the coefficient on the interaction of the outflow indicator with flows is positive and significant (0.030), indicating that flows are accommodated with cash by about 3 cents more during periods of outflows. For every new dollar of inflows, about 6 cents is accommodated through cash, and for every dollar of outflows, about 9 cents is accommodated through cash. Active funds have a similar response to outflows. From column (4), about 8 percent of inflows to active funds are stored in cash, and in periods of outflows, an additional 3 cents more is accommodated through cash. Thus, active funds are more likely to use cash to meet redemptions than they are to store new flows in cash.

Cash in explicit index funds, by contrast, does not respond significantly different during periods of outflows (Column 2). β_3 is not statistically different from zero, and $\beta_1 + \beta_3$ is jointly insignificant, with a p-value of 0.12. Cash in closet index funds funds responds slightly stronger. Closet indexers suffer from a relatively much smaller number of observations, making inference of their response difficult. $\beta_1 + \beta_3$ are weakly significant, with a combined effect of about 5 cents and a p-value of 0.06. This suggests closet indexers use cash during periods of outflows, but by a lesser extent than active funds.

Overall, the results in this section show that active funds use cash asymmetrically in periods of outflows versus inflows. Active funds and closet indexers become slightly more aggressive in using cash to accommodate flows during periods of outflows than inflows. Explicit indexers behave no differently in periods of outflows; cash is not used to meet redemptions.

2.4.2 Sustained capital outflows

One period of negative flows may not be a true measure of financial stress. Funds likely react differently to one period of negative flows than during periods of sustained financial stress. Table 2.8 considers a prolonged period of outflows as a measure of stress. Equation (2) is estimated again, with an indicator if, instead, the fund experienced consecutive periods of outflows:

$$\Delta Cash_{i,t} = \beta_1 Flows_{it} + \beta_2(Crisis_{it}) + \beta_3(Flows_{it})(Crisis_{it}) + \alpha_i + \alpha_{tc} + \varepsilon_{i,t} \quad (3)$$

The variable 'crisis' is equal to one if the fund received outflows in consecutive periods t, t-1, and t-2. On average, cash does not behave significantly different during periods of consecutive outflows but the response varies by fund type. Across all funds, the coefficient on the interaction term is negative, though economically small and statistically weak. In explicit index funds, cash is not used significantly different during periods of consecutive outflows. The overall response is similar to that in normal times (Table 2.6), with a coefficient of 0.010. In closet index funds and active funds, the relationship between cash and flows weakens. In closet index funds, β_3 is -0.065, though insignificant. $\beta_1 + \beta_3$ is not statistically different from zero, with a p-value of 0.52, indicating that that while in normal times, about 9% of flows are accommodated by cash, in periods of sustained outflows this falls to zero. In active funds, cash also has a weaker response in periods of prolonged outflows. While in normal times the coefficient is 0.13, in periods of crisis it falls by 0.03. Active funds still use cash to accommodate flows during crises but to a lesser extent than in normal times. With active funds holding more cash on average (as shown in Figure 2.5), we may expect them to be more likely to respond to redemptions through variations in cash

without having to liquidate or reallocate money across countries. These results however show that active funds are less likely to accommodate flows with cash during crises than in normal times.

While the relationship between cash and flows appeared somewhat stronger in periods of outflows than inflows, the relationship weakens in periods of sustained outflows. Equity mutual funds are more likely to use new funds to build up cash reserves than they are to draw upon cash holdings in periods of stress. This contrasts with what has been shown in the literature for bond funds. This could be a function of asset liquidity. Since equity funds invest in more liquid securities than bond funds, they may be more able to sell assets fairly easily when needed without price impact. Overall, active funds have greater capacity to meet investor redemptions with cash than index funds, but the buffer they provide is smaller than we might expect and weakens as financial stress grows.

2.4.3 Capital surges and retrenches

Finally, I consider the behavior of cash during periods of extreme capital flows, either particularly high inflows (capital surges) or high outflows (capital retrenches). I define capital surges (retrenches) to be periods in which a fund's flows were in the top (bottom) two deciles of flows across all fund-month observations.

In Table 2.9, equation (2) is modified to include an indicator for whether the fund experienced a capital surge (Panel A) or capital retrench (Panel B). Cash behaves differently in period of extreme flows. In either extreme inflows or extreme outflows, the relationship between cash and flows weakens relative to normal times. In Panel A, β_3 is negative for all fund types; in periods of particularly high inflows, funds do not use it as an opportunity to

build cash reserves but rather invest the additional flows into assets. On average, new flows are accommodated through cash by about 9% less in periods of capital surges relative to normal times (column 1). Active funds have a similar response: during high volumes of flows into the fund, 9 cents per dollar of new flows less is stored in cash relative to normal times. In total, about 4% of new flows are stored in cash during capital surges, compared to 8-12% during normal times (Tables 2.6 and 2.7).

Index funds also store a smaller percentage in cash during surges. The β_3 coefficients are insignificant for closet and explicit funds but negative. The joint significance of β_1 + β_3 is insignificant. Explicit and closet indexers, then, store no significant fraction of capital surges in cash; these flows are invested directly into securities. During good times, index funds continue to transact primarily in securities rather than use it as an opportunity to build cash reserves.

In periods of extreme outflows, cash also responds weaker to flows relative to normal times (Panel B of Table 2.9). Across all funds, β_3 is -0.06; on average, 3 cents (the combined effect of β_1 and β_3) per dollar of outflows are accommodated through cash during severe outflows. This is almost a third of the amount of cash used during periods of sustained but more moderate outflows (9 cents in Table 2.8). By fund type, active funds have the strongest response to extreme outflows, with a coefficient of -0.067 (column 4). In total, about 4% of extreme outflows are accommodated by cash in active funds. For closet indexers, β_3 is negative but insignificant. However, β_1+ β_3 is not significantly different from zero, indicating that in capital retrenches, cash plays no role.

Explicit index funds have a significant response to capital retrenches, with a β_3 similar to that of active funds, -0.044 (column 2). In contrast to periods of capital surges, explicit

index funds respond strongly to capital retrenches. In total, the response of cash in these funds during periods of extreme outflows is countercyclical - cash holdings increase in periods of extreme outflows. For every dollar of outflows, cash increases by about 0.03 cents (the combined effect of β_1 and β_3). This suggests some degree of cash hoarding by explicit index funds: in periods of large outflows, these funds sell securities in the underlying portfolio beyond what is needed to meet the obligation. This has been documented for bond funds previously. Morris, Shim, and Shin (2017), for example, create a measure of such discretionary sales, and estimate that for every 100 dollar of sales due to investor redemptions in emerging market bond funds, there is an additional 10 dollars of discretionary sales. For funds that hold more liquid bonds, such as advanced economy bond funds, the magnitude of sales are much smaller, about 3 dollars. While I found no evidence of cash hoarding during normal times, this section shows that equity mutual funds, which hold relatively more liquid assets than bond funds, hoard cash during periods of financial stress.

These results are robust to alternative definitions of surges and retrenches. I also designate flow deciles based on the within-fund variation in flows. In Table 2.10, the indicator 'surge' ('retrench') is equal to 1 if flows are in the top (bottom) decile of a given funds flows over the sample period. During surges, the response of active, closet, and explicit index funds remains the same, relative to Table 2.9. During capital retrenches, however, β_3 is -0.11 across all funds, bringing the overall response of cash below zero. This suggests a higher prevalence of cash hoarding by this measure of capital retrenches, regardless of fund strategy. It should be noted these results also provide a more conservative estimate of the impact of outflows can potentially have, as flows are winsorized at the the 5th and 95th percentiles. In the Appendix, I show results with flows winsorized at the 1st and 99th

percentiles.

I also consider measures of aggregate financial stress, rather than fund-specific stress. In Table 2.11, funding pressure is based on aggregate fund flows, where crises are defined as periods where aggregate net flows - either across all funds or within fund type - in a given period were in the bottom two deciles of flows over the sample period. Under these measures of financial stress, cash is not used differently in periods of stress than in normal times. In other words, funds only alter their use of cash in periods of fund-specific pressure.

Overall, cash behaves differently in periods of extreme inflows or outflows. In normal times, funds store a fraction of new flows in cash (about 5-8%), but when flows are particularly high, a much lower portion of new flows is stored in cash, about 2%). During capital surges, funds are more likely to use it as an opportunity to invest than to save. This type of forced trading behavior may not be surprising in index funds, which have been shown to essentially act as a veil on behalf of investors, but in active funds, it's less expected. Similarly, in periods of extreme outflows, funds are less likely to use cash to meet redemptions. Overall, about 3% of capital retrenches are met through cash, relative to about 9% in periods of more modest outflows (Table 2.8). During severe outflows, almost all of the obligations must be met through forced asset sales, and in explicit index funds, assets are sold beyond what is needed to meet investor demands. While it's possible assets are sold in more liquid markets to minimize price impact, it's precisely in times of severe or coordinated investor redemptions such as these that forced asset sales are most likely to adversely affect asset prices.

These results highlight a financial fragility risk in mutual funds investing globally. In periods of financial stress, fund managers don't rely on cash reserves to meet investor

redemptions but rather increase holdings in periods of severe outflows. This behavior would seem to amplify the actions of investors, who typically withdraw from funds in times of stress, and amplify any destabilizing effect of redemptions on asset prices. Further, as the effect is more pronounced in passive funds, it suggests enhanced risks as the investors shift from active to passive investing. Others have noted ways in which the shift from active to passive investing is thought to reduce risks related to redemptions. Because ETF redemptions are typically in shares of the fund rather than in cash, liquidity transformation risk is lower in these funds. There is also evidence that performance-related redemptions are lower in passive funds (McCabe, 2018). My results, however, identify a new channel for increased redemption risk in passive funds.

2.5 Country Allocations

Section 2.3 showed that funds hold minimal cash buffers, and that particularly during periods of investor outflows, funds transact in cash to a minimal extent, implying that country holdings must be affected. Jotikasthira, Lundblad, and Ramadorai (2012) show that funds do adjust their equity positions in response to funding pressure from investors. In particular, they estimate the proportion of countries in which a fund increases its holdings less the proportion in which it reduces its holdings, and show that this net change is strongly relative to inflows. These type of forced asset trades are also shown to have significant price impact in emerging markets. We don't however have knowledge about which assets or countries are affected in these circumstances. Do funds tend to liquidate in countries with more liquid markets, for example, to minimize price impact? Do managers sell assets in their portfolio proportionally to raise cash for redemptions or do differences

in country performance matter? In this section, I ask whether country-specific conditions affect a fund's decision to expand or reduce positions in response to flows in any systematic way.

To answer these questions I regress country allocations on investor flows and their interaction with country-specific variables. I compute a fund's dollar allocation in a given country as the product of the self-reported country weight (w_{ct}) at the end of the month and the fund's total net assets as the end of the month: $Allocation_{c,t} = (TotalNetAssets_t)(w_{ct})$

The following panel regressions are run:

$$\Delta(Allocation)_{i,c,t} = \beta_1 flows_{it} + \beta_2(flows_{it})(X_{ct}) + \alpha_{tc} + \alpha_{it} + \varepsilon_{i,c,t} \quad (4)$$

where $\Delta Allocation_{i,ct}$ is the change in country c's allocation from t to t-1, scaled by net assets in period t. Flows are monthly net flows to the fund scaled by assets in period t, and X_{ct} are country characteristics including country returns (R_{ct}) and market liquidity conditions (stocks traded as a percentage of GDP and a stock turnover ratio).

Equation (3) is estimated for by fund type in Table 2.12. Since the response may differ in periods of forced asset sales versus asset purchases, Table 2.13 estimates equation (3) for periods negative net flows. The coefficients on the interaction of flows with selected country characteristics are strongly significant, indicating that differences across countries matter in forced asset sales. We may expect that while country conditions matter for active funds, index funds may instead reduce positions in response to flows more proportionally or toward an allocation that more closely resembles the benchmark. The results however indicate that country conditions matter for closet and explicit index funds as well.

I first consider country performance. The coefficient on the interaction of country re-

turns with net flows is strongly negative, indicating that in response to outflows (inflows), funds sell (buy) positions in countries with lower (higher) returns (Column 1). The coefficient is higher for active and closet index funds (-0.40 and -0.60 respectively, versus explicit index funds, -0.32), indicating that these funds have more discretion to reallocate across countries in response to investor flows. In periods of investor outflows, the coefficients increase for all groups. Country performance thus matters more for forced asset sales than purchases (Table 2.13).

Columns (2) and (3) consider measures of country market liquidity, specifically a turnover ratio of stocks traded and stocks traded as a percentage of GDP. β_2 is strongly significant and positive for both measures of country liquidity. In periods of positive net flows, country allocations expand in countries with higher liquidity. In periods of negative net flows, country allocations shrink in countries with higher liquidity. The coefficient increases substantially, for all fund types, in periods of outflows. Liquidity conditions become more important in times of asset sales and funds take steps to minimize adverse affects on portfolio returns. Interestingly, the response is stronger in explicit and closet index funds. These funds were shown to face the most volatile investor flows among fund types, and also maintain the smallest cash buffers. In response to investor flows, they don't appear to reduce or expand allocations in some fixed proportion but rather in a way that depends on country-specific conditions. In response to flow-induced asset sales, the behavior of index funds is not substantially different from that of active funds.

Similar results are obtained using country weights rather than country allocations. The interaction of flows and country returns is negative, and the interaction of flows and liquidity is positive (See Tables 4.14 and 4.15 of the Appendix). Jotikasthira, Lundblad, and

Ramadorai (2012) develop a simple model for the motivations of fund investors that direct flows to global funds, and assume that flows directed to a fund on account of investors' decisions translate into trading in all markets that a fund holds. My results, however, show that country conditions matter in these forced trades. The results are particularly of interest in periods of market volatility or crises. In periods of concerted investor redemptions, we would expect funds, regardless of type, to sell the countries in their portfolio with lower returns or higher market liquidity.

2.6 Conclusion

I bring a comprehensive set of data to important questions regarding how mutual funds invested globally manage capital flows from investors. Fund managers can use tools such as cash buffers to manage risks, and liquidity management decisions such as these are their first line of defense in response to redemption pressures. I provide three key results. First, I show that regardless of fund strategy, funds provide little buffer between underlying fund investors and country flows. Even among active funds, international mutual funds hold a low percentage of assets in cash and respond to flow-induced pressure from investors primarily through transacting in securities of the underlying portfolio.

Second, I show that there are differences in how funds manage liquidity by fund strategy, at least in the short-run. At a short horizon, active funds accommodate some inflows with cash, while index funds act more like a veil, trading directly on behalf of investors. Over time, however, the behavior of active funds is not substantially different from that in index funds. In periods of more severe investor withdrawals, index funds also tend to hoard cash, thus amplifying the impact of investor redemptions. As investors shift from

active to passive investing, the results suggest greater risks as managers have less capacity to mediate investor flows.

Finally, I show that in response to pressure from investors, fund tend to liquidate allocations in countries with low returns and in countries with higher market liquidity. Such country-specific conditions become more important in times of asset sales and funds take steps to minimize adverse affects on portfolio returns.

2.7 Figures and Tables

Figure 2.1: Percentage of Net Assets by Strategy

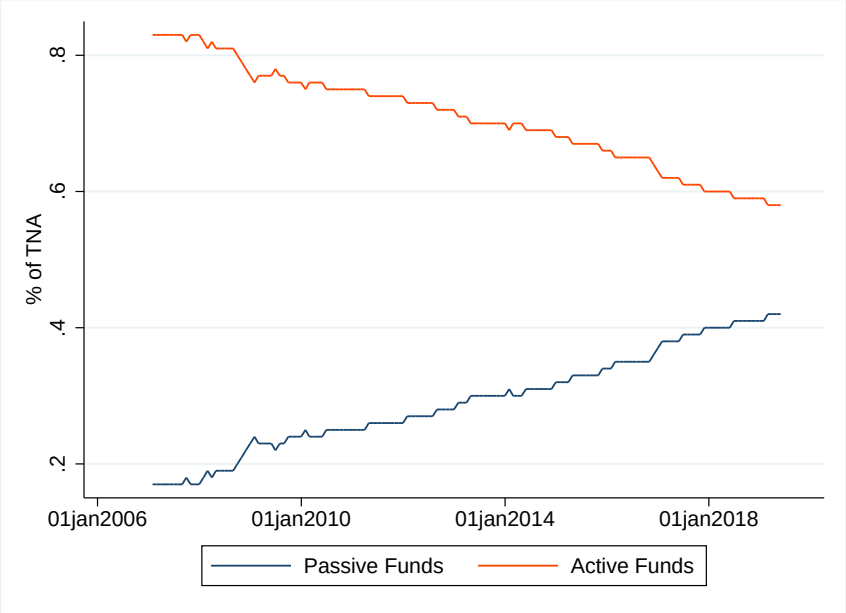


Figure 2.2: Cumulative Flows to Equity Funds

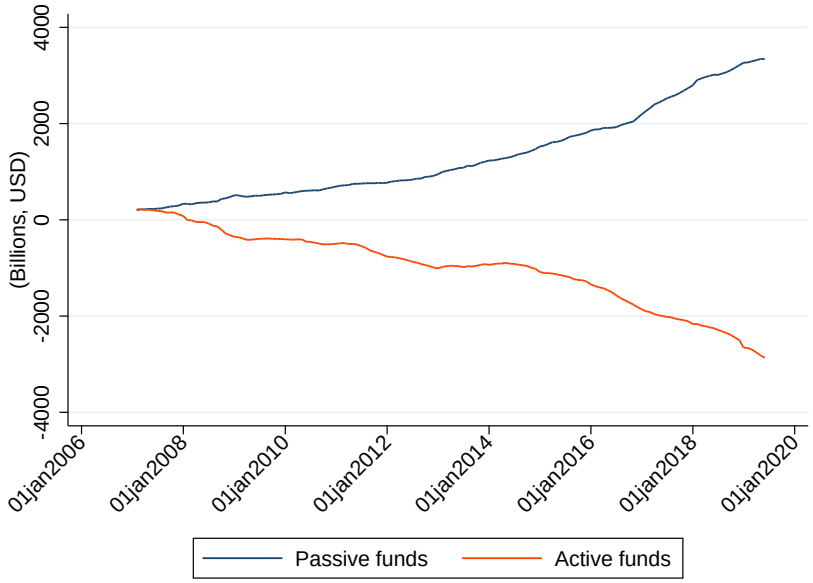


Figure 2.3: Average Investor Net Flows

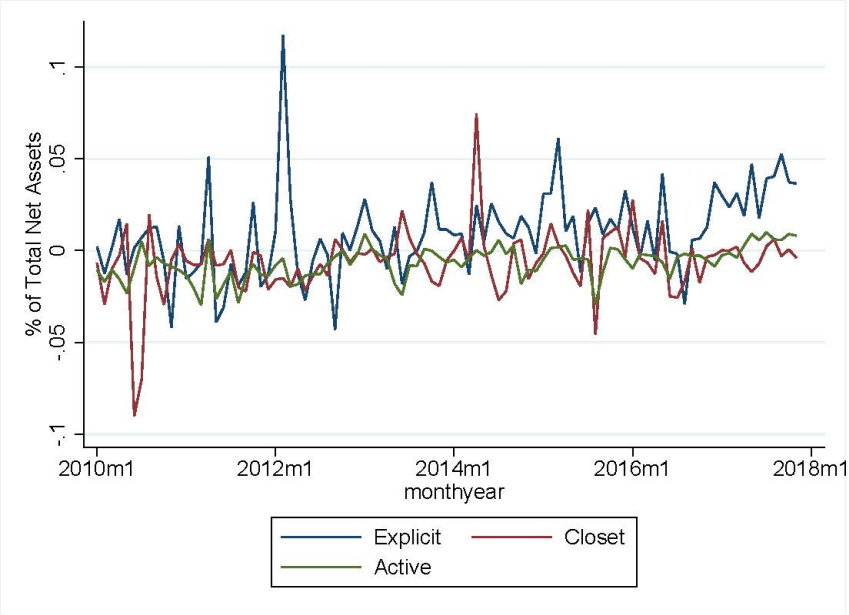


Figure 2.4: Average Investor Outflows

Figure 2.5: Average cash weights

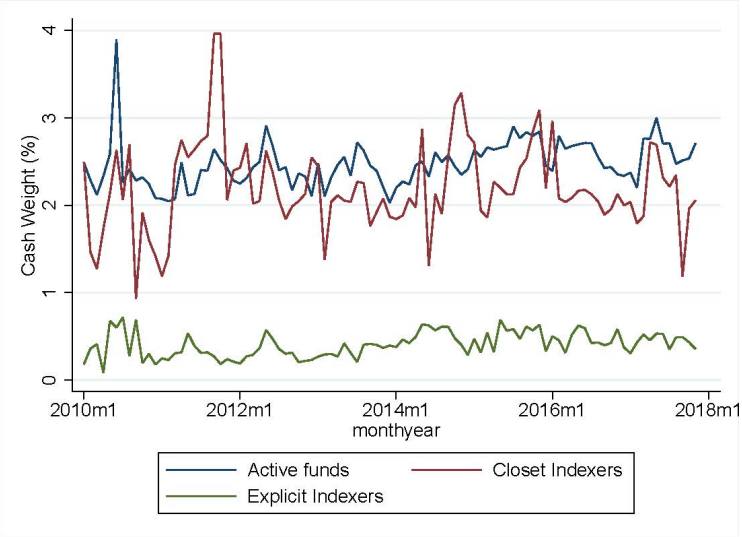


Table 2.1: Sample Fund characteristics

	Funds	Panel Obs.	% of Sample
Strategy			
Passive	266	8,510	17.66
Active	946	39,679	82.34
ETF			
ETF	226	7,618	15.81
Non-ETF	986	40,571	84.19
Investor			
Institutional			
Retail			
EM or DM			
Emerging Markets	526	23,509	48.78
Developed Markets	689	24,680	51.22
Asset Class			
Emerging Markets			
Asia ex-Japan	190	7848	18.0
BRIC	15	640	1.5
Emerging Europe	27	1,466	3.4
Global EM	231	8,836	20.3
Latin America	48	2,227	5.1
Middle East and Africa	14	409	0.9
Developed			
Global	222	6,632	15.2
Global ex-US	150	4,447	10.2
Western Europe	182	6,261	14.4
Europe ex-UK	111	4,080	9.4
Asia Pacific	24	755	1.7
Domicile			
USA	346	11,635	26.7
U.K.	141	6,033	13.8
Other Europe	514	23,356	53.6
Other	214	2,577	5.9

Table 2.1 reports statistics for the sample of equity mutual funds used in analysis by selected characteristics – strategy, investor class, fund structure, target region, and country in which the fund is based. The strategy classification here is self-reported (active vs passive).

Table 2.2: Summary Statistics

	Mean	**p10**	**p25**	**p50**	**p75**	**p90**	**St.Dev**
Cash Weight (%)							
All	2.38	0.30	0.70	1.64	3.20	5.40	2.42
Explicit	0.68	0.09	0.24	0.46	0.75	1.31	0.95
Closet	2.19	0.30	0.71	1.55	2.84	4.77	2.26
Active	2.77	0.50	1.05	2.06	3.63	5.90	2.49
$NetFlows(\%TNA)$							
All	-0.22	-3.10	-1.43	-0.20	0.70	2.97	2.54
Explicit	0.53	-2.42	-0.05	0.00	1.68	4.25	2.70
Closet	-0.31	-2.91	-1.39	-0.44	0.57	2.60	2.41
Active	-0.40	-3.22	-1.59	-0.43	0.55	2.59	2.48
$Inflows(\%TNA)$							
All	2.04	0.07	0.42	1.34	3.10	5.25	2.03
Explicit	2.36	0.00	0.40	1.80	3.81	5.82	2.22
Closet	1.97	0.14	0.44	1.24	2.89	5.18	1.99
Active	0.02	0.00	0.43	1.24	2.86	5.01	1.95
$Outflows(\%TNA)$							
All	-1.74	-4.25	-2.41	-1.21	-0.51	-0.14	1.69
Explicit	-1.77	-5.12	-2.80	-1.02	-0.02	0.00	2.03
Closet	-1.62	-3.81	-2.10	-1.09	-0.55	-0.22	1.57
Active	-1.75	-4.18	-2.40	-1.23	-0.56	-0.19	1.65

Flows have been winsorized at the 5th and 95th percentile

Table 2.3: Change in Cash Holdings

	$\left(\frac{\Delta Cash_{i,t\to t-1}}{TNA_{i,t-1}}\right)$			
	All Funds	Explicit	Closet	Active
$Flows$	0.127***	0.013***	0.109***	0.155***
	(0.005)	(0.004)	(0.021)	(0.005)
$Flows_{t-1}$	-0.084***	-0.024***	-0.090***	-0.098***
	(0.004)	(0.005)	(0.017)	(0.004)
$Flows_{t-2}$	-0.010**	0.003	-0.015	-0.013**
	(0.004)	(0.006)	(0.017)	(0.005)
$Flows_{t-3}$	-0.002	-0.004	-0.001	-0.003
	(0.004)	(0.005)	(0.015)	(0.005)
Joint significance of lags				
$F-value$	25.07	1.70	0.01	30.30
$Pr(>F)$	0.00	0.20	0.94	0.00
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.047	0.091	0.075	0.059
Observations	30186	3876	1849	23951

Table 2.3 regresses the change 1-quarter change in cash on flows in previous quarters. All variables are scaled by net assets in the initial quarter. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.4: Quarterly Change in Cash Holdings

	$\left(\frac{\Delta Cash_{i,q\to q-1}}{TNA_{i,q-1}}\right)$			
	All Funds	Explicit	Closet	Active
Flows	0.054***	0.003	0.054***	0.067***
	(0.003)	(0.003)	(0.019)	(0.004)
$Flows_{q-1}$	-0.028***	0.003	-0.043**	-0.034***
	(0.004)	(0.003)	(0.020)	(0.004)
$Flows_{q-2}$	-0.009***	-0.002	-0.005	-0.012***
	(0.004)	(0.003)	(0.020)	(0.004)
$Flows_{q-3}$	0.004	0.005	0.004	0.003
	(0.004)	(0.003)	(0.020)	(0.004)
Joint significance of lags				
$F-value$	12.15	2.35	0.08	11.54
$Pr(>F)$	0.00	0.13	0.78	0.00
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.009	0.031	-0.003	0.029
Observations	8142	1027	476	6513

Table 2.4 regresses the change 1-quarter change in cash on flows in previous quarters. All variables are scaled by net assets in the initial quarter. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.5: Change in Cash Holdings

	$\left(\frac{\Delta Cash_{i,t\to t-6}}{TNA_{i,t-6}}\right)$			
	All Funds	Explicit	Closet	Active
$Flows$	0.145***	0.006	0.142***	0.177***
	(0.006)	(0.006)	(0.028)	(0.008)
$Flows_{t-1}$	0.052***	0.010	-0.026	0.067***
	(0.007)	(0.006)	(0.029)	(0.008)
$Flows_{t-2}$	0.034***	0.014**	0.008	0.038***
	(0.007)	(0.006)	(0.029)	(0.008)
$Flows_{t-3}$	0.029***	0.011	0.032	0.032***
	(0.007)	(0.006)	(0.029)	(0.008)
$Flows_{t-4}$	0.010	0.006	-0.018	0.013
	(0.007)	(0.007)	(0.029)	(0.008)
$Flows_{t-5}$	0.007	-0.008	0.017	0.009
	(0.007)	(0.007)	(0.029)	(0.008)
$Flows_{t-6,t-11}$	-0.021***	0.000	-0.015**	-0.026***
	(0.001)	(0.002)	(0.006)	(0.002)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.103	0.158	0.071	0.119
Observations	20897	2251	1221	17037

Table 2.5 regresses the change in cash holdings over a 6-month period on net flows. $Flows_{t-6,t-11}$ is the aggregated flows in periods t-6 through t-11. All variables are scaled by net assets in period t-6. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.6: Change in Cash

	All Funds	Explicit	Closet	Active
Flows	0.095***	0.010***	0.078***	0.119***
	(0.003)	(0.003)	(0.012)	(0.003)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.040	0.075	0.058	0.046
Observations	38964	6102	2451	29889

Table 2.6 regresses the change 1-month change in cash on flows in the current period. All variables are scaled by net assets in the initial quarter. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.7: Cash During Outflows

	All Funds	Explicit	Closet	Active
Flows	0.055***	0.008*	0.052**	0.077***
	(0.005)	(0.005)	(0.025)	(0.007)
Outflow	-0.002***	-0.000	-0.002**	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)
(Outflow)(Flow)	0.030***	0.003	-0.006	0.025**
	(0.009)	(0.009)	(0.038)	(0.011)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.031	0.060	0.048	0.040
Observations	38879	6071	2449	29833

Table 2.7 regresses the change in cash holding from the previous period on flows and an indicator for whether the fund experienced an outflow in period t. The dependent variable and flows variables are scaled by net assets in period t-1. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.8: Cash During Sustained Outflows

	All Funds	Explicit	Closet	Active
Flows	0.103***	0.010***	0.094***	0.132***
	(0.003)	(0.003)	(0.015)	(0.004)
Crisis	0.001***	0.001	0.001	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
(Crisis)(Flows)	-0.017*	0.017	-0.065	-0.034***
	(0.010)	(0.016)	(0.043)	(0.012)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.029	0.060	0.048	0.039
Observations	38879	6071	2449	29833

Table 2.8 regresses cash weights on flows and an indicator for whether the fund experienced a sustained period of outflows. Crisis is an indicator equal to 1 if the fund experienced outflows in the previous three periods. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.9: Cash During Capital Surges and Retrenches

Panel A:Surges

	All Funds	Explicit	Closet	Active
Flows	0.113***	0.013**	0.082***	0.133***
	(0.005)	(0.006)	(0.023)	(0.006)
Surge	0.003***	0.000	0.002	0.003***
	(0.000)	(0.000)	(0.002)	(0.000)
(Flows)(Surge)	-0.085***	-0.009	-0.044	-0.085***
	(0.010)	(0.010)	(0.042)	(0.012)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.030	0.060	0.046	0.039
Observations	38879	6071	2449	29833

Panel B: Retrenches

	All Funds	Explicit	Closet	Active
Flows	0.092***	0.009**	0.089***	0.120***
	(0.004)	(0.004)	(0.019)	(0.005)
Retrench	-0.003***	-0.002***	-0.002	-0.003***
	(0.000)	(0.001)	(0.002)	(0.001)
(Flows)(Retrench)	-0.059***	-0.044***	-0.078	-0.067***
	(0.013)	(0.016)	(0.054)	(0.015)
Adjusted R^2	0.029	0.062	0.046	0.038
Observations	38879	6071	2449	29833

In Panel A, surge is an indicator equal to one if flows in a given month are in the top two deciles of flows across all fund-month observations. In Panel B, the variable retrench is equal to one if flows are in the bottom two deciles. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.10: Cash During Capital Surges and Retrenches

Panel A:Surges

	All Funds	Explicit	Closet	Active
Flows	0.121***	0.016***	0.093***	0.143***
	(0.004)	(0.005)	(0.019)	(0.005)
Surge	0.002***	0.000	0.002	0.002**
	(0.001)	(0.001)	(0.003)	(0.001)
(Flows)(Surge)	-0.091***	-0.014	-0.059	-0.093***
	(0.014)	(0.013)	(0.065)	(0.019)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.030	0.060	0.046	0.038
Observations	38879	6071	2449	29833

Panel B: Retrenches

	All Funds	Explicit	Closet	Active
Flows	0.099***	0.014***	0.091***	0.126***
	(0.004)	(0.004)	(0.017)	(0.005)
Retrench	-0.005***	-0.000	-0.007*	-0.005***
	(0.001)	(0.001)	(0.004)	(0.001)
(Retrench)(Flows)	-0.111***	-0.021	-0.183**	-0.118***
	(0.020)	(0.024)	(0.087)	(0.025)
Adjusted R^2	0.029	0.061	0.048	0.038
Observations	38879	6071	2449	29833

In Table 2.10, capital surges or retrenches are based on the within-fund variation in flows. In Panel A, surge is an indicator equal to one if flows in a given month are in the top two deciles of a given funds flows over the sample period. In Panel B, the variable retrench is equal to one if flows are in the bottom two deciles. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.11: Cash During Aggregate Funding Pressure

Panel A:

	All Funds	Explicit	Closet	Active
Flows	0.095***	0.013***	0.079***	0.120***
	(0.003)	(0.003)	(0.015)	(0.004)
Retrenches	-143.841	-149.329	-49.235	-81.834
	(...)	(...)	(...)	(...)
(Retrenches)(Flow)	0.001	-0.018**	-0.006	-0.002
	(0.007)	(0.008)	(0.032)	(0.009)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.061	0.045	0.037
Observations	38879	6071	2449	29833

Panel B:

	All Funds	Explicit	Closet	Active
Flows	0.095***	0.012***	0.067***	0.121***
	(0.003)	(0.004)	(0.015)	(0.004)
Retrench	-143.841	-14.118	-346.382	-65.920
	(...)	(...)	(...)	(...)
Retrench (Flows)	0.001	-0.007	0.072**	-0.009
	(0.007)	(0.007)	(0.036)	(0.009)
Fund FE	Yes	Yes	Yes	Yes
Time-Domicile FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.060	0.047	0.037
Observations	38879	6071	2449	29833

In Table 2.11, 'Retrench' is an indicator variable based on aggregate net flows. In Panel A, 'Retrench' is equal to 1 if aggregate net flows to all funds in the month were in the bottom two deciles; in Panel B, the indicator is equal to one if aggregate flows to a given fund type (Explicit, Closet, Active) where in the bottom two deciles.

Table 2.12: Country Allocations

	(1)	(2)	(3)	(4)
Active Funds				
R_{ct}	0.083***			0.087***
	(0.000)			(0.001)
Flows	0.082***	-0.101***	0.008**	-0.005
	(0.001)	(0.005)	(0.003)	(0.003)
R_{ct} × Flows	-0.404***			-0.443***
	(0.018)			(0.021)
Stock Turnover		-0.003***		
		(0.000)		
Stock Turnover × Flows		0.048***		
		(0.001)		
Stocks Traded (%)			0.001***	-0.000
			(0.000)	(0.000)
Stocks Traded (%) × Flows			0.022***	0.024***
			(0.001)	(0.001)
Flows				0.000
				(.)
Adjusted R^2	0.106	0.036	0.033	0.072
Observations	435146	345426	341675	342366
Closet Index				
R_{ct}	0.099***			0.123***
	(0.003)			(0.004)
Flows	0.112***	-0.122***	-0.005	-0.012
	(0.007)	(0.045)	(0.029)	(0.029)
R_{ct} × Flows	-0.598***			-0.722***
	(0.140)			(0.171)
Stock Turnover		-0.005***		
		(0.001)		
Stock Turnover × Flows		0.064***		
		(0.011)		
Stocks Traded (%)			0.001	0.001
			(0.001)	(0.001)
Stocks Traded (%) × Flows			0.039***	0.040***
			(0.008)	(0.008)
Flows				0.000
				(.)
Adjusted R^2	0.022	-0.004	-0.005	0.012
Observations	33939	21900	21053	21109
Explicit Index				
R_{ct}	0.047***			0.051***
	(0.000)			(0.000)
Flows	0.068***	-0.127***	-0.022***	-0.021***
	(0.001)	(0.004)	(0.003)	(0.003)
R_{ct} × Flows	-0.317***			-0.401***
	(0.015)			(0.018)
Stock Turnover		-0.002***		
		(0.000)		
Stock Turnover × Flows		0.053***		
		(0.001)		
Stocks Traded (%)			0.000	-0.000***
			(0.000)	(0.000)
Stocks Traded (%) × Flows			0.027***	0.027***
			(0.001)	(0.001)
Flows				0.000
				(.)
Adjusted R^2	0.154	0.099	0.090	0.097
Observations	148594	106925	105974	106418

Table 2.12 regresses the 1-month change in country allocation on the following country variables and their interaction flows: country returns (in decimal), stocks traded as a percentage of GDP (in log), and the turnover ratio of stocks traded (in logs). * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2.13: Country Allocations during Outflows

	Active Funds			
	(1)	(2)	(3)	(4)
R_{ct}	0.082***			0.086***
	(0.001)			(0.001)
Flows	0.085***	-0.111***	0.014**	-0.117***
	(0.002)	(0.010)	(0.007)	(0.010)
R_{ct} × Flows	-0.526***			-0.511***
	(0.036)			(0.040)
Stock Turnover		-0.003***		-0.000**
		(0.000)		(0.000)
Stock Turnover × Flows		0.052***		0.051***
		(0.003)		(0.002)
Stocks Traded (%)			0.000**	
			(0.000)	
Stocks Traded (%) × Flows			0.022***	
			(0.002)	
Flows				0.000
				(.)
Adjusted R^2	0.109	0.026	0.023	0.054
Observations	265271	210258	207927	211154
	Closet Index			
R_{ct}	0.099***			0.121***
	(0.008)			(0.009)
Flows	0.145***	-0.179*	-0.009	-0.171
	(0.018)	(0.108)	(0.070)	(0.106)
R_{ct} × Flows	-0.808**			-0.756**
	(0.336)			(0.370)
Stock Turnover		-0.005***		-0.001
		(0.002)		(0.002)
Stock Turnover × Flows		0.086***		0.081***
		(0.026)		(0.026)
Stocks Traded (%)			0.000	
			(0.002)	
Stocks Traded (%) × Flows			0.050***	
			(0.018)	
Flows				0.000
				(.)
Adjusted R^2	0.000	-0.021	-0.023	-0.025
Observations	20553	13457	12932	13562
	Explicit Index			
R_{ct}	0.045***			0.047***
	(0.001)			(0.001)
Flows	0.080***	-0.162***	-0.012*	-0.148***
	(0.002)	(0.011)	(0.007)	(0.011)
R_{ct} × Flows	-0.648***			-0.767***
	(0.039)			(0.047)
Stock Turnover		-0.002***		-0.000
		(0.000)		(0.000)
Stock Turnover × Flows		0.067***		0.062***
		(0.003)		(0.003)
Stocks Traded (%)			-0.000	
			(0.000)	
Stocks Traded (%) × Flows			0.030***	
			(0.002)	
Flows				0.000
				(.)
Adjusted R^2	0.172	0.067	0.055	0.047
Observations	46552	33169	32770	34097

Table 2.13 regresses the 1-month change in country allocation on the following country variables and their interaction with an indicator for outflows: country returns (in decimal), stocks traded as a percentage of gdp (in log), and the turnover ratio of stocks traded (in logs). Outflows is an indicator equal to 1 if the fund experienced outflows in period 1. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Chapter 3: Leverage and Risk in Hedge Funds[1]

3.1 Introduction

Since the demise of Long-Term Capital Management in 1998, regulators, academics, and financial market participants have been keenly aware of the potential systemic risks associated with excessive leverage in hedge funds. Leverage increases the magnitudes of both profits and losses, and exposes funds to possible margin calls, fire sales from forced deleveraging, and ultimately the chance of outright failure. Leverage risks are sufficiently acute that constraints on leverage exist in a variety of contexts: public mutual funds are restricted in their use of leverage, margin and haircuts on collateral effectively restrict the maximum leverage attainable, and Regulation T establishes limits on the amount of borrowing permitted for various types of collateral. Yet despite its potential systemic importance, significant data limitations have precluded even a basic understanding of leverage in hedge fund portfolios.

To complicate matters, alternative theories of capital market equilibrium make dramatically different predictions about the associations between leverage, risk, and return, and have meaningfully different implications for systemic risk. For instance, the classical theories of Markowitz (1952), Sharpe (1964), and Lintner (1965) imply that all investors hold risky securities in identical proportions. Expected returns are a function of a single parameter, market beta, which measures the sensitivity of the security's return to the return on the

[1] Joint work with Daniel Barth and Phillip Monin, Office of Financial Research, U.S. Department of Treasury. An earlier version was published as Barth, Hammond, and Monin (2020)

tangency (market) portfolio. In this case, leverage is linearly related to both the total and systematic risk of the portfolio. That is, greater leverage necessarily implies greater risk.

Conversely, newly revived theories of leverage constraints suggest that naturally high-risk assets are in excess demand, driving their prices up and expected returns down (Black (1972), Garleanu and Pedersen (2011), Frazzini and Pedersen (2014), Boguth and Simutin (2018)). Perhaps the most appealing feature of these models is that they predict the "low-beta anomaly," the robust empirical finding that low-beta assets earn higher alphas.[2] [3] These theories imply that unconstrained investors hold leveraged portfolios of low-risk, high-alpha assets, while leverage-constrained investors hold less-leveraged portfolios of high-risk assets.[4] In this case, leverage and asset risk are *negatively* associated, primarily through a negative association between leverage and market beta. Because low-risk assets are most heavily leveraged, the relationship between leverage and portfolio risk is undetermined — it could be positive, flat, or even negative. These theories also predict that alpha and market beta are negatively related, and therefore leverage and alpha are positively correlated.

In this paper, we use new regulatory data on hedge fund activities to show that theories of leverage constraints explain many empirical features of hedge fund leverage. Our analyses are made possible by a rich panel of information on hedge fund characteristics and activities collected on the Securities and Exchange Commission's (SEC) Form PF. The Dodd-Frank Wall Street Reform and Consumer Protection Act mandates information on

[2] Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), Baker, Hoeyer, and Wurgler (2016).

[3] Alpha measures the excess return on an investment relative to a market index, and beta measures the volatility or risk of an investment relative to the market. For example, an asset that earns 10% while the S&P 500 earns 5% has an alpha of 5. An asset with a beta equal to 2 is twice as volatile as the S&P 500.

[4] In Section 3.2 we describe a few additional innocuous assumptions needed for this result.

private funds be collected for the dual purposes of investor protection and systemic risk assessment. Our data constitutes the first systematic, regulatory collection of data on large private funds. The data contain proprietary information on hedge fund assets, including long and short exposures in broad asset classes, the illiquidity of the portfolio, and the gross and net assets of the fund. The ratios of gross assets and notional exposures (gross, long, short, and net, separately) to net assets comprise the measures of leverage we use in our analyses. Our data also contain information on hedge funds' liabilities, such as borrowing, collateral, investor share restrictions, the term structure of financing, and much more.

Our data constitute the most comprehensive view of the hedge fund industry to date and offer an unprecedented view of the activities of large hedge funds. One of the defining features of hedge funds is their use of leverage, yet even today very little is known about leverage in hedge funds. The few existing studies that have analyzed hedge fund leverage rely on public databases, which suffer from a number of data limitations. Reporting to the public databases (such as Lipper TASS and Hedge Fund Research) is done on a voluntary basis only and thus contain potentially severe selection biases. Large funds also tend not to report to any of the public hedge fund data services, thus these data services predominantly comprise smaller funds (Edelman, Fung, and Hsieh 2013). Our data is therefore much more representative of the industry based on total assets under management, and contains detailed data on hedge fund characteristics and activities not available elsewhere.

Our headline finding is that leverage is strongly *negatively* related to the risk of the assets held in hedge fund portfolios. This result is robust to alternative measures of risk, including the realized volatility of returns and the likelihood of an extreme return, and to

alternative measures of leverage, including the ratios of gross to net assets, gross notional exposures to net assets, and long and short exposures (separately) to net assets.

Using the Fama and French (2015) five-factor model, we show that the negative relationship between leverage and asset risk holds for both systematic risk — the risk determined by exposures to standard asset pricing risk factors — and the residual idiosyncratic risk of the assets. However, the leverage-risk gradient is steeper for systematic asset risk than for idiosyncratic asset risk. This leads to our second main finding: at the level of the portfolio (the combination of assets and leverage), leverage and risk are weakly negatively related. This weak association results because leverage and systematic portfolio risk are strongly negatively correlated, while leverage and idiosyncratic portfolio risk are positively related. In aggregate, the association with systematic risk dominates, but is substantially attenuated by the positive effect of idiosyncratic risk.

Our next set of results provide more support for theories of leverage constraints, which predict that *market beta* in particular drives the negative relationship between leverage and systematic risk. Guided by this prediction, we show that the average market beta on hedge funds' assets alone explains 20% of the variation in hedge fund leverage. Among the subsample of funds with equity-based strategies, the R^2 grows to 47%. In the full sample, we estimate that a fund with a leverage ratio of two will hold assets with an average market beta that is more than one full standard deviation smaller than the beta on assets held by an unleveraged fund (0.331 versus 0.662). Adding the betas on the size, value, profitability and investment factors to the regression has little effect on this relationship. Further, none of the coefficients on the remaining betas approach the economic magnitude or statistical significance of the coefficient on market beta. Exposure to market risk appears to be a

predominant source of the negative relationship between leverage and systematic risk.

Our last set of analyses focuses on hedge fund alpha. Theories of leverage constraints offer an explanation for the low-beta anomaly, the empirical observation that low-beta securities tend to have high alphas. Because leverage is empirically negatively associated with market beta, it follows that leverage and alpha are likely to be positively related. Indeed, we find that a fund leveraged two-to-one has an average alpha that is 1.81 percentage points higher per year than a fund with no leverage. We then show that the entire association between leverage and portfolio alpha is due to market beta. That is, there is no relationship between leverage and alpha once the market beta of the assets is included in the regression. This suggests an important source of variation in hedge fund leverage is unconstrained funds profiting from the low-beta anomaly.

Our results have important implications for systemic risk. We show that greater leverage does not necessarily imply greater portfolio risk because of the negative association between leverage and the risk of the underlying assets. However, this relationship between leverage and risk may not necessarily hold during financial crises. The weakly negative association between leverage and portfolio risk results from two competing forces: a negative relationship between leverage and systematic risk, in particular market beta, and a positive relationship between leverage and idiosyncratic risk. If market betas increase during financial crises then the anchoring effect of low-beta assets will diminish, and leverage and risk could become positively correlated. Similarly, leverage and risk could become positively correlated if the association between idiosyncratic risk and leverage steepens during crises. Our results also do not consider additional channels through which leverage may associate with risk, such as counterparty linkages and rollover risk from financing. Nonetheless, our

results demonstrate that greater leverage does not necessarily imply greater portfolio risk.

Our results also suggest that policies aimed at reducing potential systemic risks in private funds, such as the explicit leverage limits being considered in the European Union, may have unintended consequences.[5] For instance, our findings suggest that formally unconstrained funds may invest more heavily in high market-beta securities if they become leverage constrained as a result of leverage limits. This could increase the concentration of holdings in high-beta betas, possibly leading to more highly correlated trades and more tightly coupled performance, particularly in down markets.

Because our ultimate interest is in the relationship between hedge fund leverage and systemic risk, our study begins by utilizing the richness of our data to provide the first thorough decomposition of the sources and characteristics of hedge fund leverage. Very little is known about how and why hedge funds use leverage, so we view this as an important contribution in its own right. Ang, Gorovyy, and van Inwegen (2011) use data from a fund of funds to examine the time-series of hedge fund leverage, both prior to and during the financial crisis. However, we find that over 89% of the variation in hedge fund leverage in the post-crisis period can be explained by fund fixed effects, suggesting leverage is largely a cross-sectional attribute of hedge fund portfolios during this time. The Ang, Gorovyy, and van Inwegen (2011) study is also based on only a few hundred funds, whereas our data contain about 2,900 unique, large hedge funds. Liang and Qiu (2019) uses data from the Lipper TASS hedge fund database to examine various cross-sectional characteristics of hedge fund leverage. But due to the voluntary nature of the data and the infrequency

[5] See the recommendation of the European Systemic Risk Board on liquidity and leverage risks in investment funds https://www.esrb.europa.eu/pub/pdf/recommendations/esrb.recommendation180214_ESRB_2017_6.en.pdf?c8d7003d2f6d7609c348f4a93ced0add

with which leverage information is updated, this analysis may suffer from selection issues. Instead, our data comprise the first systematic collection of hedge fund data that is largely free from selection and survivorship biases.[6]

Perhaps surprisingly, we find that broad fund strategy explains only 7.2% of the cross-sectional variation in hedge fund leverage. [7] However, the fraction of total borrowing done through repurchase agreements (repo) holds significant explanatory power, on its own explaining 6.1% of variation. We also find that portfolio illiquidity is inversely related to leverage, while investor share illiquidity is positively related. Fund size is only weakly related to leverage. In total, the set of cross-sectional characteristics we examine explains nearly 20% of the total cross-sectional variation in fund leverage. While the variation explained by these characteristics is substantial, our findings suggest that much of the cross section of hedge fund leverage remains to be explained.

Our analysis primarily focuses on balance sheet leverage. This is because it most directly ties to the theories of leverage constraints that we test, which specifically consider constraints on borrowing. However, leverage can be measured in many other ways, and the measurement of leverage in investment funds is of significant and ongoing international debate. In November 2018, the International Organization of Securities Commissions (IOSCO) proposed a framework for assessing leverage in investment funds, responding to a request from the Financial Stability Board (FSB) to find measures of leverage in funds that can be broadly applied and meaningfully inform the financial stability implications of

[6]The Form PF data are not entirely free from selection bias. Because only advisers with at least $150 million in private fund assets report, our sample is biased toward larger funds. Further, only funds advised by advisers who must register with the SEC report on Form PF. Nonetheless, reporting is not endogenous conditional on fund size and SEC registration. We offer a more detailed description of the data in Section 3.3.

[7]Broad fund strategies are determined by the value of funds assets reported in various strategy categories such as ”Credit” or ”Event Driven”

fund leverage. The IOSCO report describes the benefits and drawbacks several potential leverage metrics intended to capture aspects of both financial and synthetic leverage.

Our results also provide the first microfoundational evidence of the leverage-constraint mechanism at the level of the investor's portfolio. Previous studies have focused on empirical predictions at the level of the asset class or broad investor type.[8] However, our results demonstrate that even within the hedge fund industry, leverage constraints are likely to vary considerably, and variation in these constraints helps explain variation in hedge fund leverage. The finding that leverage is strongly negatively associated with the market beta of the assets, and that leverage and alpha are positively related but only through market beta, suggests that relatively unconstrained investors are profiting from the ability to leverage low-beta, high-alpha assets. To our knowledge, this is the first paper to provide evidence in support of theories of leverage constraints using the actual leverage decisions of investors.

The paper is organized as follows: Section 3.2 specifies the relevant empirical predictions that arise from the theories of leverage constraints developed in Frazzini and Pedersen (2014) and Boguth and Simutin (2018); Section 3.3 describes the data, defines our leverage measures, and examines various characteristics that are associated with the cross-section of hedge fund leverage; Section 3.4 examines the relationship between leverage and risk; Section 3.5 studies the relationship between leverage and returns, including betas and alpha; and Section 3.6 concludes.

[8] See Frazzini and Pedersen (2014), Jylha (2018), and Boguth and Simutin (2018).

3.2 A Simple Theory of Leverage Constraints

In the classical theories of Markowitz (1952), Sharpe (1964), and Lintner (1965), investors hold portfolios of risky assets in identical proportions and take long or short positions in a risk-free asset to achieve a desired level of portfolio risk. All investors are leverage-unconstrained and can borrow and lend at the risk-free rate. Along with additional assumptions about myopia, identical beliefs, and a few others, this setting gives rise to the capital asset pricing model (CAPM), which establishes that expected returns are linearly related to their sensitivity to the market (tangency) portfolio.

A number of empirical predictions arise from this setup. First, because all investors hold identical risky portfolios, leverage and *asset* risk — the risk of the portfolio prior to the imposition of leverage — are uncorrelated. Because leverage and asset risk are uncorrelated, leverage and *portfolio* risk — the risk associated with the leveraged assets — will be positively linearly correlated. In this world, greater leverage automatically implies greater risk. Further, because all investors hold the market portfolio as the single risky asset, market beta and leverage are also linearly positively associated. Finally, alphas are zero for all assets, and thus alphas and leverage are trivially uncorrelated.

In contrast, newly revived theories on leverage constraints deliver starkly different predictions (Black (1972), Frazzini and Pedersen (2014), Garleanu and Pedersen (2011), Boguth and Simutin (2018)). In particular, these theories offer an explanation for the "low-beta anomaly," the robust empirical fact that low-beta assets have higher alphas than high-beta assets. To derive the empirical predictions that arise from this class of models, we reproduce the model of Boguth and Simutin (2018) below, which is nested in the model of

Frazzini and Pedersen (2014).

The Boguth and Simutin (2018) setting consists of two investors: an unconstrained hedge fund and a leverage-constrained mutual fund. Our interest is in hedge funds specifically, so we instead consider the case where one hedge fund is unconstrained and the other is constrained. This is done for expositional convenience. Hedge funds are not the only investors in the economy, and are likely to be less leverage-constrained than other large investors such as mutual funds and pensions. All of the empirical predictions derived below are unchanged in a more flexible model that allows for a large number of investors all with potentially unique leverage constraints. This is the setting developed in Frazzini and Pedersen (2014), and we refer the reader to that model for additional details.

The assumption that not all hedge funds are leverage-unconstrained is justified. While hedge funds are not directly leverage-constrained by regulation, there are many ways in which hedge funds may still be constrained. For instance, many hedge funds state an explicit leverage limit in their offering documents. Funds are also limited by Regulation T, which restricts the amount of leverage obtainable using different types of collateral. Jylha (2018) shows that variation in the leverage limits implied by Regulation T leads to different slopes of the security market line, a finding consistent with leverage constraints affecting the relationship between alpha and beta. Leverage is also limited by the collateral value of the assets; risky and illiquid securities often have large haircuts, which effectively constrains leverage. Together, these restrictions imply that hedge funds are likely to vary in the extent to which they can obtain leverage.

Denote the wealth of the unconstrained hedge fund by W_u and of the leverage constrained hedge fund by $W_c = 1 - W_u$. There are K risky securities in positive net supply

and a risk-free asset. Both agents maximize mean-variance preferences given their risk aversion $\gamma_i \in \{\gamma_u, \gamma_c\}$:

$$\max_{\omega_i} \; E(\omega_i' R^e + R_f) - \frac{\gamma_i}{2} \omega_i' \Sigma \omega_i, \tag{3.1}$$

where ω_i is the vector of portfolio weights on the K risky securities.

Additionally, the constrained hedge fund faces a leverage constraint: $\omega_c' \mathbf{1} \leq C$, where $C \geq 1$ establishes the maximum leverage ratio the constrained fund can obtain. For example, $C = 2$ means that the fund can borrow at most 100% of the value of their wealth, W_u, for a leverage ratio of two to one. We restate that while this setting considers only two types of funds, constrained and unconstrained, the results extend straightforwardly to a setting with a continuum of funds each with a possibly unique leverage constraint, C_i.

In equilibrium, this setting delivers a linear pricing equation:

$$ER^e = \beta(ER^e_M - \psi) + \psi \mathbf{1}, \tag{3.2}$$

where ER^e_M is the excess return on the market portfolio and $\psi \geq 0$ is the shadow value of the leverage constraint weighted by the constrained fund's wealth and risk aversion. In economic terms, ψ measures the tightness of the funding constraint; ψ is large when the constraint is particularly costly.

Figure 3.1 offers a visual description of this framework, where for simplicity we assume the constrained fund is entirely prohibited from borrowing ($C = 1$). If the constrained fund's leverage constraint does not bind, then both the constrained and unconstrained funds

hold the mean-variance efficient tangency portfolio (portfolio A) in combination with the risk-free asset, and the CAPM holds.

The more interesting scenario is one in which the unconstrained investor uses leverage and the leverage-constrained investor wants more risk than is delivered by the tangency portfolio. In this case, the leverage constraint binds, funds differ in their use of leverage, and the theory delivers a number of empirical predictions the depart substantially from the classical theory. The constrained fund will move along the efficient frontier to a portfolio with more risk than the tangency portfolio (portfolio B), and the unconstrained fund will invest in the tangency portfolio with equity capital and borrowing (portfolio A'). The market portfolio is no longer the tangency portfolio, and the CAPM no longer holds. Instead, the market portfolio (M) lies on the efficient frontier between portfolios A and B.

This provides the first empirical prediction we highlight from the model:

Proposition 1: Leverage and asset risk are negatively related in equilibrium.

Because the constrained fund, which cannot use leverage, holds a riskier portfolio of assets than the unconstrained fund ($\sigma_B > \sigma_A$ in Figure 3.1), leverage and asset risk are negatively correlated. This constitutes one of many important distinctions between classical theories and those of leverage constraints. Classical theories do not deliver any association between leverage and the risk of the underlying assets, since asset mix does not vary by investor.

Next, because leverage is associated with lower-risk assets, the relationship between leverage and total portfolio risk is undetermined. Portfolio risk could be increasing, flat, or even decreasing in leverage depending on the risk preferences and leverage choices of the constrained and unconstrained hedge funds. In Figure 3.1, $\sigma_{A'}$ could be larger, smaller, or

equal to σ_B. This is proposition two:

Proposition 2: The equilibrium relationship between leverage and portfolio risk is undetermined.

While the constrained investor may optimally deviate from the tangency portfolio, the fundamental positive association between risk and expected return remains. Because leveraged funds hold less risky assets, they must also hold assets with lower expected returns ($ER_A < ER_B$). This is proposition three:

Proposition 3: More leveraged funds hold assets with lower expected returns.

Finally, equation (3.2) shows that leverage constraints deliver a security market line that is too flat relative to the CAPM because expected return is a linear function of two parameters: β and ψ. Still, because the assets held by the constrained fund have higher expected returns, equation (3.2) shows that they must have higher betas. This gives us proposition 4:

Proposition 4: Leverage and the average market beta of the fund's assets are negatively related.

Further, equation (3.2) implies that alpha and beta are negatively related: $\alpha_k = \psi(1-\beta_k)$. Thus, we have our fifth and final empirical prediction:

Proposition 5: Leverage and the average alpha of the fund's assets are negatively related.

Theories of leverage-constrained investors like the one presented here offer a vastly different set of empirical predictions for leverage, risk, and return than do classical theories

of financial markets. Classical theories predict: leverage and asset risk are uncorrelated; a linear, positive association between leverage and portfolio risk; a linear, positive association between leverage and market beta; and no relationship between leverage and alpha. Alternatively, theories of leverage constraints predict that leverage and asset risk are negatively associated, the relationship between leverage and portfolio risk is undetermined, leverage and the average market beta of the assets are negatively associated, and leverage and alpha are positively associated.

These divergent predictions have significantly different implications for systemic risk. If leverage and risk are strongly positively associated, then very high levels of leverage in the aggregate or at individual funds should raise concerns for policy makers and regulators. A build up of hedge fund leverage would also indicate greater risks of fund failure. Instead, if leverage and risk are negatively related or unrelated, then high or increasing leverage would not necessarily imply greater threats to financial stability. These opposing predictions, and their varied implications for systemic risk, motivate the empirical analyses in Sections 3.4 and 3.5.

3.3 Data and Summary Statistics

We use fund-level data from the Securities and Exchange Commission's (SEC) Form PF, which was adopted in 2011 as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. Form PF is filed by investment advisers registered with the SEC who manage at least $150 million in private fund assets, such as in hedge funds and private equity funds. Private fund advisers file annually and report items such as gross and net asset values, monthly returns, total borrowings, strategies, investor composition, and

their largest counterparties. *Large hedge fund advisers*, those with at least $1.5 billion in assets managed in hedge funds, are required to report this information at a quarterly frequency as well as more detailed information regarding portfolio, investor, and financing illiquidity, asset class exposures, collateral posted, risk metrics, and more, for each of their *qualifying hedge funds*. A qualifying hedge fund has a net asset value (NAV) of at least $500 million as of the last day in any month in the fiscal quarter immediately preceding the adviser's most recently completed fiscal quarter. In order to have quarterly values for leverage and other variables of interest, we focus only on qualifying hedge funds in our analyses.[9] Our sample of funds is therefore representative of large funds with at least one U.S. investor.[10]

We make several data restrictions to mitigate the effects of outliers or potential data errors. Due to data quality concerns at the beginning of the Form PF data collection, we limit our sample to filings that occur after 2012 and exclude observations with a net asset value below $10 million. In our cross-sectional analysis, we include only funds with non-missing average values for the each of our primary variables of interest: portfolio liquidity, investor liquidity, net assets, gross assets, borrowing, and gross notional exposure. In sections 3.4 and 3.5 we also restrict our sample to funds with balance sheet leverage less than 10, to minimize potential data errors. To avoid return outliers, we include funds with

[9]While the qualifying hedge fund threshold is in terms of net assets, the thresholds for filing Form PF and for the large hedge fund adviser classification are on a gross basis. When determining whether a reporting threshold is met, an advisers must aggregate private funds, parallel funds, dependent parallel managed accounts, and master-feeder funds. It must also include these items for its related persons that are not separately operated. While the determination of whether a set of funds in a parallel fund structure or master-feeder arrangement constitutes a Qualifying Hedge Fund is on an aggregated basis, advisers are permitted to report fund data either separately or on an aggregated basis. Thus some funds in our sample have NAV much less than the qualifying hedge fund threshold of $500 million.

[10]Form PF data are confidential. The form itself is publicly available and can be downloaded here: https://www.sec.gov/rules/final/2011/ia-3308-formpf.pdf. For more detail on the history and structure of Form PF, see Flood, Monin, and Bandyopadhyay (2015) and Flood and Monin (2016).

a Sharpe ratio within +/- 2 and with an alpha between the 2.5th and 97.5th percentiles from the five-factor model of Fama and French (2015).[11] Finally, based on the strategy methodology described below, we exclude funds categorized as Invests in Other Funds (funds that primarily invest in other private funds) from the sample.

Our sample contains 35,397 fund-quarter observations spanning January 2013 to March 2019. Table 3.1 reports summary statistics. The first set of variables regard fund size. Net asset value represents investors' capital. The average NAV is $1.60 billion, with a standard deviation of $2.21 billion and a median of $0.91 billion. Gross asset value (GAV) represents the regulatory assets of the fund, which is akin to balance sheet assets.[12] The average GAV is $2.61 billion, with a standard deviation of $4.55 billion.

Hedge funds' derivatives positions are not fully reflected on the balance sheet. Derivatives are generally reported on Form PF at notional values, except for options, which are delta-adjusted, and interest rate derivatives, which are reported at 10-year bond equivalents. Gross notional exposure (GNE) is the sum of these adjusted notional amounts, both long and short, over all of the asset classes. GNE reflects the economic footprint of the hedge fund's investments. The average GNE is $5.88 billion, with a median of $1.93 billion and a standard deviation of $12.90 billion, suggesting that GNE is highly skewed. Long notional exposure (LNE) is the part of GNE composed of long positions, while short notional exposure (SNE) is the part composed of short positions. The mean LNE is $3.77 billion, with a standard deviation of $7.23 billion. The mean SNE is $2.11 billion, with a standard

[11] Whereas our data are generally reported on a quarterly basis, funds report returns on a monthly basis. Rather than rates of return, some funds appear to report an internal rate of return (IRR). We make the restriction on Sharpe ratios to exclude funds that may be reporting IRRs instead of rates of return.

[12] Regulatory assets under management is defined in Form ADV Part 1A Instruction 5.b. At the fund level, it is essentially equal to balance sheet assets plus uncalled capital commitments, the latter of which are more relevant for private equity funds than hedge funds.

deviation of $5.87 billion. Finally, net notional exposure (NNE) is the difference between LNE and SNE. Its mean is $1.65 billion and its standard deviation is $2.65 billion.

The next variables listed in Table 3.1 include portfolio illiquidity, investor share illiquidity, and fees. The portfolio illiquidity measure is a weighted average of the percentages of the fund's portfolio that can be liquidated within a set of time horizons (0-1, 2-7, 8-30, 31-90, 91-180, 181-365, or more than 365 calendar days) under the market conditions prevailing during the reporting period and assuming no fire sale discounting. Similarly, funds report the percentages of NAV that can be redeemed by their investors over the same horizons, which we use to compute a measure of investor share illiquidity.[13] The average portfolio illiquidity is 67.7 days, with a median of 13.4 days. The mean investor share illiquidity is 170.6 days, with a median of 140.1 days. Managers typically charge two sets of fees: a recurring management fee, and a performance fee if, due to good performance, fund assets exceed their previous high water mark. These fees are not reported on Form PF; instead, we estimate them using reported gross- and net-of-fee returns according to a method originated in Barth and Monin (2019) and outlined in Appendix 4.3.1. The mean estimated management fee is 1.02% with a standard deviation of 0.99%, and the mean estimated performance fee is 13.37% with a standard deviation of 9.25%.

Finally, the bottom of Table 3.1 lists the number of fund-quarter observations per broad investment strategy. Funds report gross asset value allocated to 22 investment strategies that are contained within 8 broad strategy categories: Credit, Equity, Event Driven, Macro, Relative Value, Managed Futures, Invests in Other Funds, and Other. We classify a fund as

[13] See Barth and Monin (2019), Aragon, Ergun, Getmansky, and Girardi (2017b), and Aragon, Ergun, Getmansky, and Girardi (2017a) for more on these liquidity measures.

pursuing a given broad strategy if 75% or more of its assets are allocated to that strategy. If there is no broad strategy category that contains 75% or more of the fund's assets, we classify the fund as Multi-strategy. We exclude funds that invest predominantly in other private funds. The most common strategy according to Table 3.1 is Equity, representing about one third of all observations. The second most common is Multi-strategy, which is followed by Event Driven, Relative Value, Credit, and Macro.

3.3.1 Leverage Measures and Sources

Leverage refers to a technique used to increase exposure to an investment or risk factor beyond what would be possible with only equity capital. Leverage plays an important role in the efficient portfolio management of several hedge fund strategies, allowing the fund to tailor risk and return profiles and to increase its potential gains on investments that would otherwise be insufficiently attractive. However, while leverage can enhance investment returns, it can also amplify losses. In contrast to most investment funds, such as mutual funds, there are no legal limits on the use of leverage by hedge funds. Instead, any limits on hedge funds' use of leverage rely on the market discipline imposed by counterparties and regulations on markets and other financial institutions.

There are two broad ways to generate leverage. Leverage can be generated directly by borrowing cash or securities from counterparties, which is known as financial leverage, or indirectly by investing in derivative securities such as futures, options, or swaps, which is called synthetic leverage. In each case, the gross exposure of the leveraged position is greater than the equity capital supporting it.

Leverage is typically expressed as a ratio of exposure to capital. There are several

ways to measure exposure and thus several ways to measure leverage. The measurement of leverage is of significant and ongoing international debate. In November 2018, the International Organization of Securities Commissions (IOSCO) proposed a framework for assessing leverage in investment funds such as hedge funds, responding to a request from the Financial Stability Board (FSB) to find measures of leverage in funds that can be broadly applied and meaningfully inform the financial stability implications of fund leverage.[14]

The IOSCO report describes the benefits and drawbacks of several potential leverage metrics intended to capture aspects of both financial and synthetic leverage. We consider several similar measures in this paper. Balance sheet leverage is equal to the ratio of a fund's balance sheet assets (gross assets) to its net assets (GAV/NAV). Balance sheet leverage captures financial leverage. A fund with no balance sheet leverage will have gross assets equal to net assets, while a fund that borrows an amount equivalent to net assets will have a leverage ratio of two.

A virtue of balance sheet leverage is that it is easy to compute from accounting statements. However, it does not account for synthetic leverage arising from off-balance sheet derivatives transactions. Alternative measures of leverage may better account for synthetic exposures. These measures use adjusted notional exposures, which include the notional values of derivatives and other investment positions in the fund's portfolio. Options are delta-adjusted to better reflect the exposure of an option to its underlying asset, and interest rate derivatives are converted to 10-year bond equivalents for similar reasons. Our data allow us to separate adjusted notional exposures associated with long investments and short investments. We thus obtain four leverage measures: long leverage (LNE/NAV), short

[14] See The Board of the International Organization of Securities Commissions (2018)

leverage (SNE/NAV), gross leverage (GNE/NAV), and net leverage (NNE/NAV). These measures differ in the assumptions they make about the netting and hedging of positions. For instance, gross leverage (GNE/NAV), implicitly assumes that long and short positions add to risk, which will overstate risk if at least some of the short positions are in fact hedges of long positions. Conversely, net leverage (NNE/NAV) assumes that all short positions are perfect hedges of long positions.[15]

In this paper, we focus on balance sheet leverage. This is largely because it most directly ties to the theories of leverage constraints that we describe in Section 3.2. Panel A of Table 3.2 shows the distribution of balance sheet leverage in our sample. Funds have an average leverage ratio of 1.74, with a median of 1.19 and a 90th percentile of 2.65. Leverage, particularly in the tails, depends on fund strategy. Macro, Multi-strategy, and Relative Value funds have average leverage levels over two; Relative Value, Macro, and Multi-strategy funds have 90th percentile values of 4.76, 3.42, and 3.35 respectively.

Panel B of Table 3.2 examines the distribution of the variation in leverage within fund over time.[16] The median standard deviation across all funds is 0.08, and the 90th percentile is 0.54. Given a lower bound on balance sheet leverage of one, Panel B demonstrates that leverage changes little across time for a given fund. Naturally, leverage changes are on average larger for more leveraged funds. The median standard deviation of leverage for Relative Value and Macro funds are well above that of the unconditional median, and the

[15]Our notion of gross notional exposure (GNE) corresponds to the concept of *adjusted* gross notional exposure in The Board of the International Organization of Securities Commissions (2018), and our measures of leverage are similar to those considered in Ang, Gorovyy, and van Inwegen (2011) and The Board of the International Organization of Securities Commissions (2018).

[16]In Panel B, we restrict observations to funds with at least four quarters of data on both gross and net assets, and report the standard deviation of leverage across all observations for that fund in the sample. We report only one observation per fund

90^{th} percentile values are 1.47 and 1.41, respectively. Nonetheless, within-fund variation in leverage appears to be modest over the sample.

In Table 3.3, we examine the sources of balance sheet leverage. Funds obtain balance sheet leverage primarily through direct borrowing from their prime brokers or through repo markets. Across all funds, the average amount of a fund's borrowing sourced from their prime broker is 62.1%, with repo comprising only 17.2%. However, for the most leveraged strategies such as Macro and Relative Value, repo comprises the majority of the funds' borrowing, with values of 53.1% and 53.9%, respectively. Although most funds mainly source borrowing through their prime brokers, the total amounts of hedge fund borrowing done through repo and prime brokerage are roughly similar (see Figure 3.2). Further, the most leveraged funds rely heavily on repo borrowing. Among the top-25 most leveraged funds at the end of 2018, 63.5% of their total borrowing was procured through repo. The reliance on repo by the most leveraged funds is likely partly due to low haircuts on safe collateral (U.S. Treasuries and G-10 sovereigns) that are widely available in repo markets, and the economics of fixed income relative value strategies in which duration-matched positions, financed with repo, must be significantly leveraged to make the resulting returns sufficiently attractive.

Table 3.4 reports summary statistics for the LNE/NAV, SNE/NAV and NNE/NAV leverage measures, both in aggregate and by strategy. Unsurprisingly, the ratio of long notional exposure to net assets is consistently larger than the ratio of gross to net assets, particularly in the upper tail.[17] The median LNE/NAV for all funds is 1.44 compared to a median of

[17] We also note that many funds have relatively small short positions, so that LNE will generally be larger than SNE, and that the ratio of LNE or SNE to NAV can be below one depending on the tilt of the portfolio

1.19 for the balance sheet leverage. The most leveraged funds have dramatically higher LNE/NAV; in the 90th percentiles, Relative Value and Macro funds have values of 7.91 and 15.55, respectively.

Table 3.5 shows the rank correlation of balance sheet leverage and other leverage measures. All of the leverage measures are positively correlated. Balance sheet leverage has a moderately high rank correlation of about 61% to long, short, and gross leverage, while long, short and gross leverage are all nearly perfectly correlated.

While Tables 3.2 and 3.4 show considerable heterogeneity in the cross-section of leverage, the cross-sectional distribution of leverage is largely stable over time. Figure 3.3 plots GAV/NAV, LNE/NAV, and SNE/NAV. While there is sizeable variation over time in the 99th percentile, lower quantiles appear to change very little over the sample. For example, the 90th percentile value of GAV/NAV is a around three from 2013 through March 2019.

3.3.2 The Cross Section of Hedge Fund Leverage

Table 3.2 showed considerable heterogeneity in the balance sheet leverage of hedge funds. Within-fund variation is relatively small compared to the variation across funds, suggesting that hedge fund leverage in the post-crisis period is largely a cross-sectional characteristic. The literature has yet to fully identify the hedge fund traits that are associated with leverage.[18] This primarily arises from a lack of detailed data on hedge fund characteristics. Our data allow us to examine a rich set of hedge fund attributes that may be associated with leverage, including fund size, broad fund strategy, borrowing composition,

[18] Ang, Gorovyy, and van Inwegen (2011) find that the relevant explanatory factors for hedge fund leverage are almost exclusively macro and time-series indicators — fund characteristics play only a small role in the total variation in hedge fund leverage. Liang and Qiu (2019) examine the cross-sectional characteristics associated with *changes* in leverage, or for leverage levels in new funds, but not leverage levels across all funds.

asset and investor share illiquidity, investor composition, and fees. We are interested in two related questions: what fund attributes are correlated with average fund leverage, and how much of the cross-sectional variation can we explain. Our base analysis focuses on balance sheet leverage.

In Table 3.6, we compute the within-fund mean balance sheet leverage ratio and regress its reciprocal on various hedge fund characteristics. We choose the reciprocal as our dependent variables because the distribution of balance sheet leverage is highly skewed. This is also done for consistency with the analyses in Sections 3.4 and 3.5. Note that the reciprocal of balance sheet leverage can be interpreted as the ratio of equity capital to assets (capital ratio). Throughout the paper, we will refer to the capital ratio and inverse leverage interchangeably. We first estimate the total amount of variation in leverage due to funds' time-invariant characteristics. Column (1) reports results from a panel regression of the funds' capital ratio on only fund fixed effects; 89% of the total variation in capital ratios is explained by fund fixed effects. This confirms that hedge fund leverage is largely a cross-sectional characteristic.

We begin by considering fund size and strategy. Larger funds may benefit from better financing arrangements with their prime brokers, and funds engaged in equities-based strategies likely employ less leverage than funds engaged in relative value trades (Kruttli, Monin, and Watugala (2019)). Column (2) of Table 3.6 supports the view that larger funds employ more leverage, though size explains only 0.1% of the variation in leverage. Column (3) examines the relationship between balance sheet leverage and broad strategy by regressing leverage on strategy dummy variables (with Equity the excluded strategy). Consistent with the summary statistics in Table 3.2, we find that Relative Value and Multi-

strategy funds take significantly more leverage on average than Equity funds, while Credit, Event Driven, and Managed Futures funds take significantly less balance sheet leverage. These relationships are highly statistically significant.

Perhaps surprisingly, the full set of broad strategy indicators explains only 7.2% of the variation in average hedge fund leverage. This suggests that while certain broad strategy indicators are strongly associated with fund leverage, considerable heterogeneity remains within each category. This may in part result from funds self-reporting their strategy classifications. Funds within a given strategy, however, are likely to be heterogeneous in their use of leverage. For example, Relative Value funds that make bets on the shape of the yield curve may use considerably more balance sheet leverage than Relative Value funds that make bets through futures and other derivatives (which would instead increase the synthetic leverage of the fund).

In column (4) of Table 3.6 we make further progress by examining the relationship between average balance sheet leverage and the fraction of fund borrowing conducted through repurchase agreements (repos).[19] Table 3.3 shows that for most funds, repo borrowing comprises little of their total borrowing. However, funds engaging in fixed income relative value trades that require large notional positions are more likely to obtain these positions through repo because safe collateral is in high demand and generally requires low haircuts in repo markets. Column (4) finds that the fraction of total borrowing conducted through repo is highly associated with leverage. A fund that does all of its borrowing through repo will have 20.6 percentage points less capital relative to its assets than a fund that does no borrowing through repo, with a robust t-statistic of over 10. Further, repo borrowing alone

[19]For funds with no repo borrowing, this variable is set to zero.

explains 6.1% of the cross-sectional variation in leverage, close to the amount explained by the full set of strategy indicators. This suggests that a defining feature of strategies that make high use of leverage is the extent of participation in repo markets, regardless of the broad strategy classification.

Funds obtain the vast majority of their balance sheet leverage through collateralized borrowing. The more volatile and illiquid the collateral, the higher the required haircut and lower the leverage. Additionally, illiquid assets paired with short-term funding may expose funds to fire sale risk if declining collateral values force funds to sell assets quickly. Market discipline and prudent risk management therefore suggest that leverage and portfolio illiquidity are likely to be negatively related. Previous studies have documented a negative relationship between share restrictions and leverage using publicly available data (Liang and Qiu (2019)), but share restrictions embed both the liquidity of the assets and other factors such as manager discretion (Agarwal and Naik (2004)).

The data in Form PF offers a way forward. Column (5) of Table 3.6 regresses the average capital ratio (the inverse of leverage) on the log of average portfolio illiquidity. The relationship is strongly statistically significant and suggests that an additional log-day of portfolio illiquidity is associated with an increase in the capital ratio of 1.7 percentage points. Column (6) regresses average fund leverage on the log of average portfolio illiquidity together with the log of average investor share illiquidity. Conditional on the illiquidity of investors' shares, portfolio illiquidity becomes even more strongly (negatively) related to leverage. However, investor share illiquidity has the opposite effect on leverage: funds with more restricted shares, such as those with longer lockups or redemption notice periods, are less susceptible to runs by investors that could force untimely sales of leveraged posi-

tions. Funds that make heavier use of leverage are therefore more likely to secure funding for longer terms, or conversely, funds with tighter share restrictions are able to take more leveraged positions. These results suggest that market discipline and the risk-management practices of funds, as well as the threat of investor runs, produce limitations on the extent to which illiquid assets are financed through borrowing.

A hedge fund characteristic available only in regulatory data is the distribution of investor capital by investor type. Due to various risk-management policies, certain investor types may be less likely to invest in leveraged hedge funds if such funds are seen as excessively risky. Further, it may be that some investors have shorter investment horizons or provide flows that are more sensitive to short-term fund performance. We might expect funds that cater to such investors to avoid leverage as well.

Column (7) of Table 3.6 separates the fraction of equity capital into six distinct investor types, aggregated from a set of 12 finer categories: individual (US and non-US persons), financial (broker dealers, insurance companies, and banking entities), investment fund (investment companies and private funds), non-profit (non-profits, pension plans, and state or municipal entities), government (government entities and foreign official institutions), and "Other." The individual share is the excluded category. Column (7) finds little evidence of a clientele effect on leverage. Relative to individual investors, financial companies and non-profits invest in slightly less leveraged funds, while investment funds invest in funds with slightly higher average. Further, the full set of investor-type indicators produces an R^2 of just over 3%. Thus investor type appears to be only a weak explanatory factor for the cross-section of leverage.

Our last set of characteristics relate to fees. Because fees may alter the incentives of

fund managers, or may associate with unobservable characteristics that are correlated with leverage (such as skill), fees may be an explanatory factor for hedge fund leverage. Table 3.7 shows the relationship between fees and leverage. The smaller number of observations relative to Table 3.6 arises due to the data restrictions associated with the fees estimation as described in the Appendix. Columns (1) - (3) show that both the management fee and performance fee are strongly positively associated with leverage, both alone and together. According to the estimation in Column (3), a 1.0 percentage point increase in the management fee (about one standard deviation) is associated with a 2.0 percentage point decrease in capital relative to assets. The effect is stronger for the performance fee. A one standard deviation increase in the performance fee, or about 9.3 percentage points, is associated with a 4.9% decrease in capital relative to assets. These results are consistent with Liang and Qiu (2019), who also find an association between leverage and the performance fee in the TASS data.

While the relationship between the performance fee and leverage may suggest excessive risk-taking due to misaligned incentives, this is unlikely to be a satisfactory interpretation. Very little of the total variation in leverage is explained by the performance fee. Further, to preview results, Section 3.4 will show that leverage and risk are actually *negatively* related. If higher performance fees led to greater risk-taking through leverage, then one would expect leverage to associate with greater risk. Instead, leverage appears to predict lower risk. This suggests that the relationship between the performance fee and leverage arises from factors other than misaligned incentives and excessive risk-taking.

Finally, in column (8) of Table 3.6 we regress fund leverage on all of the variables we have considered (excluding fees). Many of the relationships are maintained in the multiple

regression setting. The full set of controls nearly 20% of the variation in average hedge fund leverage. This represents significant progress. Previous work has had identified few characteristics other than the volatility of returns that associate with leverage (Ang, Gorovyy, and van Inwegen (2011)). However, this result also demonstrates that the vast majority of variation in balance sheet leverage is yet to be explained. We return to this topic in Section 3.5.2, where we examine the association between leverage and exposures to specific risk factors.

In Tables 4.17 and 4.18 of the Appendix, we repeat the analysis in Table 3.6 but use as the dependent variable an indicator equal to one if the fund uses leverage and an indicator for whether the fund has leverage in the top 75th percentile, respectively. These restrictions do not improve the cumulative variation in hedge fund leverage we are able to explain in Table 3.6.

3.4 Leverage and Risk in Equilibrium

3.4.1 Balance Sheet Leverage and Return Volatility

Section 3.2 discussed the empirical implications for leverage, risk, and return that arise from different theories of capital markets. Perhaps the most important distinction is the predicted relationship between leverage and portfolio risk, which has immediate implications for systemic risk. Classical theories predict no association between leverage and the risk of the assets held in the portfolio, which implies a linear relationship between leverage and total portfolio risk. Alternatively, theories of leverage constraints predict leverage and asset risk are *negatively* correlated, which implies the relationship between leverage and

portfolio risk could be positive, flat, or even negative. These are Propositions 1 and 2 in Section 3.2.

Our empirical analyses therefore begin by examining the relationship between balance sheet leverage and the risk of the underlying assets. There are many ways to measure risk. Motivated by Figure 3.1, we start by measuring risk as the ex-post realized volatility of the returns on funds' assets.[20] We do not observe asset returns directly, only the returns to the total portfolio (which includes leverage). To measure the returns to the assets held in the portfolio we "deleverage" returns by dividing the gross-of-fee returns of the portfolio by the fund's balance sheet leverage in that quarter and year. This gives the returns that would result if the portfolio were financed only with equity capital.

While the data are collected quarterly, returns are provided at a monthly frequency. To eliminate outliers, we restrict returns to those satisfying basic restrictions on Sharpe ratios and alphas from standard factor models, as discussed in Section 3.3. Table 3.8 reports the distributions of average gross portfolio and asset returns, as well as the within-fund standard deviations of asset and portfolio returns, across all funds in the sample.

The top panel of Figure 3.4 shows a binscatter plot of asset return volatility against leverage. Consistent with Proposition 1 and theories of leverage constraints, the relationship between balance sheet leverage and the ex-post volatility of asset returns is strongly negative. Because the relationship is highly nonlinear, the bottom panel plots return volatility against inverse leverage (the capital to asset ratio), which delivers a more linear association. Each demonstrates a tight model fit. Because the relationship between inverse

[20] Mean-variance analysis is based on the true variances and covariances of the assets, which we do not observe. We therefore treat ex-post observed volatility as the empirical counterpart to actual (unobservable) risk.

leverage and risk appears nearly linear, we will focus on inverse leverage as our measure of fund leverage throughout the remainder of the paper.

Column (1) in Panel A of Table 3.9 shows the economic and statistical significance of this relationship by regressing asset volatility on inverse leverage. The coefficient on inverse leverage is 2.73 and has a t-statistic of more than 23. The coefficient is economically large; it implies that a fund leveraged two-to-one will have a nearly one full standard deviation smaller asset risk than a fund with no leverage. The R^2 of the regression is more than 23%, which demonstrates that a substantial portion in the variability of asset returns can be explained by fund leverage.

The classical theory outlined in Section 3.2 imposes that all investors hold the same risky portfolio. But, this is likely too strict. It is well known that hedge funds often specialize in particular markets and asset classes. A less restrictive adaptation of the model would be that funds within a particular strategy hold identical risky portfolios. Figure 3.5 shows that even within fund strategy, a strong negative relationship between leverage and asset risk persists. Column (2) in Panel A of Table 3.9 shows that coefficient on leverage remains economically large and statistically significant when strategy controls are included in the regression. Further, compared to column (1), the coefficient is little changed and continues to have a t-statistic greater than 23. Fund strategy appears to have little impact on the estimated relationship between asset risk and leverage.

The strong negative association between leverage and the risk of the underlying assets is compelling evidence in support of theories of leverage constraints. Unfortunately, such theories make no obvious predictions about the relationship between leverage and risk in the complete portfolio (Proposition 2). However, portfolio risk is likely the most relevant

for financial stability because the threat of excessively poor performance, fire sales, and spillovers to counterparties ultimately manifest at the portfolio level.

Figure 3.6 plots the relationship between inverse leverage and the volatility of portfolio returns. The association is considerably weaker than in Figure 3.4; the slope is much flatter and leverage appears to explain much less of the variation in portfolio volatility than asset volatility. Nonetheless, the relationship between leverage and portfolio risk remains negative. Additionally, Figure 3.7 shows that the negative relationship between leverage and portfolio risk holds for some, but not all strategy types, further highlighting the association weakens at the portfolio level.

Combined with the results on asset risk, this suggests that funds leverage low-risk assets but not to the point of comparable risk to funds that use no leverage. That is, more highly leveraged funds continue to generate less volatile returns even at the level of the complete portfolio. These results are shown formally in columns (3) and (4) in Panel A of Table 3.9, which report results from regressions of portfolio volatility on inverse leverage with and without additional controls. The R^2 in these regressions also fall substantially, from 23% in column (1) to under 1% in column (3). To our knowledge, the weakly negative relationship between leverage and portfolio risk that results from a strong negative relationship between leverage and asset risk has not been shown elsewhere in the literature.

3.4.2 Leverage and Extreme Returns

The volatility of returns, while theoretically motivated, is not the only way to measure risk. One alternative is the probability of extreme returns. Fund failures are often precipitated by consecutive periods of severely negative performance, which suggests the

incidence of extremely poor returns is a useful metric for examining potential systemic risks. While the previous section examined return volatility, a larger variation of returns does not necessarily suggest a higher likelihood of extreme outcomes. Consider the hypothetical example of Capital Decimation Partners described in Lo (2010). This is a fund that takes heavy exposure to crash risk by selling deep out-of-the-money puts on the market index. The return series to such a fund would look highly stable until its eventual demise. In such a series, the standard deviation of returns may look relatively low, because it is an average of a large number of months with low return variation and a few months with very big variation.

Extreme returns therefore offer an alternative approach to measuring risk. In Panel B of Table 3.9, we again regress asset risk on inverse leverage, but use as the dependent variable an indicator equal to one if the return to the fund's assets in that month is below the 10^{th} percentile across all fund-month observations in the sample. We estimate the relationship on the full panel sample, without the restrictions on returns described in Section 3.4.1. The results are consistent with those in columns (1) and (2) of Panel A. More leveraged funds hold assets that are much less likely to have an excessively bad return in-sample. A fund with a leverage ratio of two holds assets that on average are 9.7 to 10.0 percentage points less likely to have an extreme bad return than funds that use no leverage. The coefficients are highly statistically significant, with t-statistics over 19. Columns (3) and (4) regress the likelihood of an extreme negative portfolio return on inverse leverage. In this case, the coefficient falls but remains positive and significant. At the portfolio level, leverage remains inversely related to the likelihood of an extreme bad return.

Together, the results in Panels A and B of Table 3.9 show that leverage is strongly

negatively correlated with asset risk and weakly negatively correlated or uncorrelated with portfolio risk. Both offer supportive evidence for theories of leverage constraints.

3.4.3 Systematic versus Idiosyncratic Risk

Section 3.4.1 showed that hedge fund leverage is strongly negatively related to the volatility of returns on hedge fund assets, and weakly negatively related to the volatility of portfolio returns. Both are consistent with theories of leverage constraints, and inconsistent with classical theories of capital markets. Return volatility, however, comprises two parts: a systematic part determined by exposures to risk factors, and the idiosyncratic volatility that is independent of systematic risk factors. Theories of leverage constraints specifically predict a negative association between leverage and systematic risk, in particular market beta, and are silent on the association with idiosyncratic risk.

In this section, we decompose the relationship between leverage and return volatility into its constituent parts. To do so, we estimate a standard asset pricing factor model for each fund i:

$$R_{i,t} - r_f = \alpha_i + \beta_i' F_t + \varepsilon_{i,t}, \tag{3.3}$$

$$\sigma_{i,R}^2 = Var(R_{i,t}) = \sigma_{i,F}^2 + \sigma_{i,\varepsilon}^2, \tag{3.4}$$

$$\sigma_{i,F}^2 = \beta_i' \Sigma \beta_i, \tag{3.5}$$

$$\sigma_{i,\varepsilon}^2 = Var(\varepsilon_{i,t}), \tag{3.6}$$

where $R_{i,t}$ is the gross-of-fee return for fund i in period t, F_t is a $K \times T$ matrix of risk factors, β_i is fund $i's$ vector of risk factor exposures, $\varepsilon_{i,t}$ is a mean zero error term, and α_i is the

unexplained portion of fund $i's$ average return. When estimating equation (3.3) we restrict the sample to only funds with at least 24 months of return observations.

The systematic risk of fund $i's$ returns, denoted $\sigma^2_{i,F}$, is defined as the product of the fund's risk factor exposures and the covariance matrix of the risk factors F_t. The idiosyncratic variance, $\sigma^2_{i,\varepsilon}$, is the variance of the error term.

We estimate equation (3.3) using the Fama French developed-country five-factor model (Fama and French (2015)) for both asset returns and portfolio returns. We use the developed country model, rather than the factors based on only U.S. equities, because hedge funds often manage portfolios of global securities. All of our results are robust to alternative models, including the Fung and Hsieh (2004) style portfolios. The Fama French five-factor (FF5) model includes: the Fama and French (1992) market, size, and value factors (MKT, SMB, HML), a profitability factor based on Novy-Marx (2013) (PROF), and an investment factor based on Titman, Wei, and Xie (2004) and Hou, Xue, and Zhang (2014) (INV). Note that both the systematic and idiosyncratic variances are estimated entirely in sample. Table 3.8 reports summary statistics for average fund returns, estimated betas, and alphas.

Figure 3.8 plots realized return volatility against each estimated beta. Higher absolute betas are associated with higher return volatility for each risk factor, and the increases in volatility appear roughly linear. We note that in a multi-factor setting, this doesn't have to be true. If, for instance, higher market beta was associated with lower betas on other risk factors, then the relationship between factor exposures and total return volatility may be flat or even decreasing. Figure 3.8 shows this is not the case, higher betas on *each* risk factor are on average associated with greater total risk.

With estimated betas in hand, we next turn to an examination of the relationship be-

tween systematic risk, idiosyncratic risk, and leverage. We leave an analysis of leverage and individual betas for Section 3.5. For comparability to Section 3.4.1, we use $\widehat{\sigma}_{i,F,a} = \sqrt{\widehat{\sigma}^2_{i,F,a}}$ and $\widehat{\sigma}_{i,\varepsilon,a} = \sqrt{\widehat{\sigma}^2_{i,\varepsilon,a}}$ as the measures of systematic and idiosyncratic risk, where a denotes assets and p denotes portfolio. Results are unchanged if variances are used instead of standard deviations. The upper-left panel of Figure 3.9 plots fund $i's$ average (inverse) leverage against $\widehat{\sigma}_{i,F,a}$. Consistent with leverage constraint predictions, Figure 3.9 shows that leverage and the systematic volatility of the assets are strongly negatively correlated. That is, more highly leveraged funds invest in assets with considerably lower systematic risk.

The upper-right panel of Figure 3.9 plots average leverage against $\widehat{\sigma}_{i,\varepsilon,a}$, the idiosyncratic volatility of the assets. The theories discussed in Section 3.2 are largely silent on the relationship between leverage and the idiosyncratic volatility of the assets, but the relationship between leverage and idiosyncratic risk is still of interest for systemic risk assessment. Just as with systematic volatility, idiosyncratic volatility and leverage are negatively correlated. This may not be particularly surprising, as both systematic and idiosyncratic volatility may shrink mechanically with total volatility.[21] Still, this result suggests that funds' leverage decisions are not solely due to the systematic component of return variability, but instead consider both dimensions when making leverage decisions.

Columns (1) and (2) in Panel C of Table 3.9 report regression results to demonstrate the plotted relationships formally. In each case, the coefficient on leverage is strong and highly statistically significant. However, the relationship between leverage and idiosyncratic volatility appears slightly weaker than the relationship between leverage and system-

[21] If returns are given by $R_{i,t} = \alpha_i + B_i' F_t + \varepsilon_{i,t}$, then dividing returns by a factor $q > 1$ reduces total return volatility, systematic volatility, and idiosyncratic volatility all by a factor of $1/q^2$.

atic volatility. The estimated intercept in the systematic risk regression is much smaller (more negative) than in the idiosyncratic risk regression. Further, the coefficient estimates indicate a much flatter relationship between leverage and idiosyncratic risk than between leverage and systematic risk. The R^2 in column (1) is also nearly double the value in column (2). These findings imply that the association between leverage and systematic and idiosyncratic risk at the portfolio level, after assets have been leveraged, may be different.

The middle row of Figure 3.9 plots inverse leverage against the systematic and idiosyncratic return volatility of the portfolio. In this case, systematic portfolio risk remains strongly negatively related to leverage, while the relationship between leverage and idiosyncratic risk becomes positive. This offers insight into the weakly-negative relationship between total portfolio volatility and leverage; the component of risk due to systematic risk factors is negatively related to leverage, while the idiosyncratic part is positively related. In total, these effects largely cancel out, and produce a relationship between leverage and portfolio volatility that is roughly flat. Columns (3) and (4) in Panel C of Table 3.9 report the regression results corresponding to these findings. Each shows the coefficients on leverage are economically and statistically significant.

Finally, in the bottom row of Figure 3.9, we examine whether the *fraction* of the total asset volatility due to systematic risk is increasing or decreasing in leverage. Consistent with the other findings in this section, the fraction of total return variation due to systematic risk is decreasing in leverage. More leveraged funds tilt their portfolios away from systematic risk compared to less leveraged funds. In the next section, we decompose systematic risk further and investigate the relationship between leverage, the betas on the specific risk factors, and alphas.

3.5 Leverage and Returns

3.5.1 Leverage and Expected Returns

The results from the previous section showed leverage and asset risk, and in particular systematic risk, are negatively related. However, true risk is unobservable, and ex-post measures of ex-ante risk may be estimated with error, as may factor betas estimated from time-series regressions. Theory stipulates that in equilibrium, risk and return must be positively associated. Thus, for leverage to be negatively related to asset risk, leverage must also be negatively associated with asset returns. This is stated explicitly in Proposition 3 in Section 3.2. Again, we contrast this prediction with what is implied by traditional theories of capital markets. If all investors hold risky assets in identical proportions, we should see no relationship between leverage and the average expected returns on the assets.

Section 3.4 also argued that while idiosyncratic volatility and leverage are similarly negatively related, the negative relationship between leverage and systematic risk is much stronger. Further, there is ample empirical evidence that higher idiosyncratic risk is associated with *lower* expected returns (Ang, Hodrick, Xing, and Zhang (2006), Stambaugh, Yu, and Yuan (2015)). This would produce a *positive* relationship between leverage and returns, since leverage and idiosyncratic risk are negatively related. Thus, if systematic risk is more strongly negatively associated with leverage, then leverage and expected returns should also be negatively related. If not, then leverage and expected asset returns will be unrelated or positively related.

Table 3.10 regresses the expected returns of the assets on inverse leverage. Column (1)

shows that the coefficient on inverse leverage is positive, large, and economically significant. That is, leverage and the average expected return of the assets are strongly negatively related. A fund with a leverage ratio of two will hold assets with a 0.305% lower expected return *per month* than a fund that is not leveraged. This is nearly as large as one full standard deviation of average asset returns (0.42%), and is equal to 3.7% (percentage points) per year. Further, leverage can explain 11% of the cross-sectional variation in expected returns, or equivalently, expected returns on assets can explain 11% of the variation in leverage. Column (2) shows that adding controls for size and strategy has little effect on the estimated coefficient.

Columns (3) and (4) examine expected returns at the portfolio level. While the coefficient on (inverse) leverage decreases substantially, it nonetheless remains economically and statistically significant. This suggests that while funds use leverage to increase the average payoffs of low-volatility assets, leverage is not used to the point of equating expected returns across leverage levels. This is consistent with leverage being negatively related to systematic risk and positively related to idiosyncratic risk at the portfolio level, since expected returns are increasing in systematic risk but *decreasing* in idiosyncratic risk. Figure 3.10 demonstrates these results visually through binscatter plots of average asset and portfolio returns on inverse leverage.

3.5.2 Leverage and Betas

The previous section showed that leverage is negatively related to the systematic risk of both the underlying assets and the complete portfolio. However, as highlighted in Proposition 4 of Section 3.2, the theories of leverage constraints developed in Black (1972), Frazz-

ini and Pedersen (2014), and Boguth and Simutin (2018) make predictions specifically about the relationship between leverage and the *market* beta of the assets. In this section, we investigate the relationship between leverage and individual factor betas estimated from the Fama and French (2015) model.

Table 3.11 reports results from regressions of each beta on inverse leverage, with and without controls for size and strategy. Column (1) shows that leverage is strongly negatively related to the market beta of funds' assets. A fund with no leverage will own assets with an average market beta that is roughly 0.331 (half of the coefficient estimate of 0.662) larger than the assets held by a fund that is leveraged two-to-one. The magnitude of this estimate is significant; the median asset market beta in this sample is 0.19, and the standard deviation is 0.34. That is, a fund with leverage ratio of two will hold assets with nearly one full standard deviation smaller average market beta than a fund with no leverage.

Column (1) also shows how important a predictor leverage is for the market beta of the assets funds choose to hold in their portfolios. Leverage alone explains 20% of the average market beta of funds' assets. Column (2) shows that when controls for size and fund strategy are included, the estimated coefficient on inverse-leverage changes very little, from 0.662 to 0.644. The R^2 does increase significantly though, from 0.204 to 0.381, and this is due almost entirely to fund strategy.

Columns (3) through (10) of Table 3.11 show how leverage relates to betas on the HML, SMB, PROF, and INV portfolios. While SMB, HML, and PROF betas have some relationship with leverage, depending on whether or not controls are included, for each coefficient the magnitudes and R^2 are much smaller than for estimated market beta. Without additional controls, leverage never explains more than 1.3% of the variation of any of the

other four factor betas. While leverage is negatively related to exposures to SMB, HML, and PROF factors, the economic size of these relationships are small and leverage explains little of their variation. This suggests that much of the relationship between leverage and systematic risk is coming from market beta. Regressions results (not shown) confirm this intuition; in a regression of systematic asset risk on inverse leverage, the coefficient is 2.15 (column (1) of Panel C in Table 3.9), and shrinks to 0.69 when the average market beta of the assets is included. That is, the relationship between leverage and systematic risk falls by 68% once market beta is accounted for.

The findings in Table 3.11 also cast doubt on an alternative hypothesis of volatility targeting. If funds aim to achieve a target return volatility, then low volatility assets will be leveraged and high volatility asset will not. Because factor betas are mechanically tied to the total volatility of the asset's return[22], we may incorrectly infer that market beta is an important explanatory factor when instead it is simply volatility (from any source). However, this intuition would presumably apply to *all* risk factor betas, not only the market factor. This is especially true given the results in Figure 3.8, which show volatility scales up with the absolute value of each beta. Yet, Table 3.11 shows that the betas on the non-market factors have a weak economic and statistical relationship with leverage. This suggests aggregate volatility targeting is a less-compelling explanation for the leverage-volatility relationship than is market beta.

Table 3.12 reverses the dependent and independent variables in Table 3.11, and instead

[22]The estimated beta on a factor f_t can be written as $\beta_{i,f} = \rho_{i,f}\frac{\sigma_i}{\sigma_f}$, where $\rho_{i,f}$ is the correlation coefficient between the return to asset i and the factor f_t, σ_i denotes the estimated volatility of asset i's return, and σ_f denotes the volatility of the (return to) the factor. All else equal, a lower volatility of the asset's return implies a lower estimated beta.

asks how much of the variation in leverage can be explained by the estimated betas on fund assets. Column (1) includes only the market beta on the assets. As previously shown, market beta alone can explain 20% of the variation in hedge fund leverage. Column (2) includes betas on the remaining factors. The addition of the four remaining factors barely increases the R^2, from 0.204 to 0.207. Virtually all of the explanatory power for leverage derives from exposure to the market factor.

Hedge funds often manage global investment strategies that span many asset classes. While theories of leverage constraints do not limit attention solely to equities, it is nonetheless reasonable to expect that leverage constraints may be particularly important for funds specializing in equity-based strategies. In columns (3) and (4) of Table 3.12, we repeat the specifications in columns (1) and (2) but restrict the sample to funds that manage equity-style strategies. Within the subsample of equity funds, asset market beta can explain over 47% of the variation in hedge fund leverage, and the coefficient on market beta increases significantly, from 0.309 to 0.373. Once again, including betas on the other four factors does little to improve the model fit or attenuate the estimated coefficient on market beta.

We offer one last piece of evidence in support of theories of leverage constraints. Among the funds that have market betas greater than one, the median leverage level is 1.01, the 90^{th} percentile is 1.07, and the standard deviation is 0.077. That is, among funds with an average market beta on assets greater than one, virtually none of them use leverage in any meaningful way.

To summarize the results in this section, the average estimated market beta on the assets held in fund portfolios appears to strongly associate with leverage. Market beta can explain 20% of the variation in hedge fund leverage, and this explanatory power grows to 47%

for the subsample of equity-style funds. This finding offers strong supportive evidence for theories of leverage constraints, which predict less-constrained funds will hold leveraged portfolios of low-risk, and in particular low-market beta assets. The low-beta anomaly also indicates that low-beta assets will earn high alphas, and therefore suggests a positive association between leverage and alpha. This is the focus of the next section.

3.5.3 Leverage and Alphas

The last empirical prediction we explore is the relationship between hedge fund leverage and alpha. Theories of leverage constraints predict that low-beta securities have high alphas. This prediction has empirical support spanning nearly 50 years (Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), Baker, Hoeyer, and Wurgler (2016), Jylha (2018)). The previous section showed that hedge fund leverage is strongly negatively associated with the average market beta of the assets, which suggests leverage should be positively related to average alpha. This is Proposition 5 in Section 3.2.

Table 3.13 investigates the relationship between leverage and alpha. Column (1) regresses the estimated alpha on fund assets on inverse leverage. Inconsistent with Proposition 5 and theories of leverage constraints, column (1) indicates a negative association between leverage and hedge fund alpha. That is, more leveraged funds hold assets with lower alphas on average.

However, alpha on hedge fund assets may arise from a variety of sources, some of which may be negatively associated with leverage. For instance, if funds specialize in particular securities or strategies, then the alphas available to investors may vary by specialty or over time. Funds with access to high alphas may not need to employ leverage. But

if the alphas available to some funds are small, those funds may need to leverage those investments to produce larger alphas and remain competitive with other funds.

Column (2) of Table 3.13 offers support for this hypothesis by including the market beta on the assets as an additional control. Column (2) highlights two competing effects on alpha: a strong positive association between asset alpha and market beta, and a strong negative association between leverage and alpha *controlling* for the effect of market beta. Said differently, the remaining association between asset alpha and leverage is strongly negative, once the negative relationship between leverage and market beta (and therefore the positive relationship between leverage and alpha) has been accounted for. The reason asset alpha and leverage are not positively related, as predicted by theories of leverage constraints, is because of the strong offsetting negative association between alpha and leverage that arises from economic forces independent of market beta.

Because leverage associates with asset alpha through two channels with opposite signs, the relationship between leverage and portfolio alpha is unclear. Column (3) examines this relationship by regressing portfolio alpha — the leveraged alpha on the assets — on inverse leverage. At the portfolio level, the positive association between alpha and leverage that results from the low-beta (high-alpha) anomaly dominates the residual negative association between leverage and alpha. A fund leveraged two-to-one will have an average monthly alpha that is 0.151% larger than a fund with no leverage, equivalent to an additional alpha of 1.81% per year.

Column (4) shows these competing effects clearly; when average asset beta is included in the regression, the entire association between leverage and portfolio alpha disappears. That is, the entire positive relationship between leverage and portfolio alpha results from

more leveraged funds holding low-beta, high-alpha assets.

The relationship between leverage and alpha at the portfolio level makes sense. A negative association between leverage and asset alpha will get weaker at the portfolio level, since low-alpha assets are leveraged to be similar in magnitude to unleveraged high-alpha assets. Instead, the positive association between alpha and leverage that results from the low-beta anomaly will be magnified by leverage, since high-alpha assets get leveraged to produce even larger alphas, while unleveraged alphas are unchanged. Thus, when leverage is applied the negative association between alpha and leverage weakens while the positive association strengthens, leading to a strong positive association between portfolio alpha and leverage that arises entirely from investments in low-beta securities.

Column (4) of Table 3.13 also offers preliminary evidence for the "competitive forces" argument for the negative association between leverage and asset alpha that arises once market beta is included. On average, alphas are leveraged to be roughly equal — that is, to the point where leverage and alpha at the portfolio level are uncorrelated. We caution, however, that there are numerous explanations for the results linking alpha and leverage conditional on market beta, and we view these findings as only suggestive and deserving of further study.

Columns (5) and (6) of Table 3.13 show that the takeaways from columns (1) – (4) are unchanged when the remaining betas or controls for size and strategy are included in the regression. While the coefficients on the SMB, HML, and PROF betas are statistically significant, they display different signs, and little theory is available to guide the interpretation of these results. We leave an analysis of non-market betas as an interesting area for future research.

In total, our results establish strong empirical support for theories of leverage constraints at the level of the investor. We find that market beta is strongly negatively associated with leverage, that betas on other risk factors appear largely inconsequential, and that leverage and portfolio alpha are positively related but only through market beta. The low-beta anomaly appears to be an important determinant of hedge fund leverage. While significant variation in leverage remains conditional on asset beta, as does variation in alpha conditional on leverage and market beta, our findings suggest that exploiting low-beta, high-alpha assets through leverage is a important part of the investment strategy of leverage-unconstrained investors.

3.6 Conclusion

The failure of Long-Term Capital Management left regulators and policy-makers acutely aware of the potential systemic importance of large hedge funds. One of the most frequently discussed threats to financial stability emanating from hedge funds is excessive leverage (see The Board of the International Organization of Securities Commissions (2018) and Financial Stability Board (January 2017) as examples).

Until recently, data limitations have made assessing the potential systemic risks from hedge fund leverage difficult. This difficulty is magnified by the dramatically different predictions made by alternative models of hedge fund portfolio choices. Classical models imply hedge fund leverage and portfolio risk are linearly related. In this case, excessively leveraged hedge funds are likely to be highly risky, and may deserve additional regulatory scrutiny. This is largely in line with conventional wisdom.

However, an alternative class of theories centered around leverage constraints predict

that leverage and asset risk are negatively correlated. Theories of leverage constraints deliver a security market line that is too flat, resulting in the well-known "low-beta anomaly" — the robust empirical finding that low market-beta assets have high alphas. In this case, leverage-unconstrained funds will invest in low-risk, high-alpha assets, while leverage constrained funds will invest in naturally higher risk assets. In these models, the most leveraged funds may be no more risky, or even less risky, than funds that employ little or no leverage.

In this paper, we offer considerable empirical support for theories of leverage constraints. Our main finding is that leverage and asset risk, measured a number of ways, are strongly negatively related. The leveraging of low risk assets results in a weakly-negative relationship between leverage and portfolio risk; in equilibrium, leverage does not necessarily imply greater risk on average.

Further motivated by theories of leverage constraints, we then explicitly examine the relationship between leverage and the average market beta on the funds' assets, which such theories predict should be strongly related. Indeed, we find that funds that use the most leverage invest in securities with the lowest market betas. Market beta explains 20% of the variation in hedge fund leverage, and in the subsample of funds following an equity-based strategy, explains 47%. We also show that leverage and portfolio alpha are strongly positively related, but only through market beta, again consistent with theories of leverage constraints.

The consequences of our work for monitoring systemic risk are straightforward. Our results suggest that more leveraged funds do not necessarily pose the greatest risk to financial stability. Because leverage and asset risk are negatively related, the equilibrium relationship between leverage and risk is more nuanced. We caution, however, that our

results do not necessarily imply that leverage and risk will be unrelated in a financial crisis. If during times of stress market betas spike, then the negative association between leverage and the market beta on assets will weaken. If it weakens enough, greater leverage will imply greater risk. Further, if the weakly positive relationship between leverage and idiosyncratic portfolio risk strengthens during periods of stress, this may also produce a positive association between leverage and risk. Because our data span only the relatively tranquil bull market of the post-crisis period, such issues warrant additional inspection.

Our results also do not speak to the potential spillovers to counterparties or the financing liquidity risk that accompany greater leverage. Kruttli, Monin, and Watugala (2019) show that idiosyncratic liquidity shocks to a prime broker can be propagated to the hedge funds to whom it lends. Brunnermeier and Pedersen (2009) show that liquidity spirals can arise when collateral values fall and leveraged investors are forced to sell assets to raise additional capital. All of these issues suggest the relationship between leverage and systemic risk is complex and involves more than the realized volatility of returns.

Nonetheless, our results provide context for evaluating policy proposals related to limits on private fund leverage, such as those being considered in the European Union.[23] Perhaps most important is that limits on leverage may have unintended consequences. Limits on leverage may make previously unconstrained funds leverage constrained, since leverage unconstrained funds are likely to be the heaviest users of leverage. But if leverage-unconstrained funds' appetite for risk remains the same, then such funds may tilt toward higher risk — and in particular higher market beta — assets. That is, leverage limits may

[23] See the recommendation of the European Systemic Risk Board on liquidity and leverage risks in investment funds https://www.esrb.europa.eu/pub/pdf/recommendations/esrb.recommendation180214_ESRB_2017_6.en.pdf?c8d7003d2f6d7609c348f4a93ced0add

push funds to invest in higher beta assets, which may lead to more correlated and crowded trades and more coordinated outcomes. Further, the riskiest funds are likely to be those that leverage high-risk assets. But for reasons discussed in this paper, those funds may not be the most highly leveraged, since risky assets are often accompanied by large haircuts and margin requirements. Thus, the findings in this paper suggest that while leverage limits may promote financial stability, their imposition may also result in more complex effects than are currently appreciated.

Finally, our work constitutes the first microfoundational empirical evidence of leverage constraints at the level of the investor. Previous work has focused on the implications of leverage constraints at the level of the asset class or broad investor type. Instead, our work demonstrates that leverage constraints at the level of the individual hedge fund matters for funds' market risk exposures, aggregate fund risk, and hedge fund alpha.

3.7 Tables and Figures

3.7.1 Tables

Table 3.1: Summary Statistics

Panel A: Panel Variables

Variable	**Mean**	**Std. Dev.**	25^{th} **Percentile**	50^{th} **Percentile**	75^{th} **Percentile**	**Obs.**
NAV ($ Billions)	1.60	2.21	0.50	0.91	1.80	35,397
GAV ($ Billions)	2.61	4.55	0.61	1.26	2.69	35,397
GNE ($ Billions)	5.88	12.90	0.74	1.93	5.07	35,397
LNE ($ Billions)	3.77	7.23	0.62	1.48	3.55	35,397
SNE ($ Billions)	2.11	5.87	0.02	0.33	1.43	35,397
NNE ($ Billions)	1.65	2.65	0.31	0.80	1.88	35,397
Portfolio Illiquidity (days)	67.72	109.10	3.27	13.41	67.60	35,397
Investor Illiquidity (days)	170.57	137.66	52.68	140.13	308.41	35,397

Panel B: Cross-Sectional Variables

Management Fee (%)	1.02	0.99	0.00	0.96	1.69	1,229
Performance Fee (%)	13.37	9.25	3.35	15.29	20.59	1,229

Panel C: Observation Counts by Strategy

Credit	2,550
Equity	11,586
Event Driven	3,206
Macro	2,011
Managed Futures	685
Multi-strategy	5,571
Relative Value	2,575
Other	7,213

Table 3.1 reports summary statistics for our main sample. Panel A includes the variables for our panel sample: net asset value (NAV), gross asset value (GAV), long notional exposure (LNE), short notional exposure (SNE), net notional exposure (NNE), portfolio liquidity, and investor liquidity. Panel B reports statistics on fund-level management and performance fees, and Panel C reports observations by strategy for the panel sample.

Table 3.2: Balance Sheet Leverage (GAV/NAV)

Panel A: Leverage Levels

Strategy	**Mean**	**10th**	**25th**	**50th**	**75th**	**90th**	**St.Dev.**
All	1.74	1.00	1.03	1.19	1.66	2.65	2.29
Credit	1.48	1.00	1.01	1.10	1.51	2.14	1.55
Equity	1.57	1.00	1.03	1.34	1.71	2.59	0.84
Event Driven	1.53	1.01	1.06	1.19	1.44	1.95	1.92
Macro	2.11	1.01	1.04	1.18	1.92	3.42	2.64
Managed Futures	1.37	***	1.01	1.07	1.28	***	1.02
Multi-strategy	2.15	1.02	1.11	1.35	2.11	3.35	2.65
Relative Value	3.02	1.00	1.06	1.41	2.43	4.76	5.53
Other	1.42	***	1.00	1.05	1.31	1.98	1.54

Panel B: Within Fund Variation in Leverage

Strategy	**Mean**	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	**St. Dev.**
All	0.31	0.00	0.02	0.08	0.21	0.54	1.09
Credit	0.22	0.00	0.01	0.08	0.20	0.50	0.60
Equity	0.16	0.00	0.02	0.08	0.17	0.36	0.30
Event Driven	0.25	0.01	0.03	0.07	0.15	0.36	0.82
Macro	0.66	0.01	0.03	0.13	0.49	1.41	1.55
Managed Futures	0.26	***	0.01	0.03	0.16	***	1.02
Multi-strategy	0.39	0.02	0.06	0.12	0.29	0.89	0.91
Relative Value	0.80	0.00	0.05	0.18	0.54	1.47	2.09
Other	0.26	***	0.00	0.03	0.12	0.38	1.38

Table 3.2 reports summary statistics in total and by strategy for balance sheet leverage, gross asset value over net asset value (GAV/NAV). Panel A reports summary statistics for the within-fund mean leverage, and Panel B reports summary statistics for the within-fund standard deviation of leverage.

*** Data are masked to avoid potential disclosure of proprietary information of individual Form PF filers.

Table 3.3: Composition of Borrowing by Strategy

Strategy		Mean	St. Dev.
All	Prime Brokerage (%)	62.1	45.2
	Repo (%)	17.2	33.7
	Other Secured (%)	20.7	37.7
Credit	Prime Brokerage (%)	38.4	43.9
	Repo (%)	19.0	34.6
	Other Secured (%)	42.6	46.6
Equity	Prime Brokerage (%)	93.7	22.0
	Repo (%)	1.0	8.2
	Other Secured (%)	5.3	20.4
Event Driven	Prime Brokerage (%)	74.7	39.8
	Repo (%)	3.8	13.7
	Other Secured (%)	21.5	37.8
Macro	Prime Brokerage (%)	33.3	40.3
	Repo (%)	53.1	42.1
	Other Secured (%)	13.6	27.2
Managed Futures	Prime Brokerage (%)	83.2	23.8
	Repo (%)	8.7	15.2
	Other Secured (%)	8.1	21.8
Multi-strategy	Prime Brokerage (%)	68.2	38.8
	Repo (%)	22.1	33.4
	Other Secured (%)	9.8	24.4
Relative Value	Prime Brokerage (%)	33.7	43.2
	Repo (%)	53.9	43.8
	Other Secured (%)	12.5	27.5
Other	Prime Brokerage (%)	22.0	39.4
	Repo (%)	22.6	38.8
	Other Secured (%)	55.4	47.3

Table 3.3 reports cross-sectional statistics on the composition of funds' secured borrowing. Secured borrowing is classified according to the legal agreement governing the borrowing, e.g. Global Master Repurchase Agreement for repo and Prime Brokerage Agreement for prime brokerage.

Table 3.4: Other Leverage Measures (Long, Short, and Net Notional Exposure)

Strategy	Measure	Mean	10th	25th	50th	75th	90th	St. Dev.
All	LNE/NAV	2.38	0.83	1.03	1.44	2.30	4.40	3.32
	SNE/NAV	1.33	0.00	0.02	0.38	1.19	3.17	3.05
	NNE/NAV	1.05	0.28	0.70	0.99	1.16	1.78	0.86
Credit	LNE/NAV	1.44	0.44	0.80	1.09	1.70	2.32	1.82
	SNE/NAV	0.57	***	0.00	0.09	0.50	1.26	1.77
	NNE/NAV	0.89	0.22	0.50	0.88	1.10	1.70	0.61
Equity	LNE/NAV	1.81	1.00	1.08	1.47	1.98	3.06	1.29
	SNE/NAV	0.89	0.00	0.07	0.54	1.11	2.12	1.27
	NNE/NAV	0.93	0.47	0.82	0.99	1.04	1.21	0.43
Event Driven	LNE/NAV	1.40	0.79	1.06	1.23	1.56	2.24	0.73
	SNE/NAV	0.45	0.00	0.08	0.31	0.64	1.10	0.52
	NNE/NAV	0.95	0.34	0.70	0.95	1.11	1.41	0.57
Macro	LNE/NAV	6.02	1.40	2.01	3.14	6.82	15.55	6.79
	SNE/NAV	4.54	0.07	0.53	2.08	5.20	14.74	6.25
	NNE/NAV	1.60	0.05	0.52	1.11	1.86	3.65	1.84
Managed Futures	LNE/NAV	6.25	***	2.87	4.99	7.23	***	4.82
	SNE/NAV	3.52	***	1.26	2.24	4.33	***	3.81
	NNE/NAV	2.30	***	1.47	2.04	3.07	***	1.55
Multi-strategy	LNE/NAV	3.26	1.00	1.26	1.90	3.90	5.97	3.65
	SNE/NAV	2.19	0.03	0.29	0.96	2.88	4.83	3.41
	NNE/NAV	1.06	0.29	0.58	0.92	1.24	1.86	0.94
Relative Value	LNE/NAV	3.61	1.00	1.17	1.67	3.34	7.91	5.24
	SNE/NAV	2.60	0.00	0.05	0.55	2.35	8.33	5.13
	NNE/NAV	1.09	0.08	0.76	1.01	1.32	1.94	0.89
Other	LNE/NAV	1.62	0.39	0.90	1.10	1.70	2.63	2.40
	SNE/NAV	0.56	***	0.00	0.04	0.32	1.06	2.12
	NNE/NAV	1.05	0.24	0.69	1.00	1.21	1.88	0.76

Table 3.4 reports summary statistics in total and by strategy for leverage measures based on notional exposure: long notional exposure (LNE), short notional exposure (SNE), and net notional exposure (NNE).

*** Data are masked to avoid potential disclosure of proprietary information of individual Form PF filers.

Table 3.5: Rank Correlation of Leverage Measures

	GAV/ NAV	GNE/ NAV	LNE/ NAV	SNE/ NAV	NNE/ NAV
GAV/NAV	1.00				
GNE/NAV	0.62	1.00			
LNE/NAV	0.61	0.98	1.00		
SNE/NAV	0.61	0.98	0.94	1.00	
NNE/NAV	0.11	0.31	0.43	0.17	1.00

Table 3.5 reports the rank correlations of average fund-level leverage metrics: gross asset value to net asset value (GAV/NAV), gross notional exposure to net asset value (GNE /NAV), long notional exposure to net asset value (LNE/NAV), short notional exposure to net asset value (SNE/NAV), and net notional exposure to net asset value (NNE/NAV)

Table 3.6: The Cross Section of Hedge Fund Balance Sheet Leverage

	(1) $1/Lev_{it}$	(2) $1/\overline{Lev}_i$	(3) $1/\overline{Lev}_i$	(4) $1/\overline{Lev}_i$	(5) $1/\overline{Lev}_i$	(6) $1/\overline{Lev}_i$	(7) $1/\overline{Lev}_i$	(8) $1/\overline{Lev}_i$
Log NAV		-0.007**						-0.008**
		(0.004)						(0.003)
Strategy								
Credit			0.062***					0.051***
			(0.016)					(0.015)
Macro			-0.011					0.054***
			(0.022)					(0.020)
Managed Futures			0.113***					0.083***
			(0.025)					(0.024)
Multi-Strategy			-0.063***					-0.053***
			(0.015)					(0.014)
Other			0.111***					0.079***
			(0.011)					(0.012)
Event Driven			0.057***					0.042***
			(0.015)					(0.015)
Relative Value			-0.088***					-0.027
			(0.021)					(0.021)
Repo Borrowing				-0.206***				-0.189***
				(0.019)				(0.019)
Portfolio Illiquidity					0.017***	0.038***		0.032***
					(0.002)	(0.003)		(0.003)
Investor Illiquidity						-0.039***		-0.035***
						(0.003)		(0.003)
Ownership								
Financial							0.079**	0.022
							(0.031)	(0.029)
Investment Fund							-0.072***	-0.064***
							(0.024)	(0.022)
Non-Profit							0.086***	0.071***
							(0.021)	(0.019)
Government							-0.024	-0.031
							(0.033)	(0.030)
Other							0.021	-0.017
							(0.024)	(0.023)
Adjusted R^2	0.891	0.001	0.072	0.061	0.020	0.077	0.031	0.196
Observations	35397	2916	2916	2916	2916	2916	2916	2916

Column (1) of Table 3.6 regresses inverse leverage on fund fixed effects for the full panel sample. Columns (2) - (8) regress average fund inverse leverage on the following fund characteristics: net asset value, broad fund strategy, the fraction of borrowing conducted through repo, portfolio liquidity, investor liquidity, and investor composition (the fraction of a fund's equity owned by individuals, financial companies, investment funds, non-profits, government, or other; 'Individuals' is the excluded category). Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3.7: Performance and Management Fees

	$(1 / \overline{Lev}_i)$	$(1 / \overline{Lev}_i)$	$(1 / \overline{Lev}_i)$
Mgmt Fee	-2.755***		-1.991***
	(0.709)		(0.712)
Perf Fee		-0.521***	-0.485***
		(0.077)	(0.077)
Adjusted R^2	0.012	0.039	0.045
Observations	1218	1218	1218

Table 3.7 reports regressions of inverse balance sheet leverage on hedge fund performance fees (in decimals) and management fees (in decimals). Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3.8: Fund Returns, Estimated Betas, and Alpha

Panel A: Portfolio

	Mean	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	**St. Dev.**
Avg. Gross Return	0.61	0.02	0.32	0.58	0.89	1.20	0.50
Sd. Dev Returns	2.54	0.93	1.45	2.36	3.37	4.41	1.42
MKT Beta	0.34	-0.03	0.07	0.26	0.57	0.95	0.38
SMB Beta	-0.02	-0.43	-0.18	0.00	0.14	0.36	0.36
HML Beta	-0.05	-0.67	-0.26	0.02	0.23	0.46	0.51
PROF Beta	-0.19	-1.03	-0.51	-0.11	0.16	0.61	0.74
INV Beta	-0.04	-0.71	-0.27	-0.04	0.21	0.60	0.59
FF Alpha	0.35	-0.19	0.06	0.34	0.62	0.95	0.49

Panel B: Assets

	Mean	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	**St. Dev.**
Avg. Gross Return	0.42	-0.02	0.17	0.37	0.64	0.96	0.42
Sd. Dev Returns	1.95	0.57	0.93	1.66	2.72	3.70	1.30
MKT Beta	0.29	-0.02	0.04	0.19	0.48	0.80	0.34
SMB Beta	-0.01	-0.32	-0.13	0.00	0.09	0.30	0.29
HML Beta	-0.03	-0.49	-0.19	0.01	0.16	0.36	0.41
PROF Beta	-0.14	-0.77	-0.38	-0.07	0.10	0.44	0.58
INV Beta	-0.04	-0.50	-0.22	-0.04	0.13	0.43	0.48
FF Alpha	0.24	-0.17	0.02	0.21	0.43	0.70	0.40

Table 3.8 reports summary statistics of average monthly gross (of fee) returns, standard deviation of monthly gross returns, estimated betas (see Fama and French (2015)), and alphas. Panel A reports the distributions for portfolio returns and Panel B reports distributions asset returns.

Table 3.9: Leverage and Risk

Panel A: Leverage and Return Volatility

	Vol (Assets)	Vol (Assets)	Vol (Portfolio)	Vol (Portfolio)
1 / $\overline{Lev}_i$	2.730***	2.601***	0.590***	0.396**
	(0.115)	(0.109)	(0.161)	(0.155)
Size Controls	No	Yes	No	Yes
Strategy Controls	No	Yes	No	Yes
Adjusted R^2	0.232	0.427	0.008	0.278
Observations	1555	1555	1555	1555

Panel B: Leverage and Extreme Returns

	Bad Ret (Assets)	Bad Ret (Assets)	Bad Ret (Portfolio)	Bad Ret (Portfolio)
1 / $\overline{Lev}_{i,t-1}$	0.199***	0.194***	0.039***	0.030**
	(0.010)	(0.010)	(0.012)	(0.012)
Strategy Controls	No	Yes	No	Yes
Adjusted R^2	0.023	0.042	0.001	0.024
Observations	25396	25396	25396	25396

Panel C: Systematic and Idiosyncratic Volatility

	Sys Vol (Assets)	Id Vol (Assets)	Sys Vol (Portfolio)	Id Vol (Portfolio)	% Sys Vol (Assets)
1 / $\overline{Lev}_i$	2.153***	1.446***	1.061***	-0.449***	0.381***
	(0.083)	(0.090)	(0.103)	(0.134)	(0.025)
Constant	-1.724***	0.653*	-0.602	2.635***	-0.326***
	(0.322)	(0.387)	(0.382)	(0.467)	(0.099)
Size Controls	Yes	Yes	Yes	Yes	Yes
Strategy Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.478	0.259	0.377	0.150	0.249
Observations	1555	1555	1555	1555	1555

Panel A of Table 3.9 regresses volatility of monthly gross-of-fee returns on inverse leverage. Columns (1) and (2) regress asset volatility on inverse leverage and columns (3) and (4) regress portfolio volatility on inverse leverage. Panel B regresses the probability of a bad return on inverse leverage, where the dependent variable is an indicator equal to one if the return is in the bottom 10th percentile. Panel C regresses the systematic (columns (1) and (3)) and idiosyncratic (columns (2) and (4)) components of volatility on inverse leverage. Size controls include net asset value, and strategy controls include indicators for each strategy category. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3.10: Leverage and Expected Returns

	Avg. Return Assets	Avg. Return Assets	Avg. Return Port	Avg. Return Port
$1 / \overline{Lev_i}$	0.610***	0.632***	0.188***	0.215***
	(0.039)	(0.039)	(0.060)	(0.063)
Constant	-0.031	-0.372*	0.465***	-0.158
	(0.025)	(0.194)	(0.048)	(0.248)
Size Controls	No	Yes	No	Yes
Strategy Controls	No	Yes	No	Yes
Adjusted R^2	0.110	0.150	0.007	0.053
Observations	1555	1555	1555	1555

Table 3.10 reports cross-sectional regressions of the average monthly gross-of-fee return on inverse average leverage (the average capital ratio) and other controls. Returns are calculated at both the asset level (the deleveraged portfolio returns), and the portfolio level. Size controls include net asset value, and strategy controls include indicators for each strategy category. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3.11: Betas and Leverage

	MKT	MKT	SMB	SMB	HML	HML	PROF	PROF	INV	INV
$1 / \overline{Lev}_i$	0.662***	0.644***	0.151***	0.148***	0.092**	0.134***	0.167***	0.110*	-0.017	-0.103**
	(0.029)	(0.029)	(0.029)	(0.029)	(0.039)	(0.039)	(0.058)	(0.059)	(0.047)	(0.048)
Size Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Strategy Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.204	0.381	0.013	0.042	0.002	0.089	0.004	0.076	-0.001	0.051
Observations	1555	1555	1555	1555	1555	1555	1555	1555	1555	1555

Table 3.11 reports cross-sectional regressions of factor betas estimated from the Fama and French (2015) five-factor model on inverse average leverage (the average capital ratio) and other controls. Betas are estimated from monthly returns on assets (the deleveraged portfolio returns). Size controls include net asset value, and strategy controls include indicators for each strategy category. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3.12: Betas and Leverage

	$1 / \overline{Lev}_i$	$1 / \overline{Lev}_i$	$1 / \overline{Lev}_i$	$1 / \overline{Lev}_i$
MKT (Asset) Beta	0.309***	0.305***	0.373***	0.387***
	(0.014)	(0.014)	(0.019)	(0.019)
SMB (Asset) Beta		0.027		-0.018
		(0.018)		(0.018)
HML (Asset) Beta		0.010		-0.051**
		(0.018)		(0.024)
PROF (Asset) Beta		0.017		0.010
		(0.011)		(0.016)
INV (Asset) Beta		-0.001		-0.071***
		(0.011)		(0.015)
Equity Strategy Only	No	No	Yes	Yes
Adjusted R^2	0.204	0.207	0.471	0.497
Observations	1555	1555	552	552

Table 3.12 reports cross-sectional regressions of inverse leverage on individual betas estimated from the Fama and French (2015) five-factor model. Betas are estimated from monthly returns on assets (the deleveraged portfolio returns). Equity Strategy Only is an indicator equal to one if the fund manages an equity-style strategy. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3.13: Alpha and Leverage

	FF5 Alpha Assets	FF5 Alpha Assets	FF5 Alpha Port	FF5 Alpha Port	FF5 Alpha Port	FF5 Alpha Port
$1 / \overline{Lev_i}$	0.130***	0.394***	-0.301***	-0.015	0.033	0.088
	(0.039)	(0.045)	(0.055)	(0.061)	(0.060)	(0.065)
MKT (Asset) Beta		-0.398***		-0.431***	-0.461***	-0.458***
		(0.043)		(0.045)	(0.042)	(0.047)
SMB (Asset) Beta					0.141***	0.100**
					(0.049)	(0.049)
HML (Asset) Beta					-0.103**	-0.141***
					(0.052)	(0.053)
PROF (Asset) Beta					-0.242***	-0.210***
					(0.034)	(0.034)
INV (Asset) Beta					-0.011	-0.002
					(0.035)	(0.035)
Size Controls	No	No	No	No	No	Yes
Strategy Controls	No	No	No	No	No	Yes
Adjusted R^2	0.005	0.094	0.020	0.090	0.197	0.213
Observations	1555	1555	1555	1555	1555	1555

Table 3.13 reports results from regressions of alpha estimated from the Fama and French (2015) five-factor model on inverse leverage and individual estimated betas. Alphas are estimated using both returns to the fund's assets (the deleveraged portfolio returns), and portfolio returns. Size controls include net asset value, and strategy controls include indicators for each strategy category. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

3.7.2 Figures

Figure 3.1: Investment Under Leverage Constraints

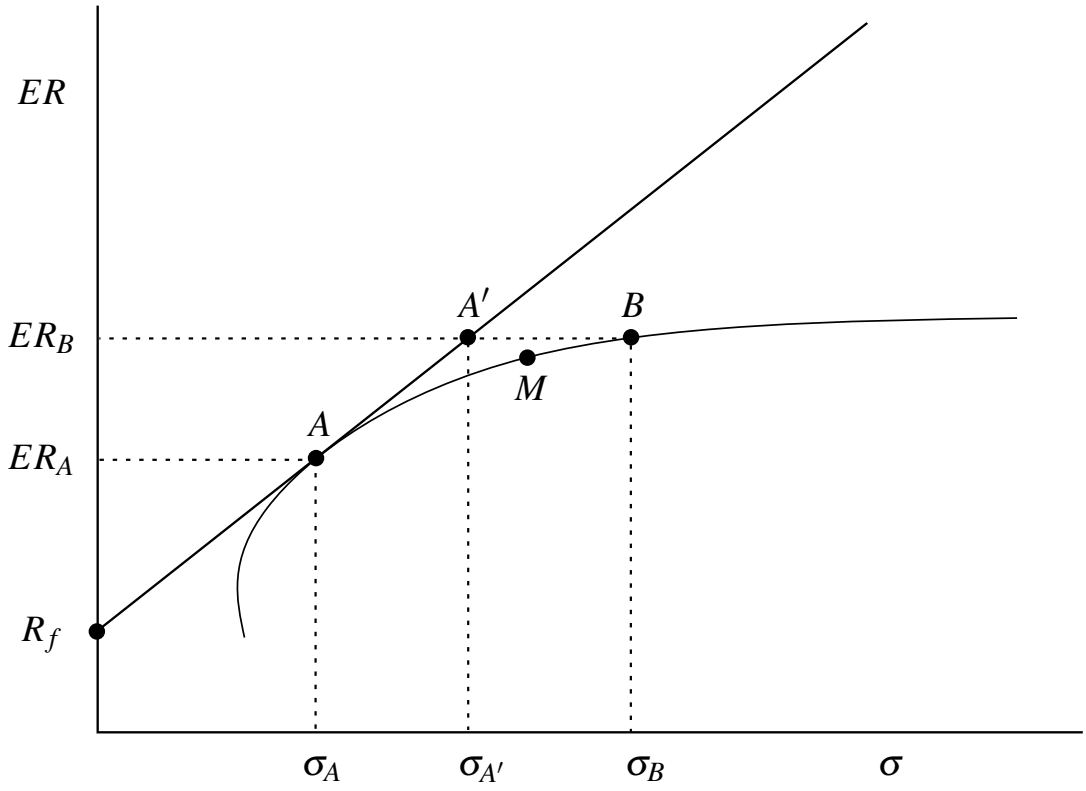


Figure 3.1 depicts the efficient frontier and optimal portfolio choices under leverage constraints. If the leverage constraint does not bind, both the constrained and unconstrained funds hold the tangency portfolio A. If the constraint binds, the constrained fund moves along the frontier to a portfolio with more risk, portfolio B. In this case, the market portfolio lies between portfolios A and B.

Figure 3.2: Hedge Fund Secured Borrowing ($ billions)

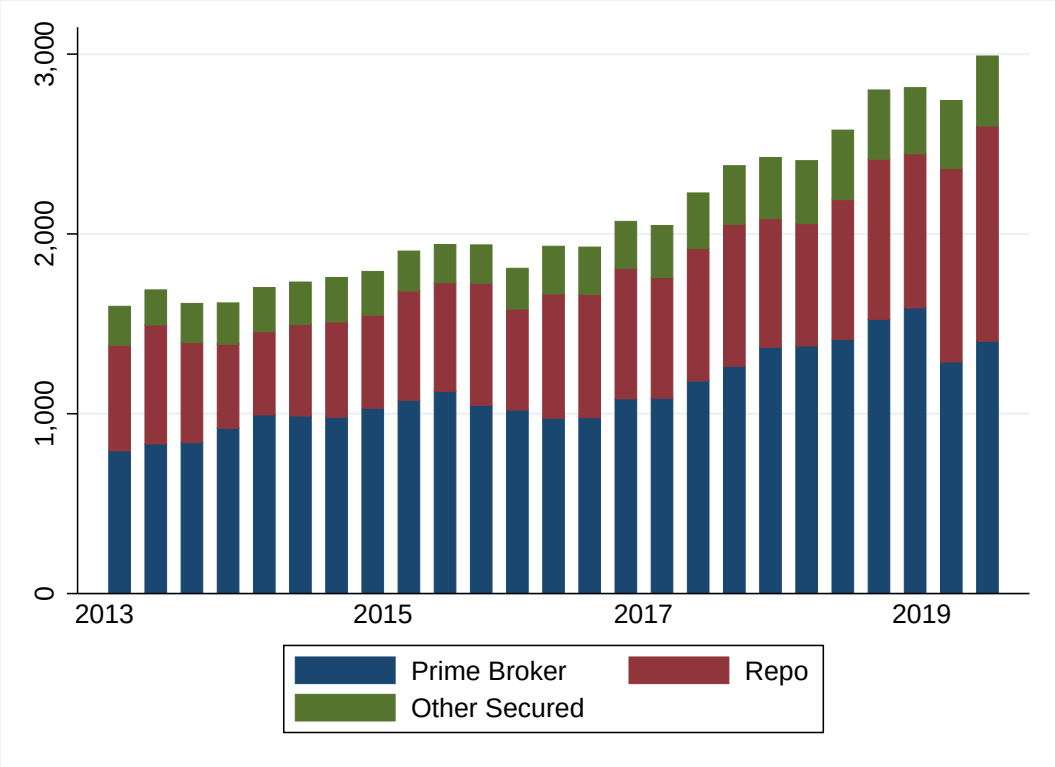


Figure 3.2 shows the dollar amount of secured borrowing by type. Secured borrowing is classified according to the legal agreement governing the borrowing, e.g. Global Master Repurchase Agreement for repo and Prime Brokerage Agreement for prime brokerage.

Figure 3.3: Leverage Over Time

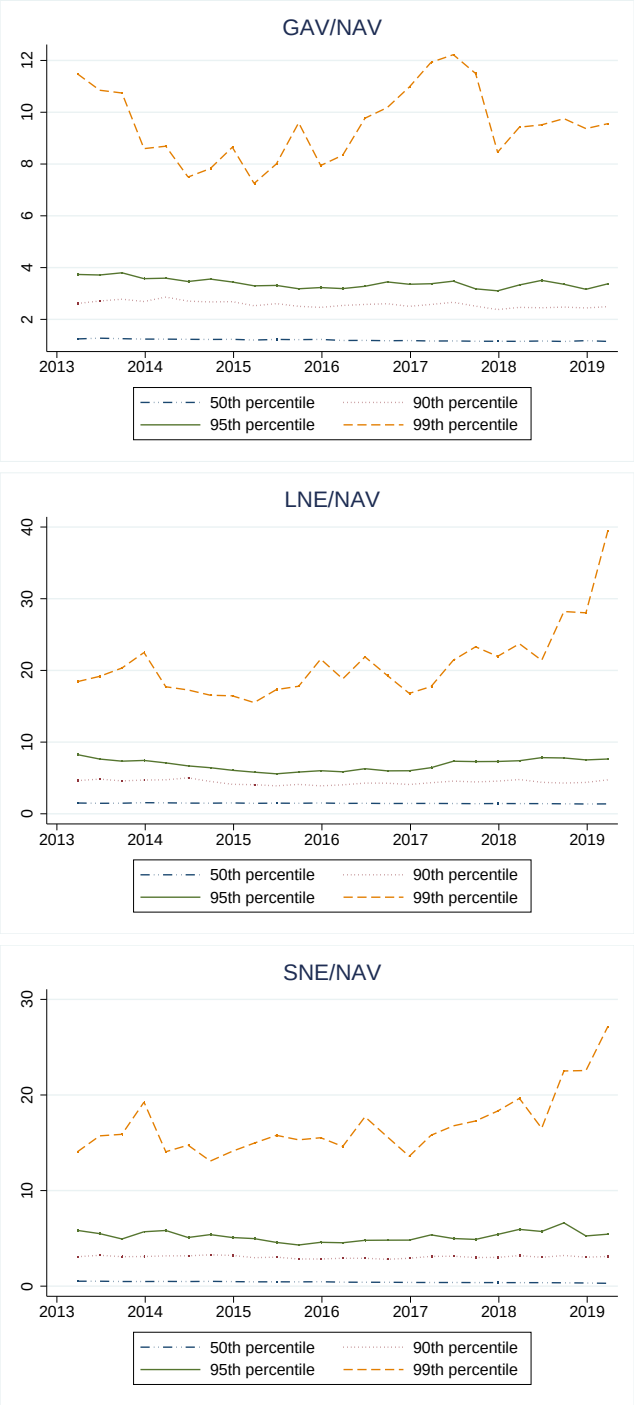


Figure 3.3 plots distributional quantiles over time of the ratios of gross to net assets (GAV/NAV), long notional exposure to net assets (LNE/NAV), and short notional exposure to net assets (SNE/NAV)

Figure 3.4: Asset Volatility vs. Leverage

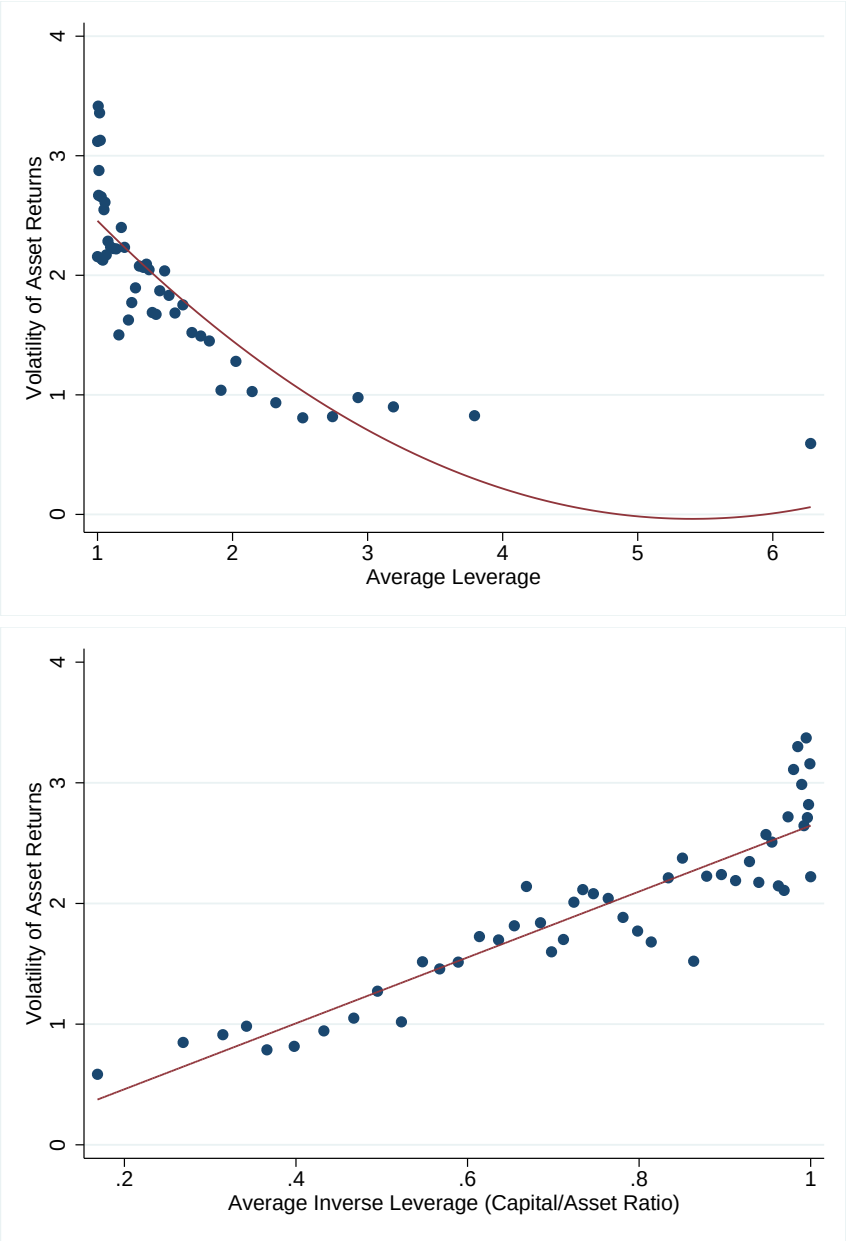


Figure 3.4 shows binscatter plots of average leverage (top figure) or average inverse leverage (bottom figure) versus realized volatility of monthly asset returns.

Figure 3.5: Asset Volatility vs. Inverse Leverage by Strategy

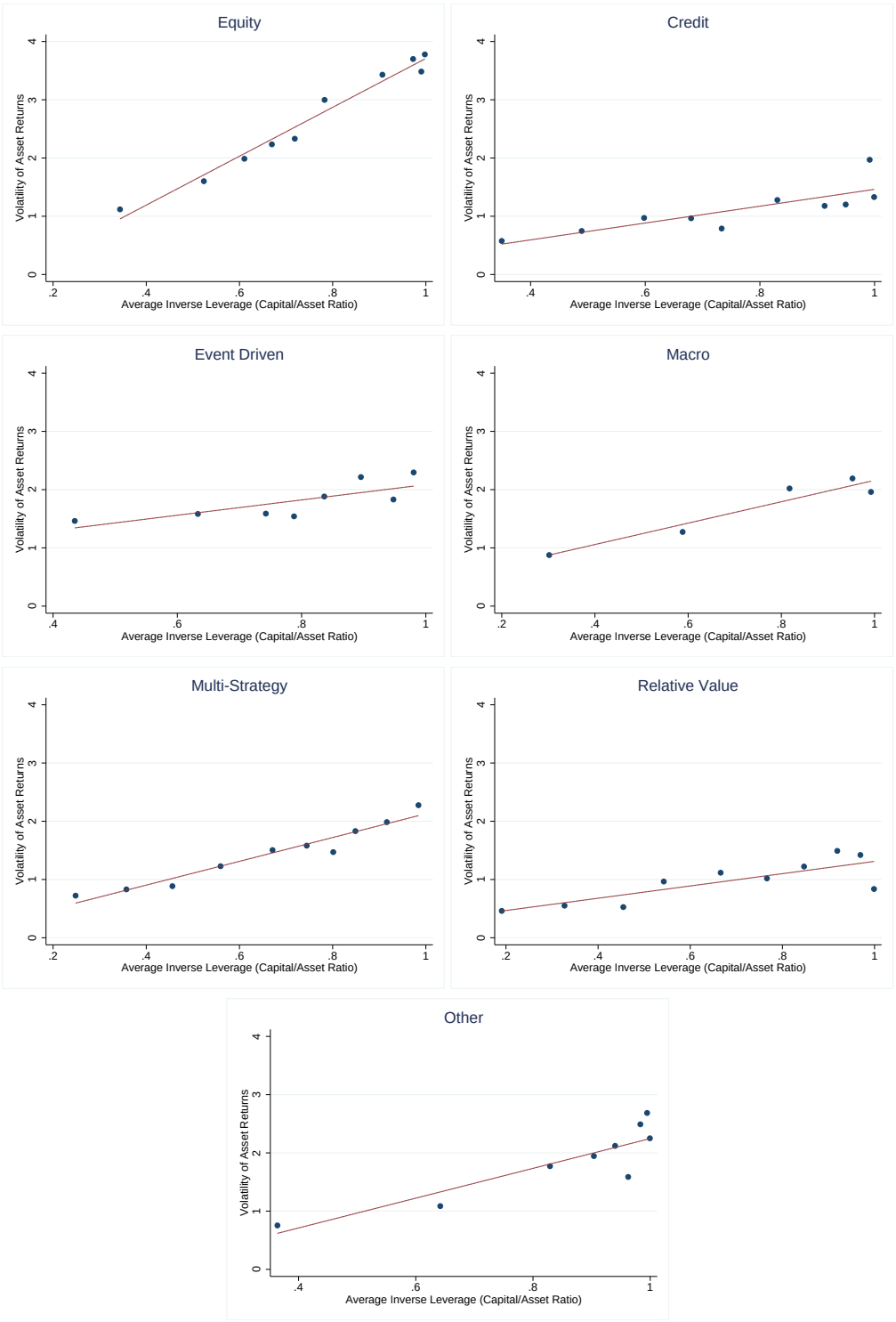


Figure 3.5 shows binscatters plots of inverse leverage versus realized volatility of monthly asset returns by fund strategy

Figure 3.6: Portfolio Volatility vs Leverage

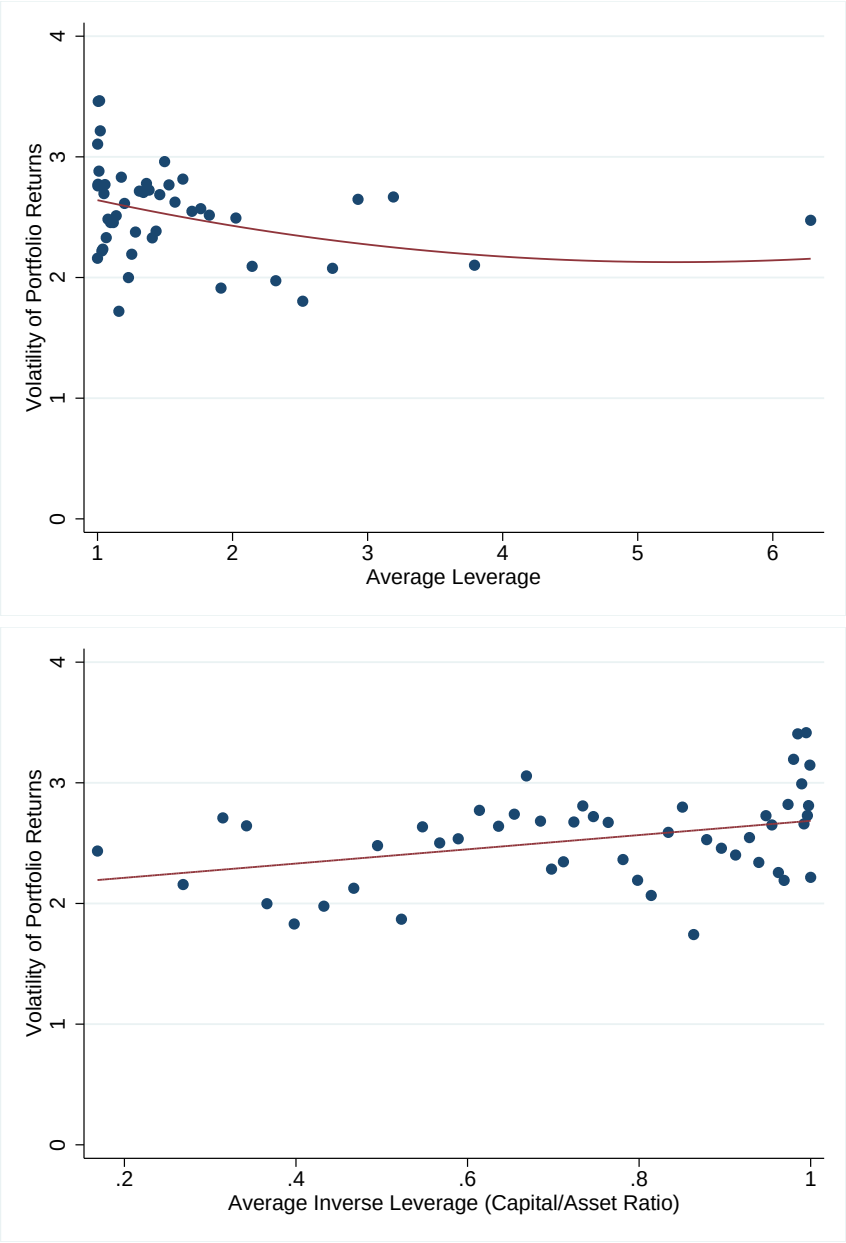


Figure 3.6 shows binscatter plots of average leverage (top figure) or average inverse leverage (bottom figure) versus realized volatility of monthly portfolio returns.

Figure 3.7: Portfolio Volatility vs Inverse Leverage by Strategy

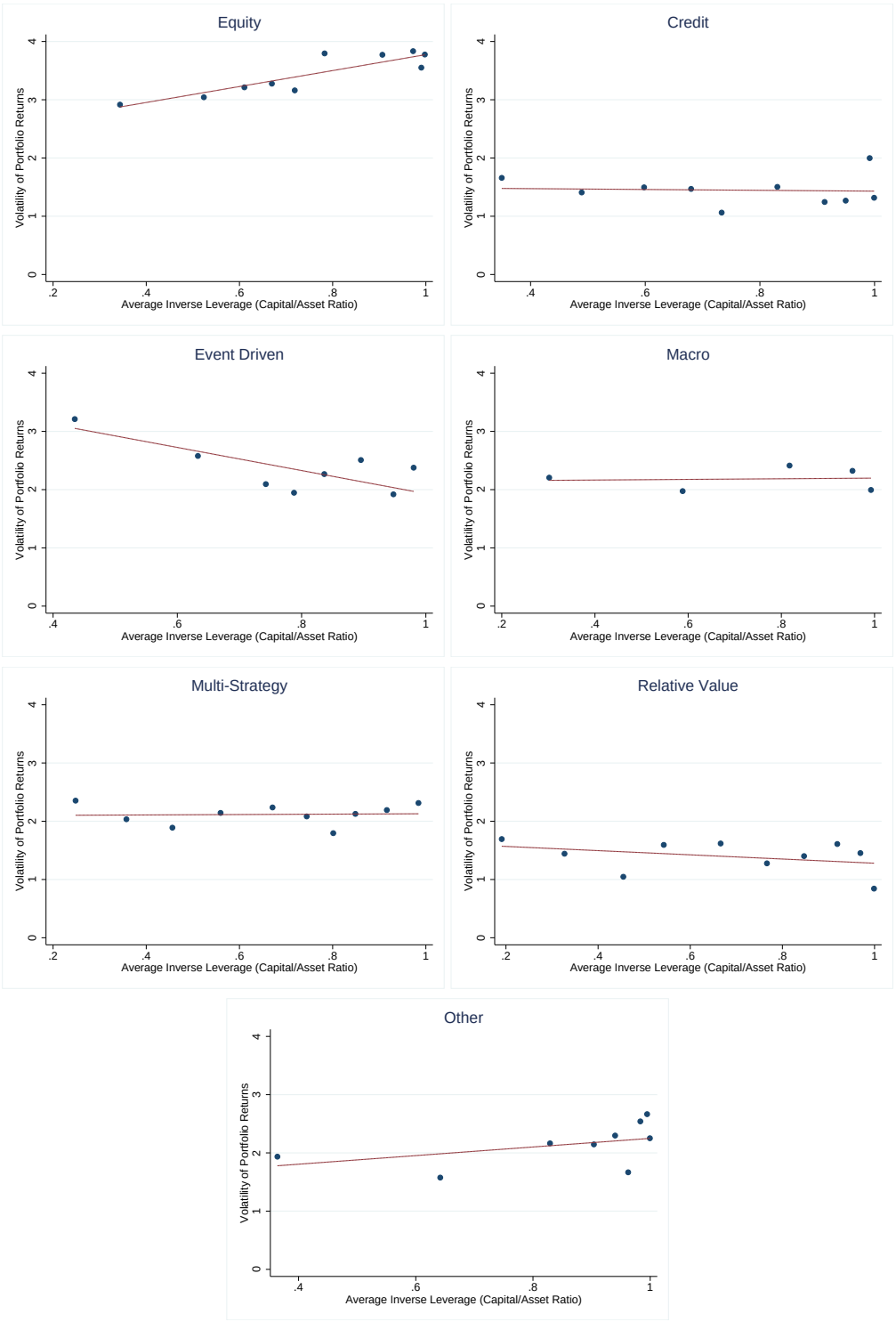


Figure 3.7 shows binscatter plots of inverse leverage versus volatility of monthly portfolio returns by fund strategy.

Figure 3.8: Portfolio Return Volatility and Risk Factor Betas

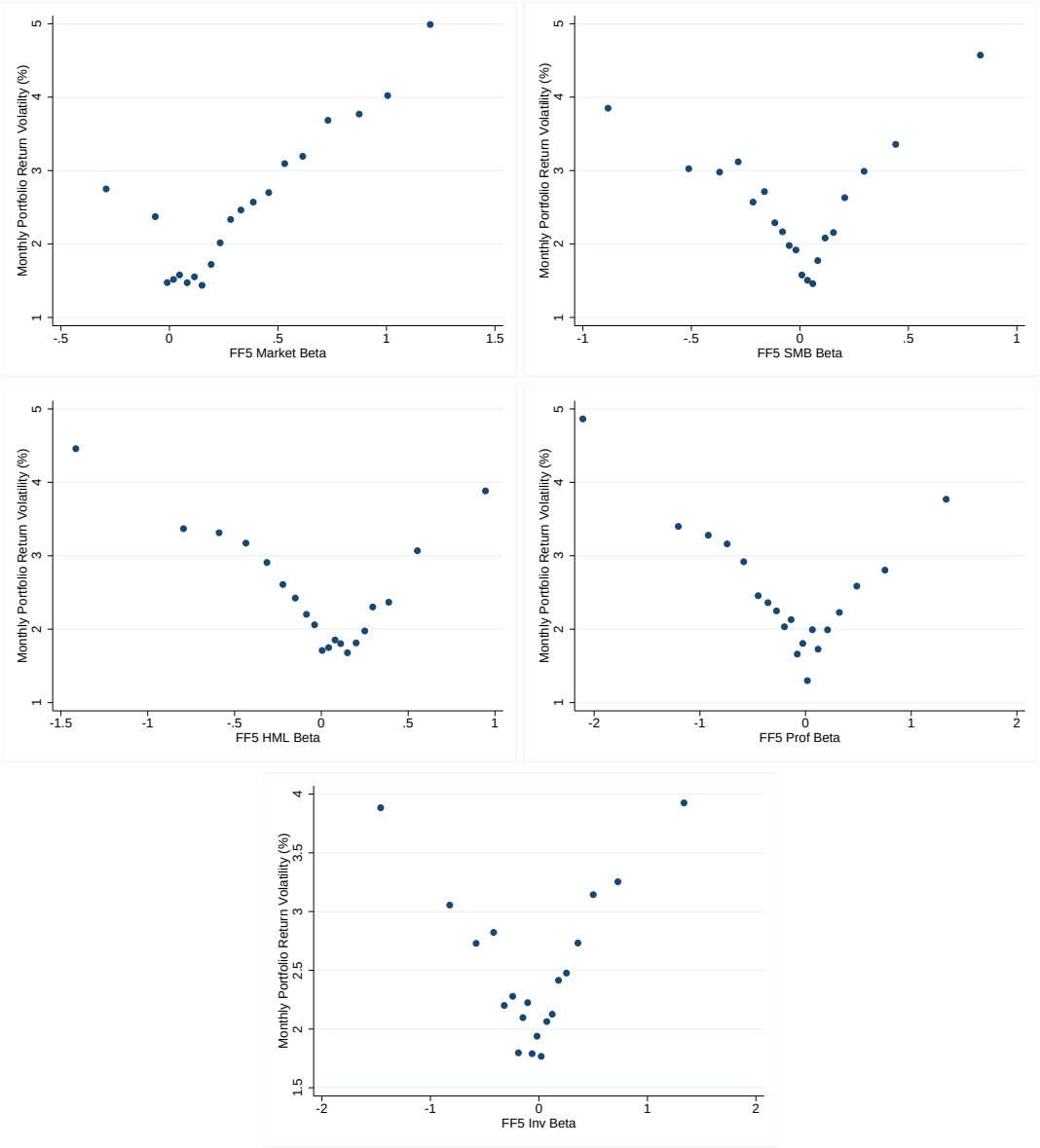


Figure 3.8 shows binscatter plots of realized monthly portfolio return volatility versus estimated betas from the Fama French five-factor model (FF5).

Figure 3.9: Leverage versus Systematic and Idiosyncratic Return Volatility

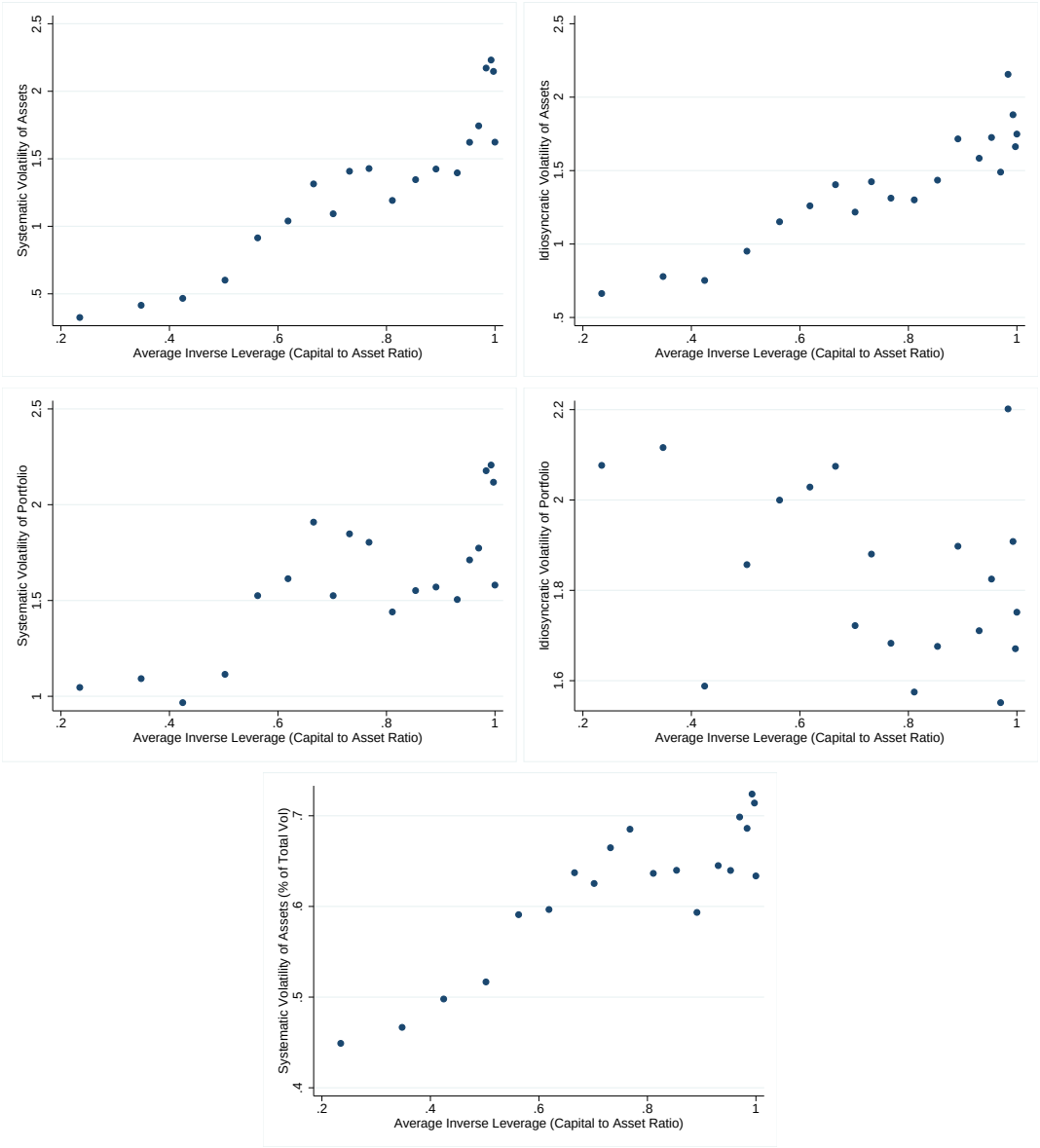


Figure 3.9 shows binscatter plots of average inverse leverage versus the components of total return volatility. The upper row plots inverse leverage against idiosyncratic and systematic monthly asset return volatility. The middle row plots inverse leverage against the systematic and idiosyncratic monthly portfolio return volatility. The bottom row plots inverse leverage against the fraction of asset volatility due to systematic risk.

Figure 3.10: Leverage and Unadjusted Gross Returns

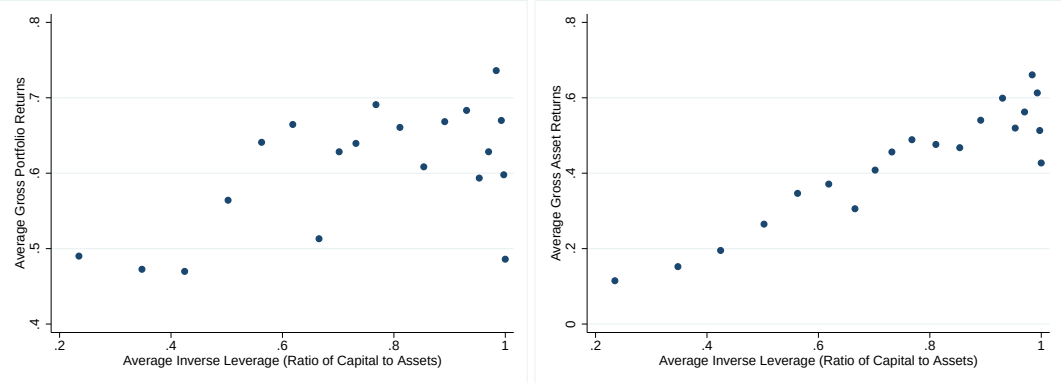


Figure 3.10 shows binscatter plots of average gross (of fee) monthly returns on inverse leverage.

Appendix

4.1 Appendix for Chapter 1

4.1.1 Sample Construction

Data for 64 benchmarks are not available, and thus funds following these benchmarks were excluded from the main analysis. Their exclusion is not expected to generate any biases. Funds associated with these benchmarks have average statistics similar to those of the funds included in the analysis.

Table 4.1: Summary Statistics of Excluded funds

Panel A

	No. of Funds
Strategy	
Passive	36
Active	261
ETF	
ETF	39
Non-ETF	257
EM or DM	
Emerging Markets	91
Developed Markets	206
Asset Class	
Emerging Markets	
Asia ex-Japan	24
BRIC	8
Emerging Europe	15
Global EM	21
Latin America	14
Middle East and Africa	8
Developed	
Global	114
Global ex-US	41
Western Europe	31
Asia Pacific	20
Domicile	
USA	93
Europe	186
Asia	4
Other	15

Panel B

	Mean	Std	p10	p25	p50	p75	p90
Country Weight (%)	6.32	10.31	0.34	1.02	2.53	6.55	16.02
Total Net Assets (%)	924.43	1867.04	18.27	68	294.11	962.67	2577

Table 4.2: Excluded Benchmarks

MSCI Europe Large Cap
MSCI AC World ex-US Growth
MSCI Europe Small Cap
MSCI Europe Risk Weighted Top 100
50% MSCI AC Far East + 50% MSCI AC Far East ex-Japan
80% MSCI World + 20% MSCI France
67% MSCI World + 33% MSCI Emerging Markets
MSCI AC World IMI
MSCI Emerging Markets Investable Market
MSCI Emerging & Frontier Markets
50% MSCI AC Far East Free + 50% MSCI AC Far East Free ex-Japan
50% MSCI Japan + 50% MSCI AC Pacific Free ex-Japan
MSCI Emerging Europe 10/40
65% MSCI EFM Central and Eastern Europe Commonwealth of Independent States (CEEC) ex Russia + 35% MSCI Russia yearly
75% MSCI AC Far East Free ex-Japan + 25% MSCI Japan
MSCI Latin America 10/40
MSCI Europe Value Weighted 50% MSCI AC Far East 50% MSCI AC Far East ex-Japan
40% MSCI Singapore + 40% MSCI Hong Kong + 20% MSCI Australia
MSCI Emerging Markets High Dividend Yield
MSCI Emerging Markets Latin America
MSCI AC Golden Dragon
MSCI Europe Momentum
60% MSCI AC Asia Pacific ex-Japan + 40% MSCI Japan
MSCI Eastern Europe
FTSE Developed All Cap ex North America
FTSE World Europe inc UK
FTSE All-World
MSCI AC Pacific Free
MSCI AC World Free
MSCI Emerging Markets Euro
MSCI AC Asia Free ex-Japan
MSCI EMF Latin America
MSCI Emerging East Europe
50% MSCI Pacific Rim ex-Japan + 50% MSCI Pacific Rim incl Japan
MSCI Emerging Markets Free
50% MSCI Frontier Markets + 50% MSCI Frontier Markets ex GCC
MSCI EM Europe, Middle East & Africa
80% Hang Seng 20% Taiwan Stock Exchange
MSCI EAFE ESG Focus
MSCI ACWI
MSCI Europe Minimum Volatility
MSCI Europe US Dollar Hedged
FTSE Developed All Cap ex North America 100% Hedged to CAD
MSCI World ex-USA
75% MSCI Arabian Markets ex Saudi Arabia + 25% MSCI Saudi Arabian Domestic
MSCI Eastern Europe 10/40
50% MSCI Japan + 50% MSCI AC Asia-Pacific Free ex-Japan
MSCI World Growth
MSCI Emerging Markets EMEA
MSCI Europe Value
MSCI Europe Growth
MSCI Asia ex-Japan
MSCI EM Europe & Middle East 10/40
25% MSCI Brazil+25% MSCI Russia+25% MSCI India+25% MSCI China
MSCI Latin America
MSCI AC Pacific ex-Japan
MSCI AC World ex-US
MSCI Far East ex-Japan
MSCI EMEA
MSCI Far East
MSCI Emerging and Frontier Markets Africa
WisdomTree Emerging Markets Equity Income
MSCI Emerging Markets ESG
MSCI Europe Investable Market
MSCI Europe SRI
MSCI AC Pacific
MSCI Emerging Europe
MSCI Asia Pacific ex-Japan

4.1.2 Results for ETFs

Table 4.3: Log Country Weights by Strategy

	All Funds		Active		Closet Indexer		Explicit Indexer			
							Non-ETF		ETF	
Lagged log country weight	0.879***	0.878***	0.882***	0.878***	0.832***	0.904***	0.844***	0.908***	0.830***	0.852***
	(0.005)	(0.001)	(0.005)	(0.001)	(0.037)	(0.013)	(0.070)	(0.033)	(0.014)	(0.012)
Relative returns	0.943***	0.964***	0.985***	1.003***	1.070***	1.112***	0.821***	0.825***	0.787***	0.818***
	(0.014)	(0.014)	(0.018)	(0.017)	(0.093)	(0.071)	(0.041)	(0.044)	(0.020)	(0.021)
Benchmark weight	0.003***	0.004***	0.002***	0.003***	0.003	0.005***	0.004***	0.003**	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Country Crisis		-0.009***		-0.011***		-0.025**		-0.005		0.002
		(0.002)		(0.002)		(0.010)		(0.004)		(0.003)
Adjusted R^2	0.983	0.982	0.974	0.973	0.994	0.995	0.997	0.997	0.996	0.997
Observations	261789	194951	200339	155321	3636	2435	10144	6232	47670	30963

Table 4.3 regresses log country weights on the country weight in the previous period, relative returns and the exogenous component of the benchmark weight. Standard errors are clustered at the fund-time level.

4.1.3 Alternative Closet Indexer Classification

This section presents results using alternative classifications of closet indexers, based on a higher active share threshold. In Table 4.4 closet indexers are defined as funds that declare to be active and have an active share less than 6.9, and in Table 4.5 defined to have an active share of less than 10, or within 1 standard deviation of the mean of explicit indexers.

Table 4.4: Log Country Weights by Strategy (Alternative Closet Classification)

	All Funds		Active		Closet Indexer		Explicit Indexer	
Lagged Country Weight	0.879***	0.878***	0.883***	0.879***	0.831***	0.843***	0.832***	0.862***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.023)	(0.027)	(0.016)	(0.013)
Relative returns	0.943***	0.964***	0.975***	0.995***	1.093***	1.110***	0.793***	0.819***
	(0.014)	(0.016)	(0.018)	(0.020)	(0.077)	(0.092)	(0.018)	(0.019)
Benchmark weight	0.003***	0.004***	0.002***	0.003***	0.007***	0.010***	0.008***	0.007***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Country Crisis		-0.009***		-0.011***		-0.011		0.001
		(0.002)		(0.002)		(0.007)		(0.002)
Fund FE	No	No	No	No	No	No	No	No
Time FE	No	No	No	No	No	No	No	No
Fund-country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.983	0.982	0.973	0.972	0.991	0.990	0.996	0.997
Observations	261789	194951	195281	150887	10253	7306	57814	37195

Table 4.4 regresses log country weights on the country weight in the previous period, relative returns and the exogenous component of the benchmark weight. Closet index funds are defined as having an active share less than 6.9. Standard errors are clustered at the fund-time level.

Table 4.5: Log Country Weights by Strategy (Alternative Closet Classification)

	All Funds		Active		Closet Indexer		Explicit Indexer	
Lagged country weight	0.879***	0.878***	0.884***	0.881***	0.832***	0.834***	0.832***	0.862***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.012)	(0.015)	(0.016)	(0.013)
Relative returns	0.943***	0.964***	0.965***	0.981***	1.104***	1.162***	0.793***	0.819***
	(0.014)	(0.016)	(0.018)	(0.021)	(0.053)	(0.063)	(0.018)	(0.019)
Benchmark weight	0.003***	0.004***	0.002***	0.002***	0.008***	0.010***	0.008***	0.007***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Country Crisis		-0.009***		-0.012***		-0.001		0.001
		(0.002)		(0.002)		(0.006)		(0.002)
Fund FE	No	No	No	No	No	No	No	No
Time FE	No	No	No	No	No	No	No	No
Fund-country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.983	0.982	0.973	0.972	0.986	0.984	0.996	0.997
Observations	261789	194951	183667	142602	21867	15591	57814	37195

Table 4.5 regresses log country weights on the country weight in the previous period, relative returns and the exogenous component of the benchmark weight. Closet index funds are defined as having an active share less than 10. Standard errors are clustered at the fund-time level.

Table 4.6: Relative Flows by Strategy

	All Funds	Active	Closet Indexer	Explicit Indexer
Fund FE	No	No	No	No
Time FE	No	No	No	No
Fund-country FE	Yes	Yes	Yes	Yes
Fund-time FE	Yes	Yes	Yes	Yes

Table **??** regresses log country weights minus log buy-and-hold weights on relative returns and the exogenous component of the benchmark weight. Standard errors are clustered at the fund-time level.

4.2 Appendix for Chapter 2

4.2.1 Alternative Flows Winsorization

In Sections 2.3 and 2.4, flows are winsorized at the 10% level. This is the level used in existing literature and also produces a range of monthly net flows that seems reasonable. In this section, I repeat the results using a smaller winsorization of flows. At a 2% winsorization, monthly net flows range from -27% to 24% of total net assets. Across all funds, average monthly flows are little changed, at -0.21% of net assets. Explicit indexers continue to have the highest monthly net flows, 1.01%, while flows to closet and active funds are much lower -0.50%.

Overall, the immediate impact of flows on cash is smaller at the shorter winsorization. By fund type, the relative liquidity management in response to flows by groups remains the same, with active and closet funds accommodating a larger portion of flow through cash. As in section 2.3, after two periods, the impact of flows on cash remains small, but positive for active funds, and fades to zero for closet and explicit index funds.

In periods of crises or extreme capital flows, cash is used less relative to normal times

regardless of fund type. In periods of crises, capital surges, or capital retrenches, active funds continue to accommodate a positive, albeit small, fraction of flows with cash. The use of cash in closet and explicit funds falls to zero during these periods. The conclusions from 2.3 remain unchanged with the alternate flows winsorization.

Table 4.7: Change in Cash

	All Funds	Explicit	Closet	Active
Flows	0.057***	0.009***	0.059***	0.077***
	(0.002)	(0.001)	(0.008)	(0.002)
Flows(t-1)	-0.033***	-0.007***	-0.031***	-0.044***
	(0.002)	(0.001)	(0.008)	(0.002)
Flows(t-2)	-0.005***	0.001	-0.015*	-0.007***
	(0.002)	(0.002)	(0.008)	(0.002)
Flows(t-3)	-0.001	-0.000	-0.001	-0.001
	(0.002)	(0.002)	(0.007)	(0.002)
Adjusted R^2	0.051	0.090	0.086	0.060
Observations	38336	6047	2403	29401

In Table 4.7, flows are winsorized at the 1st and 95th percentile

Table 4.8: Cash During Outflows

	All Funds	Explicit	Closet	Active
Flows	0.022***	0.008***	0.022*	0.034***
	(0.002)	(0.002)	(0.012)	(0.003)
Outflow	-0.003***	-0.000	-0.002***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.000)
(Outflow)(Flow)	0.017***	-0.001	0.018	0.014***
	(0.004)	(0.003)	(0.018)	(0.005)
Adjusted R^2	0.044	0.078	0.070	0.051
Observations	42104	7047	2657	31889

In Table 4.8, flows are winsorized at the 1st and 95th percentile

Table 4.9: Cash during Sustained Capital Outflows

	All Funds	Explicit	Closet	Active
Flows	0.046***	0.009***	0.057***	0.066***
	(0.002)	(0.001)	(0.008)	(0.002)
Crisis	0.001***	0.000	0.001	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
(Crisis)(Flows)	-0.006	0.007	-0.038*	-0.020***
	(0.005)	(0.006)	(0.019)	(0.006)
Adjusted R^2	0.038	0.078	0.071	0.045
Observations	42104	7047	2657	31889

Flows are winsorized at the 1st and 95th percentile

Table 4.10: Cash Weights during Capital Surges

	All Funds	Explicit	Closet	Active
Flows	0.055***	0.008***	0.056***	0.067***
	(0.003)	(0.003)	(0.012)	(0.003)
Surge	0.003***	0.000	0.001	0.004***
	(0.000)	(0.000)	(0.001)	(0.000)
(Surge)(Flow)	-0.044***	-0.001	-0.030	-0.047***
	(0.004)	(0.003)	(0.019)	(0.005)
Adjusted R^2	0.042	0.078	0.068	0.048
Observations	42104	7047	2657	31889

Flows are winsorized at the 1st and 95th percentile

Table 4.11: Cash Weights during Capital Retrenches

	All Funds	Explicit	Closet	Active
Flows	0.038***	0.008***	0.038***	0.057***
	(0.002)	(0.001)	(0.010)	(0.003)
Retrench	-0.003***	-0.001**	-0.002*	-0.004***
	(0.000)	(0.000)	(0.001)	(0.000)
(Retrench)(Flow)	-0.025***	-0.009*	-0.012	-0.038***
	(0.005)	(0.005)	(0.020)	(0.006)
Adjusted R^2	0.041	0.079	0.068	0.047
Observations	42104	7047	2657	31889

Flows are winsorized at the 1st and 95th percentile

4.2.2 Cash Pre- and Post-2015

Table 4.12: Cash Behavior Pre- and Post-2015

	All Funds		Explicit		Closet		Active	
	Pre-2015	Post-2015	Pre-2015	Post-2015	Pre-2015	Post-2015	Pre-2015	Post-2015
Flows	0.135***	0.116***	0.015**	0.009	0.075**	0.121***	0.154***	0.154***
	(0.006)	(0.008)	(0.006)	(0.007)	(0.029)	(0.040)	(0.008)	(0.010)
$Flows_{t-1}$	-0.089***	-0.080***	-0.013**	-0.016***	-0.072***	-0.104***	-0.098***	-0.102***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.024)	(0.030)	(0.006)	(0.009)
$Flows_{t-2}$	-0.020***	-0.008	-0.001	-0.002	-0.027	-0.009	-0.023***	-0.011
	(0.006)	(0.006)	(0.006)	(0.008)	(0.024)	(0.041)	(0.007)	(0.009)
$Flows_{t-3}$	-0.003	-0.000	0.012**	-0.004	0.010	-0.039	-0.005	0.003
	(0.006)	(0.008)	(0.006)	(0.005)	(0.022)	(0.031)	(0.006)	(0.010)
Adjusted R^2	0.052	0.007	0.150	0.040	0.075	-0.007	0.062	0.026
Observations	14502	10966	1010	2187	1050	514	12203	8071

Table 4.12 regresses the change 1-month change in cash on flows in previous months. All variables are scaled by net assets in period t-1. Standard errors are clustered by time. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

4.2.3 Log Cash Weights

In Section 2.3, I study the impact of flows on changes in cash allocations, which I compute from a fund's cash weight and net assets. Here, I consider an alternative specification using the fund's self-report cash weight directly.

Table 4.13: Log Cash Weights

	All Funds	Explicit	Closet	Active
Lagged cash weight	0.721***	0.639***	0.620***	0.628***
	(0.004)	(0.011)	(0.022)	(0.005)
$Flows(t)$	4.889***	1.547***	5.533***	6.485***
	(0.210)	(0.505)	(1.126)	(0.230)
$Flows(t-1)$	-3.420***	-1.939***	-2.920***	-2.643***
	(0.216)	(0.525)	(1.128)	(0.238)
$Flows(t-2)$	-0.188	0.849*	-0.109	0.273
	(0.207)	(0.495)	(1.046)	(0.228)
Adjusted R^2	0.555	0.569	0.453	0.443
Observations	32307	4485	1684	25657

Table 4.13 shows regressions of log cash weights on lagged log cash weights, and lagged net flows. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

4.2.4 Log Country Weights

In Section 2.5, I study the impact of flows on changes in country allocations, which I compute from a fund's country weight and net assets. Here, I repeat the analysis using the fund's self-reported country weight directly.

Table 4.14: Log Country Weights

	(1)	(2)	(3)
Active Funds			
Lagged Country Weight	0.893***	0.892***	0.892***
	(0.001)	(0.001)	(0.001)
Rct	0.466***		
	(0.006)		
Flows	-0.149***	-0.260***	-0.181***
	(0.013)	(0.067)	(0.044)
Rct × Flows	-0.739***		
	(0.247)		
Stock Turnover		-0.004***	
		(0.002)	
Stock Turnover × Flows		0.041**	
		(0.017)	
Stocks Traded (%)			0.020***
			(0.001)
Stocks Traded (%) × Flows			0.018
			(0.011)
Adjusted R^2	0.776	0.775	0.775
Observations	427118	338842	335144
Explicit Indexers			
Lagged Country Weight	0.851***	0.844***	0.842***
	(0.001)	(0.002)	(0.002)
Rct	0.398***		
	(0.007)		
Flows	-0.056***	-0.156**	-0.044
	(0.013)	(0.073)	(0.045)
Rct × Flows	0.428		
	(0.265)		
Stock Turnover		0.011***	
		(0.003)	
Stock Turnover × Flows		0.032*	
		(0.019)	
Stocks Traded (%)			0.034***
			(0.002)
Stocks Traded (%) × Flows			0.001
			(0.012)
Adjusted R^2	0.714	0.704	0.705
Observations	142850	101879	100937

Table 4.14 regresses the log country weights on the following country variables and their interaction with monthly net flows: country returns (in decimal), stocks traded as a percentage of gdp (in log), and the turnover ratio of stocks traded (in logs).

Table 4.15: Log Country Weights during Outflows

	(1)	(2)	(3)
Lagged Country Weight	0.890***	0.890***	0.890***
	(0.001)	(0.001)	(0.001)
Rct	0.456***		
	(0.009)		
Outflow	0.006***	0.012***	0.008***
	(0.001)	(0.003)	(0.002)
Outflow × Rct	0.021*		
	(0.012)		
Stock Turnover Ratio		-0.002	
		(0.002)	
Outflow × Stock Turnover Ratio		-0.002***	
		(0.001)	
Stocks Traded (%)			0.022***
			(0.001)
Outflow × Stocks Traded (%)			-0.001*
			(0.001)
Adjusted R^2	0.772	0.771	0.771
Observations	470287	372666	368400

Table **??** regresses the log country weights on the following country variables and their interaction with an indicator for outflows: country returns (in decimal), stocks traded as a percentage of gdp (in log), and the turnover ratio of stocks traded (in logs). Outflows is an indicator equal to 1 if the fund experienced outflows in period 1.

4.3 Appendix for Chapter 3

4.3.1 Sample Construction

Fee Estimation

The data do not contain explicit information on the components of hedge fund fees, such as management and performance fees or high water marks. Instead, only total gross-of-fee and net-of-fee returns are reported, and we use this information to estimate the performance and management fees. We limit observations to those with a gross-of-fee return that is at least as large as the net-of-fee return. This excludes data errors and funds offering rebates. We estimate the management fee as the maximum fee charged by the fund during negative-return months. The goal is to isolate the management fee by excluding the performance fee, which would only possibly be charged in months with positive returns. We then winsorize the estimated management fee at the 5^{th} and 95^{th} percentiles. Performance fees are usually charged quarterly or annually. To estimate the performance fee, we divide the total fee minus the estimated management fee by the total gross return minus the management fee, all in annual percentages, and winsorize at the 10^{th} and 90^{th} percentiles. Barth and Monin (2019) show that this procedure produces credible estimates for the management and performance fees, both unconditionally and based on a matched sample of funds that appear both Form PF and TASS, the latter of which fee data is collected explicitly.

4.3.2 Additional Results and Summary Statistics

4.3.3 Summary Statistics

In this section, we present additional summary statistics for leverage. Panel A of Table 4.16 reports the distribution, in aggregate and by strategy, for the inverse of average balance sheet leverage ($1/\overline{Lev_i}$). Panel B reports the distribution of the within-fund variation in balance sheet leverage over time.

Cross-Sectional Determinants

This section reports additional results for the cross-sectional variation in leverage. Table 4.17 repeats the specification in Table 3.6 but uses as the dependent variable an indicator equal to one if the fund uses leverage. Table 4.18 repeats the same specification, but uses as the dependent variable an indicator equal to one if the fund's leverage is at or above the 75^{th} percentile.

Robustness: Leverage and Risk

In this section, we repeat the specifications in columns Panel A of Table 3.9 using different measures of leverage: the ratio of long notional exposures to net assets, short notional exposures to net assets, and gross notional exposure to net assets. To compute inverse leverage for these measures, we restrict to values greater than 0.01 for LNE/NAV, SNE/NAV, and GNE/NAV. These results are shown in Table 4.19.

Returns

Tables 4.20 and 4.21 report regression results related to the time-series variation in returns. Table 4.20 regresses future returns on the contemporaneous percentage change in leverage. Dependent variables are the one-quarter ahead, two-quarter ahead, three-quarter ahead, and four-quarter ahead quarterly returns. Table 4.21 reverses the timing of the regressions, and instead regress the contemporaneous percentage change in leverage on prior quarterly returns, lagged up to four quarters.

Table 4.16: Inverse Balance Sheet Leverage (1 / $\overline{Lev_i}$)

Panel A: Leverage Levels

	Mean	**10th**	**25th**	**50th**	**75th**	**90th**	**St. Dev.**
All	0.76	0.38	0.60	0.84	0.98	1.00	0.24
Credit	0.80	0.47	0.66	0.91	0.99	1.00	0.22
Equity	0.74	0.39	0.58	0.74	0.97	1.00	0.22
Event Driven	0.79	0.51	0.69	0.84	0.94	0.99	0.19
Macro	0.73	0.29	0.52	0.85	0.96	0.99	0.28
Managed Futures	0.85	0.66	0.78	0.94	0.99	***	0.20
Multi-strategy	0.68	0.30	0.47	0.74	0.90	0.98	0.26
Relative Value	0.66	0.21	0.41	0.71	0.94	1.00	0.30
Other	0.85	0.51	0.76	0.95	1.00	1.00	0.21

Panel B: Within Fund Variation in Leverage

Strategy	**Mean**	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	**St. Dev.**
All	0.06	0.00	0.01	0.04	0.07	0.13	0.06
Credit	0.06	0.00	0.01	0.04	0.08	0.14	0.06
Equity	0.05	0.00	0.02	0.04	0.06	0.10	0.05
Event Driven	0.06	0.01	0.03	0.05	0.07	0.13	0.06
Macro	0.08	0.01	0.02	0.05	0.12	0.19	0.08
Managed Futures	0.06	***	0.01	0.02	0.09	***	0.08
Multi-strategy	0.06	0.01	0.03	0.05	0.08	0.12	0.05
Relative Value	0.07	0.00	0.02	0.05	0.10	0.16	0.07
Other	0.05	***	0.00	0.02	0.06	0.12	0.06

Table 4.16 reports summary statistics in total and by strategy for inverse leverage, the leverage metric we use in regressions. Inverse leverage is computed as the inverse of gross to net assets. The top panel reports variation in the cross-section. Each statistic is on the average value for the fund over the full set of observations for which we observe it. The bottom panel reports variation over time.
*** Data are masked to avoid potential disclosure of proprietary information of individual Form PF filers

Table 4.17: The Cross Section of Hedge Fund Leverage (Leverage Indicator)

Dep.Var: Leverage > 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log NAV	0.049***						0.049***
	(0.006)						(0.006)
Strategy							
Credit		-0.068**					-0.058*
		(0.032)					(0.031)
Macro		0.053*					0.032
		(0.031)					(0.032)
Managed Futures		-0.067					0.037
		(0.055)					(0.053)
Multi-Strategy		0.111***					0.081***
		(0.020)					(0.021)
Other		-0.171***					-0.146***
		(0.023)					(0.025)
Event Driven		0.097***					0.084***
		(0.025)					(0.025)
Relative Value		0.070***					0.034
		(0.026)					(0.029)
Repo Borrowing			0.183***				0.162***
			(0.021)				(0.024)
Portfolio Liquidity				0.001	-0.035***		-0.026***
				(0.004)	(0.005)		(0.005)
Investor Liquidity					0.067***		0.061***
					(0.006)		(0.006)
Ownership(%)							
Financial						-0.262***	-0.107*
						(0.063)	(0.061)
Investment Fund						-0.010	-0.010
						(0.041)	(0.040)
Non-Profit						-0.137***	-0.124***
						(0.040)	(0.039)
Government						-0.117*	-0.151**
						(0.061)	(0.059)
Other						-0.125***	-0.034
						(0.046)	(0.044)
Adjusted R^2	0.021	0.054	0.016	-0.000	0.058	0.014	0.139
Observations	2916	2916	2916	2916	2916	2916	2916

Table 4.17 regresses an indicator variable equal to one if the fund uses leverage on the following fund characteristics: net asset value, the percentage of portfolio in various asset classes, broad fund strategy, the percentage of borrowing conducted through repo, portfolio liquidity, investor liquidity, and investor composition (% of fund's equity owned by individuals, financial companies, investment funds, non-profits, government, or other). 'Equity' is the excluded category for the asset class and strategy breakouts; for the ownership categories, 'individuals' is the excluded category. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4.18: The Cross Section of High Hedge Fund Leverage (Top Decile)

Dep.Var: $1/\overline{Lev_i}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log NAV	0.007						0.009*
	(0.005)						(0.004)
Strategy							
Credit		-0.008					-0.013
		(0.020)					(0.021)
Macro		-0.088***					-0.028
		(0.023)					(0.026)
Multi-Strategy		-0.070***					-0.063***
		(0.015)					(0.013)
Other		-0.005					-0.018
		(0.016)					(0.018)
Event Driven		-0.003					-0.018
		(0.026)					(0.026)
Relative Value		-0.109***					-0.069***
		(0.019)					(0.020)
Repo Borrowing			-0.124***				-0.096***
			(0.017)				(0.019)
Portfolio Liquidity				0.013***	0.008**		0.009***
				(0.003)	(0.003)		(0.003)
Investor Liquidity					0.012**		0.010**
					(0.005)		(0.004)
Ownership(%)							
Financial						-0.086*	-0.003
						(0.049)	(0.049)
Investment Fund						-0.105***	-0.062**
						(0.032)	(0.029)
Non-Profit						-0.022	-0.006
						(0.032)	(0.031)
Government						-0.103**	-0.077*
						(0.041)	(0.040)
Other						-0.075**	-0.036
						(0.036)	(0.034)
Adjusted R^2	0.002	0.080	0.097	0.027	0.035	0.027	0.172
Observations	714	714	714	714	714	714	714

Table 4.18 regresses inverse leverage, conditional on leverage in the top 75th percentile of leverage, on net asset value, the percentage of portfolio in various asset classes, broad fund strategy, the percentage of borrowing conducted through repo, portfolio liquidity, investor liquidity, and investor composition (% of fund's equity owned by individuals, financial companies, investment funds, non-profits, government, or other). 'Equity' is the excluded category for the asset class and strategy breakouts; for the ownership categories, 'individuals' is the excluded category. The Managed Futures strategy is omitted to avoid revealing proprietary information about individual Form PF filers. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4.19: Other Measures of Leverage and Risk

Panel A: LNE/NAV

	Vol (Assets)	Vol (Assets)	Vol (Portfolio)	Vol (Portfolio)
$1 / \overline{Lev}_{i,t-1}$	0.315^{***}	0.272^{**}	0.107	0.066
	(0.122)	(0.111)	(0.085)	(0.073)
Size Controls	No	Yes	No	Yes
Strategy Controls	No	Yes	No	Yes
R^2	0.026	0.258	0.003	0.280
Observations	1555	1555	1555	1555

Panel B: SNE/NAV

	Vol (Assets)	Vol (Assets)	Vol (Portfolio)	Vol (Portfolio)
$1 / \overline{Lev}_{i,t-1}$	0.016^{***}	0.018^{***}	0.002	0.006^{**}
	(0.003)	(0.003)	(0.003)	(0.003)
Size Controls	No	Yes	No	Yes
Strategy Controls	No	Yes	No	Yes
R^2	0.029	0.253	0.001	0.267
Observations	1375	1375	1375	1375

Panel C: GNE/NAV

	Vol (Assets)	Vol (Assets)	Vol (Portfolio)	Vol (Portfolio)
$1 / \overline{Lev}_{i}$	0.496^{***}	0.443^{***}	0.146	0.094
	(0.165)	(0.158)	(0.095)	(0.081)
Size Controls	No	Yes	No	Yes
Strategy Controls	No	Yes	No	Yes
R^2	0.044	0.272	0.003	0.280
Observations	1555	1555	1555	1555

Table 4.19 shows regressions of volatility on the inverse of the following alternative measures leverage: the ratio of long notional exposure to net assets (LNE/NAV), the ratio of short notional exposure to net assets (SNE/NAV), and the ratio of gross notional exposure to net assets (GNE/NAV). Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4.20: Leverage and Future Returns

	$\widetilde{R}_{q+1}$	$\widetilde{R}_{q+2}$	$\widetilde{R}_{q+3}$	$\widetilde{R}_{q+4}$
$\%\Delta Lev_t$	0.002	0.004**	-0.000	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Size Controls	Yes	Yes	Yes	Yes
Strategy Controls	Yes	Yes	Yes	Yes
R^2	0.002	0.002	0.004	0.002

Table 4.20 shows results from regressions of future returns on the percentage change in leverage. Dependent variables are the one-quarter ahead, two-quarter ahead, three-quarter ahead, and four-quarter ahead quarterly returns. Size controls include controls for average net asset value, and strategy controls include indicators for each broad strategy. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4.21: Leverage and Lagged Returns

	$\%\Delta Lev_t$	$\%\Delta Lev_t$	$\%\Delta Lev_t$	$\%\Delta Lev_t$
$\widetilde{R}_{q-1}$	-0.001	-0.000	0.000	0.001
	(0.024)	(0.024)	(0.024)	(0.024)
$\widetilde{R}_{q-2}$		-0.018	-0.017	-0.016
		(0.019)	(0.019)	(0.019)
$\widetilde{R}_{q-3}$			-0.012	-0.009
			(0.031)	(0.033)
$\widetilde{R}_{q-4}$				-0.039
				(0.032)
Size Controls	Yes	Yes	Yes	Yes
Strategy Controls	Yes	Yes	Yes	Yes
R^2	0.001	0.001	0.001	0.001

Table 4.21 shows results from regression of the percentage change in leverage on quarterly returns, lagged up to four quarters. Size controls include controls for average net asset value, and strategy controls include indicators for each broad strategy. Heteroskedasticity-robust standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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