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The Who and How of Hedge Fund Risk Shifting

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Why These Findings Are Important

Hedge funds use different strategies with varying levels of risk that ultimately drive returns. Fund managers attempt to meet certain performance benchmarks to attract investors and maximize their compensation. In this paper, the authors examine whether compensation incentives distort the risk choices that fund managers make. Greater risk yields either higher returns or larger losses, depending on how markets move. Because hedge funds have become large intermediaries, their risk-taking can affect the broader financial markets.

Key Findings

1. **Both the best- and worst-performing funds increase portfolio volatility relative to their peers.**

2. **Funds with lax redemption policies and concentrated ownership increase portfolio volatility more aggressively in response to underperformance.**

3. **Poorly performing managers amplify volatility with more leverage and modified asset class allocations, while top performers pursue contrarian strategies.**

How the Authors Reached These Findings

The authors analyze hedge fund risk choices and managers' compensation incentives to understand the relationship between the two. Using data from Form PF filings collected by the Securities and Exchange Commission, they find that a fund's relative and absolute performance affect future risk-taking behavior. The analysis uses regulatory filings to examine how various fund characteristics, like redemption policies and ownership structure, influence risk-taking and the channels through which funds amplify risk.

The Who and How of Hedge Fund Risk Shifting*

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Abstract

Given the emergence of hedge funds as large intermediaries whose risk-taking affects financial markets, we investigate whether compensation incentives distort the risk choices of fund managers. Using confidential supervisory data on hedge fund returns and characteristics, we find strong evidence of risk-shifting behavior consistent with managers attempting to meet performance benchmarks and maximize investor flows. Both the best- and worst-performing funds increase portfolio volatility relative to their peers, as do those below their high-water marks. Funds with permissive redemption policies and those with concentrated ownership risk shift most aggressively. Laggard managers amplify volatility by increasing leverage and modifying asset class allocations, while top performers instead pursue contrarian strategies.

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1 Introduction

The hedge fund industry has grown tremendously over the past several decades. According to commercial data vendors, the assets under management (AUM) of hedge funds recently surpassed \$4 trillion (e.g., Hedge Fund Research, 2023). As the industry has become larger, so too has its influence on the financial system. The turmoil that followed the collapses of Long-Term Capital Management in the late 1990s and Lehman Brothers during the 2007-09 financial crisis demonstrated, for instance, how distress can flow between hedge funds and their prime brokers (Chan et al., 2006; Aragon and Strahan, 2012). Given the expanding role of hedge funds as key intermediaries across multiple asset classes (Haddad and Muir, 2021; Siriwardane et al., 2022), understanding the mechanisms that govern their risk-taking behavior has become a matter of paramount importance.

The extant literature has identified several features of managerial contracts that may distort funds' investment allocations. A fund manager's compensation is typically based on a fixed percentage of assets and an additional incentive fee if returns exceed a predetermined benchmark. The convex nature of the compensation structure might induce managers to shift risk by increasing portfolio volatility following periods of underperformance (e.g., Goetzmann et al., 2003; Hodder and Jackwerth, 2007). The well-founded flow-performance relationship for hedge funds (Fung et al., 2008; Agarwal et al., 2018) has the potential to exacerbate the use of such "variance strategies," as laggard funds may take on additional risk in an attempt to stem outflows. Evidence from mutual funds suggests that top performers might also raise volatility (e.g., Hu et al., 2011), as strong relative returns attract inflows. Many contracts therefore contain measures intended to better align the incentives of managers and investors (Agarwal et al., 2009). For example, roughly 85% of funds reporting to a prominent industry data vendor in 2020 utilized high-water marks (HWMs), which require recouping losses before awarding variable pay (Eurekahedge, 2021). Despite the prevalence of such provisions, they may not fully curb excess risk taking (Panageas and Westerfield, 2009; Aragon and Nanda, 2012).

In this paper, we explore the relationship between hedge fund risk choices and the compensation incentives faced by managers. Using information from Form PF filings collected by the Securities and Exchange Commission (SEC), we show that both relative and absolute performance impact risk-taking behavior. The best- and worst-performing managers increase portfolio volatility relative to their peers as do those below their HWMs. We utilize the breadth of the regulatory filings to examine how various fund characteristics, many of which are not available through commercial data sources, influence the use of variance strategies. Our analysis reveals that permissive redemption policies and concentrated ownership increase a manager's incentive to risk shift. The richness of the data also allows us to provide direct evidence about the mechanisms by which managers alter their return volatility. We demonstrate that funds adjust their portfolio turnover rates, leverage levels, and asset class allocations following periods of underperformance. Collectively, our findings address several inconsistent empirical findings and untested theoretical predictions present in the literature.

We first investigate whether hedge funds risk shift by testing if recent performance affects the risk choices of managers. More concretely, we regress changes in volatility across the two halves of the year on midyear performance. We find that relative performance is negatively associated with risk taking, even after controlling for potential confounders, such as mean reversion in the standard deviation of returns. A fund at the bottom of the midyear performance distribution has a second-half return volatility that is 0.2% larger on average than a fund at the top. Separately considering funds in the first and fifth quintiles of cumulative midyear returns reveals that while laggard managers drive the overall effect, the best-performing funds also increase portfolio volatility. The U-shaped pattern stands in stark contrast to the results of Brown et al. (2001), who show that hedge funds with strong relative returns decrease risk-taking and that return volatility remains unchanged for poor performers. The discrepancy may be attributable to differences in our respective data sources. Brown et al. (2001) use the Lipper TASS database, which is primarily composed of smaller funds and captures a much lower share of industry AUM than the supervisory records we employ (Aiken et al., 2013; Barth et al., 2023). Moreover, funds strategically report to commercial data vendors by withholding and smoothing poor returns (e.g., Agarwal et al., 2011; Aragon and Nanda, 2017). Because the Form PF data are confidential and funds are required to file, our findings are unlikely to be as affected by strategic reporting practices.

Given the ubiquity of HWM provisions, we examine whether weak absolute performance leads to risk shifting as well. We use funds' return histories to construct a measure of their HWMs to test whether managers below this threshold at mid-year increase portfolio volatility more during the second half of the year. Our findings are similar to those of Aragon and Nanda (2012) and complementary to those of Brown et al. (2001). We show that funds under their HWM benchmarks at the end of June have monthly return standard deviations 0.2% higher than their better-performing counterparts during the latter part of the year. The result suggests that managerial incentives may lead hedge funds to amplify market turmoil as they are liable to take on additional risk following negative aggregate shocks.

After demonstrating that managers risk shift, we investigate whether fund characteristics impact the use of variance strategies. The depth of the regulatory filings enables us to explore the effects of several novel investor attributes. We show that funds with investors who can easily access their capital risk shift more aggressively than funds with stricter withdrawal restrictions. This finding is consistent with managers most concerned about performance-driven outflows choosing to raise portfolio volatility in response to poor returns. We also demonstrate that funds with concentrated ownership have a higher propensity to employ variance strategies. Because redemptions by large stakeholders are especially disruptive (Kruttli et al., 2019), these funds again have a strong incentive to avoid outflows.

We additionally test whether portfolio characteristics affect risk shifting behavior. Funds which borrow may be more responsive to underperformance than their unlevered counterparts, as they can increase volatility by scaling up positions. On the contrary, creditors may curtail excess risk-taking by imposing implicit or explicit limits on their hedge fund borrowers. In line with the latter hypothesis, we find no indication that funds that borrow are particularly disposed to employ variance strategies. Instead, levered funds risk shift less than their peers. We also show that funds below their HWMs are more inclined to raise volatility if they have a high portfolio turnover rate. Similarly, funds below their HWMs risk shift more if they are able to exit positions quickly with minimal price impact. These results indicate that managers with liquid holdings are better able to alter their risk profiles. Our findings complement those of Huang et al. (2011), which shows that illiquid mutual funds are more likely to utilize variance strategies. While there are a number of institutional differences across fund types, our results suggest that the widespread use of withdrawal restrictions by hedge funds may ease investors' concerns about payoff complementarities.

We conclude by examining the mechanisms by which managers amplify return volatility. We demonstrate that midyear performance is positively associated with heightened turnover. Funds in the bottom quintile of the return distribution decrease their average monthly turnover by 4.6 percentage points relative to their peers. This shift suggests that laggard managers may attempt to improve returns by taking on positions that are costlier to exit. The results for changes in leverage are more mixed but we find evidence that laggard managers lever up more than their better-performing counterparts. We also show that strong performers are more inclined to employ contrarian strategies. Relative to their peers, these funds decrease betas with respect to an index of industry returns produced by Eurekahedge. The effect continues to emerge when we use strategy-specific indices instead of the industry aggregate. Furthermore, top performers modify their asset class allocations less than funds with weak returns. Together, our findings suggest that managers with strong returns risk shift by altering their positions within the same asset classes, while laggard funds are more willing to change the types of securities they hold.

2 Literature Review and Hypothesis Development

Our paper adds to the literature examining how fund managers' incentives and recent performance affect their risk-taking decisions. Early theoretical work on the topic recognized that convexity in a manager's compensation structure may induce them to make suboptimal portfolio allocations from the perspective of investors (Starks, 1987; Grinblatt and Titman, 1989). Subsequent empirical studies, which primarily focused on mutual funds, posited that even symmetric compensation plans might give rise to tournament incentives due to the convex nature of the flow-performance relationship (e.g., Brown et al., 1996; Chevalier and Ellison, 1997). These papers indeed find that funds performing poorly relative to their peers at the end of June increase risk more than their peers over the latter half of the year.

As the hedge fund industry has grown, so too has the body of theoretical work investigating risk shifting incentives specific to the emergent investment vehicle. Many of these studies have identified factors that might curtail the implementation of variance strategies. Carpenter (2000) demonstrates, for example, that it may not be optimal for risk-averse managers to increase portfolio volatility in response to poor performance. Later work finds that HWMs, long-term career considerations, and personal capital stakes may also limit risk taking by underperformers (Basak et al., 2007; Panageas and Westerfield, 2009; Lan et al., 2013). On the contrary, managers with short investment horizons or strong outside options may be particularly inclined to chase incentive fees by taking on additional risk (Hodder and Jackwerth, 2007; Drechsler, 2014).

Despite the sizable number of empirical studies on mutual fund risk shifting, little work has centered on hedge funds. This gap is likely attributable to the lack of data available on the latter set of entities. Furthermore, results from the existing work on hedge funds has been mixed. Brown et al. (2001) show that funds with strong midyear returns relative to their peers decrease portfolio volatility, but they find limited evidence that poor performers employ variance strategies. They also demonstrate that managers do not adjust risk in response to absolute performance and conclude that long-term reputation concerns mitigate short-term compensation incentives. In contrast, Aragon and Nanda (2012) find that both relative and absolute midyear performance are negatively associated with future risk taking, but that these effects are dampened for funds that utilize HWMs. The study does not separately consider the best and worst performers in their benchmark specifications, so it is difficult to ascertain whether the findings on relative performance are driven by laggard funds or, as in Brown et al. (2001), those with the best returns.

Given the varied theoretical and empirical results in the extant literature, it is unclear if we should expect our sample of Form PF filers to engage in risk shifting. On one hand, these funds have large AUMs and tend to be well established, so the benefit of preserving future management fees might outweigh that of a single year of incentive pay (Lim et al., 2016; Yin and Zhang, 2023). On the other hand, PF filers are likely to be far from their liquidation thresholds and to have managers with strong reputations, so the downsides of extremely poor performance may be limited (Drechsler, 2014). Moreover, since the regulatory data are confidential, funds have less incentive to dampen volatility by smoothing or strategically reporting returns (e.g., Getmansky et al., 2004; Agarwal et al., 2013; Jorion and Schwarz, 2014) in an attempt to stem investor outflows. We therefore arrive at our first set of hypotheses:

- *H1a: Funds with poor relative midyear returns increase portfolio volatility more than their better-performing peers.*
- *H1b: Funds below their HWM at the end of June increase risk more than funds above this threshold.*

The Form PF data give us access to information about a number of novel fund characteristics, so we next investigate how these qualities affect risk shifting incentives. The mutual fund literature demonstrates that the flow-performance relationship motivates the use of variance strategies. We therefore posit that funds whose investors face stringent redemption and withdrawal restrictions will risk shift less aggressively than funds that allow investors easy access to their capital. Funds with highly concentrated ownership are likely to be similarly wary of investor outflows (Kruttli et al., 2019), so these funds are also apt to increase portfolio volatility following periods of under-performance. In contrast, prior work shows that managers who invest in their funds are less likely to distort portfolio allocations, because they share the downsides of variance (e.g., Lan et al., 2013).

The effects hedge fund borrowing might have on risk shifting behavior are decidedly less clear. Theoretical studies often assert that managers will alter return volatility by varying their use of leverage (e.g., Drechsler, 2014). Funds with established lending relationships may thus have a greater propensity to employ variance strategies than their counterparts without access to credit. Some models, however, account for the fact that borrowing from prime brokers is not frictionless (e.g., Buraschi et al., 2014). In such frameworks, managers are averse to risk shifting because prime brokers have the ability to raise collateral requirements. Managers close to their borrowing constraints seek to avoid margin calls, which potentially necessitate the costly unwinding of levered positions. Ultimately, our prior is that funds with the most borrowing will be less inclined to risk shift. We also investigate whether the length of financing impacts the use of variance strategies. Funds whose borrowing is mostly short-term may be more impaired by downturns in performance than their counterparts with longer arrangements. Alternatively, the tenor of lending terms may not matter given the stickiness of creditor relationships (Kruttli et al., 2022).

The last set of characteristics we consider pertains to portfolio construction. Evidence from studies on mutual funds suggests that illiquid holdings lead to a more concave flow-performance relationship, because investors are mindful of payoff complementarities (Chen et al., 2010). It follows that laggard hedge funds with positions that are costly to exit may have heightened incentives to increase return volatility. These motives might be moderated, however, by the widespread adoption of withdrawal restrictions (Teo, 2011). Moreover, as hedge funds may invest in extremely illiquid assets, high transaction costs and other frictions could curtail a manager's ability to reallocate capital. We therefore expect that funds with high turnover and those that can easily exit positions are more likely to employ variance strategies. All told, we hypothesize the following:

- *H2a: Funds with investors who can quickly access capital and those with concentrated investor bases employ variance strategy more aggressively. Underperforming managers with personal investments in their funds are less inclined to alter volatility.*
- *H2b: Funds that borrow and those with large amounts of leverage risk shift less intensely. The length of financing agreements has no effect on the use of variance strategies.*
- *H2c: Funds with high turnover and liquid portfolios are more inclined to risk shift.*

Our last set of predictions relates to the mechanisms by which managers could alter portfolio volatility. If laggard funds overhaul their investment allocations in search of better returns, their turnover rate is likely to increase. On the other hand, managers may increase variance by investing in more illiquid assets. Turnover is likely to decrease in this scenario as heightened transaction costs make frequently entering and exiting positions less palatable. Also, while managers operating close to their leverage constraints may have difficulty risk shifting, those with more capacity to borrow are liable to do so. Following the theoretical literature, we therefore expect that underperformers will lever up.

Prior empirical work documents that hedge funds have a tendency to style shift (Jiang et al., 2022). Managers seeking to bolster portfolio volatility may be particularly inclined to modify their investment strategies. While we do not observe security-level holdings, such changes might result in changes in funds' asset class allocations. Furthermore, a manager pursuing better returns may be more willing to employ contrarian strategies that deviate from industry indices. Thus, we predict:

- *H3a: Risk shifting managers alter their turnover rates and use of leverage.*
- *H3b: Midyear performance is associated with changes in asset class allocations and the use of contrarian strategies.*

3 Data and Summary Statistics

Our data come primarily from the SEC's Form PF, which collects information about the operations of private funds. Through the filings, we have access to quarterly fund characteristics as well as monthly returns. Form PF is intended to allow the Financial Stability Oversight Council to fulfill its monitoring obligations in accordance with the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.[1] The data are processed using a procedure similar to that of Kruttli et al. (2022). We consider only hedge funds that are mandated to submit filings each quarter and impose several data quality filters.[2] First, we assign funds to broad strategy classes based on their responses to Question 20.[3] Funds that do not provide information on their investment strategies and, due to inconsistent reporting practices, funds of funds are excluded from the sample. We then drop observations if a fund's net asset value (NAV) is either greater than its gross asset value (GAV) or less than its unencumbered cash. Finally, we exclude funds with clear reporting issues and fund-years with any missing monthly returns. We supplement the Form PF data with additional information from the SEC's Form ADV. To avoid the undue influence of outliers and any remaining reporting errors, we winsorize all unbounded, continuous variables at the 1% and 99% levels. In total, our sample consists of 10,274 fund-year observations from 2013 through 2022.

Summary statistics from the cleaned data are presented in Table 1 and additional information about variable construction is available in Appendix A. The average annual return across fund-years is 13% and the average standard deviation of monthly returns is 4%. The median NAV for funds in our sample is $1.1 billion, which is considerably larger than what is reported in studies relying on commercial databases. $AbsWin$ is a derived indicator intended to capture whether a fund is above its HWM at the end of June. Because we do not directly observe HWMs, we use the threshold measure developed by Aragon and Nanda (2012). More concretely, for each year y, we define a fund's asset level, A_y, and HWM, H_y, as:

$$A_y = A_{y-1} \times (1 + R_y^{net})$$

$$H_y = \max\{H_{y-1}, A_y\}$$

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[1] See the final rule requiring private funds to file Form PF: https://www.federalregister.gov/documents/2011/11/16/2011-28549/reporting-by-investment-advisers-to-private-funds-and-certain-commodity-pool-operators-and-commodity.

[2] Funds mandated to file quarterly are those with a NAV of at least $500 million. Advisers are required to aggregate private funds, parallel funds, dependent parallel managed accounts, and master feeder funds to determine whether the size criterion is fulfilled, but they are permitted to submit separate filings for these structures. As a result, some funds in our data have a NAV of less than $500 million. The smallest of these filers frequently leave questions unanswered, so we follow Kruttli et al. (2022) and drop funds whose NAV is less than $25 million.

[3] The broad strategy classes are credit, equity, event driven, fund of funds, macro, managed futures, multi-strategy, relative value, and other. We assign a fund to a strategy type if at least 75% of its assets are allocated to that broad class. If no single class meets this threshold, we classify the fund as multi-strategy.

where R_y^{net} is the annual net-of-fees return. Funds are assumed to initially be at their HWM, so $A_0 = H_0 = 1$. We then set $AbsWin$ equal to one if a fund is above its HWM from the preceding December at midyear and zero otherwise.

[Table 1 about here.]

The remainder of the variables are fund and portfolio characteristics that may moderate the use of variance strategies. The first set of these measures pertain to investors. *ManagerStakeInd* is an indicator equal to one if the manager has a stake in the fund and *Top5Stake* is the total equity stake of the five investors with the largest ownership shares. The means of these variables demonstrate that managers frequently hold stakes in Form PF filers and that ownership of these funds is highly concentrated despite their size. To gauge investor liquidity, we define *InvestorLiq* as the proportion of a fund's NAV that can be withdrawn or redeemed by investors within 30 days. This window length is motivated by Teo (2011), who classifies funds that allow for monthly redemptions as having favorable redemption terms. As evidenced by the median value of zero, many funds impose lockup periods or other restrictions that preclude investors from accessing their capital in short order.

The next group of variables is related to borrowing and leverage. *BrrwInd* is an indicator equal to one if the fund does any borrowing in a given year. For funds that do borrow, *FinLiq* is the proportion of financing with a term of at most 30 days. While hedge funds are known to use overnight repurchase agreements, the mean value of 69% indicates that an appreciable number relies on longer-term credit. To measure leverage, we define *LevGNE* as a fund's total gross notional exposure (GNE) divided by its NAV. We include both balance sheet assets and off-balance sheet exposures in the GNE metric. Form PF filers use a substantial amount of leverage on average, but the distribution is right skewed.

The final set of variables describes investment allocations. *TurnoverRate* is a fund's average monthly turnover divided by its GNE. As evidenced by the distance between the mean and median, this measure has a heavy right tail. *DerivUser*, which is an indicator equal to one if the fund has derivative positions, reveals that a large majority of funds in the sample use derivatives. For consistency, our measure of portfolio liquidity, *PortLiq*, is defined as the proportion of a fund's portfolio that can be sold at or near its carrying value within 30 days. The mean value of 74%

suggests that hedge funds can unwind most of their positions in less than a month with minimal price impact, but that they do also hold illiquid assets.

4 Results

In this section, we test our main hypotheses regarding hedge fund risk shifting. Following the extant literature, we explore whether funds' mid-year performance explains changes in return volatility over the second half of the year. We also investigate how certain fund characteristics, such as investor liquidity, leverage, and derivative usage moderate the use of variance strategies. Finally, we study the association between mid-year performance and investment allocations to shed light on the mechanisms by which hedge funds risk shift.

4.1 Baseline Specifications

To facilitate comparison with prior studies, we employ an empirical framework similar to that of Aragon and Nanda (2012). Formally, we estimate the regression:

$$\Delta\text{Risk}_{i,y} = \alpha_y + \gamma_{s(i)} + \beta_1\text{Perf}_{i,y} + \beta_2\text{LagRisk}_{i,y} + \beta_3\Delta\rho_{i,t} + \beta_4\text{Flow}_{i,t} + \epsilon_{i,t} \tag{1}$$

where $\Delta\text{Risk}_{i,y}$ is the difference between the standard deviations of fund i's gross returns in the second and first halves of the year y, $\text{Perf}_{i,y}$ is a measure of midyear performance, $\text{LagRisk}_{i,y}$ is the standard deviation of gross returns in the first half of the year, $\Delta\rho_{i,t}$ is the change in the autocorrelations of gross returns between the two halves of the year, $\text{Flow}_{i,t}$ is percentage of net flow during the last six months of the year, α_y is a year fixed effect, and $\gamma_{s(i)}$ is a strategy fixed effect. Standard errors are clustered by fund to account for correlation across time. As noted in Section 3, unbounded, continuous variables are winsorized at the 1% and 99% levels to avoid the undue influence of outliers and reporting errors.

We use three measures of performance in the analysis that follows: RelRank, RelQuintile, and AbsWin. RelRank, which captures relative performance, is defined as the percentile rank of a fund's cumulative return in the first half of a given year. The variable falls in the interval $(0, 1]$ and takes on larger values for better performers, so a negative regression coefficient implies that laggard funds increase variance more than their peers. RelQuintile separates funds into quintiles based on their midyear performance, which allows us to differentiate behavior at the top (TopQntl) and bottom (BtmQntl) of the return distribution. Finally, to capture the effects of absolute performance, we use the AbsWin variable, which equals one if a fund is above its HWM at midyear and zero otherwise. Again, a negative coefficient indicates that funds increase risk when they are below their HWM benchmark.

The remaining regressors serve as controls. The inclusion of the LagRisk variable ensures that the results are not driven by mean reversion in volatility (e.g., Kempf and Ruenzi, 2008). We account for changes in return autocorrelation, $\Delta\rho$, so return smoothing (e.g., Getmansky et al., 2004) does not contaminate our estimates. Lastly, the flow measure, Flow, accounts for changes in performance that may arise solely due to outflows (e.g., Koski and Pontiff, 1999).

Results from the baseline specifications are presented in Table 2. Columns 1 and 2 show that, as in Aragon and Nanda (2012), poor absolute performance leads to risk shifting. The standard deviation of monthly returns increases 0.1% more over the latter half of the year for funds below HWMs at the end of June than for their peers. The coefficients on RelRank in Columns 3 and 4 are negative and significant, consistent with laggard funds engaging in risk shifting. A drop from the top to the bottom relative performance rank corresponds to a 0.2% increase in monthly return standard deviation during the second half of the year. Switching from the continuous rank measure to quintiles suggests a U-shaped pattern in the use of variance strategies, with the poorest performers increasing volatility the most. These results stand in stark contrast to those of Brown et al. (2001), which finds little change in risk for laggard funds and a decrease in volatility for those with the strongest returns. The discrepancies may stem from a variety of factors, such as strategic reporting to commercial databases, changes in industry practices over time, or heterogeneity in the set of funds captured by our respective samples.

[Table 2 about here.]

To affirm the presence of a U-shaped relation between relative midyear performance and changes in volatility, we re-estimate Equation 1 with quintile indicators and plot the results in Figure 1. Each coefficient is relative to the omitted median quintile and the vertical lines represent 95% confidence intervals for the estimates. The figure demonstrates that risk shifting is most pronounced for funds at the tails of the midyear performance distribution. The pattern continues to emerge when we separate funds into septiles or deciles and all of the results in Table 2 hold under a host of alternate specifications, including those with different controls and winsorization thresholds. Though our findings complement the hedge fund literature, they align with existing work on mutual funds (e.g., Hu et al., 2011). These studies posit that significantly underperforming managers are likely to be fired and therefore choose to increase risk in hopes of staving off termination. In contrast, overperforming managers are secure in their roles and, thus, look to benefit from the convexity in their payoff structure.

[Figure 1 about here.]

4.2 Partitioning by Year and Strategy

We next investigate whether the baseline estimates are stable across time and broad strategy classes. To do so, we first omit the time fixed effects and re-estimate Equation 1 separately for each year in our sample. The results are presented in Table 3. For brevity, coefficient estimates on the set of control variables are not reported. The point estimates in the AbsWin and RelRank columns are negative in most periods and, despite the reduced sample sizes, statistically significant in multiple years. The BtmQntl column exhibits a similar consistency, but the TopQntl estimates are slightly mixed. All told, partitioning the sample by year indicates that no single period drives our baseline results.

[Table 3 about here.]

To determine whether particular fund styles are more inclined to risk shift, we partition the sample by strategy and repeat the previous exercise. Results are presented in Table 4, with coefficient estimates for the control variables once again omitted. The point estimates on AbsWin are negative across nearly all strategy classes and especially sharp for equity and event driven funds. A similar pattern emerges for RelRank, though the Other category is also statistically significant. Underperformers in many strategy classes increase portfolio volatility in the second half of the year, but among top performers, the behavior is primarily limited to macro, multi-strategy, and relative value funds.

[Table 4 about here.]

4.3 Effects of Fund Characteristics

A number of fund characteristics have been shown to affect hedge fund risk taking and the flow-performance relationship (e.g., Agarwal et al., 2009; Teo, 2011). We therefore next study whether certain attributes also affect the use of variance strategies. To start, we consider the influence of investor characteristics. In particular, we test whether concentrated ownership, managerial equity stakes, and short redemption periods make funds more likely to risk shift. Formally, we estimate the baseline regression model with an extra term for the characteristic of interest as well as an interaction between this variable and the midyear performance measure:

$$
\begin{aligned}
\Delta\text{Risk}_{i,y} = & \alpha_y + \gamma_{s(i)} + \beta_1 \text{Perf}_{i,y} + \beta_2 \text{LagChar}_{i,y} + \beta_3 \text{Perf}_{i,y} \times \text{LagChar}_{i,y} \\
& + \beta_4 \text{LagRisk}_{i,y} + \beta_5 \Delta\rho_{i,t} + \beta_6 \text{Flow}_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

where $LagChar_{i,y}$ is the value of the characteristic of interest at the end of June and the other variables are defined as before. We continue to cluster standard errors by fund and winsorize unbounded, continuous variables at the 1% and 99% levels.

Results are presented in Table 5. The interaction terms in Columns 1 and 2 between investor liquidity, which is defined as the proportion of a fund's NAV that can be withdrawn or redeemed by investors within 30 days, and the performance measures are negative and significant, amplifying the negative association between midyear returns and risk taking. They demonstrate that under-performing managers are more inclined to risk shift when investors can easily access their capital. The positive coefficient on the BtmQntl interaction term in Column 3 implies that the pooled interaction effect in Column 2 is driven by the laggards. A fund in the lowest quintile of midyear returns whose investors can withdraw all their funds within a month increases monthly portfolio volatility 0.2% more, on average, than a comparable fund with investors that cannot withdraw any funds in this time frame. In contrast, the top quintile interaction term is insignificant. The results accord with the notion that managers most concerned about redemptions induced by bad performance have the strongest incentive to employ variance strategies.

[Table 5 about here.]

The middle columns of Table 5 pertain to the concentration of fund ownership. The main effects of AbsWin and RelRank are positive and insignificant in these specifications, but the negative interaction terms between $Top5Stake$ and the midyear performance measures in Columns 4 and 5 demonstrate that the incentive for underperformers to risk shift increases with the share of equity held by the five investors with the largest stakes. Separating the top and bottom performers reveals that the total interaction effect is driven by laggard funds. The findings align with Kruttli et al. (2019), who show that funds with highly concentrated ownership are liable to face disruptive outflows.

In the final third of Table 5, we consider the impact of managers holding stakes in their funds. Columns 7 and 8 show that, consistent with Aragon and Nanda (2012) and Lan et al. (2013), the associations between both absolute and relative midyear performance and changes in volatility are weakened when managers have personal capital invested. Column 9 suggests, however, that the pooled effect on relative returns is due primarily to well-performing funds increasing variance more if managers hold an equity stake and not better incentive alignment for poor performers.

We next investigate whether leverage and borrowing characteristics alter the propensity to risk shift. Results are presented in Table 6. The positive interaction terms in Columns 1 and 2 dampen the main effects, demonstrating that managers who borrow are less inclined to employ variance strategies when their performance is weak. Borrowing funds below their HWMs at the end of June increase monthly portfolio volatility 0.1% less over the second half of the year, on average, than their counterparts that do not borrow. The estimates accord with credit-constrained funds being less able to risk shift, perhaps because they are forced to deleverage or because of monitoring by their creditors.

[Table 6 about here.]

The middle three columns of Table 6 include our primary measure of leverage. The AbsWin and RelRank interaction terms are again positive, though only the latter is statistically significant. Results are similar when we consider only balance sheet assets or use the natural logarithm of leverage. Taken together, Columns 1-6 concretely demonstrate that levered funds do not risk shift more than their unlevered counterparts. If anything, these funds appear to employ variance strategies less aggressively than their peers. In the final third of Table 6, we investigate how financing terms impact a manager's ability to increase volatility in response to underperformance. Consistent with the stickiness of creditor relationships (Kruttli et al., 2022), we find no evidence that the intensity of risk shifting depends on the tenor of financing.

The last set of characteristics we study pertains to portfolio composition. In Columns 1 and 2 of Table 7, the positive derivatives usage interaction terms attenuate the negative association between performance and fund risk. For example, a shift from the top to the bottom of the midyear return distribution is associated with a 0.8% smaller increase in the standard deviation of monthly returns for derivatives users compared to funds that do not hold such products. The estimates appear to align with (Chen, 2011), who shows that managers employing derivatives are less inclined to utilize variance strategies. Decomposing the relative effect reveals that laggard derivatives users decrease volatility more than their counterparts, while the best performers that hold derivatives actually take on comparatively more risk. Derivatives usage therefore appears to be a double-edged sword as it facilitates both hedging and risk taking.

[Table 7 about here.]

The middle three columns of Table 7 display results from specifications that include Turnover-Rate, which is defined as average monthly turnover divided by GNE. The negative interaction terms in Columns 4 and 5 compound the main effects, indicating that funds with large amounts of turnover risk shift more intensely than their peers. Columns 7-9 consider interaction terms between the performance measures and portfolio liquidity, which is the share of positions that can be unwound in at most 30 days with no price impact. Funds with liquid portfolios appear likelier than their peers to increase volatility when they are below their HWMs. Relative performance does not elicit a differential response. These results are robust to shortening the unwinding period and complement the mutual fund literature demonstrating that managers with illiquid holdings are more inclined to risk shift (Huang et al., 2011). Our findings suggest that the pervasive use of redemption restrictions may ease investors' concerns about payoff complementarities.

4.4 Investment Allocations

In the prior subsections, we established that fund managers shift risk in response to poor absolute and relative performance, and that the intensity of this response is governed by certain fund characteristics. We now study the mechanisms by which managers amplify portfolio volatility. We first test whether midyear returns are associated with modifications in leverage and turnover. To do so, we regress changes in these characteristics on our performance measures. More specifically, we estimate regressions of the following form:

$$\Delta Char_{i,y} = \alpha_y + \gamma_{s(i)} + \beta_1 \text{Perf}_{i,y} + \beta_2 LagChar_{i,y} + \beta_2 LagRisk_{i,y} + \beta_3 \Delta\rho_{i,t} + \beta_4 \text{Flow}_{i,t} + \epsilon_{i,t} \quad (3)$$

where $\Delta Char_{i,y}$ is the change of the given characteristic for fund i between the first and second halves of the year and the other variables are defined as before. Standard errors remain clustered by fund, and we continue to winsorize unbounded, continuous measures at the 1% and 99% levels.

Results are presented in Table 8. The dependent variable in the first three columns is the percentage change in average monthly turnover. We therefore consider only funds that report some turnover in the first half of a given year. Columns 1 and 2 indicate that fund performance is positively associated with trading volume. Managers above their HWMs at midyear increase turnover 2.6 percentage points more than their counterparts. Separating the top and bottom quintiles of relative performance demonstrates that the total effect stems primarily from laggard funds transacting less.

[Table 8 about here.]

The dependent variable in the second three columns is the difference in leverage across the two halves of the year. Though the point estimates on the focal measures are negative, Columns 4 and 5 reveal no statistically significant association between midyear performance and leverage changes. Decomposing the relative performance variable indicates, however, that the worst performers increase leverage 10 percentage points more than their peers during the second half of the year. This result accords with managers levering up when attempting to amplify returns. The corresponding coefficient is negative, but statistically insignificant when we consider only balance sheet leverage (i.e., GAV divided by NAV), suggesting that off-balance sheet assets facilitate risk shifting.

We next test for an association between midyear performance and percentage changes in derivatives exposures. Because different products may be used for different purposes, we estimate Equation 3 separately for each class of derivatives. Coefficient estimates on the focal performance measures are presented in Table 9. When all derivatives are pooled together, we find no evidence that laggard funds change their positions in an attempt to improve returns. Results are similarly weak across classes, with the exception of credit products. It appears that the best performing funds increase their holdings of credit default swaps.

[Table 9 about here.]

Funds may also increase return volatility by altering the types of securities they hold. To investigate this possibility, we utilize Questions 26 and 30 of Form PF, which measure firms' long and short holdings in a wide variety of asset classes. Using these positions, we compute the cosine similarity between exposures at the end of June and the end of December for every firm-year in the sample. We then estimate Equation 3 without the LagChar term using cosine similarity as the dependent variable. The first half of Table 10 reports results when we do not aggregate long and short positions of the same class. Larger cosine similarity values correspond to holdings that are more alike so the positive coefficients in Columns 1 and 2 indicate that worse performing funds alter their portfolios more during the second half of the year. Decomposing the estimate for relative performance reveal that top performers drive the effect. In Columns 3-6, we repeat the exercise but sum long and short exposures for each security type. The coefficients are very similar across specifications. Taken together, the results in Tables 8 and 10 suggest that managers with strong returns risk shift by turning over their positions within a given asset class, while laggard funds are more willing to alter the types of securities they hold.

[Table 10 about here.]

In the final set of tests, we examine whether midyear performance is associated with the use of contrarian strategies. We first compute the beta of each fund with respect to the flagship Eurekahedge Hedge Fund Index, an equal-weighted index composed of more than 3,000 constituent funds, in each half year. We then estimate Equation 3 with the change in beta as the dependent variable. Results are presented in Table 11. We observe significant negative coefficients in Columns 1 and 2, consistent with better performing funds deviating more from their peers during the second half of the year. Column 3 reveals a contrast in the extremes of the return distribution. Betas for laggard funds increase while the returns of top performers correlate less strongly with those of the index.

[Table 11 about here.]

Because hedge funds employ a broad array of styles, we repeat the prior exercise using more refined indices. To do so, we first pair the strategy classes listed in Q20 of Form PF with style indices from Eurekahedge.[4] We then use the strategy weights provided in Q20 to construct fund-specific weighted averages of the Eurekahedge style indices. If a Form PF Q20 strategy does not correspond to a Eurekahedge style index, we allocate the corresponding weight to the flagship Eurekahedge Hedge Fund Index. Finally, we compute the beta of each fund with respect to its strategy weighted average index in each half year and estimate Equation 3 with the change in beta as the dependent variable. The middle third of Table 11 contains results from these regressions. The results are very similar to those from the prior specifications, indicating that the findings are not due to the use of an unrelated reference index. Finally, we conduct tests using the standard equity market factor. The absolute return measure no longer loads significantly, but the AbsWin coefficient remains negative and statistically significant.

5 Conclusion

In this paper, we study whether convex payoff structures induce hedge fund managers to risk shift. Using confidential data from the SEC's Form PF, we find a strong association between midyear performance and the use of variance strategies. Complementary to prior studies, we show that poorly performing funds, both in an absolute and relative sense, increase return volatility more than their peers over the second half of the year. Funds at the top of the midyear return distribution appear to take on more risk as well. We demonstrate that certain characteristics moderate the propensity to risk shift. In particular, funds that are susceptible to investor outflows and those with high portfolio turnover are more inclined to increase return variance in response to underperformance. We also investigate the mechanisms by which managers risk shift. Laggard

[4] In particular, we use the equity market neutral, equity long-short, equity long bias, event driven, fixed income, macro, managed futures, and relative value indices.

funds are inclined to alter the types of securities they hold, while strong performers pursue more contrarian strategies without changing their asset class composition.

Our findings illustrate that compensation considerations distort managers' portfolio allocation decisions. Hedge funds' tendency to increase return variance when they are below HWMs suggests the volatility of the industry as a whole is liable to increase following negative aggregate shocks. Given the expanding role of hedge funds in financial markets, such excess risk taking may propagate systemic turmoil. The departures of our results from earlier work also highlight that the incentives and constraints of funds reporting to commercial databases may be vastly different than those of the larger, more established funds that do not.

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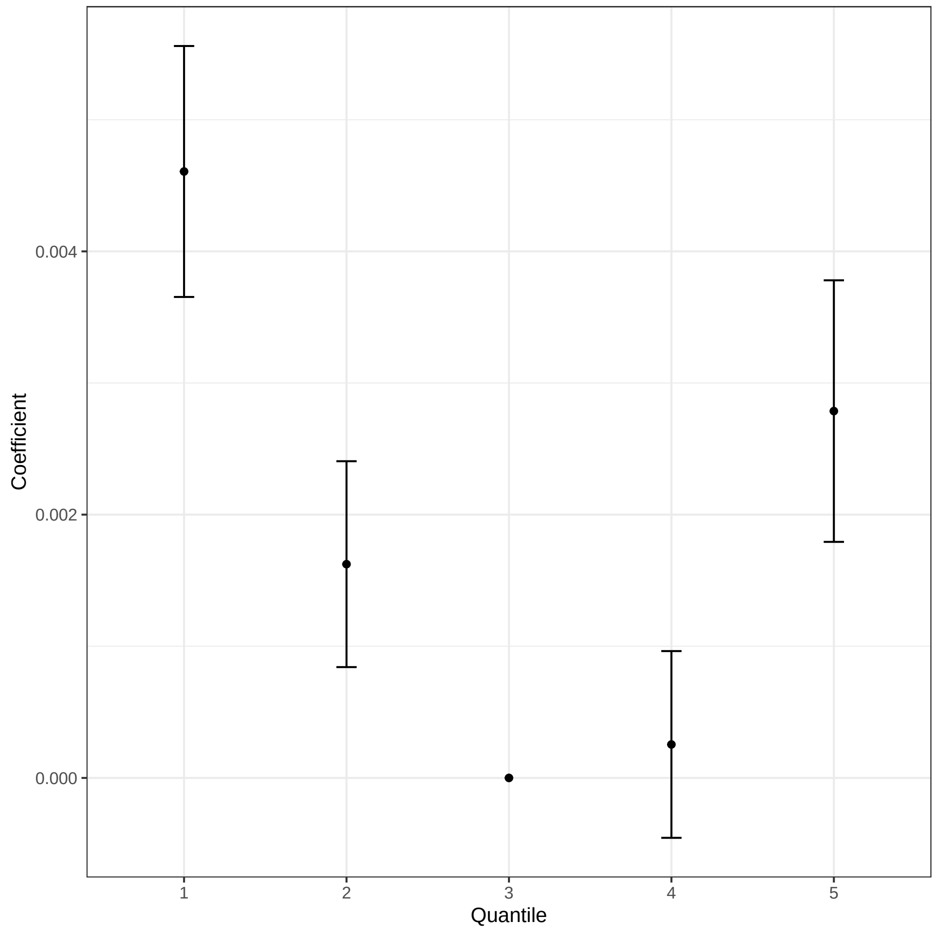
Figure 1: Relative Performance Coefficients by Quintile



Notes: This figure depicts results when Equation 1 is estimated using RelQuintile as the risk measure. The dependent variable is the change in the standard deviation of returns for a given fund between the two halves of the year. The plotted coefficients are relative to the omitted median quintile. The vertical lines represent 95% confidence intervals based on standard errors clustered by fund. Source: SEC Form PF, Authors' analysis.

Table 1: Summary Statistics

Variable	Observations	Mean	Std.Dev	Median
Annual Gross Ret.	10,274	0.13	0.42	0.08
Volatility	10,274	0.04	0.03	0.03
NAV ($1 bn)	10,274	2.13	3.65	1.07
AbsWin	10,274	0.63	0.48	1.00
MgrStakeInd	9,991	0.73	0.44	1.00
Top5Stake	10,274	63.47	27.91	61.00
InvestorLiq	10,274	24.66	41.82	0.00
BrrwInd	10,274	0.73	0.44	1.00
LevGNE	10,274	5.00	10.46	2.04
FinancingLiq	7,516	68.89	41.42	100.00
DerivsInd	10,274	0.88	0.32	1.00
TurnoverRate	10,259	25.63	94.69	1.23
PortfolioLiq	10,274	74.18	34.46	93.00

Notes: This table reports summary statistics from the 10,274 fund-year observations in our cleaned sample. *Annual Return* is the yearly gross return based on compounded monthly returns. *Return Volatility* is the standard deviation of monthly gross returns. *AbsWin* is an indicator equal to one if the fund is above its HWM at the end of June. *NAV* is the net asset value of the fund. *Leverage* is defined as a fund's gross net exposure (GNE) divided by its NAV. *Borrower* is an indicator equal to one if the fund borrows from creditors. *FundingLiq* is the percentage of a fund's borrowing that has a maturity of at most 30 days. *PortLiq* is the percentage of a fund's NAV that can be sold within 30 days without causing price movements. *TurnoverRate* is a fund's average monthly turnover divided by its GNE. *DerivUser* is an indicator equal to one if the fund uses derivatives. *InvestorLiq* is the percentage of a fund's NAV that can be withdrawn or within 30 days. *Top 5 Share* is the percentage of a fund's NAV held by the five investors with the largest equity shares. *ManagerStake* is an indicator equal to one if the manager has an equity stake in the fund. All unbounded, continuous variables are winsorized at the 1% and 99% levels. Source: SEC Form ADV, SEC Form PF, Authors' analysis.

Table 2: Midyear Performance and Changes in Risk

	(1)	(2)	(3)	(4)	(5)	(6)
AbsWin	-0.001^{***}	-0.001^{***}				
	(0.0004)	(0.0004)				
RelRank			-0.002^{***}	-0.002^{***}		
			(0.001)	(0.001)		
BtmQntl					0.004^{***}	0.004^{***}
					(0.0004)	(0.0004)
TopQntl					0.002^{***}	0.002^{***}
					(0.0005)	(0.0005)
LagRisk	-0.474^{***}	-0.479^{***}	-0.470^{***}	-0.476^{***}	-0.486^{***}	-0.493^{***}
	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
$\Delta\rho$		0.002^{***}		0.002^{***}		0.002^{***}
		(0.0003)		(0.0003)		(0.0003)
Flow		0.001		0.001		0.002
		(0.001)		(0.001)		(0.001)
Observations	10,274	10,142	10,274	10,142	10,274	10,142
R^2	0.460	0.465	0.460	0.465	0.464	0.470

Notes: This table reports results from Equation 1. The dependent variable is the change in the standard deviation of returns for a given fund between the two halves of the year. The focal variables measure relative (RelRank, TopQntl, BtmQntl) and absolute (AbsWin) performance at mid-year. All specifications include year and style fixed effects. The volatility and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis.

Table 3: Midyear Performance and Changes in Risk by Year

Year	Observations	AbsWin	RelRank	BtmQntl	TopQntl
2013	772	-0.00334^{*}	-0.00152	0.00367^{**}	0.00263^{**}
		(0.00172)	(0.00238)	(0.0015)	(0.00126)
2014	905	-0.00124	0.00153	0.00145	0.00366^{***}
		(0.00132)	(0.00172)	(0.00111)	(0.00107)
2015	1000	0.00034	0.00095	-0.00158	-0.00118
		(0.00095)	(0.00174)	(0.00109)	(0.00124)
2016	1018	0.00106	-0.00173	0.00401^{***}	0.00247^{**}
		(0.0007)	(0.00163)	(0.00107)	(0.00098)
2017	1040	-0.0039^{***}	-0.0044^{***}	0.00483^{***}	0.00181^{*}
		(0.00092)	(0.00168)	(0.00116)	(0.00093)
2018	1093	-0.00168^{*}	-0.00233	0.00221^{*}	0.00099
		(0.00094)	(0.00168)	(0.00114)	(0.00121)
2019	1082	-0.00321^{***}	-0.00851^{***}	0.00503^{***}	-0.00188
		(0.00119)	(0.00239)	(0.0012)	(0.00163)
2020	985	0.00284^{**}	0.0062^{**}	0.00193	0.00636^{***}
		(0.0013)	(0.00268)	(0.00159)	(0.00172)
2021	1126	-0.00073	0.00304	0.00013	0.00331^{**}
		(0.00129)	(0.00208)	(0.00138)	(0.00165)
2022	1121	-0.00821^{***}	-0.02493^{***}	0.01461^{***}	-0.00527^{***}
		(0.00115)	(0.00252)	(0.002)	(0.00139)

Notes: This table reports results when Equation 1 is estimated separately for each year in the sample. The dependent variable is the change in the standard deviation of returns for a given fund between the two halves of the year. Only coefficients on the focal midyear performance measures are displayed. The volatility and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis.

Table 4: Midyear Performance and Changes in Risk by Strategy

Strategy	Observations	AbsWin	RelRank	BtmQntl	TopQntl
Credit	719	-0.00291^{*}	-0.00102	0.00134	0.00044
		(0.00166)	(0.00151)	(0.00108)	(0.00099)
Equity	3502	-0.00245^{***}	-0.00311^{***}	0.00124	-0.00055
		(0.00067)	(0.00115)	(0.00077)	(0.0008)
Event Driven	962	-0.00533^{***}	-0.007^{***}	0.00847^{***}	0.00191
		(0.00179)	(0.00263)	(0.00214)	(0.00156)
Macro	557	-0.00202	-0.00023	0.003	0.00357^{**}
		(0.00164)	(0.0032)	(0.00191)	(0.00158)
Managed Futures	212	0.00295	0.00493	0.00129	0.00418
		(0.00268)	(0.00481)	(0.00349)	(0.00328)
Multi-Strategy	1811	-0.0007	0.00076	0.00405^{***}	0.00518^{***}
		(0.00084)	(0.00114)	(0.00088)	(0.001)
Other	1528	-0.00029	-0.00428^{***}	0.00302^{***}	-0.00033
		(0.00083)	(0.00136)	(0.00097)	(0.00108)
Relative Value	851	-0.00054	0.00097	0.00298^{***}	0.00333^{***}
		(0.00123)	(0.00138)	(0.00081)	(0.00087)

Notes: This table reports results when Equation 1 is estimated separately for each broad strategy class. The dependent variable is the change in the standard deviation of returns for a given fund between the two halves of the year. Only coefficients on the focal midyear performance measures are displayed. The volatility and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis.

Table 5: Midyear Performance and Changes in Risk: Investor Characteristics

	InvLiq			Top5Stake			MgrStakeInd		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AbsWin	−0.0002			0.001			−0.003***		
	(0.0005)			(0.001)			(0.001)		
AbsWin x LagChar	−0.00003***			−0.00004***			0.003***		
	(0.00001)			(0.00001)			(0.001)		
RelRank		−0.001*			0.002			−0.005***	
		(0.001)			(0.002)			(0.001)	
RelRank x LagChar		−0.00003**			−0.0001***			0.004***	
		(0.00001)			(0.00002)			(0.001)	
BtmQntl			0.003***			0.002			0.005***
			(0.001)			(0.001)			(0.001)
TopQntl			0.002***			0.004***			0.001
			(0.001)			(0.001)			(0.001)
BtmQntl x LagChar			0.00002**			0.00004**			−0.001
			(0.00001)			(0.00002)			(0.001)
TopQntl x LagChar			0.00000			−0.00003			0.002*
			(0.00001)			(0.00002)			(0.001)
LagChar	0.00005***	0.00004***	0.00002***	0.00003***	0.00005***	0.00001	−0.003***	−0.004***	−0.002***
	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.001)	(0.001)	(0.0004)
LagRisk	−0.480***	−0.478***	−0.495***	−0.480***	−0.477***	−0.494***	−0.482***	−0.479***	−0.496***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$\Delta\rho$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Flow	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10,142	10,142	10,142	10,142	10,142	10,142	9,859	9,859	9,859
R^2	0.468	0.468	0.473	0.465	0.466	0.470	0.470	0.471	0.475

Notes: This table reports results from Equation 2 using the characteristics listed in the column headings. The dependent variable is the change in the standard deviation of returns for a given fund between the two halves of the year. The focal variables measure relative (RelRank, TopQntl, BtmQntl) and absolute (AbsWin) performance at mid-year. All specifications include year and style fixed effects. The volatility and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form ADV, SEC Form PF, Authors' analysis.

Table 6: Midyear Performance and Changes in Risk: Borrowing Characteristics

	BrrwInd			LevGNE			FinancingLiq		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AbsWin	−0.002***			−0.002***			−0.001		
	(0.001)			(0.0004)			(0.001)		
AbsWin x LagChar	0.001*			0.00004			−0.00001		
	(0.001)			(0.00004)			(0.00001)		
RelRank		−0.005***			−0.003***			−0.001	
		(0.001)			(0.001)			(0.001)	
RelRank x LagChar		0.004***			0.0002**			0.00000	
		(0.002)			(0.0001)			(0.00002)	
BtmQntl			0.004***			0.004***			0.005***
			(0.001)			(0.001)			(0.001)
TopQntl			0.001			0.002***			0.002**
			(0.001)			(0.001)			(0.001)
BtmQntl x LagChar			−0.0003			−0.0001			−0.00000
			(0.001)			(0.00005)			(0.00001)
TopQntl x LagChar			0.002			0.0001			0.00001
			(0.001)			(0.0001)			(0.00001)
LagChar	−0.003***	−0.004***	−0.003***	0.00000	−0.00005	0.00003	0.00002**	0.00002	0.00002***
	(0.001)	(0.001)	(0.0005)	(0.00004)	(0.00004)	(0.00002)	(0.00001)	(0.00001)	(0.00000)
LagRisk	−0.481***	−0.478***	−0.495***	−0.479***	−0.476***	−0.493***	−0.505***	−0.502***	−0.525***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)
$\Delta\rho$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.001***	0.001***	0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Flow	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10,142	10,142	10,142	10,142	10,142	10,142	7,442	7,442	7,442
R^2	0.467	0.468	0.472	0.465	0.466	0.470	0.476	0.476	0.483

Notes: This table reports results from Equation 2 using the characteristics listed in the column headings. The dependent variable is the change in the standard deviation of returns for a given fund between the two halves of the year. The focal variables measure relative (RelRank, TopQntl, BtmQntl) and absolute (AbsWin) performance at mid-year. All specifications include year and style fixed effects. The volatility, leverage, and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis.

Table 7: Midyear Performance and Changes in Risk: Portfolio Characteristics

	DerivsInd			TurnoverRate			PortfolioLiq		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AbsWin	−0.005***			−0.001***			0.001		
	(0.001)			(0.0004)			(0.001)		
AbsWin x LagChar	0.004***			−0.00001**			−0.00003**		
	(0.001)			(0.00000)			(0.00001)		
RelRank		−0.010***			−0.002***			−0.004**	
		(0.002)			(0.001)			(0.002)	
RelRank x LagChar		0.008***			−0.00002***			0.00002	
		(0.002)			(0.00001)			(0.00002)	
BtmQntl			0.008***			0.004***			0.003**
			(0.001)			(0.0005)			(0.001)
TopQntl			−0.0004			0.003***			0.001
			(0.001)			(0.0005)			(0.001)
BtmQntl x LagChar			−0.005***			−0.00000			0.00002
			(0.001)			(0.00000)			(0.00001)
TopQntl x LagChar			0.003**			−0.00002***			0.00002
			(0.001)			(0.00000)			(0.00002)
LagChar	−0.005***	−0.007***	−0.002***	0.00001**	0.00001***	0.00001***	0.00002**	−0.00001	−0.00000
	(0.001)	(0.001)	(0.001)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)
LagRisk	−0.481***	−0.477***	−0.494***	−0.479***	−0.476***	−0.494***	−0.479***	−0.477***	−0.493***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)
$\Delta\rho$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Flow	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10,142	10,142	10,142	10,127	10,127	10,127	10,142	10,142	10,142
R^2	0.467	0.468	0.472	0.465	0.466	0.471	0.465	0.465	0.470

Notes: This table reports results from Equation 2 using the characteristics listed in the column headings. The dependent variable is the change in the standard deviation of returns for a given fund between the two halves of the year. The focal variables measure relative (RelRank, TopQntl, BtmQntl) and absolute (AbsWin) performance at mid-year. All specifications include year and style fixed effects. The volatility, turnover, and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis.

Table 8: Midyear Performance and Changes in Turnover and Leverage

	Turnover			LevGNE		
	(1)	(2)	(3)	(4)	(5)	(6)
AbsWin	0.026**			−0.044		
	(0.012)			(0.047)		
RelRank		0.057***			−0.097	
		(0.018)			(0.072)	
BtmQntl			−0.048***			0.106**
			(0.015)			(0.052)
TopQntl			0.003			0.019
			(0.013)			(0.059)
LagChar	−0.000***	−0.000***	−0.000***	−0.039***	−0.039***	−0.039***
	(0.000)	(0.000)	(0.000)	(0.008)	(0.008)	(0.008)
LagRisk	−0.313	−0.362	−0.248	−2.826***	−2.746***	−3.082***
	(0.262)	(0.258)	(0.266)	(1.011)	(0.999)	(1.043)
$\Delta\rho$	0.038***	0.038***	0.039***	0.014	0.014	0.013
	(0.010)	(0.010)	(0.010)	(0.037)	(0.038)	(0.038)
Flow	0.163***	0.167***	0.163***	−0.950***	−0.956***	−0.943***
	(0.028)	(0.028)	(0.028)	(0.126)	(0.126)	(0.127)
Observations	10,044	10,044	10,044	10,142	10,142	10,142
R^2	0.032	0.033	0.033	0.051	0.052	0.052

Notes: This table reports results from Equation 3. The dependent variables are the difference in leverage and the percentage change in turnover for a given fund between the two halves of the year. The focal variables measure relative (RelRank, TopQntl, BtmQntl) and absolute (AbsWin) performance at mid-year. All specifications include year and style fixed effects. The dependent, volatility, and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis.

Table 9: Midyear Performance and Changes in Derivatives Exposures

Year	Observations	AbsWin	RelRank	BtmQntl	TopQntl
All	8916	−0.00869	−0.00503	0.01742	0.07152*
		(0.04062)	(0.05771)	(0.04634)	(0.04225)
Commodity	2389	−0.06868	0.34084	0.15456	0.26881
		(0.17523)	(0.26748)	(0.21439)	(0.22102)
Credit	3966	0.13245**	0.22596**	−0.09536	0.18276**
		(0.05787)	(0.08907)	(0.05893)	(0.07824)
Equity	7192	0.14489	0.27985*	−0.11083	0.15714
		(0.09367)	(0.15423)	(0.11198)	(0.11467)
Foreign Exchange	6869	0.06335	−0.19835*	0.02529	−0.10488
		(0.07231)	(0.11164)	(0.09848)	(0.07426)
Interest Rate	3868	−0.15928	−0.15168	0.15146	−0.00775
		(0.17952)	(0.24337)	(0.20605)	(0.20905)
Other	2091	−0.30685	0.4075	0.8685	1.67526**
		(0.52132)	(0.95502)	(0.65085)	(0.74308)

Notes: This table reports results when Equation 3 is estimated separately for each derivatives class. The dependent variable is the percentage change in derivatives exposures for a given fund between the two halves of the year. Only coefficients on the focal midyear performance measures are displayed. The dependent, volatility, and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis.

Table 10: Midyear Performance and Changes in Asset Allocation

	Longs and Shorts Separate			Longs and Shorts Combined		
	(1)	(2)	(3)	(4)	(5)	(6)
AbsWin	0.009***			0.009***		
	(0.003)			(0.002)		
RelRank		0.015***			0.014***	
		(0.004)			(0.003)	
BtmQntl			−0.005			−0.003
			(0.003)			(0.003)
TopQntl			0.007***			0.008***
			(0.003)			(0.002)
LagRisk	−0.076	−0.098*	−0.111**	−0.043	−0.064	−0.086*
	(0.051)	(0.050)	(0.050)	(0.047)	(0.046)	(0.046)
$\Delta\rho$	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Flow	0.025***	0.027***	0.027***	0.022***	0.023***	0.024***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Observations	10,091	10,091	10,091	10,091	10,091	10,091
R^2	0.055	0.056	0.055	0.039	0.039	0.039

Notes: This table reports results when Equation 3 is estimated using the cosine similarity of a fund's asset exposures between the two halves of the year as the dependent variable. Only coefficients on the focal midyear performance measures are displayed. The volatility and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Authors' analysis

Table 11: Midyear Performance and Changes in Betas

	Aggregate Index			Strategy Weighted Average Index			Market Factor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AbsWin	-0.121^{***}			-0.111^{***}			-0.015		
	(0.041)			(0.040)			(0.012)		
RelRank		-0.271^{***}			-0.289^{***}			-0.061^{***}	
		(0.067)			(0.060)			(0.019)	
BtmQntl			0.112^{**}			0.088^{*}			-0.014
			(0.047)			(0.045)			(0.014)
TopQntl			-0.077^{*}			-0.114^{***}			-0.075^{***}
			(0.046)			(0.041)			(0.013)
LagBeta	-0.654^{***}	-0.650^{***}	-0.651^{***}	-0.731^{***}	-0.729^{***}	-0.730^{***}	-0.763^{***}	-0.763^{***}	-0.767^{***}
	(0.019)	(0.019)	(0.019)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
LagRisk	6.670^{***}	6.759^{***}	6.828^{***}	5.517^{***}	5.613^{***}	5.870^{***}	2.587^{***}	2.596^{***}	2.920^{***}
	(1.229)	(1.226)	(1.247)	(1.186)	(1.174)	(1.178)	(0.382)	(0.381)	(0.385)
$\Delta\rho$	0.018	0.018	0.017	-0.007	-0.006	-0.007	-0.015^{*}	-0.014^{*}	-0.014
	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.008)	(0.008)	(0.008)
Flow	0.082	0.064	0.065	0.090	0.075	0.069	-0.014	-0.016	-0.026
	(0.087)	(0.085)	(0.086)	(0.084)	(0.082)	(0.083)	(0.026)	(0.026)	(0.026)
Observations	10,142	10,142	10,142	10,140	10,140	10,140	10,142	10,142	10,142
R^2	0.266	0.267	0.266	0.303	0.305	0.304	0.405	0.406	0.407

Notes: This table reports results when Equation 3 is estimated using changes in return betas between the two halves of the year as the dependent variable. The betas are computed with respect to the benchmark Eurekahedge Hedge Fund Index, the strategy weighted averages of Eurekahedge style indices, and the equity market factor. The beta, volatility, and flow variables are winsorized at the 1% and 99% levels. Standard errors clustered by fund are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: SEC Form PF, Eurekahedge, Authors' analysis.

Appendix A Variable Construction

Table A1: **Variable Construction**

Variable Name	Description	Relevant Question(s)
AbsWin	A derived indicator equal one if a fund is above its HWM from the preceding December at the end of June. For each year y, we define a fund's asset level, A_y, and HWM, H_y, as $A_y = A_{y-1} \times (1 + R_y^{net})$ and $H_y = \max\{H_{y-1}, A_y\}$, where R_y^{net} is the annual net-of-fees return. Funds are assumed to initially be at their HWM, so $A_0 = H_0 = 1$.	Form PF Q17 (net returns)
RelRank	The percentile rank of a fund's cumulative return in the first half of a given year. The variable falls in the interval (0,1] and takes on larger values for better performers.	Form PF Q17 (net returns)
BtmQntl	An indicator equal to one if the fund falls in the bottom quintile of the return distribution in the first half of the year.	Form PF Q17 (net returns)
TopQntl	An indicator equal to one if the fund falls in the top quintile of the return distribution in the first half of the year.	Form PF Q17 (net returns)
LagRisk	The volatility of the fund's monthly gross returns over the first half of the year.	Form PF Q17 (gross returns)
$\Delta\rho$	The change in return autocorrelation between the first and second halves of the year.	Form PF Q17 (gross returns)
Flow	The fund's net flow during the first half of the year.	Form PF Q3 (net AUM), Q17 (net returns)
Annual Return	The yearly gross return based on compounded monthly returns.	Form PF Q17 (gross returns)
Return Volatility	The standard deviation of monthly gross returns.	Form PF Q17 (gross returns)
NAV	The net asset value of the fund.	Form PF Q9
Leverage	A fund's gross net exposure (GNE) divided by its NAV.	Form PF Q9 (NAV), Q26 and Q30 (GNE)
Borrower	An indicator equal to one if the fund borrows from creditors.	Form PF Q43
FundingLiq	The percentage of a fund's borrowing that has a maturity of at most 30 days.	Form PF Q46
PortLiq	The percentage of a fund's NAV that can be sold within 30 days without causing price movements.	Form PF Q32
TurnoverRate	A fund's average monthly turnover divided by its GNE.	Form PF Q27 (turnover), Q26 and Q30 (GNE)
DerivUser	An indicator equal to one if the fund uses derivatives.	Form PF Q26
InvestorLiq	The percentage of a fund's NAV that can be withdrawn or within 30 days.	Form PF Q50
Top 5 Share	The percentage of a fund's NAV help by the five investors with the largest equity shares.	Form PF Q15
ManagerStake	An indicator equal to one if the manager has an equity stake in the fund.	Form ADV Section 7.B.(1) Q14