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Alpha or Beta in the Eye of the Beholder: What Drives Hedge Fund Flows?

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March 2017

CAPM alpha explains hedge fund flows better than alphas from more sophisticated models. This suggests that investors pool together sophisticated model alpha with returns from exposures to traditional (except for the market) and exotic risks. We decompose performance into traditional and exotic risk components and find that while investors chase both components, they place greater relative emphasis on returns associated with exotic risk exposures that can only be obtained through hedge funds. However, we find little evidence of persistence in performance from traditional or exotic risks, which cautions against investors' practice of seeking out risk exposures following periods of recent success.

JEL Classification: G11, G20

Keywords: Hedge Funds, Investor Flows, Alpha, Alternative Beta, Exotic Beta

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CAPM alpha explains hedge fund flows better than alphas from more sophisticated models. This suggests that investors pool together sophisticated model alpha with returns from exposures to traditional (except for the market) and exotic risks. We decompose performance into traditional and exotic risk components and find that while investors chase both components, they place greater relative emphasis on returns associated with exotic risk exposures that can only be obtained through hedge funds. However, we find little evidence of persistence in performance from traditional or exotic risks, which cautions against investors' practice of seeking out risk exposures following periods of recent success.

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I tried telling a hedge fund manager, "You don't have alpha. Your returns can be replicated with a value-growth, momentum, currency and term carry, and short-vol strategy." He said, "'Exotic beta' is my alpha. I understand those systematic factors and know how to trade them. My clients don't." He has a point.

– Cochrane (2011)

The last twenty years have witnessed considerable advances in our understanding of the unique risks that hedge funds seek out to achieve returns.[1] While traditionally all returns unrelated to the market have been interpreted as manager skill (alpha), investors have begun to recognize the return implications of other traditional risks (such as size and value) as well as more exotic risks (such as momentum and option-like investments) generally only available through hedge funds. Despite the large literature on hedge fund performance and a plethora of risk models put forth by academics, it remains unclear how investors evaluate performance. In this article, we take a revealed preference approach as in Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016) to address three research questions. First, which risk model do investors use to evaluate hedge fund performance? Second, do investors respond differently to the returns due to traditional risks and the returns attributable to exotic risks? Finally, are investors' capital allocation decisions justified by funds' future alphas and returns due to traditional and exotic risks?

We begin our empirical analysis by conducting a flow-performance horse race to infer which risk model hedge fund investors use when allocating capital. Given the significant model uncertainty associated with evaluating hedge fund performance, we measure risk-adjusted performance using a range of single and multi-factor models

[1] A partial list includes Fung and Hsieh (1997, 2001, 2004), Ackermann, McEnally, and Ravenscraft (1999), Liang (1999, 2001), Mitchell and Pulvino (2001), Agarwal and Naik (2000, 2004), Kosowski, Naik, and Teo (2007), Bali, Gokcan, and Liang (2007), Brown, Goetzmann, Liang, and Schwarz (2008, 2009, 2012), Fung, Hsieh, Naik, and Ramadorai (2008), Agarwal, Bakshi, and Huij (2009), Patton (2009), Jagannathan, Malakhov, and Novikov (2010), Aggarwal and Jorion (2010), Bali, Brown, and Caglayan (2011, 2012, 2014), Titman and Tiu (2011), Brown, Gregoriou, and Pascalau (2012), Cao, Chen, Liang, and Lo (2013), Agarwal, Arisoy, and Naik (2016), and Agarwal, Ruenzi, and Weigert (2016).

including the CAPM, the Carhart (1997) 4-factor model, the Carhart model augmented with the option-based factors of Agarwal and Naik (2004), the trend-following 7-factor model of Fung and Hsieh (2004), and a 12-factor combined model which also includes an emerging market factor.

We find that CAPM consistently wins the race, with hedge fund flows being better explained by CAPM alpha than alphas from more sophisticated models. CAPM alpha also weakly dominates raw returns in explaining hedge fund investors' capital allocation decisions. The success of CAPM alpha in explaining hedge fund flows is consistent with recent evidence for mutual funds (Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016). However, hedge funds offer a much wider range of risk exposures than mutual funds, and hedge fund investors are viewed as more sophisticated than mutual fund clienteles and pay substantial performance-based fees.[2]

CAPM's success is surprising and helps motivate the rest of our analysis. In particular, this finding suggests that hedge fund investors only control for general aggregate market risk when evaluating fund performance. That is, they pool together manager skill (sophisticated model alpha) with the returns associated with traditional risk exposures other than the aggregate equity market, and exotic risk exposures.[3] Investors appear either indifferent to the nature of risks inherent in certain hedge fund strategies, or

[2] Berk and van Binsbergen (2016) argue that CAPM's success in explaining mutual fund flows suggests it necessarily also explains flows into other investments such as hedge funds. Although this may be true in a complete, frictionless market, there are a number of institutional impediments that prevent flows from revealing the "true" underlying risk model, such as the inability to short bad fund managers. We interpret our findings as shedding light on how hedge fund investors evaluate performance rather than revealing the true hedge fund risk model. We discuss this issue further in Section 2.

[3] Exotic risks are also referred to as "advanced," "alternative," or "smart" beta in the literature (e.g., Carhart et al. 2014). In our taxonomy, we separate premium-bearing risks into those that are generally available through liquid, low-cost, and transparent investment vehicles such as index mutual funds or ETFs (traditional beta) from those that can typically only be obtained through hedge funds (exotic beta). We also use the shorthand of referring to sources of risk other than the aggregate US stock market as "non-market" risks, although the size and book-to-market factors may also capture aspects of market risk.

they actively seek out these risks following periods of recent success. To determine whether hedge fund investors are indifferent to non-market risks or actively seek them out, we decompose fund performance into components related to manager skill and returns associated with traditional and exotic risk exposures.

Our evidence suggests that investors do seek out non-market risks, and they distinguish between hedge fund returns arising from conventional risk exposures that may be obtained more cheaply through mutual funds, and exotic risk exposures that can only be obtained through hedge fund investments. While investor flows respond to all three return components, they place greater relative emphasis on the returns arising from exotic rather than traditional risk exposures. For example, using the Fung and Hsieh (2004) model we find a one percent increase in lagged hedge fund returns attributable to exotic risk exposures leads to a 9.5% increase in inflows, compared to 5.5% for a one percent increase in lagged returns due to traditional risk exposures. This evidence suggests that investors credit hedge fund managers not only for their skill to produce alpha, but also for their ability to deliver returns through taking opportune exposures to exotic risk factors and to a lesser extent traditional risk factors.

Implicit in hedge fund investors' strategy of allocating capital based on past return components is that these sources of return should persist in the future. Our final set of tests explores whether hedge fund investors' flow response to three return components is justified by the data. To that end, we evaluate the persistence over time for hedge fund alpha, returns attributable to traditional risk exposures, and returns arising from exotic risk exposures. We find mixed evidence for persistence in alphas and little evidence of persistence in returns due to either traditional risks or exotic risks. We further explore the relatively weak persistence in fund returns due to traditional or exotic risks by separately examining the persistence in factor returns and betas. We find that while hedge fund risk exposures (betas) do significantly persist, the factors returns themselves do not exhibit evidence of persistence.

Taken together, our findings suggest that hedge fund investors' emphasis on CAPM alpha when allocating capital does not reflect a lack of awareness of non-market risks, but rather a specific tendency to chase recent returns associated with both traditional and exotic risk exposures. Since these components of hedge fund performance fail to persist, our evidence suggests that this investor practice is suboptimal. Exotic risk exposures may well earn a premium on average, and our evidence does not imply that investing in exotic risks is misguided. However, our finding of lack of persistence in returns due to risk exposures do suggest that investors should not select exposures based on their contributions to funds' recent performance.

Our evidence indicates that investors would benefit from using more sophisticated models that adjust for traditional as well as exotic risks when evaluating fund performance. For example, consider investors that chase alphas from a 3-factor model. These investors essentially pool together "manager skill" with returns attributable to exposures to exotic risk factors. Some funds will exhibit high 3-factor alphas in a given year because their exotic risk exposures happened to perform well. However, new investors in these funds will tend to be disappointed since returns associated with exotic risk exposures do not persist. Thus, our evidence suggests that investors would benefit from separating traditional risks from exotic risks by employing sophisticated models to evaluate fund performance.

Our findings contribute to several streams of literature. While Agarwal, Daniel, and Naik (2004), Fung, Hsieh, Naik, and Ramadorai (2008), Getmansky, Liang, Schwarz, and Wermers (2010), Jorion and Schwarz (2015), and Lim, Sensoy, and Weisbach (2016) show that successful hedge funds receive capital inflows, our study is the first to show that investors react differently to distinct components of fund returns.

We extend recent research on mutual funds (Berk and van Binsbergen, 2016; and Barber, Huang, and Odean, 2016) to the hedge fund setting by studying a broad set of exotic risks not typically available through mutual funds. Investors face considerably greater model uncertainty when evaluating hedge fund performance, and we explore whether investors learn over time as they become more informed about the types of risk exposures that hedge funds seek out. We also examine whether investing clienteles vary in their reaction to different return components, and we exploit differences in the fees of hedge funds to relate fund managers' incentives to the production of alphas and beta returns. Our findings help shed light on how investors react to the considerable model uncertainty involved when evaluating hedge fund performance.

Our analysis of the persistence of different return components extends both the mutual fund and hedge fund literatures by shedding light on the effectiveness of investors' capital allocation decisions. While earlier work finds limited evidence of hedge fund performance persistence, mainly over short horizons (Brown, Goetzmann, and Ibbotson, 1999; Agarwal and Naik, 2000; Baquero, ter Horst, and Verbeek, 2005), more recent studies find evidence of persistence using a Bayesian methodology (Kosowski, Naik, and Teo, 2007), among younger fund managers (Aggarwal and Jorion, 2010), and over longer horizons (Jagannathan, Malakhov, and Novikov, 2010). We build on this literature by examining persistence in returns attributable to different sources of risk. Although we find some evidence of short-term persistence in alphas, which is consistent with recent work, we find little evidence of persistence in fund returns arising from either traditional or exotic risks. The success of CAPM alpha in explaining hedge fund flows suggests that investors suboptimally combine certain traditional and exotic risks exposures when identifying manager skill.

The paper proceeds as follows. In Section 1, we describe the sample and construction of the variables. Section 2 conducts the flow-performance horse race, and in Section 3, we examine how hedge fund flows react to different components of fund returns. Section 4 explores the implications of fund fees, investor learning, and clientele sophistication for the investor preferences between different return components. In Section 5, we examine the efficacy of investor flow behavior by studying persistence in different fund return components, and Section 6 concludes.

1. Data and variable construction

This section describes the hedge fund sample and provides details for the construction of the various performance measures.

1.1 Hedge fund database

Following Joenvaara, Kosowski, and Tolonen (2014), we create a "Union" database by merging four commercial hedge fund databases: Eurekahedge, HFR, Lipper TASS, and Morningstar. We obtain net-of-fees returns, assets under management (AUM), and other fund characteristics such as management and incentive fees, lockup, notice, and redemption periods, minimum investment amount, inception dates, fund strategies and the date added to the database. These databases have overlaps in terms of fund coverage.

We begin by converting all the non-USD observations (returns or AUM) into USD observations using the end-of-the-month spot rates. We then identify duplicate share classes of a fund within a database if their returns have a correlation of 0.99 or more and they have similar average returns and AUM (within 10% of each other). We keep only one share class for each fund using one of the following criteria in descending order of priority: 1) share class with longest return series, 2) share class with the largest AUM, 3) share class designated in USD, and 4) share class domiciled onshore. We remove duplicate funds across databases using the same criteria as for duplicate share classes for a fund within a database.

The availability of four databases enables us to resolve potential discrepancies among different databases as well as to create a comprehensive sample that is more representative of the hedge fund industry. Since we require a minimum of 24-month return history for estimating the alphas and betas from various multifactor models and examine the flows into the funds in the following year, we exclude funds with less than 3 years of monthly returns data. This provides us with a final sample of 16,185 funds from 1994 to 2012.

1.2 Fund performance measures and capital flows

We use six different models for performance evaluation, including the Capital Asset Pricing Model (*CAPM*), the Fama-French (1993) 3-factor model (*FF3*), the Carhart (1997) 4-factor model (*Carhart4*), the Agarwal and Naik (2004) option-factor model (*AN*), the Fung and Hsieh (2004) 7-factor model (*FH7*), and a combined 12-factor model (*12-factor*). The risk factors in the *CAPM*, *FF3*, and *Carhart4* models include market (*MKTRF*), size (*SMB*), value (*HML*) and momentum (*UMD*) factors. The AN model includes these four factors plus an out-of-the-money call option factor (*OTM_CALL*) and an out-of-the-money put option factor (*OTM_PUT*).[4]

The *FH7* model includes three trend-following risk factors constructed from portfolios of lookback straddle options on currencies (*PTFSFX*), commodities (*PTFSCOM*), and bonds (*PTFSBD*); two equity-oriented risk factors capturing excess market returns (*SNPMRF*) and the size premium (*SCMLC*); and two bond-oriented risk factors constructed using 10-year Treasury constant maturity bond yields (*BD10RET*) and the difference in yields of Moody's BAA bonds and 10-year Treasury constant maturity bonds (*BAAMTSY*), with all yields duration-adjusted to convert them into returns.[5] In the 12-factor model, we include *HML, UMD, OTM_CALL, OTM_PUT, PTFSFX, PTFSBD, PTFSCOM, BD10RET, BAAMTSY, SNPMRF, SCMLC*, and an emerging market factor (*MSCIEM*).

We estimate each model using 24 months of return data for each fund. For example, for the *Carhart4* model, which includes market, size, book-to-market, and momentum, we obtain factor loadings using the following regression for months *t*–23 to *t*:

$$R_{i,t} - R_{rf,t} = a + \beta_{i,mktrf} MKTRF_t + \beta_{i,smb} SMB_t + \beta_{i,hml} HML_t + \beta_{i,umd} UMD_t + \varepsilon_{i,t}, \qquad (1)$$

where $R_{i,t}$ and $R_{rf,t}$ are the fund *i*'s return and risk-free return as of month *t*. We then calculate the monthly alpha from *t–11* to *t* as the difference between realized return and

[4] The model that we refer to as AN model in this paper differs from Agarwal and Naik (2004) model to the extent that they use a stepwise approach to select significant factors from a broader set of risk factors. Following their work, the OTM option strategy involves buying a two months to maturity European call or put option on the S&P 500 index that is, on average, 1% out of the money. The return to this strategy is based on the change in the market price of the OTM option over one month.

[5] Bond, commodity, and currency trend following factors are obtained from David A. Hsieh's data library available at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm. Equity-oriented and emerging market risk factors are from Datastream. Bond-oriented risk factors are from the Board of Governors of the Federal Reserve System.

model-fitted return. Finally, we compound the monthly alphas to compute annual alpha for the year leading to month t as follows:

$$\alpha_{i,t} = \prod_{t-11}^{t}\left(1 + R_{i,t} - \hat{R}_{f,t}\right) - 1, \tag{2}$$

where $\hat{R}_{f,t}$ is the monthly fitted return, calculated as the sum of the risk-free rate and the factor loadings multiplied by the factor realizations for each month t.[6]

We calculate annual net flows (i.e., inflows net of outflows) for fund i in year t as follows:

$$Flow_{i,t} = \frac{AUM_{i,t}}{AUM_{i,t-1}} - \left(1 + R_{i,t}\right), \tag{3}$$

where $AUM_{i,t}$ represents assets under management of fund i in year t. The timing for the flow-performance relation is illustrated in Figure 1. We use information on fund assets at the end of each year since monthly or quarterly information can be missing or stale.

1.3 Summary Statistics

Table 1 reports the summary statistics for our final sample consisting of 71,117 fund-year observations for 16,185 unique funds from 1994 to 2012. All the flow and alpha variables are winsorized at the 1% and 99% levels. The annual flow over this period has a mean of 13.43% and a median of –3.22%, consistent with a positively skewed flow measure. The average fund has an annual return of 9.10% and assets under management of roughly $180 million. The average fund age is 79 months (6.5 years), and the median management fee of 1.5% and median incentive fee of 20% are in line with industry standards.

[6] As an additional robustness check, we estimate each fund's out-of-sample alpha every month using 24-month rolling windows. Our results are also similar using this alternative alpha measure.

19% of funds in our sample have a hurdle rate, and 67% of funds have a high water mark provision. The average lockup days for the sample funds with non-missing and non-zero lockup information is roughly one year (376 days), and the average restriction (sum of redemption and notice periods) days is close to a quarter (102 days). There is substantial variation in the average annualized alphas estimated from the six models, 2.73% to 5.14%, suggesting significant uncertainty about unobserved managerial skill, for which alphas are intended to be a proxy.

The ambiguity about the different models is further confirmed when we examine the correlations between different model alphas. Table 2 reports both parametric Pearson correlations and nonparametric Spearman correlations in panels A and B, respectively. Pairwise correlations exhibit a large range from 0.34 to 0.95 for Pearson correlations and 0.35 to 0.94 for Spearman correlations.

2. Which risk model best explains capital flows into hedge funds?

Our goal is to ascertain which types of systematic risk hedge fund investors adjust for when evaluating fund performance. Our approach is to infer how investors evaluate hedge fund performance by examining their capital allocation decisions. The underlying assumption is that investments in managed portfolios should trend towards zero net present value. Outperformance signals manager skill and should attract capital inflows, whereas underperformance indicates low skill and should lead to fund outflows. Therefore, we would expect to observe a positive relation between performance and subsequent investor flows, with the strongest relation being observed for the specific risk model employed by investors. For example, if investors are only concerned with market risk, fund flows should react more strongly to CAPM alphas than to the alphas from more elaborate models. Alternatively, if investors also adjust for more exotic risks such as those from option factors in the *AN* or *FH7* model, we would expect fund flows to react more strongly to *AN* or *FH7* alphas.

2.1 Estimation of the flow-performance relation

Our methodology follows two recent papers from the mutual fund literature: Berk and van Binsbergen (2016) (BvB), and Barber, Huang, and Odean (2016) (BHO). BvB motivate their flow-performance tests as a revealed preference approach for inferring the true asset pricing model, i.e., using mutual fund flows to uncover which types of risk should earn premiums. Although this relation holds in their theoretical derivation, there are a number of market frictions that may prevent flows from revealing the true risk model. For example, it is not feasible to short bad fund managers, and therefore negative alpha managers may persist if a subset of investors use the wrong risk model. Positive alpha managers may also persist for extended periods of time if informed investors choose to mimic their strategies rather than allocate capital to their funds.[7] Moreover, investors may wish to adjust fund performance for certain risk factors even if they are priced (such as size or value), since these risk exposures are relatively easy to obtain and may not warrant high fees. Similar to BHO, we interpret our flow-performance analysis as shedding light on how hedge fund investors evaluate performance rather than revealing the true hedge fund risk model.

To conduct a horserace between the alphas from the different models, we estimate the sensitivity of investor flows to annual returns and alphas calculated from each of the

[7] See Barber, Huang, and Odean (2016) for more discussion of this point. An important caveat is that mimicking hedge fund strategies is more difficult for hedge funds than for mutual funds since less disclosure regarding holdings, etc. is required.

six models: *CAPM*, *FF3*, *Carhart4*, *AN*, *FH7*, and 12-factor model. Since our investigation is at the yearly level, we use fund-year observations in our analysis.

As in BvB, we first test for a positive relation between flows and performance.[8] Specifically, whether the regression coefficient of the sign of the subsequent flows on the sign of the performance measure (α) is positive.[9] Define Φ as a simple sign function that returns the sign of a real number, taking values of 1 for a positive number, –1 for a negative number, and 0 for zero. The test hypothesis can therefore be written in the following way:

$$\beta_{Flow,\, performance} = \frac{cov\left(\Phi\left(Flow_{i,t}\right), \Phi\left(\alpha_{i,t-1}\right)\right)}{var\left(\Phi\left(\alpha_{i,t-1}\right)\right)} > 0\,. \tag{4}$$

Furthermore, we can infer which of the two models (*m1* and *m2*) better captures how investors measure outperformance when allocating capital by comparing their flow-performance regression coefficients, $\beta_{Flow,\, performance}$. BvB, in their proposition 5, derive a method for empirically distinguishing between models by regressing $\Phi\left(\mathrm{Flow}_{\mathrm{it}}\right)$ on $\frac{\Phi\left(\alpha_{it-1}^{m1}\right))}{var\left(\Phi\left(\alpha_{it-1}^{m1}\right)\right)} - \frac{\Phi\left(\alpha_{it-1}^{m2}\right))}{var\left(\Phi\left(\alpha_{it-1}^{m2}\right)\right)}$:

$$\Phi\left(Flow_{it}\right) = a + b_1\left(\frac{\Phi\left(\alpha_{it-1}^{m1}\right))}{var\left(\Phi\left(\alpha_{it-1}^{m1}\right)\right)} - \frac{\Phi\left(\alpha_{it-1}^{m2}\right))}{var\left(\Phi\left(\alpha_{it-1}^{m2}\right)\right)}\right) + \zeta_{it}. \tag{5}$$

[8] BvB examine the relation between contemporaneous flows and mutual fund performance. We study the relation between flows and lagged performance to ensure that hedge fund performance is in the information set of investors, and to account for the greater restrictions on flows into and out of hedge funds.
[9] BvB use the signs (instead of magnitudes) of flows and performance to avoid having to specify the functional form of the relation between performance and flows. We also consider the BHO approach that examines the relation between relative magnitudes of flows and performance.

If the coefficient of this regression is positive, that is $b_1 > 0$, it implies the flow-performance regression coefficient of model *m1*, $\beta^{m1}_{Flow,performance}$, is larger than that of model *m2*, $\beta^{m2}_{Flow,performance}$, which implies that model *m1* better explains subsequent investor flows than model *m2*.

For the regression in equation (5), and all the subsequent flow-performance and performance-persistence analyses in the paper, we follow BvB and BHO and double cluster the standard errors by fund and year. Clustering by fund helps address serial correlation in residuals over time for a given fund, and clustering by year helps address cross-sectional correlation in residuals across funds at a given point in time.[10]

We present the results for the regression coefficients $\beta_{Flow,Performance}$ from equation (4) in Table 3 for the sample period from 1994 to 2012.[11] For ease of interpretation, the table reports $\left(\beta_{Flow,Performance}+1\right)/2$, which is the average probability that the sign of the fund flow is positive (negative) conditional on the sign of alpha being positive (negative). If flows and alpha are unrelated, we would expect the probability to be 50% in which case $\beta_{Flow,Performance}=0$.

The first inference from Table 3 is that all of the flow-performance sensitivity likelihood estimates, $\left(\beta_{Flow,Performance}+1\right)/2$, are significantly greater than 50%, implying that a positive flow-performance relation exists for all of the different performance measures. Second, we observe that the sensitivity is the largest for the CAPM alpha even

[10] As an additional robustness check, we double cluster standard errors by both fund and style × time to further address the issue of correlation in residuals across funds within a style for a given year. Our results continue to hold using this approach, and we report the results in Table IA.8 in the Internet Appendix.
[11] We conduct the analysis for two sub-periods from 1994 to 2004 and from 2005 to 2012. Results are similar to the overall sample period. We discuss additional sub-period analysis in Section 4.

surpassing that for the raw return. At the same time, we notice that none of the measures perform better than 62%, which suggests that a significant fraction of flows remains unexplained due to unobserved criteria being used by investors to make their capital allocation choices.

Table 4 presents the results from a formal model horserace test, with columns 3 through 9 reporting the *t*-statistics of the pairwise test coefficient b_1 in equation (5). The evidence in Table 4 further confirms that with the exception of raw returns, the CAPM alpha wins the horserace of flow-performance sensitivity. The evidence from the BvB approach suggests that investors adjust only for the market risk while assessing the risk-adjusted performance of hedge funds. In other words, investor's flow preferences are best explained by performance when the returns from other risk factors are subsumed in the CAPM alpha. The evidence in Tables 3 and 4 is also consistent with CAPM alpha explaining investor flows better than raw returns, although the formal test is not statistically significant.

We next follow the pairwise approach in BHO to estimate the relation between flows and a fund's decile ranking based on two different models at a time by estimating the following regression:

$$Flow_{i,t} = a + \sum_{k}\sum_{l} b_{kl} D_{kl,i,t-1} + cX_{i,t-1} + Style \times Year_{i,t} + \eta_{i,t}, \tag{6}$$

where the dependent variable, $Flow_{it}$, is the fund flow for hedge fund *i* in year *t*. D_{klit-1} is an indicator variable that takes on a value of one if fund *i* in year *t–1* is in decile *k* based on the first model and decile *l* based on the second model. To estimate the regression in equation (6), the indicator variable for *k=5* and *l=5* is excluded.

The matrix X_{it-1} represents the control variables which include flow in year *t–1*, log of fund size at year *t–1*, fund age at year *t–1*, the fund's return standard deviation estimated over the prior 12 months, management fee, incentive fee, lockup days, restriction days, an indicator variable for fund's use of high water mark, an indicator variable for fund's use of hurdle rate, and an indicator variable for offshore funds. It is plausible that there is commonality in flows across funds due to flows into a certain style. To control for such commonality in annual flows, we also include style × year fixed effects in the regression.

The key coefficients of interest are $b_{kl}, k = 1, 2, ..., 10$ and $l = 1, 2, ..., 10$, which can be interpreted as the percentage flows received by a fund in alpha decile *k* for the first model and alpha decile *l* for the second model relative to a fund that ranks in the fifth decile based on alphas from both the models. Each pair of coefficients b_{kl} and b_{lk} can be tested to see whether investors are more sensitive to the alpha estimated using the first model or using the second model. For each pairwise comparison of alphas from two models, we can make 45 such comparisons. We test the null hypothesis that the summed difference across all 45 comparisons is equal to zero, and we also calculate a binomial test statistic which tests the null hypothesis that the proportion of differences is equal to 50%.

We report the horserace results using the BHO methodology in Table 5. It is clear that investors are more responsive to fund performance based on the CAPM alpha compared to alphas from other models. The summed differences are all significantly positive for all the pairwise comparisons between CAPM alphas and alphas from other models. The percentages of differences are all larger than 80%, which means that CAPM wins at least 36 out of 45 total comparisons between the coefficient b_{kl} and b_{lk} in each of the pairwise model comparisons.[12]

The ability of the CAPM alphas to explain investor flows also weakly dominates that of the raw returns. The proportion of differences greater than zero is significantly different from 50%. The sum of differences is negative, although it is statistically indistinguishable from zero. The results using the BHO methodology further corroborate that investors prefer the CAPM alpha over the alphas from more sophisticated models, suggesting that investors adjust only for the market risk while evaluating hedge funds' risk-adjusted performance.

CAPM's dominance does not appear to be driven by the differences in estimation errors across models. Following prior literature (e.g., Fung, Hsieh, Naik, and Ramadorai, 2008; Titman and Tiu, 2011; Sun, Wang, and Zheng, 2012), we estimate factor exposures using 24-month windows and focus on one-year alphas. However, our findings remain similar using a longer estimation period (36 months). Moreover, double sorts on alpha and the precision of the alpha estimate provide no evidence that the success of CAPM in explaining investor flows is driven by concerns regarding estimation error. These results are reported in Table IA.6 in the Internet Appendix.

2.2 Comparisons with the evidence for mutual funds

Our horse race tests are similar in spirit to recent work on mutual funds by Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016), and it is natural to compare our hedge fund evidence with the findings for mutual funds. Despite the

[12] Each pairwise test involves 45 different regressions. For the sake of brevity, we do not tabulate all the pairwise coefficients. However, for illustration purposes, we report the full pairwise comparison between the alphas from the *CAPM* and *FF3* models in Appendix Table A1.

multitude of risk models that have been developed to address the additional risks that hedge funds are able to seek out, the success of the one-factor CAPM alpha in explaining hedge fund flows is generally consistent with the mutual fund evidence.

Our Table 3, which reports the likelihood of agreement between the sign of fund flows and past performance, is analogous to Table 2 in BvB. We find the direction of flow and performance agrees 61.1% of the time for CAPM alpha, versus 60.8% for raw returns and 59.0% for FF 3-factor alpha. These values are similar to the analogous one-year horizon estimates reported in BvB (for their 1977–2011 sample period): 63.4% for CAPM alpha, 63.1% for the FF 3-factor model, and 57.7% for raw returns.[13] For both hedge funds and mutual funds, CAPM alpha explains investor flows better than raw returns or alphas from more sophisticated models.

BHO's approach classifies abnormal performance into decile ranks and examines in a pairwise fashion which model better explains flows when the models disagree on the performance rank. Our Table 5 indicates that in 82.2% of the cases, investors allocate more capital to hedge funds when the fund's CAPM alpha performance rank exceeds its FF 3-factor alpha performance rank than vice versa (i.e., when the fund's FF 3-factor alpha performance rank exceeds its CAPM alpha performance rank). The extent to which investors prefer CAPM alpha over the Carhart 4-factor model alpha rises to 86.7%. The comparable estimates in BHO are in Panel A of their Table 4, in which they find CAPM alpha better explains flows 100% of the time for both 3-factor and 4-factor alphas. Taken together, the evidence suggests that CAPM alpha best explains investor flows for both hedge funds and mutual funds, although the incremental success of CAPM over other performance measures is somewhat weaker for hedge funds.

[13] BvB's findings are similar when considering other flow-performance horizons.

Although capital flows into hedge funds are best explained by CAPM alpha, it is possible that investors react differently to returns associated with traditional risks such as size and value, and more exotic risk exposures generally only available through hedge funds. In the next section, we decompose performance into components related to alpha, traditional risk exposures, and exotic risk exposures.

3. Characterizing investor flows into hedge funds

The evidence from the previous section indicates that hedge fund investors are most responsive to the CAPM alpha among all the alpha measures from the six risk models. The results suggest that after controlling for broad equity market exposure, investors pool together manager skill along with returns from exposure to non-market risks. In this section, we examine whether investors react differently to returns arising from traditional versus exotic risks.

Some risk exposures can be obtained more easily than others. Mutual funds typically charge fixed management fees of less than one percent and provide exposures to traditional risks, such as market, size, and value. Hedge funds, on the other hand, often carry higher fixed fees (between 1.5% and 2.0% of assets) as well as charge incentive fees of typically 20% of the profits (i.e., returns). The perceived benefit of investing in hedge funds is that they provide unfettered opportunities for managers to utilize their investment skill. Another important potential benefit of hedge funds is the chance to gain exposures to premium-bearing exotic risks.[14]

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[14] There is a large literature that shows that hedge funds take exotic risks that include option-based factors to capture nonlinear risks (Fung and Hsieh, 1997, 2001, 2004; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004, and Hasanhodzic and Lo, 2007) in addition to correlation risk (Buraschi, Kosowski, and Trojani, 2014), liquidity risk (Aragon, 2007; Sadka, 2010; Teo, 2011), macroeconomic uncertainty risk (Bali, Brown, and Caglayan, 2014), tail risk (Agarwal, Ruenzi, and Weigert, 2016) and volatility risk (Bondarenko, 2004; Agarwal, Bakshi, and Huij, 2009; Agarwal, Arisoy, and Naik, 2016).

In principle, investors should be willing to pay high hedge fund fees only for risk-adjusted abnormal return (alpha or manager skill). However, it is also conceivable that investors may be willing to pay premium fees for returns that arise from exotic risk exposures, since these are not widely available from low-cost investment vehicles such as exchange traded funds (ETFs) or index mutual funds. Do investors differentiate between returns arising from traditional risks from those arising from more exotic risks? To address this question, we decompose returns into three parts, alpha, traditional beta return, and exotic beta return, and examine the sensitivity of investor flows to these three return components.

We classify the risk factors into traditional and exotic categories based on the effort and cost involved in gaining exposure to the risk factors. For example, the size premium can be relatively easily and inexpensively achieved through small market cap mutual funds. On the other hand, extracting the premium from the different lookback straddles in the *FH7* model requires more sophisticated knowledge and dynamic trading skills, and this strategy is not cheaply available through standard products in financial markets. We categorize the traditional and exotic factors for each model as follows:

Model	Traditional Risk Components	Exotic Risk Components
Carhart-4	Equity Market (MKTRF), Size (SMB), Value (HML)	Momentum (UMD)[15]
AN	MKTRF, SMB, HML	UMD, Call Option (OTM_CALL), Put Option (OTM_PUT)
FH7	Equity Market (SNPMRF), Size (SCMLC), Term spread (BD10RET), Default spread (BAAMTSY)	Currency options (PTFSFX), Bond options (PTFSBD), Commodity options (PTFSCOM)
12-factor	HML, SNPMRF, SCMLC,	UMD, OTM_CALL,

[15] We classify momentum as a source of exotic risk due to the effort and expense to implement momentum strategy (Berk and van Binsbergen, 2015). Classifying momentum as a traditional risk exposure does not change our conclusions regarding traditional versus exotic risk exposures.

	BD10RET, BAAMTSY, Emerging Markets (MSCIEM)	OTM_PUT,PTFSFX, PTFSBD, PTFSCOM

To fix the idea of how returns are decomposed, we consider the *Carhart4* model in equation (1). At the end of year *t*, we calculate the monthly mean excess return for the hedge fund over the prior 12 months (*t–11* to *t*): $\overline{R_{i,t}-R_{rf,t}}=\sum_{t-11}^{t}\left(R_{i,t}-R_{rf,t}\right)\big/12$. Similarly, the mean factor realizations of market, size, value, and momentum factors ($\overline{MKTRF}_t, \overline{SMB}_t, \overline{HML}_t$, and $\overline{UMD}_t$, respectively*)* are calculated over the same 12 months prior to the end of year *t*. We then decompose the excess return of each fund into three components, alpha component, traditional beta component, and exotic beta component:

$$
\begin{aligned}
&\overline{R_{i,t}-R_{rf,t}}=\overline{\alpha_{i,t}}+Trad\ Beta\ Comp_{i,t}+Exotic\ Beta\ Comp_{i,t},\\
&\text{where}\\
&\quad Trad\ Beta\ Comp_{i,t}=\hat{\beta}_{i,mktrf,t}\overline{MKTRF}_t+\hat{\beta}_{i,smb,t}\overline{SMB}_t+\hat{\beta}_{i,hml,t}\overline{HML}_t,\\
&\quad Exotic\ Beta\ Comp_{i,t}=\hat{\beta}_{i,umd,t}\overline{UMD}_t.
\end{aligned}
\tag{7}
$$

Using the return decomposition in equation (7), we test whether investors respond differently to the components of returns by estimating the following regression:

$$
\begin{aligned}
Flow_{i,t}&=a+b_1\overline{\alpha_{i,t-1}}+b_2 Trad\ Beta\ Comp_{i,t-1}+\\
&\quad b_3 Exotic\ Beta\ Comp_{i,t-1}+cX_{i,t-1}+Style\times Year_{i,t}+\nu_{it},
\end{aligned}
\tag{8}
$$

where the matrix of control variables, X_{it-1}, and the style × year fixed effects ($Style\times Year_{i,t}$) are as defined earlier in equation (6). The parameter estimates of interest in equation (8) are $b_i, i=1,2,3$. For investors who use alpha from *Carhart4* model to evaluate fund performance, we expect $b_1>0$. For investors who also value returns from exotic risk exposures, we expect $b_3 > 0$. If investors also respond to traditional beta component, we should observe $b_2 > 0$. Furthermore, if investors respond to returns from exotic betas more than those from the traditional betas, we expect to observe $b_3 > b_2$. The CAPM, *FF3*, and *Carhart4* models are nested within each other. Since there are no exotic risk factors included in the *CAPM* and *FF3* models based on our classification, we conduct the return decomposition analysis for the remaining four models: *Carhart4, AN*, *FH7*, and 12-factor.

Table 6 reports the summary statistics of each of the three return components for the four models for which we conduct the return decomposition analysis. The average monthly alpha varies from 0.15% for the 12-factor model to 0.39% for the *FH7* model. The average monthly traditional beta return varies from –0.06% for the *AN* model to 0.23% for the 12-factor model, and the average monthly exotic beta return varies from –0.01% for the 12-factor model to 0.29% for the *AN* model. These figures highlight considerable cross-sectional variation in the return components. Table 6 also reports the correlations between each of the return components. Observed correlations are typically low and mostly negative with a few exceptions, suggesting that a fund delivering traditional beta returns will not necessarily provide exotic beta returns.

Table 7 presents the results from the return decomposition exercise. First, we observe that the sensitivities to all the three return components are significantly positive across all five models, that is $b_1 > 0$, $b_2 > 0$, and $b_3 > 0$. This evidence confirms our conjecture that investors respond to all three return components. The coefficient of 11.77 on alpha from *Carhart4* model suggests that an increase of 1% in the monthly average alpha is associated with an increase of 11.77% in annual flows next year. Similar economic interpretation applies to other coefficients in the table.[16]

Next we focus on whether investors distinguish between the returns from traditional risks and the returns from exotic risks. In all four models, the sensitivity of exotic beta returns is greater than that of traditional beta returns. This suggests that investors are more sensitive to exotic beta returns compared to traditional beta returns. Results from a formal test of $b_3 > b_2$ are reported alongside each model in the table. The sensitivity of investor flows to exotic beta returns is statistically greater than the sensitivity to traditional beta returns in two models out of the four: *FH7* and12-factor, although only at the 10% level.[17]

In sum, the findings in this section tie in nicely with those from the previous section where we observe that CAPM alpha wins the horserace among the various alpha measures. Specifically, investors not only care about CAPM alpha when allocating capital, they also exhibit a stronger preference for returns arising from exotic risks and a weaker preference for returns from non-market traditional risks.[18]

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[16] We also consider the potential effect of illiquidity on the flow-performance relation by interacting the three return components with an indicator variable for lockup (1 if the fund has a lockup, 0 otherwise) and restriction period (1 if the sum of redemption and notice periods is greater than the median, 0 otherwise). Including these interaction terms does not change the relative importance of the return components for explaining fund flows.

[17] Table 6 indicates considerable negative correlation between returns attributable to traditional and exotic risk exposures for the AN and 12-factor models, which is related to the AN option factors being correlated with equity market returns. We orthogonalize the AN option factors with respect to the market and repeat the return decomposition analysis. Orthogonalizing the option factors reduces the correlation between the traditional and exotic risk return components considerably for the AN and 12-factor models. Although it weakens somewhat the evidence regarding investors' greater relative emphasis on exotic risk returns over the entire sample period, we observe that investors continue to prefer exotic risk returns during the recent subsample (2005–2012). We tabulate these findings in Table IA.7 in the Internet Appendix.

[18] Our tests in this section assume a linear relation between performance and flows. Evidence of nonlinearity is mixed in the hedge fund literature (Agarwal, Daniel, and Naik, 2004; Baquero and Verbeek, 2005; Getmansky, Liang, Schwarz, and Wermers, 2010; Goetzmann, Ingersoll, and Ross, 2003; and Jorion and Schwarz, 2015). For robustness, we repeat our analysis while allowing for an asymmetric flow

4. Fees, clientele sophistication, and learning about exotic risks

In this section, we first analyze whether hedge fund fees influence the relation between investor flows and the returns associated with exotic and traditional risk exposures, and we also examine whether high-fee hedge funds deliver greater return components (alphas, traditional beta returns, and exotic beta returns). We next examine whether investors learn about exotic risks over time and explore whether hedge fund managers cater to the investors by delivering higher returns from exotic risks over time. Finally, we investigate whether clientele sophistication influences capital allocations by comparing the investment allocation decisions of retail investors relative to institutional investors. For the sake of brevity, tabulated findings are presented in the Internet Appendix.

4.1 Hedge fund fees and traditional and exotic risk exposures

An important feature distinguishing hedge funds from mutual funds is the substantial performance-based incentive fee charged by hedge fund managers. We explore whether hedge fund investors who pay higher performance fees are more discerning between traditional and exotic return components by repeating our return decomposition tests using subsamples grouped by incentive fee. Table IA.1 in the Internet Appendix reports the results for the return decomposition for the incentive fee subsamples. We find that investors that pay high performance fees are relatively more sensitive to returns associated with exotic risk exposures. In other words, the evidence is consistent with investors expecting that their more highly compensated hedge fund managers span nontraditional risks that are not available through ETFs and mutual funds.

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response to positive and negative fund return components. In results not tabulated, we continue to find that investors chase the returns associated with exotic beta more so than returns arising from traditional beta.

A natural question that arises from the flow-performance findings in Table IA.1 is whether high-fee funds also deliver higher alphas, higher exotic beta returns, and lower traditional beta returns compared to low-fee funds. We test this hypothesis by comparing each return component for the two incentive fee subsamples. We report the results in Table IA.2. We observe that high-fee funds deliver significantly higher alphas. However, the traditional beta component and exotic beta component are not significantly different between high-fee and low-fee funds. Since the fees are set at fund's inception, this evidence is consistent with investors selecting high-fee funds with the expectation of higher alphas and exotic returns. Although high-fee funds do deliver higher alphas, we find no evidence that their exotic risk returns are different from the traditional risk returns.

4.2 Investor learning about exotic risks

We hypothesize that investors' awareness of exotic risks may have improved over time. The midpoint of our sample period roughly coincides with the 2004 publication of Agarwal and Naik (2004) and Fung and Hsieh (2004), which introduced more sophisticated hedge fund models that consider exotic risk factors such as option factors and trend-following factors. We explore whether investors become more cognizant of exposures to such exotic risk factors over time by repeating the return decomposition exercise for two sub-periods from 1994 to 2004 and 2005 to 2012. If investors tilt their preferences toward exotic risks in the second sub-period, it would support the investor learning hypothesis.

Table IA.3 in the Internet Appendix reports the results for the return decomposition results for the two sub-periods. During the first sub-period from 1994 to 2004, the sensitivity to traditional beta returns is either statistically indistinguishable or larger than the sensitivity to exotic beta returns. This indicates that during the first half of the sample period, investors do not seem to differentiate between returns associated with traditional risk exposures and exotic risk exposures. In sharp contrast, the results for the more recent sub-period from 2005 to 2012 show that the sensitivity to traditional beta returns, b_2, is significantly smaller than the sensitivity to exotic beta returns, b_3, for all four models. The evidence from the sub-period analysis is consistent with investor learning. Investors appear to differentiate between traditional and exotic risks in the recent sub-period that coincides with the advent of more sophisticated risk models for evaluating hedge fund performance.[19]

4.3 Clientele sophistication and risk model preferences

It is conceivable that investors' approach to evaluate fund performance may vary in their sophistication. Institutional investors are generally considered to be more sophisticated than retail investors, and they may employ more sophisticated risk models when measuring abnormal performance or place greater emphasis from returns attributable to exotic rather than traditional risk exposures when allocating capital. In this section, we consider two approaches for testing the clientele sophistication hypothesis. Our first approach uses data on the hedge fund investments of registered funds of hedge funds (FoFs), and our second test uses Form ADV data that allows us to identify hedge funds' clientele type.

Following Agarwal, Aragon, and Shi (2016) and Aiken, Clifford, and Ellis (2013, 2015a, 2015b), we collect the quarterly portfolio holdings of FoFs that register with the

[19] We also observe no evidence that fund managers shift their emphasis towards exotic risk exposures in their investment portfolios in recent years to cater to investors' preferences for exotic risks (more evidence is provided in Section IA.2 of the Internet Appendix).

U.S. Securities and Exchange Commission (SEC) as closed-end funds under the Investment Company Act of 1940. We repeat our model horserace and flow-performance sensitivity tests using FoF investments in hedge funds as the flow variable. Table IA.4 in the Internet Appendix present the results from this analysis of FoFs' investments in hedge funds. We find no evidence that FoFs evaluate hedge fund performance using more sophisticated models than other hedge fund investors.

Our second approach follows Ben-David, Franzoni, and Moussawi (2012), and Chen (2013). In particular, we obtain funds' clientele information from the Form ADV filings with the SEC from 2001 to 2012 to classify funds as institution-oriented and retail-oriented. Table IA.5 in the Internet Appendix presents the results of capital allocation decisions made by the investors in retail-oriented and institutional funds. The table provides evidence that the emphasis on exotic beta returns over the traditional beta returns appears to be driven by the investors in the institution-oriented rather than retail-oriented funds.

In summary, we find that investors allocating their capital to high-fee funds appear to be more cognizant of sources of returns, and they place greater relative emphasis over time on returns due to such risks, which is consistent with learning. Furthermore, our clientele analysis indicates that our findings of a preference for CAPM alphas are not driven by a specific clientele type. However, there is some evidence suggesting that the preference for the exotic beta return over the traditional beta return is driven by institution-oriented funds.

5. Do investor flows respond optimally to hedge fund return components?

Our analysis of investors' capital allocation choices has uncovered a strong preference for alpha but also a tendency to invest in funds with returns associated with exotic and to lesser extent traditional risks. In this section, we investigate whether investors' revealed preferences for the three return components are consistent with future performance of these components.

If hedge funds operate in an environment with diseconomies to scale, Berk and Green (2004) argue that fund performance should not persist in equilibrium, as investor flows adjust across funds until each manager earns zero alpha. Our persistence analysis therefore also provides evidence on the extent to which investors eliminate abnormal fund performance through their capital allocation decisions.

5.1 Investor flows and hedge fund performance persistence

Our estimation of betas relies on rolling 24-month windows that overlap for one year between two successive estimations, which can mechanically introduce persistence. Therefore, we examine persistence for each of the three return components using non-overlapping 24-month windows, as in the following regressions:

$$\begin{aligned}\alpha_{i,t+2} &= a + b\alpha_{i,t} + cX_{i,t} + Style \times Year_{i,t+2} + \lambda_{i,t+2},\\ Trad\,Beta\,Comp_{i,t+2} &= a + b'Trad\,Beta\,Comp_{i,t} + c'X_{i,t} + Style \times Year_{i,t+2} + \psi_{i,t+2},\\ Exotic\,Beta\,Comp_{i,t+2} &= a + b''Exotic\,Beta\,Comp_{i,t} + c''X_{i,t} + Style \times Year_{i,t+2} + \chi_{i,t+2}.\end{aligned} \tag{9}$$

where $\alpha_{i,t+2}$, $Trad\,Beta\,Comp_{i,t+2}$, $Exotic\,Beta\,Comp_{i,t+2}$ are two-year alpha, two-year traditional return component, and two-year exotic beta component calculated using betas estimated with 24-month window from year *t+1* to *t+2. Similarly,* $\alpha_{i,t}$, $Trad\,Beta\,Comp_{i,t}$, $Exotic\,Beta\,Comp_{i,t}$ are two-year alpha, two-year traditional return component, and two-year exotic beta component calculated using betas estimated with

24-month window from year *t–1* to *t*. Control variables, $X_{i,t}$, are as defined earlier in equation (6) except that we exclude flows at time *t*. If any of the return components persist, we expect to observe the corresponding coefficient, b, b', or b'', to be positive.

Table 8 reports the results for the persistence test of equation (9). Reported *p*-values are based on standard errors clustered both at the fund and year level to allow for the serial correlation and cross-sectional correlation in the residuals. The results in Table 8 show no evidence of persistence either in traditional beta returns or in exotic beta returns.[20] We find weak evidence of persistence in alphas with only FH7 alpha being significantly persistent at the 5% level, albeit with small economic magnitude (0.05).

The general lack of persistence in performance associated with traditional and exotic risk exposures suggests that either hedge fund betas do not persist, or the factor returns themselves are uncorrelated over time. We explore this issue by separately examining persistence in the factor exposures to the different risk factors (or betas) and in the factor returns themselves.

The results are presented in Table 9. We find evidence of persistence in most factor betas. Our factor return sample consists of annual observations from 1995 to 2011, which makes it challenging to detect significant persistence in the factor returns. Nevertheless, we also conduct this analysis and report the results in the first column of Table 9. Unsurprisingly, we find little evidence of persistence in factor realizations, although we do observe two cases of reversals for the currency trend-following and term spread factors.

[20] As a robustness check, we implement the procedure in Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns to correct for the serial correlation or smoothing bias. Our persistence results (not tabulated) remain unchanged after adjusting for the smoothing bias.

We also consider the role of estimation error in explaining low persistence in beta estimates by examining the persistence in the *t*-statistics of betas instead of their magnitudes. We previously used this approach to address estimation error in alphas following prior literature (e.g., Kosowski, Naik, and Teo, 2007; Jagannathan, Malakhov, and Novikov, 2010; and Avramov, Barras, and Kosowski, 2013, see Section IA.4 of the Internet Appendix). We report the results in Appendix Table A2. The evidence regarding persistence in beta *t*-statistics is qualitatively similar to the evidence based on the magnitude of beta estimates, which suggests that potential estimation errors in the beta estimates do not materially influence our persistence analysis.

Using non-overlapping two-year windows to estimate alphas and betas helps mitigate overestimating persistence but also results in lengthening the horizon over which persistence is tested. Since prior research has shown that hedge fund persistence decays with horizon (e.g., Agarwal and Naik, 2000), evidence of lack of persistence in Table 8 could be due to the longer horizon. Therefore, we test persistence over a shorter horizon of two years using non-overlapping one-year estimation windows for the relatively parsimonious Carhart (1997) 4-factor model. We report the results from this analysis in Appendix Table A3. Panel A continues to show no evidence of significant persistence in any of the three return components (alphas, traditional beta returns, and exotic beta returns). Similarly, in panel B, we continue to observe significant persistence in betas and *t*-statistics of betas. Together, these findings suggest that testing of persistence over longer horizon do not seem to materially influence our inferences.

Taken together, the analysis in this section shows that the relatively weak persistence in returns associated with traditional and exotic risk exposures appears to be driven by the lack of persistence in the factor realizations rather than the lack of persistence in betas. This does not rule out the possibility that these factors, on average, deliver a risk premium to investors. Also, the evidence of persistence in betas supports the view that funds follow their investment objectives, which should allow investors to engage in style investing. However, the evidence of beta persistence alone does not justify investors' behavior of chasing returns due to the traditional and exotic risk factors.[21]

5.2 Robustness to backfilling bias

Our findings on the flow-performance relation and performance persistence may be influenced by backfilling bias in the hedge fund databases. For example, Evans (2010) studies mutual fund incubation, in which funds are made public only after a period of successful private performance, and finds that backfilled performance leads to flows. In a hedge fund setting, Jagannathan, Malakhov, and Novikov (2010) point out that backfilled data of successful hedge funds, together with the omission of unsuccessful early funds, can spuriously lead to evidence of persistence in hedge fund performance.

Our analysis relies on four commercial hedge fund databases (as described in Section 1.1): Eurekahedge, HFR, Lipper TASS, and Morningstar. Three of the four databases (excluding Morningstar) provide information regarding the date on which each funds was added to the database, which allows us to precisely correct for backfilling bias by eliminating the returns between a fund's inception date and the date of their addition to the database.

For funds in Eurekahedge, HFR, and Lipper TASS, we calculate the median backfilling period to be 24 months. We remove backfilled performance on a fund-by-fund basis for these three databases, and we exclude 24 months of performance data for funds listed only in Morningstar. We then repeat the analysis in Tables 4, 5, 7, and 8, and report the variables of interest in Table IA.7 in the Internet Appendix. The evidence suggests that despite the significant loss of observations (roughly 50% of the sample), our key findings regarding the success of CAPM in explaining flows, the importance of exotic risk returns relative to traditional risks, and the lack of persistence in performance components remain unchanged when precisely correcting for potential backfilling bias.

5.3 Discussion

The flow-performance evidence in Section 2 suggests that hedge fund investors are more likely to evaluate performance using simple models such as the CAPM rather than more sophisticated risk models. However, rather than being indifferent to non-market risks, we find in Section 3 that investors actively seek out exotic risks and to a certain extent traditional risks following periods of success, which implicitly assumes these components of hedge fund returns will persist.

We find only weak evidence of persistence in returns attributable to exotic risk in Section 5, and no evidence of persistence in traditional risk returns. The lack of significant persistence in these return components suggests hedge fund investors' capital allocation decisions are suboptimal. We note that our findings are not inconsistent with factor investing (Ang, 2013), and exotic factors may indeed offer a return premium as compensation for risk. However, an important implication of our findings is that investors should not choose exposures to exotic or traditional risks based on their recent performance. Regardless of whether alpha persists, our analysis suggests investors would be better off employing sophisticated models that distinguish between the types of risk taken by hedge funds. Since market risk and other traditional risks such as size and value can often be obtained at lower cost through mutual funds, investors would be wise to avoid hedge funds that offer returns attributable to traditional risk exposures.

6. Conclusions

Hedge funds are unique among investment vehicles in that they are relatively unconstrained in their use of derivative investments, short-selling, and leverage. This flexibility allows investment managers to span a broad spectrum of distinct risks. In our analysis, we explore the extent to which investors adjust for various sources of risk when allocating capital into hedge funds. We find that CAPM alpha consistently outperforms more sophisticated measures of risk-adjusted performance when explaining the relation between past hedge fund performance and investor flows. The results suggest investors pool together manager skill (alpha) with the returns associated with a variety of non-market risks (betas).

Although CAPM wins the model horserace, we do find evidence that investors distinguish between hedge fund returns arising from conventional risk exposures such as size and value, and more exotic risk exposures that can only be obtained through hedge fund investments. We decompose hedge fund returns into components related to alpha, traditional risks, and exotic risks and find that while investor flows respond to all three return components when allocating capital, they place greater relative emphasis on the returns arising from exotic rather than traditional risk exposures.

The relative emphasis on returns from exotic risk is greater among high-fee funds, and increases over time, consistent with investors learning about which risk exposures warrant the high fees of hedge funds. We find the greater emphasis on exotic risk returns are largely driven by hedge funds with institutional rather than retail investors. Similar to institutional funds, we find FoFs capital allocations emphasize exotic risk over traditional risk exposures, although we find no evidence that FoFs employ more sophisticated models than other hedge fund investors.

We next explore whether hedge fund investors' flow response to past performance of the three return components is justified by future fund performance. In particular, we evaluate the persistence over time for hedge fund alphas, returns attributable to traditional risk exposures, and returns arising from exotic risk exposures. We find weak evidence that fund alphas are persistent, and virtually no evidence that returns attributable to either exotic or traditional risk exposures are persistent.

Taken together, our evidence highlights an important caveat to the "exotic beta *is* alpha" view of hedge fund investing. By treating returns from exotic risks as alpha, investors appear to suboptimally chase past returns arising from such risks. In light of the weak evidence of return persistence for exotic risk exposures, our findings suggest investors should not select such exposures based on their recent performance. Instead investors will be better off adjusting for exotic risks by using sophisticated models to evaluate hedge fund performance.

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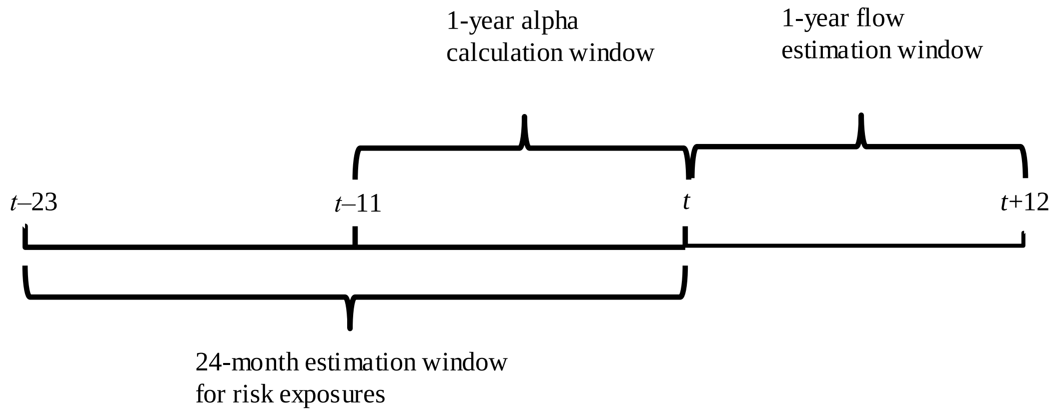
Figure 1. Estimation of Performance and Flow for the flow-performance relation



The figure shows the period over which hedge fund abnormal performance and future capital inflows are measured for examining the flow-performance relation, where t is in calendar months. Returns from month t–23 to t are used to estimate model risk loadings, alphas are calculated over month t–11 to t, and flows are measured over month t+1 to t+12.

Table 1. Summary statistics

This table summarizes the statistics for the sample of 16,185 hedge funds and funds of hedge funds from 1994 to 2012. Panel A reports statistics for the panel data on flows, performance, age, and assets under management (AUM) using fund-year observations. All variables are winsorized at the 1% and 99% levels. Panel B presents the statistics for funds' contractual characteristics using one observation for each fund. Reported statistics include the number of observations (N), average (Mean), median (Median), and standard deviation (SD).

Variables	N	Mean	Median	SD
Panel A: Flows, Performance, Age, and Assets under Management				
Annual Flow	71117	0.1343	–0.0322	0.90
Annual Return	71117	0.0910	0.0801	0.21
AUM ($M)	71117	180	47.90	382.60
Age (months)	69965	79	64	51.35
CAPM alpha	71117	0.0485	0.0343	0.1513
FF3 alpha	71117	0.0372	0.0249	0.1416
Carhart4 alpha	71117	0.0361	0.0241	0.1370
AN alpha	71117	0.0340	0.0203	0.1513
FH7 alpha	71117	0.0514	0.0341	0.1475
12-factor alpha	71117	0.0273	0.0140	0.1685
Panel B: Contractual characteristics of funds				
Management Fee (%)	15524	1.52	1.50	0.79
Incentive Fee (%)	15001	14.66	20.00	8.10
Hurdle Rate	16185	0.1922	0	0.39
High Water Mark	15166	0.6708	1	0.47
Lockup (days)	14199	87	0	193.00
Restriction (days)	12898	102	65	97.32

Table 2. Correlations between different performance measures

This table reports correlations between different performance measures: Annual Return, and alphas from CAPM, FF3, Carhart4, AN, FH7, and 12-factor models.

Panel A. Pearson Correlations

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
(a) Annual Return	1						
(b) CAPM alpha	0.844	1					
(c) FF3 alpha	0.757	0.918	1				
(d) Carhart4 alpha	0.718	0.878	0.949	1			
(e) AN alpha	0.582	0.733	0.806	0.838	1		
(f) FH7 alpha	0.607	0.770	0.794	0.766	0.649	1	
(g) 12-factor alpha	0.335	0.480	0.547	0.587	0.723	0.683	1

Panel B. Spearman Correlations

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
(a) Annual Return	1						
(b) CAPM alpha	0.826	1					
(c) FF3 alpha	0.732	0.903	1				
(d) Carhart4 alpha	0.706	0.864	0.940	1			
(e) AN alpha	0.573	0.725	0.805	0.829	1		
(f) FH7 alpha	0.599	0.742	0.770	0.737	0.631	1	
(g) 12-factor alpha	0.351	0.477	0.553	0.579	0.703	0.672	1

Table 3. Univariate flow-performance sensitivity estimations

This table reports the beta estimates from the following equation for different risk models:

$$\beta_{Flow,\,performance} = \frac{cov\left(\Phi\left(Flow_{i,t}\right),\Phi\left(\alpha_{i,t-1}\right)\right)}{var\left(\Phi\left(\alpha_{i,t-1}\right)\right)} > 0\ ,$$

where Φ is a function that returns the sign of a real number, taking values of 1 for a positive number, –1 for a negative number, and 0 for zero. The sample period is from 1994 to 2012. For ease of interpretation, the table reports $\left(\beta_{Flow,\,performance}+1\right)/2$ which denotes the average probability that the sign of the fund flow [*S(Flow)*] is positive (negative) conditional on the sign of the performance measure [*S(performance)*] being positive (negative). Each row corresponds to a different performance measure. Standard errors are clustered both at the fund and year levels, and *p*-values are reported below each coefficient in parentheses.

	S (Flow)
S (Annual Return)	60.79%
	(0.0000)
S (CAPM alpha)	61.14%
	(0.0000)
S (FF3 alpha)	59.00%
	(0.0000)
S (Carhart4 alpha)	59.81%
	(0.0000)
S (AN alpha)	57.45%
	(0.0000)
S (FH7 alpha)	59.21%
	(0.0000)
S (12-factor alpha)	56.06%
	(0.0000)
N	71,117

Table 4. Flow-performance risk model horserace: Berk and van Binsbergen (2016) pairwise model comparison

This table reports the results from pairwise comparisons of raw returns and different alphas as in Berk and van Binsbergen (2016). The first two columns provide the beta estimates from the following equation:

$$\beta_{Flow,\,performance} = \frac{cov\left(\Phi\left(Flow_{i,t}\right),\Phi\left(\alpha_{i,t-1}\right)\right)}{var\left(\Phi\left(\alpha_{i,t-1}\right)\right)} > 0\ ,$$

where Φ is a function that returns the sign of a real number, taking values of 1 for a positive number, –1 for a negative number, and 0 for zero. The t-statistics are after clustering standard errors both at the fund and year levels. The remaining columns display the t-statistics for the pairwise test coefficient b_1 in the following equation:

$$\Phi\left(Flow_{it}\right) = a + b_1\left(\frac{\Phi\left(\alpha_{it-1}^{m1}\right)}{var\left(\Phi\left(\alpha_{it-1}^{m1}\right)\right)} - \frac{\Phi\left(\alpha_{it-1}^{m2}\right)}{var\left(\Phi\left(\alpha_{it-1}^{m2}\right)\right)}\right) + \zeta_{it},$$

where we compare the flow-performance regression coefficients, $\beta_{Flow,\,performance}$ the two models *m1* and *m2*. The sample period is from 1994 to 2012.

			Pairwise t-stats						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	b_1	Univ. t-stat	Return	CAPM	FF3	Carhart4	AN	FH7	12-factor
Return	0.2157	7.52	0	–0.97	1.14	0.62	1.90	0.69	1.89
CAPM	0.2228	8.97		0	3.58	3.00	4.23	2.20	2.69
FF3	0.1800	6.35			0	–1.69	1.64	–0.15	1.73
Carhart4	0.1962	8.91				0	4.28	0.41	2.35
AN	0.1490	5.31					0	–1.18	1.17
FH7	0.1842	8.01						0	2.49
12-factor	0.1211	4.62							0

Table 5. Flow-performance risk model horserace: Barber, Huang, and Odean (2016) pairwise model comparison

This table presents the results of pairwise comparisons of different performance measures to predict fund flows as in Barber, Huang, and Odean (2016). We first estimate the relation between flows and a fund's decile ranking based on different performance measures by estimating the following regression with $Flow_{it}$ being the fund flow for hedge fund *i* in year *t*:

$$Flow_{i,t} = a + \sum_k \sum_l b_{kl} D_{kl,i,t-1} + cX_{i,t-1} + Style \times Year_{i,t} + \eta_{i,t}.$$

D_{klit-1} is an indicator variable that is one if fund *i* in year *t–1* is in decile *k* (*l*) based on the first (second) performance measure and X_{it-1} is a vector of control variables that includes: flow in year *t–1*, log of fund size at year *t–1*, age of fund at year *t–1*, a fund's return standard deviation estimated over the prior 12 months, management fee, incentive fee, lockup days, restriction period (sum of redemption and notice period), an indicator variable for fund's use of high water mark, an indicator variable for fund's use of hurdle rate, and an indicator variable for offshore funds. We also include style × year fixed effects. For each pairwise comparison of performance measures, we obtain 45 pairs of flow-performance sensitivity estimates. We test the hypothesis that the summed difference across the 45 pairs of estimates equals zero, and we also perform a binomial test which examines the null hypothesis that the proportion of differences equals 50%. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Risk Model	Sum of Difference	% of Differences >0
Return vs CAPM	–0.0080	0.4222***
Return vs FF3	2.4828*	0.7111***
Return vs Carhart4	3.5214**	0.7111***
Return vs AN	5.5565***	0.8666***
Return vs FH7	4.8932***	0.8666***
Return vs 12-factor	6.5622***	0.9777***
CAPM vs FF3	5.8006***	0.8222***
CAPM vs Carhart4	6.6316***	0.8666***
CAPM vs AN	7.6518***	0.9111***
CAPM vs FH7	7.0987***	0.9555***
CAPM vs 12-factor	8.3229***	1.0000***
FF3 vs Carhart4	5.7027***	0.7333***
FF3 vs AN	6.6599***	0.9777***
FF3 vs FH7	4.2522***	0.7555***
FF3 vs 12-factor	7.9765***	0.9555***
Carhart4 vs AN	5.9030***	0.8666***
Carhart4 vs FH7	2.5284**	0.7333***
Carhart4 vs 12-factor	7.5597***	0.9777***
AN vs FH7	–1.4180	0.2888***
AN vs 12-factor	6.3603***	0.9777***
FH7 vs 12-factor	7.1989***	0.9777***

Table 6. Return decomposition summary statistics

This table reports the descriptive statistics for each return component for *Carhart4* model, *AN* model, *FH7* model, and 12-factor model. Return components are calculated using the following equation and averaged over the 12 months leading up to year *t*:

$$\overline{R_{i,t} - R_{rf,t}} = \overline{\alpha_{i,t}} + Trad\ Beta\ Comp_{i,t} + Exotic\ Beta\ Comp_{i,t},$$

where

$$Trad\ Beta\ Comp_{i,t} = \hat{\beta}_{i,mktrf,t}\overline{MKTRF}_t + \hat{\beta}_{i,smb,t}\overline{SMB}_t + \hat{\beta}_{i,hml,t}\overline{HML}_t,$$

$$Exotic\ Beta\ Comp_{i,t} = \hat{\beta}_{i,umd,t}\overline{UMD}_t.$$

All variables are winsorized at the 1% and 99% levels. Reported statistics include the average (*Mean*), median (*Median*), and standard deviation (*SD*). The table also reports the correlations between the three return components for each model.

				Return Correlations		
Carhart 4-factor model	Mean	Median	SD	a)	b)	c)
a) Alpha	0.28%	0.22%	1.09%	1		
b) Traditional: Market, Size, and Value Risk	0.13%	0.13%	1.07%	0.061	1	
c) Exotic: Momentum Risk	0.06%	0.00%	0.39%	–0.041	–0.123	1
AN model						
a) Alpha	0.24%	0.18%	1.20%	1		
b) Traditional: Market, Size, and Value Risk	–0.06%	0.03%	1.65%	0.034	1	
c) Exotic: Momentum, Call and Put Option Risk	0.29%	0.11%	1.33%	–0.241	–0.623	1
FH7 model						
a) Alpha	0.39%	0.30%	1.14%	1		
b) Traditional: Market, Size, and Bond Factor Risk	0.09%	0.09%	1.15%	–0.104	1	
c) Exotic: Trending Factor Risk	–0.01%	0.00%	0.46%	–0.173	0.097	1
12-factor model						
a) Alpha	0.15%	0.12%	1.34%	1		
b) Traditional: Market, Value, Size, Bond Factor, and Emerging Market Risk	0.23%	0.16%	1.92%	–0.129	1	
c) Exotic: Momentum, Trending Factors, and Option Factor Risks	0.08%	0.07%	1.67%	–0.357	–0.520	1

Table 7. Flow-performance relation: alpha, traditional beta return, and exotic beta return

This table reports the regression coefficients b_1, b_2, and b_3 from the regression with $Flow_{i,t}$ being the fund flow for hedge fund *i* in year *t*:

$$Flow_{i,t} = a + b_1\overline{\alpha_{i,t-1}} + b_2 Trad\ Beta\ Comp_{i,t-1} + b_3 Exotic\ Beta\ Comp_{i,t-1} + cX_{i,t-1} + Style \times Year_{i,t} + v_{i,t}.$$

Traditional beta component (*Trad BetaComp*) refers to the returns due to the traditional risk factors that include market, size, value, bond, and emerging markets. Exotic beta component (*Exotic BetaComp*) refers to the returns due to the exotic risk factors that include momentum, option, and trend-following. We include style × year fixed effects and the control variables as defined in Table 5. We report the flow sensitivity coefficients corresponding to alpha and returns attributable to traditional risks and exotic risks (with adjacent *p*-values). Column $(b_2)-(b_3)$ tests whether investors have the same sensitivity to traditional and exotic risks ($b_2 - b_3 = 0$). Standard errors are clustered at both fund and year levels. Also reported are the number of observations (*N*) and the adjusted R^2 for each regression.

	N	Adj. R^2	Coefficient	*p*-value	b_2–b_3	*p*-value
Carhart 4-factor model	52,643	0.1046				
Alpha			11.766	0.0000		
Traditional: Market, Size, and Value Risk			5.517	0.0011		
Exotic: Momentum Risk			6.170	0.0062		
Traditional – Exotic					–0.653	0.6931
AN model	52,643	0.1030				
Alpha			10.833	0.0000		
Traditional: Market, Size, and Value Risk			6.305	0.0000		
Exotic: Momentum, Call and Put Option Risk			7.154	0.0000		
Traditional – Exotic					–0.849	0.1652
FH7 model	52,643	0.1039				
Alpha			11.181	0.0000		
Traditional: Market, Size, and Bond Factor Risk			5.493	0.0001		
Exotic: Trend-Following Factor Risk			9.468	0.0000		
Traditional – Exotic					–3.974	0.0540
12-factor model	52,643	0.1026				
Alpha			10.406	0.0000		
Traditional: Market, Value, Size, Bond Factor, and Emerging Market Risk			7.116	0.0000		
Exotic: Momentum, Trend-Following Factors, and Option Factor Risks			8.287	0.0000		
Traditional – Exotic					–1.171	0.0519

Table 8. Persistence in return components

This table reports the results of the following return persistence regressions with non-overlapping two-year estimation windows:

$$\alpha_{i,t+2} = a + b\alpha_{i,t} + cX_{i,t} + Style \times Year_{i,t+2} + \lambda_{i,t+2},$$

$$Trad\ Beta\ Comp_{i,t+2} = a + b'Trad\ Beta\ Comp_{i,t} + c'X_{i,t} + Style \times Year_{i,t+2} + \psi_{i,t+2},$$

$$Exotic\ Beta\ Comp_{i,t+2} = a + b''Exotic\ Beta\ Comp_{i,t} + c''X_{i,t} + Style \times Year_{i,t+2} + \chi_{i,t+2},$$

where $\alpha_{i,t+2}$, $Trad\ Beta\ Comp_{i,t+2}$, $Exotic\ Beta\ Comp_{i,t+2}$ are two-year alpha, two-year traditional return component, and two-year exotic beta component calculated using betas estimated with 24-month window from year *t+1* to *t+2*, and $\alpha_{i,t}$, $Trad\ Beta\ Comp_{i,t}$, $Exotic\ Beta\ Comp_{i,t}$ are two-year alpha, two-year traditional return component, and two-year exotic beta component calculated using betas estimated with 24-month window from year *t–1* to *t*. We include style × time fixed effects and the control variables as defined in Table 5, except the lagged flow variable. Reported *p*-values are based on standard errors clustered both at the fund and year level. The sample includes 33,522 observations from 1994 to 2012.

	Carhart4			AN			FH7			12-factor		
Return Component	Alpha	Trad. Beta	Exotic Beta	Alpha	Trad. Beta	Exotic Beta	Alpha	Trad. Beta	Exotic Beta	Alpha	Trad. Beta	Exotic Beta
Alpha	0.053			0.012			0.052			0.031		
	(0.136)			(0.630)			(0.027)			(0.154)		
Trad. Beta		-0.105			-0.066			-0.053			-0.043	
		(0.272)			(0.104)			(0.611)			(0.157)	
Exotic Beta			0.053			0.039			-0.055			-0.000
			(0.401)			(0.097)			(0.240)			(0.993)
Adj. R^2	0.180	0.433	0.177	0.159	0.280	0.146	0.151	0.456	0.142	0.142	0.202	0.106

Table 9. Persistence in betas and factor realizations

This table reports results related to the persistence in betas estimated using two-year non-overlapping windows and the annual factor realizations. Column 2 reports the persistence in annual factor realizations estimated from the following regression:

$$Factor_{t+1} = a + bFactor_{t} + u_{t+1},$$

where $Factor_{i,t+1}$ reflects each individual annual factor returns, calculated as the annual average of factor realizations in year *t+1*, and correspondingly, $Factor_{i,t}$ is calculated as the annual average of factor realizations in year *t*. Columns 3 through 6 report the estimated persistence coefficient *b* of the following return persistence regressions:

$$Beta_{i,t+2} = a + bBeta_{i,t} + cX_{i,t} + Style \times Year_{i,t+2} + \psi_{i,t+2},$$

where $\beta_{i,t+2}$ reflects the exposure to each of the factors, estimated with 24-month window from year *t+1* to *t+2,* and correspondingly, $\beta_{i,t}$ is estimated with 24-month window from year *t–1* to *t*. We include style × time fixed effects and the control variables as defined in Table 5, except for the lagged flow variable. Standard errors are clustered both at the fund and year level. The sample includes 33,522 fund-year observations from 1994 to 2012. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

(1) Factors	(2) Annual Factor Returns	(3) Carhart4	(4) AN Option	(5) FH7	(6) 12-factor
MKT	0.042	0.361***	0.025	–	–
SMB	–0.019	0.180***	0.132***	–	–
HML	–0.057	0.160***	0.142***	–	0.124***
UMD	–0.149	0.158***	0.124***	–	0.046*
OTM_CALL	0.215	–	–0.013	–	0.008
OTM_PUT	0.163	–	0.006	–	-0.002
PTFSBD	0.035	–	–	0.106***	0.080***
PTFSFX	–0.429*	–	–	0.035*	0.032*
PTFSCOM	–0.059	–	–	0.115***	0.067***
BD10RET	–0.445**	–	–	0.053*	–0.000
BAAMTSY	–0.302	–	–	0.061***	0.038*
SNPMRF	0.089	–	–	0.416***	0.007
SCMLC	0.311	–	–	0.188***	0.140***
MSCIEM	–0.379	–	–	–	0.209***

APPENDIX Table A1. Barber, Huang, and Odean (2016) model comparison: CAPM vs. Fama French 3-factor model

This table presents the results of a pairwise comparison between the alphas from the CAPM model and the Fama-French 3-factor model. We report the 45 pairs of flow-performance sensitivity coefficients and the difference between b_{kl} and b_{lk} in equation in Table 5. The last two rows report whether the summed difference across the 45 pairwise comparisons equal to zero and proportion of differences equal to 50%.

k	l	CAPM_FF3_kl	CAPM_FF3_lk	Diff.	*p*-value
10	9	0.05343	0.1134**	–0.0600	0.3843
10	8	0.08516	–0.03802	0.1232	0.3159
10	7	–0.08942	–0.1582	0.0688	0.5811
10	6	–0.1656	0.1129	–0.2785	0.3283
10	5	–0.2578***	–0.3713***	0.1135	0.2279
10	4	0.01674	–0.5391***	0.5558	0.2009
10	3	–0.03978	–0.4819**	0.4421	0.0004
10	2	–0.2805***	0.07682	–0.3573	0.5518
10	1	–0.5315***	–0.3058***	–0.2257	0.0163
9	8	–0.01509	0.03434	–0.0494	0.0915
9	7	0.002578	–0.09993**	0.1025	0.0491
9	6	–0.09466	–0.1450	0.0503	0.6712
9	5	–0.2451***	–0.3455***	0.1004	0.2590
9	4	0.009118	–0.2736*	0.2827	0.1364
9	3	–0.3503***	–0.2096**	–0.1407	0.1746
9	2	0.2614	–0.3723***	0.6337	0.0633
9	1	–0.1495	–0.4898***	0.3403	0.0030
8	7	0.03553	–0.03282	0.0684	0.0482
8	6	0.04650	–0.1902***	0.2367	0.0007
8	5	–0.1105*	–0.1907*	0.0802	0.4611
8	4	–0.1521*	–0.3450***	0.1929	0.0215
8	3	–0.1611	–0.3638***	0.2027	0.1386
8	2	–0.1100	–0.4027***	0.2927	0.0002
8	1	–0.1610	–0.3794***	0.2184	0.1226
7	6	–0.05129	–0.06935*	0.0181	0.6667
7	5	–0.05655	–0.2190***	0.1625	0.0889
7	4	–0.09328	–0.2892***	0.1959	0.0037
7	3	0.07383	–0.3638***	0.4376	0.0001
7	2	–0.2134*	–0.4110***	0.1976	0.0731
7	1	0.1641	–0.2106***	0.3747	0.0082
6	5	–0.1252**	–0.1255***	0.0003	0.9938
6	4	–0.1344***	–0.2648***	0.1304	0.0625
6	3	–0.1563**	–0.3325***	0.1762	0.0168
6	2	–0.03956	–0.2446*	0.2050	0.1697
6	1	–0.2509***	–0.2672	0.0163	0.9150
5	4	–0.1535***	–0.2202***	0.0667	0.1514
5	3	–0.2118***	–0.2752***	0.0634	0.4025
5	2	–0.09311	–0.3235***	0.2304	0.0287
5	1	–0.1061	–0.01421	–0.0919	0.7034
4	3	–0.2672***	–0.2537***	–0.0135	0.6535
4	2	–0.2150**	–0.3210***	0.1060	0.1562
4	1	–0.1979*	–0.3816***	0.1837	0.0349
3	2	–0.3142***	–0.3653***	0.0511	0.1070
3	1	–0.2226***	–0.4343***	0.2117	0.0143
2	1	–0.3312***	–0.4159***	0.0847	0.1276
			Sum of Differences	5.8006	0.0000
			Percent of Differences > 0	82.22%	0.0000

APPENDIX Table A2. Persistence in *t*-statistics of betas

The table reports the estimated persistence coefficient b from the following regressions:

$$Tstat_{i,t+2} = bTstat_{i,t} + cX_{i,t} + Style \times Year_{i,t+2} + \psi_{i,t+2},$$

where $Tstat_{i,t+2}$ reflects the t-statistics of estimated individual betas for each of the factors using observations from $t+1$ to $t+2$, and correspondingly, $Tstat_{i,t}$ is estimated using observations from $t–1$ to t. We include style × time fixed effects and the control variables as defined in Table 5, except for the lagged flow variable. Standard errors are clustered both at the fund and year level. The sample includes 33,522 fund-year observations from 1994 to 2012. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Factors	Carhart4	AN	FH7	12-factor
MKT	0.490***	0.187***	–	–
SMB	0.217***	0.156***	–	–
HML	0.180***	0.145***	–	0.131***
UMD	0.198***	0.151***	–	0.065**
OTM_CALL	–	0.024	–	0.012
OTM_PUT	–	–0.014	–	0.002
PTFSBD	–	–	0.091***	0.060**
PTFSFX	–	–	0.040**	0.022**
PTFSCOM	–	–	0.090***	0.036***
BD10RET	–	–	0.072***	0.025
BAAMTSY	–	–	0.101***	0.036*
SNPMRF	–	–	0.504***	0.077***
SCMLC	–	–	0.227***	0.182***
MSCIEM	–	–	–	0.190***

APPENDIX Table A3. Persistence in return components and betas using one-year windows

This table reports the results of persistence analysis using one-year estimation windows for betas for the *Carhart4* model. Panel A provides the results of persistence for three return components. Panel B provides the results of persistence for betas and for *t*-statistics of betas.

Panel A. Persistence in return components

	Alpha	Traditional Beta	Exotic Beta
Alpha	0.058		
	(0.140)		
Traditional Beta		0.029	
		(0.644)	
Exotic Beta			0.005
			(0.865)
N	32132	32132	32132
adj. R-squared	0.178	0.342	0.189

Panel B. Persistence in betas and *t*-statistics of betas

	Betas	*t*-stats of betas
Market	0.278***	0.322***
SMB	0.059**	0.081***
HML	0.061***	0.090***
UMD	0.048*	0.073***

Alpha or Beta in the Eye of the Beholder: What Drives Hedge Fund Flows?

Internet Appendix

This appendix consists of four parts. Section IA.1 analyzes whether hedge fund fees influence investor preferences regarding returns arising from traditional risk exposures relative to those obtained through exotic risk exposures. We also examine whether hedge funds with higher fees deliver greater return components (alphas, traditional beta returns, and exotic beta returns). In Section IA.2, we explore whether investors learn about exotic risks over time and if hedge fund managers cater to the investors by delivering higher returns from exotic risks over time. Section IA.3 investigates clientele sophistication by comparing the investment preferences of retail investors with those of the institutional investors. In Section IA.4, we conduct robustness checks to examine whether our results change qualitatively after accounting for differences in alpha precision, multicollinearity between the equity market factor and option factors, backfilling bias, and using an alternative method to adjust for cross-sectional correlations in residuals from the panel regressions.

IA.1 The relation between hedge fund fees, performance, and investor flows

An important feature distinguishing hedge funds from mutual funds is the substantial performance-based incentive fee charged by hedge fund managers. In our sample, 58.4% of hedge funds charges an incentive fee greater than or equal to 20% of the profits, among which 54.1% percent charge exactly 20%. We are interested in studying whether hedge fund investors who pay higher performance fee are more discerning between traditional and exotic return components. Therefore, we repeat our return decomposition tests using subsamples based on the incentive fee. Since there is a substantial clustering of incentive fees at the 20% level, we divide our sample into two roughly equal groups, one with incentive fee less than 20%, and one with incentive fee greater than or equal to 20%. We would expect that investors paying higher performance fees should put relatively greater weight on the exotic return component compared to investors paying lower performance fee. .

Table IA.1 reports results for the return decomposition of the incentive fee subsamples. The first column is for low-fee funds with incentive fee less than 20%, and the second column is for high-fee funds with incentive fee greater than or equal to 20%. First, the sensitivity of investor flows to traditional beta returns, b_2, is always smaller than that for the exotic beta returns, b_3, in both subsamples (except one case). If we look at the significance test of the difference, $b_2 - b_3$, we observe no significance for the low-fee group, while in three out of four models this difference is significant for the high-fee group. This suggests that investors that pay high performance fees are more sensitive to the source of fund returns being attributable to exotic risks. In other words, investors expect that their highly compensated hedge fund managers span nonconventional risks that are not available through ETFs and mutual funds.

A natural question that arises from the flow-performance findings in Table IA.1 is whether high-fee funds also deliver higher alphas, higher exotic beta returns, and lower traditional beta returns compared to low-fee funds. We test this hypothesis by comparing each return component for the two incentive fee subsamples. We report the results in Table IA.2. Columns 1 and 2 are average return components for funds with incentive fee less than 20% and funds with incentive fee greater and equal to 20%, respectively. Column 3 reports the *p*-value of the difference between these two return averages from the two subsamples. Since we have repeated observations for fund and years in the panel data, we cluster the standard errors both at the fund and year level to estimate statistical significance of the differences.

From Panel A, we observe that high-fee funds deliver significantly higher alphas. However, the results in Panels B and C show that the traditional beta component and exotic beta component are not significantly different between high-fee and low-fee funds. Since the fees are set at fund's inception, this evidence is consistent with investors selecting high-fee funds with the expectation of higher alphas and exotic returns. Although high-fee funds do deliver higher alphas, we find no evidence that their exotic risk returns are different from the traditional risk returns.

IA.2 Investor learning about exotic risks and catering by hedge fund managers

In this section, we hypothesize that investors' awareness of the exotic risks may have improved over time. Likewise, hedge fund managers may also shift the types of risk exposures they seek out over time. We explore the extent to which hedge fund investors learn about exotic risks, and we look for evidence that managers cater to the investors by providing risk exposures that match investors' preferences.

IA.2.1 Have investors become more aware of exotic risks over time?

The midpoint of our sample period roughly coincides with the 2004 publication of Agarwal and Naik (2004) and Fung and Hsieh (2004), which introduced more sophisticated hedge fund models that consider exotic risk factors such as option factors and trend-following factors. We explore whether investors become more cognizant of exposures to such exotic risk factors over time by repeating the return decomposition exercise for two sub-periods from 1994 to 2004 and 2005 to 2012. If investors tilt their preferences toward the exotic risks in the second sub-period, it would support the investor learning hypothesis.

Table IA.3 reports the return decomposition results for the two sub-periods. First, we continue to observe that all the sensitivities are significantly positive. If we look at the results for the first sub-period from 1994 to 2004, the sensitivity to traditional beta returns is either statistically indistinguishable or larger than the sensitivity of exotic beta returns. This indicates that during the first half of our sample period, investors do not appear to differentiate between traditional beta returns and exotic beta returns. In sharp contrast, the results for the second sub-period from 2005 to 2012 show that the sensitivity to traditional beta returns, b_2, is significantly smaller than the sensitivity to exotic beta returns, b_3, in all four models. The evidence from the sub-period analysis supports the investor learning hypothesis, i.e., investors increasingly differentiate between traditional and exotic risks in the recent sub-period coinciding with the advent of more sophisticated risk models.[1] Armed with this knowledge, investors seem to update their capital allocation decisions by tilting less towards returns associated with traditional risks while continuing to emphasize returns attributable to exotic risks.

IA.2.2 Do managers cater to investors by tilting their portfolios toward exotic risks over time?

In light of the evidence that investors deemphasize hedge fund performance related to traditional risk exposures over time while continuing to emphasize exotic risk returns, in this section we explore whether managers cater to the evolution in investor preferences by increasing their relative emphasis on exotic risk exposures over time.

The risk exposures of hedge funds are likely to be affected by the fund leverage. Given the finding in Farnsworth (2014) of a downward trend in leverage during our sample period, we adjust for fund leverage to examine the time-series variation in both traditional and exotic betas. To that end, as in Agarwal, Ruenzi, and Weigert (2016) and Farnsworth (2014), we use long

[1] In results not tabulated, we find little evidence that the return components themselves differ between the different sub-periods. For the four models and three components (12 tests of difference in mean returns), we find only one case (12-factor alpha) that is statistically different at the 10% level or below. This suggests that investors' preference for the exotic beta returns in the second sub-period is not due to higher returns in that period.

equity holdings information from the hedge funds' 13F filings to compute a measure of long-only leverage for each fund. We obtain the holdings data from Thomson Reuters s34 database.[2] We merge the s34 database with our Union Hedge Fund Database using a two-step process that involves fuzzy matching by company name and computing the correlation between returns imputed from the 13F quarterly holdings and returns reported in the Union Database (see Agarwal, Fos, and Jiang, 2013 for more details). This procedure gives us a final sample of 669 hedge fund firms managing 2,075 distinct hedge funds.

We examine variation in funds' risk exposures over time as follows: for each fund and each year, we calculate traditional and exotic betas for the different risk models (using 24 months of data). We take the absolute value of each beta and adjust the betas for differences in fund leverage by dividing the betas by the fund leverage ratio at the fund-year level. We then average the leverage-adjusted betas across funds for each factor, and then average across traditional and exotic categories for each model.

Figure IA.1 plots the variation in yearly average traditional and exotic betas over time for the four risk models. We observe no distinguishable shift in factor exposures over time for either traditional or exotic risks. In further analysis, we focus on the subset of funds with observations pre- and post-2004 and test whether average yearly betas are significantly different at the fund level in the two subsamples. We consider both the level changes in betas and percentage changes in betas, and in each case, we find no reliable evidence of a shift in betas. Together, our analysis reveals no discernable indication that fund managers shift their emphasis towards exotic risk

[2] We manually classify 13F institutions as hedge funds if they satisfy at least one of the following criteria: name match with the Union Hedge Fund Database, name listed as a hedge fund in Factiva or in industry publications, listed as hedge fund on the firm's website, or for individual 13F filers, if the person is materially involved in a hedge fund. See Agarwal, Fos, and Jiang (2013) for more details.

exposures in their investment portfolios in recent years to cater to investors' preferences for exotic risks.

IA.3 Clientele sophistication and the flow-performance relation

It is conceivable that investors' approach to evaluate fund performance may vary in their sophistication. Institutional investors are generally considered to be more sophisticated than retail investors, and may employ more sophisticated risk models when measuring abnormal performance or place greater emphasis from returns attributable to exotic rather than traditional risk exposures when allocating capital. In this section, we consider two approaches for testing the clientele hypothesis. Our first approach uses data on the hedge fund investments of registered funds of hedge funds (FoFs), and our second test uses Form ADV data that allows us to identify hedge funds' clientele type.

IA.3.1 Hedge fund investments of funds of hedge funds

Following Agarwal, Aragon, and Shi (2016) and Aiken, Clifford, and Ellis (2013, 2015a, 2015b), we collect the quarterly portfolio holdings of FoFs that register with the U.S. Securities and Exchange Commission (SEC) as closed-end funds under the Investment Company Act of 1940. Specifically, we hand collect this data from N-Q, N-CSR, and N-CSRS regulatory filings from 2004Q3 (when FoFs started disclosing their holdings on a quarterly basis) until 2011Q4. These regulatory filings contain the market value, the cost, and the net asset values of the FoFs. Finally, we match the underlying hedge funds with the Union hedge fund database to obtain their characteristics and performance data. Our final sample includes 79 FoFs investing in 675 hedge funds.

We repeat our model horserace and flow-performance sensitivity tests using FoF investments in hedge funds as the flow variable. Specifically, for each hedge fund in a FoF portfolio, we estimate quarterly flows as the change in the cost (i.e., cost basis for the FoF) over a given quarter. We then aggregate the quarterly flows from all FoFs investing in the same underlying hedge fund. We finally compute the annual percentage flow by summing the quarterly flows for each hedge fund each year and dividing it by the AUM of the hedge fund at the end of previous year.

Panels A and B of Table IA.4 present the results from the pairwise horserace tests between the different alphas using the BvB and BHO framework, respectively. We observe from both the panels that CAPM alphas continue to dominate alphas from the different multifactor models but not so for raw returns. The second row labeled "CAPM" in panel A shows that all the pairwise *t*-stats are positive and significant at the conventional levels with the sole exception of the FF3 model. We obtain similar inferences from the results in panel B, as both the sum and percent of pairwise differences of CAPM relative to each of the multifactor models are positive. Moreover, all the differences are significant at the conventional levels with the sole exception of the FH7 model.

Panel C reports the differences in the investors' flow sensitivities to the returns attributable to traditional risk exposures relative to the returns from exotic risk exposures. We observe that the differences are negative and significant for two out of the four models (*AN* and 12-factor), which indicates that FoFs have a preference for returns from exotic betas over the returns from traditional betas. Overall, our analysis of FoFs' investments in hedge funds provides no evidence that FoFs evaluate hedge fund performance using more sophisticated models than other hedge fund investors.

IA.3.2 Hedge fund investments of institutional and retail clients

Following prior hedge fund literature (Ben-David, Franzoni, and Moussawi, 2012, and Chen, 2013), we obtain funds' clientele information from the Form ADV filings with the SEC from 2001 to 2012 to classify them into institution-oriented versus retail-oriented.[3] For the classification, we rely on Part 1 of the ADV form that requires information about the investment adviser's businesses, clients, employees, etc. Specifically, Item 5 Question D on the Form ADV provides information on the types of clients and the approximate percentages in range (up to 10%, 11–25%, etc.) of each clientele type.

Hedge fund clients include individuals, high net worth individuals, banking or thrift institutions, investment companies, pension and profit sharing plans, pooled investment vehicles, charitable organizations, corporations, etc. Following Chen (2013), we classify a fund as retail-oriented if individuals and wealthy individual represent over 50% of its clients. In contrast, we classify a fund as institution-oriented if more than 50% of its clients fall outside the individual investor categories. We use the mid-point of each percentage range for the classification.

For our empirical analysis, we merge the ADV data with the Union hedge fund database using the fund's management company name since there is no common identifier across the two databases. This provides us with a final matched sample of 2,592 fund companies, which correspond to 7,212 funds in the Union database. Interestingly, we observe a decreasing trend in the percentage of retail-oriented funds. The percentage of such funds decreased from 30% to 21% between 2001 (the first year for which the ADV data is available) and 2012.

Table IA.5 presents the results of capital allocation decisions made by the investors in retail-oriented and institutional funds. Panels A and B report the pairwise horserace tests as in BvB and BHO, respectively. Evidence from the BvB approach indicates that both retail and

[3] In contrast to the use of one-year snapshot of ADV data in previous papers, we use time-series information on the clientele type included in the ADV filings. We obtain this data from the SEC using a request under the Freedom of Information Act (FOIA).

institutional clients display similar preferences for the CAPM alphas over alphas from multifactor models. We observe weaker statistical significance for the pairwise comparisons of CAPM alphas with each of the alphas from different multifactor models in Panel A for retail-oriented funds. Given the smaller number of observations for retail funds, this result may be due to lower statistical power in testing. However, despite the lower power, results from the BHO framework in Panel B universally show that CAPM wins over other multifactor models for both types of funds. All of the sum and percent-of-differences for the flow-performance sensitivities of CAPM alphas relative to the alphas from each of the multifactor models are positive and significant at the 5% level or better. In contrast to the alphas from the multifactor models, there is little evidence that investors differentiate between CAPM alphas and raw returns.

Panel C reports the differences in the flow-performance sensitivities to traditional beta returns and to exotic beta returns. We observe an increased preference for exotic beta returns among institutional clientele as compared to the retail clientele. Specifically, the flow-performance sensitivity for exotic beta returns is significantly greater in three out of the four models for institutional clients compared to none for retail clients.

Taken together, the results from the tests using the FoF investments in hedge funds as well as retail-oriented versus institutional funds show that our findings of preference for CAPM alphas over alphas from more sophisticated model do not seem to be driven by a specific clientele type. However, the preference for the exotic beta return over the traditional beta return seems to be driven by the investors in institution-oriented funds.

IA.4 Robustness to alpha precision, multicollinearity, backfilling bias, and residual cross-sectional correlation

IA.4.1 Alpha precision and risk model effectiveness in explaining hedge fund flows

In this section, we examine if CAPM alpha's success over multifactor-model alphas in explaining hedge fund flows is related to differences in the precision of the alpha estimates. We conduct three tests to investigate whether investors emphasize alpha precision when making their capital allocation decisions.

Our first test compares the investor flows into funds with similar alpha magnitudes but differences in estimate precision (and vice versa). In Panel A of Table IA.6, we present the average net flows into the funds sorted unconditionally into 10 by 10 portfolios by their alphas measured over a 24-month estimation window and the standard errors of CAPM alphas. We repeat this two-way sorting procedure by using the 12-factor model instead of the CAPM, and report the results in Panel B. The second-last row of the table reports the differences in the average net flows between the portfolio with highest alpha and the one with the lowest alpha, while controlling for the standard errors of the alphas. Similarly, the second-last column of the table reports the differences in the average net flows between the two portfolios with the highest and lowest standard errors of alphas, after controlling for magnitudes of alphas.

Two patterns in both the panels of Table IA.6 are noteworthy. First, controlling for the standard errors of alphas, the average flow is generally increasing when we move across columns from the lowest alpha portfolio to the highest alpha portfolio. This is not true when we move across rows from the portfolio with highest standard error of alpha to the one with the lowest standard error, after controlling for the magnitude of alphas. Second, all the (10 – 1) differences across columns are significant except in case of the decile with lowest standard error of alpha. In contrast, the (10 – 1) differences across rows are generally not significant.[4] Together these findings show that regardless of the model used for evaluating fund performance, investors seem

[4] Results for the other four models (*FF3*, *Carhart4*, *AN*, and *FH7*) show similar patterns. We do not tabulate these results here for the sake of brevity.

to care about the size but not the precision of the alpha estimates while making their capital allocation decisions.

For our second test, we consider two longer estimation windows of 36 months and 60 months that should increase the precision of alpha estimates (assuming betas do not change within the estimation window). In untabulated results, we observe that longer windows do shrink the differences in the standard errors of alphas across the different models. Put differently, the precision of the alpha estimates is more similar across models when a longer horizon is used, which suggests estimation error should have less impact on the horserace tests. Nevertheless, we continue to find that CAPM alpha dominates multifactor-model alphas in explaining investor flows.

For our third test, we follow prior hedge fund literature (Kosowski, Naik, and Teo, 2007; Jagannathan, Malakhov, and Novikov, 2010; and Avramov, Barras, and Kosowski, 2013) to use *t*-statistics of alphas instead of the alphas themselves in the horserace tests. Using *t*-statistics scales each alpha estimate by its standard error and therefore adjusts for estimate precision. In untabulated results, we continue to find that CAPM alpha wins the alpha horserace, which suggests that precision of the alpha estimates do not materially influence our findings.

Taken together, the results from the battery of tests indicate that the dominance of CAPM alpha over multifactor-model alphas in explaining hedge fund flows does not appear to be driven by the differences in the estimation errors of alphas.

IA.4.2 Multicollinearity between the option factors and the equity market factor

The option-based risk factors considered in the AN factor model are highly correlated with the market factor, as evidenced by the high (negative) correlations between the returns attributable to traditional and exotic risk returns in Table 6 in the text. This multicollinearity problem could potentially affect our multivariate regression in the decomposition analysis. In this section, we address the multicollinearity issue by orthogonalizing the option factors with respect to the market factor. Specifically, we regress each of the AN option factors on the market factor and take the residual term as the new option factors. With these new orthogonalized option factors, we repeat our return decomposition analysis for the AN model and the 12-factor model, the two models that utilize the option factors.

We conduct the analysis for the whole sample period and the two sub-periods. The results are tabulated in Table IA.7. Panel A provides summary statistics of the alpha and the two beta return components, as well as the correlations between each of the components. We observe that the summary statistics (mean, median, and standard deviation) do not change materially with the new option factors. However, the correlations between the traditional beta component and the exotic component fall considerably. Specifically, for the overall sample period, the correlation between the two beta components decreases from –62.3% to –31.7% for the AN model and from –52.0% to –24.4% for the 12-factor model.

Panel B of Table IA.7 reports the results from the return decomposition analysis. The differences between the investors' sensitivity to the traditional component and the investors' sensitivity to the exotic component are reported in the second to the last row with *p*-values reported in the last row. For the overall sample period, we continue to find that investors' sensitivity to the exotic component is higher than their sensitivity to the traditional component, with a larger magnitude but lower statistical significance than the analysis using unorthogonalized AN factors. However, if we look at the learning behavior of investors, we continue to find that investors put significantly more relative emphasis on the exotic beta component in the second half of the sample period (2005–2012) compared to the first half of the sample period (1996–2004). This is consistent with our earlier finding of investors deemphasizing hedge fund performance related to traditional risk exposures over time while continuing to emphasize exotic risk returns.

IA.4.3 Controlling for backfilling bias

In this section, we examine the robustness of our results to backfilling bias. Prior work shows that backfilling bias can affect the flow-performance relation and the persistence in performance. For example, Evans (2010) studies incubation bias in mutual funds (similar to backfilling bias in hedge funds) to show that investor flows respond to performance during the incubation period, which is subject to an upward bias as poorly performing internal funds are less likely to become open to outside investors. To avoid attributing the performance during backfilling/incubation period to managerial skill, Jagannathan, Malakhov, and Novikov (2010) correct for backfilling bias in their study of persistence in hedge fund performance.

Motivated by past work, we correct for the backfilling bias by eliminating the returns between funds' inception dates and the dates of their addition to the databases. Among the commercial databases we use in this study, HFR, Eurekahedge, and TASS provide information about the dates on which the funds are added to the databases. However, Morningstar does not provide such information. Therefore, we calculate the median backfill period in months from the other three databases (24 months for our sample) and eliminate the returns of Morningstar funds for the first 24 months since their inception to adjust for the backfilling bias.

Table IA.8 presents the main results in the paper after adjusting for the backfilling bias. Panel A contains the results from the pairwise horserace tests between the different performance measures using the Berk and van Binsbergen (2016) (BvB) and the Barber, Huang, and Odean (2016) (BHO) approach. We continue to find strong evidence of CAPM alpha outperforming multifactor alphas and weak evidence of it outperforming raw returns when we use the BHO approach (see Tables 4 and 5 in the paper for comparison).

Panel B of Table IA.8 reports the differences in the investors' flow sensitivities to the returns from traditional betas and returns from exotic betas. For three out of four models, *AN*, *FH7* and 12-factor, the sensitivity of investor flows to exotic beta returns is statistically greater than the sensitivity to traditional beta returns. This evidence is stronger than the evidence in the paper without the backfilling bias adjustment, in which two out of the four models show greater flow sensitivity to exotic beta returns (see Table 7 in the paper). Panel C reports the persistence in alpha and returns from traditional betas and from exotic betas. As in Table 8 in the paper, we find weak persistence in alpha and no evidence of persistence either in traditional beta returns or in exotic beta returns with two-year non-overlapping window. Taken together, we find that our key results remain unchanged when we correct for backfilling bias.

IA.4.4 Alternative method to adjust for cross-sectional correlation in residuals

Following Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016), in the paper we double cluster standard errors by fund, to account for serial correlation in residuals over time for a given fund, and by year, to adjust for cross-sectional correlation in residuals across funds at a given point in time. As an additional robustness check, we also double cluster standard errors by fund and style × year, to account for potential correlation in residuals across funds within a style for a given year.

Table IA.9 presents the results of this analysis. Panels A to C again report the main results repeated with the alternative method of clustering the standard errors. Our main results are robust to the alternative clustering technique, and generally have smaller standard errors compared to those from double clustering on fund and year, which is more stringent as suggested by Pastor, Stambaugh, and Taylor (2016).

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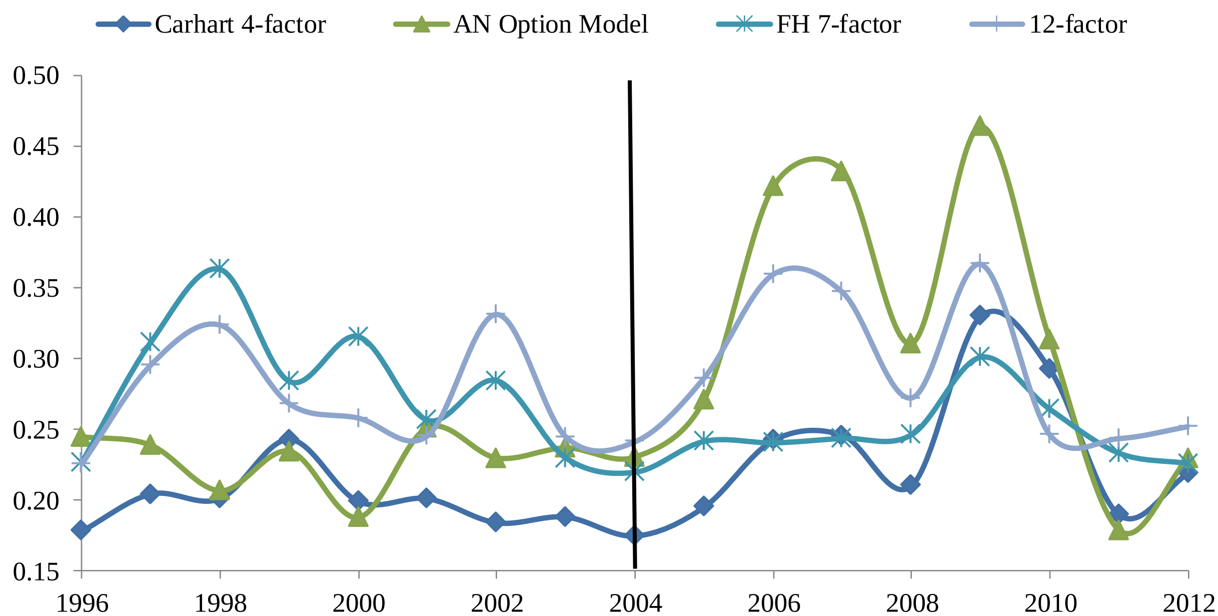
Figure IA.1 Trend in traditional and exotic risk exposures over time

The figure plots the average of absolute leverage-adjusted risk exposures over time. Leverage-adjusted risk exposure is calculated as the unadjusted risk exposure divided by the fund's leverage ratio. Each year, the average of the absolute adjusted risk exposure is computed for each traditional and exotic risk factor for each fund. The mean of the individual risk exposures across traditional and exotic risk categories and across funds is taken to obtain the average risk exposure. Panel A plots the average traditional risk exposure, and Panel B plots the average exotic risk exposure.

Panel A. Average Traditional Risk Exposures



Panel B: Average Exotic Risk Exposures

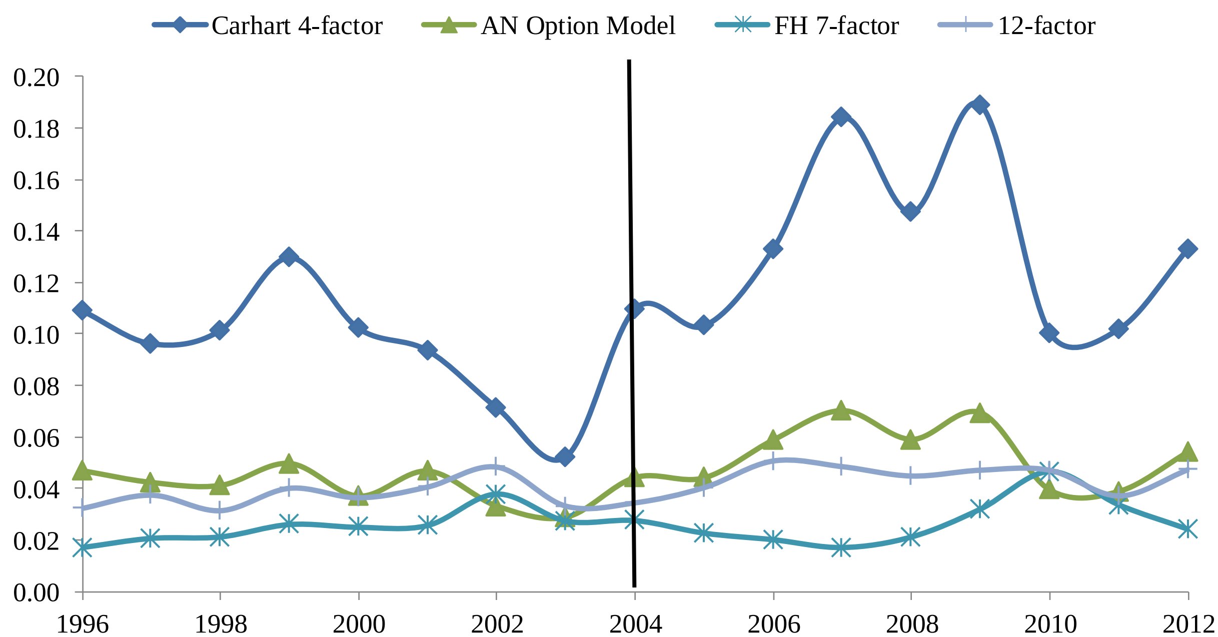


Table IA.1 Hedge fund flow-performance relation for low and high fee funds

This table reports the regression coefficients b_1, b_2, and b_3 from the regression with $Flow_{it}$ being the fund flow for hedge fund *i* in year *t*:

$$Flow_{i,t} = a + b_1\overline{\alpha_{i,t-1}} + b_2 Trad\ Beta\ Comp_{i,t-1} + b_3 Exotic\ Beta\ Comp_{i,t-1} + cX_{i,t-1} + Style \times Year_{i,t} + \nu_{i,t},$$

X_{it-1} represents a variety of control variables described in the text. We also include time fixed effects μ_t and style × year dummies $Style \times Year_{it}$. We report the flow-performance sensitivity coefficients corresponding to alpha and returns attributable to traditional betas and exotic betas (with adjacent *p*-values). Column $(b_2)-(b_3)$ tests whether investors have the same sensitivity to returns from traditional and exotic betas ($b_2 - b_3 = 0$). Also reported are the number of observations (*N*) and the adjusted R^2 for each regression.

	Low Fee Funds						High Fee Funds					
	N	Adj. R^2	Coeff.	*p*-value	b_2-b_3	*p*-value	N	Adj. R^2	Coeff.	*p*-value	b_2-b_3	*p*-value
Carhart 4-factor model	20160	0.1005					32483	0.1093				
Alpha			9.657	0.0000					12.333	0.0000		
Traditional Risk Exposures			5.904	0.0004					5.545	0.0031		
Exotic Risk Exposures			7.057	0.0164					6.035	0.0097		
Traditional – Exotic					–1.154	0.7078					–0.490	0.7723
AN model	20160	0.0997					32483	0.1072				
Alpha			9.190	0.0000					11.286	0.0000		
Traditional Risk Exposures			5.948	0.0000					6.484	0.0001		
Exotic Risk Exposures			5.790	0.0008					7.639	0.0001		
Traditional – Exotic					0.157	0.8880					–1.155	0.0634
FH7 model	20160	0.1000					32483	0.1085				
Alpha			9.459	0.0000					11.703	0.0000		
Traditional Risk Exposures			5.434	0.0000					5.638	0.0008		
Exotic Risk Exposures			7.025	0.0049					10.248	0.0000		
Traditional – Exotic					–1.591	0.6014					–4.610	0.0277
12-factor model	20160	0.1003					32483	0.1062				
Alpha			9.162	0.0000					10.704	0.0000		
Traditional Risk Exposures			6.881	0.0000					7.241	0.0000		
Exotic Risk Exposures			7.698	0.0000					8.470	0.0000		
Traditional – Exotic					–0.816	0.4686					–1.230	0.0213

Table IA.2 Return components for incentive fee subsamples

This table reports the subsample results for return components. Panel A is for alpha component, Panel B is for traditional beta return component, and Panel C is for exotic beta return component. Columns 1 and 2 are averages for funds with incentive fee less than 20% and funds with incentive fee greater and equal to 20%, respectively. Column 3 reports the *p*-value of the difference between these two averages from columns 1 and 2 after clustering the standard errors both at the fund and year level.

Panel A. Alpha

	[0%, 20%)	[20%, +∞)	*p*-value of the diff
Carhart4	0.11%	0.38%	0.0000
AN	0.07%	0.35%	0.0000
FH7	0.22%	0.49%	0.0000
12-factor	–0.04%	0.26%	0.0000

Panel B. Traditional Beta Return

	[0%, 20%)	[20%, +∞)	*p*-value of the diff
Carhart4	0.10%	0.14%	0.3887
AN	–0.13%	–0.01%	0.1294
FH7	0.05%	0.11%	0.3911
12-factor	0.17%	0.27%	0.1118

Panel C. Exotic Beta Return

	[0%, 20%)	[20%, +∞)	*p*-value of the diff
Carhart4	0.06%	0.07%	0.8398
AN	0.34%	0.26%	0.1015
FH7	–0.01%	0.00%	0.7902
12-factor	0.13%	0.06%	0.0895

Table IA.3 Hedge fund flow-performance relation: Learning about traditional and exotic risks

This table reports the regression coefficients b_1, b_2, and b_3 from the regression with $Flow_{it}$ being the fund flow for hedge fund *i* in year *t*:

$$Flow_{i,t} = a + b_1 \overline{\alpha_{i,t-1}} + b_2 Trad\ Beta\ Comp_{i,t-1} + b_3 Exotic\ Beta\ Comp_{i,t-1} + cX_{i,t-1} + Style \times Year_{i,t} + v_{i,t},$$

X_{it-1} represents a variety of control variables described in the text. We also include time fixed effects μ_t and style × year dummies $Style \times Year_{it}$. We report the flow-performance sensitivity coefficients corresponding to alpha and returns attributable to traditional betas and exotic betas (with adjacent *p*-values). Column $(b_2)-(b_3)$ tests whether investors have the same sensitivity to returns from traditional and exotic betas ($b_2 - b_3 = 0$). Also reported are the number of observations (*N*) and the adjusted R^2 for each regression.

	1994 – 2004						2005 – 2012					
	N	Adj.R^2	Coeff.	*p*-value	b_2–b_3	*p*-value	N	Adj.R^2	Coeff.	*p*-value	b_2–b_3	*p*-value
Carhart 4-factor model	16963	0.128					35680	0.079				
Alpha			12.693	0.0000					11.031	0.0000		
Traditional Risk Exposures			8.077	0.0008					3.839	0.0288		
Exotic Risk Exposures			6.564	0.0264					6.782	0.0155		
Traditional – Exotic					1.513	0.5720					–2.943	0.0088
AN model	16963	0.127					35680	0.077				
Alpha			12.291	0.0000					9.861	0.0000		
Traditional Risk Exposures			7.880	0.0000					5.099	0.0098		
Exotic Risk Exposures			6.975	0.0004					7.192	0.0018		
Traditional – Exotic					0.905	0.0132					–2.094	0.0860
FH7 model	16963	0.127					35680	0.078				
Alpha			12.047	0.0000					10.418	0.0000		
Traditional Risk Exposures			8.010	0.0016					4.011	0.0070		
Exotic Risk Exposures			8.911	0.0001					9.702	0.0008		
Traditional – Exotic					–0.901	0.7953					–5.691	0.0485
12-factor model	16963	0.127					35680	0.077				
Alpha			11.672	0.0000					9.554	0.0000		
Traditional Risk Exposures			9.192	0.0000					5.845	0.0001		
Exotic Risk Exposures			8.691	0.0000					8.100	0.0000		
Traditional – Exotic					0.501	0.3445					–2.255	0.0041

Table IA.4 Hedge fund flow-performance relation: Investments by funds of funds
This table presents the results of capital allocation decisions made by registered funds of hedge funds (FoFs). Panels A and B present the results from the tests related to pairwise horserace between the different performance measures using the BvB approach and the BHO approach, respectively. Panel C reports the differences in the investors' flow sensitivities to the returns from traditional betas and returns from exotic betas.

Panel A. Pairwise model comparison using the BvB approach

			Pairwise *t*-stats						
	b_1	Univ. *t*-stat	Return	CAPM	FF3	Carhart4	AN	FH7	12-factor
Return	0.326	17.20	0	0.24	1.01	1.47	1.87	1.39	3.20
CAPM	0.315	14.95		0	1.61	2.79	3.09	1.70	3.74
FF3	0.264	7.25			0	0.42	1.91	1.26	3.93
Carhart4	0.256	7.19				0	1.40	0.90	3.13
AN	0.201	2.68					0	–0.28	1.71
FH7	0.216	6.09						0	3.25
12-factor	0.123	2.06							0

Panel B. Pairwise model comparison using the BHO approach

Risk Model	Sum of Difference	*p*-value	Percent of Difference >0	*p*-value
CAPM vs Return	–0.1430	0.3987	0.5111	0.3822
CAPM vs FF3	0.7581***	0.0000	0.6222***	0.0060
CAPM vs Carhart4	0.8471***	0.0000	0.6666***	0.0004
CAPM vs AN	1.0490***	0.0000	0.6666***	0.0004
CAPM vs FH7	0.3388	0.1150	0.4888	0.3822
CAPM vs 12-factor	0.8405***	0.0000	0.8000***	0.0000

Panel C. Flow-Performance Relation: Traditional Beta versus Exotic Beta

Risk Model	Traditional – Exotic	*p*-value
Carhart4	–0.523	0.1844
AN	–0.437	0.0006
FH7	–0.271	0.5101
12-factor	–0.322	0.0593

Table IA.5 Hedge fund flow-performance relation: Retail vs institutional funds

This table presents the results of capital allocation decisions made by investors in retail-oriented and institution-oriented hedge funds. Panels A and B report the pairwise horserace tests as in BvB and BHO, respectively. Panel C reports the differences in the flow-performance sensitivities to traditional beta returns and to exotic beta returns.

Panel A. Pairwise model comparison using the BvB approach

			Pairwise *t*-stats						
Retail	b_1	Univ. *t*-stat	Return	CAPM	FF3	Carhart4	AN	FH7	12-factor
Return	0.2105	7.91	0	0.11	0.59	0.50	1.43	0.85	2.12
CAPM	0.2071	8.45		0	0.96	0.78	2.07	1.49	2.54
FF3	0.1874	7.02			0	–0.50	1.85	0.50	2.23
Carhart4	0.1927	8.66				0	2.62	0.61	2.53
AN	0.1489	5.22					0	–0.43	1.38
FH7	0.1677	6.13						0	1.69
12-factor	0.1132	7.64							0

			Pairwise *t*-stats						
Institution	b_1	Univ. *t*-stat	Return	CAPM	FF3	Carhart4	AN	FH7	12-factor
Return	0.2421	7.29	0	–0.13	0.86	0.52	1.67	0.58	1.62
CAPM	0.2465	8.13		0	2.65	2.34	3.79	1.95	2.27
FF3	0.2054	5.73			0	–1.54	1.71	–0	1.49
Carhart4	0.2202	7.99				0	3.99	0.4	2.02
AN	0.1686	5.20					0	–1.2	0.95
FH7	0.2056	8.13						0	2.73
12-factor	0.1418	4.98							0

Panel B. Pairwise model comparison using the BHO approach

	Retail-oriented		Institution-oriented	
Risk Model	Sum of Difference	Percent of Difference >0	Sum of Difference	Percent of Difference >0
CAPM vs Return	–1.8454	0.4000**	–0.6050	0.5555
CAPM vs FF3	6.2420***	0.6222***	5.2718***	0.7111***
CAPM vs Carhart4	4.1820**	0.5555	6.8673***	0.7333***
CAPM vs AN	5.5719***	0.6666***	7.085***	0.8444***
CAPM vs FH7	5.0254**	0.6444***	5.6351***	0.8444***
CAPM vs 12-factor	5.4350***	0.6222***	8.9471***	0.9555***

Panel C. Flow-Performance Relation: Traditional Beta Returns versus Exotic Beta Returns

Risk Model	Retail-oriented		Institution-oriented	
	Traditional – Exotic	*p*-value	Traditional – Exotic	*p*-value
Carhart4	–3.195	0.5191	–0.693	0.8099
AN	–2.823	0.1163	–1.835	0.0762
FH7	–0.234	0.9385	–5.690	0.0967
12-factor	–1.272	0.3757	–1.797	0.0026

Table IA.6 Risk model alpha precision and hedge fund flows

This table presents the average net flows into hedge funds in 10×10 portfolios sorted unconditionally by alphas measured over the 24-month estimation window and the standard errors of the alphas. The differences in the average net flows between the two extreme portfolios while controlling for magnitude of alphas and standard errors of alphas are reported in the row (10 – 1) and the column (10 – 1), respectively, and the associated *t*-statistics are reported below and to the right of the differences, respectively. Panel A shows the results for the CAPM model while Panel B presents the results for the 12-factor model.

Panel A. CAPM Model

		Standard Error of Alpha											
		Lowest 1	2	3	4	5	6	7	8	9	Highest 10	10 – 1	*t*-stats
Alpha	Lowest 1	0.06	–0.07	–0.12	–0.05	–0.05	–0.10	–0.17	–0.06	–0.06	–0.05	–0.12	–1.50
	2	0.15	0.00	–0.05	–0.11	–0.07	–0.10	–0.07	–0.06	–0.05	0.07	–0.08	–1.03
	3	0.08	–0.02	–0.03	0.00	–0.01	–0.01	0.08	0.03	–0.02	–0.03	–0.11	–1.83
	4	0.17	0.09	0.09	0.04	0.06	0.07	0.11	0.04	0.08	0.02	–0.15	–2.37
	5	0.20	0.12	0.19	0.14	0.07	0.06	0.08	0.11	0.12	0.17	–0.03	–0.43
	6	0.15	0.19	0.16	0.14	0.15	0.21	0.11	0.12	0.10	0.08	–0.07	–1.19
	7	0.20	0.19	0.18	0.20	0.16	0.17	0.29	0.20	0.09	0.18	–0.03	–0.45
	8	0.19	0.22	0.33	0.33	0.34	0.31	0.28	0.24	0.26	0.18	–0.01	–0.24
	9	0.13	0.37	0.34	0.42	0.45	0.38	0.35	0.27	0.26	0.18	0.05	0.95
	Highest 10	0.12	0.07	0.55	0.48	0.53	0.38	0.39	0.31	0.35	0.28	0.16	1.35
	10 – 1	0.05	0.14	0.66	0.53	0.59	0.48	0.56	0.38	0.41	0.34		
	t-stats	0.40	1.70	6.38	5.89	7.76	8.95	13.10	10.27	11.94	11.00		

Panel B: 12-factor Model

		Standard Error of Alpha											
		Lowest 1	2	3	4	5	6	7	8	9	Highest 10	10 – 1	*t*-stats
Alpha	Lowest 1	0.06	–0.08	–0.12	–0.08	–0.08	0.01	0.01	0.00	0.06	0.08	0.02	0.08
	2	0.16	–0.05	0.01	–0.05	0.03	0.07	0.05	0.03	0.10	0.07	–0.09	–1.24
	3	0.14	0.08	0.01	0.05	0.01	0.06	0.05	0.08	0.13	0.06	–0.08	–1.07
	4	0.19	0.03	0.09	0.06	0.03	0.07	0.07	0.13	0.15	0.09	–0.11	–1.46
	5	0.18	0.09	0.11	0.07	0.04	0.07	0.14	0.09	0.09	0.13	–0.05	–0.75
	6	0.21	0.16	0.16	0.13	0.15	0.11	0.09	0.02	0.13	0.14	–0.07	–1.07
	7	0.18	0.14	0.19	0.09	0.17	0.20	0.18	0.17	0.09	0.15	–0.03	–0.56
	8	0.01	0.18	0.23	0.24	0.18	0.25	0.30	0.26	0.14	0.20	0.18	3.34
	9	0.17	0.24	0.22	0.24	0.28	0.30	0.31	0.24	0.24	0.26	0.09	1.34
	Highest 10	0.28	0.33	0.36	0.45	0.48	0.33	0.35	0.28	0.27	0.24	–0.04	–0.25
	10 – 1	0.22	0.41	0.48	0.52	0.56	0.31	0.34	0.28	0.21	0.16		
	t-stats	0.57	2.92	4.24	6.09	7.87	6.08	7.45	7.90	6.21	5.58		

Table IA.7. Return decomposition analysis with orthogonalized option factors

This table presents return decomposition results using orthogonalized option factors for the *AN* and *12-factor* models. Panel A provides summary statistics (analogous to Table 6 in the text), and Panel B reports the regression coefficients b_1, b_2, and b_3 from equation (8) in the paper (analogous to Table 7).

Panel A. Summary Statistics

1994-2012						
				Return Correlations		
AN model	Mean	Median	SD	a)	b)	c)
a) Alpha	0.26%	0.20%	1.11%	1		
b) Traditional: Market, Size, and Value Risk	0.03%	0.05%	1.23%	0.0114	1	
c) Exotic: Momentum, Call and Put Option Risk	0.18%	0.08%	0.78%	–0.1616	–0.3172	1
12–factor model						
a) Alpha	0.17%	0.14%	1.23%	1		
b) Traditional: Market, Size, Value, Bond Factors, and Emerging Market Risk	0.21%	0.16%	1.58%	–0.2282	1	
c) Exotic: Momentum, Trending Factors, and Option Factor Risks	0.09%	0.04%	1.06%	–0.297	–0.2436	1
1994–2004						
				Return Correlations		
AN model	Mean	Median	SD	a)	b)	c)
a) Alpha	0.44%	0.36%	1.31%	1		
b) Traditional: Market, Size, and Value Risk	0.19%	0.09%	1.29%	–0.1871	1	
c) Exotic: Momentum, Call and Put Option Risk	0.08%	0.03%	0.77%	–0.1202	–0.3174	1
12–factor model						
a) Alpha	0.46%	0.35%	1.33%	1		
b) Traditional: Market, Size, Value, Bond Factors, and Emerging Market Risk	0.17%	0.11%	1.55%	–0.2331	1	
c) Exotic: Momentum, Trending Factors, and Option Factor Risks	0.07%	0.01%	0.99%	–0.2026	–0.3367	1
2005–2012						
				Return Correlations		
AN model	Mean	Median	SD	a)	b)	c)
a) Alpha	0.19%	0.14%	1.00%	1		
b) Traditional: Market, Size, and Value Risk	–0.04%	0.04%	1.20%	0.1176	1	
c) Exotic: Momentum, Call and Put Option Risk	0.21%	0.10%	0.78%	–0.1763	–0.3108	1
12–factor model						
a) Alpha	0.05%	0.05%	1.16%	1		
b) Traditional: Market, Size, Value, Bond Factors, and Emerging Market Risk	0.23%	0.18%	1.59%	–0.2268	1	
c) Exotic: Momentum, Trending Factors, and Option Factor Risks	0.09%	0.06%	1.09%	–0.3452	–0.2087	1

Table IA.7. Return decomposition analysis with orthogonalized option factors (continued)

Panel B. Flow-Performance Relation: Alpha, Traditional Beta Return, and Exotic Beta Return

	1996-2012		1996-2004		2005-2012	
	AN	12-factor	AN	12-factor	AN	12-factor
Alpha	11.276	10.579	12.577	11.718	10.303	9.6463
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Traditional	5.9582	6.8379	8.3413	9.3217	4.3659	5.3701
	0.0002	0.0000	0.0001	0.0000	0.0251	0.0002
Exotic	7.3370	8.3668	6.6512	7.9890	7.5928	8.2786
	0.0004	0.0000	0.0011	0.0000	0.0047	0.0000
N	52643	52643	16963	16963	35680	35680
Adj. R2	0.1073	0.1064	0.1340	0.1334	0.0803	0.0796
b_2-b_3	–1.3788	–1.5289	1.6901	1.3327	–3.2269**	–2.9085***
p-value	0.2256	0.1507	0.1542	0.2432	0.0182	0.0097

Table IA.8 Controlling for backfilling bias
This table presents evidence on the robustness of the findings in this paper to backfilling bias. Panel A is analogous to Tables 4 and 5 and presents results from tests related to pairwise horserace between the different performance measures using the BvB and the BHO approaches. Panel B is analogous to Table 7 and reports the differences in the investors' flow sensitivities to the returns from traditional betas and returns from exotic betas. Panel C is analogous to Table 8 and reports the persistence in alpha and returns from traditional betas and returns from exotic betas.

Panel A. Hedge Fund Flow-Performance Risk Model Horserace

Panel A.1. Pairwise model comparison using the BvB approach

			Pairwise *t*-stats						
	b_1	Univ. t-stat	Return	CAPM	FF3	Carhart4	AN	FH7	12-factor
Return	0.1997	6.78	0	–0.84	0.66	0.07	1.43	0.55	1.66
CAPM	0.2127	8.26		0	2.44	1.59	3.42	1.89	2.59
FF3	0.1785	6.12			0	–2.05	1.72	0.13	1.91
Carhart4	0.1976	8.90				0	4.22	0.77	2.60
AN	0.1485	5.47					0	–0.87	1.43
FH7	0.1749	6.88						0	2.18
12-factor	0.1166	5.20							0

Panel A.2. Pairwise model comparison using BHO approach

Risk Model	Sum of Difference	% of Diff >0
Return vs CAPM	–1.4698	0.3333***
Return vs FF3	0.8595	0.6000**
Return vs Carhart4	1.8856	0.5777*
Return vs AN	4.2509**	0.8000***
Return vs FH7	3.2980*	0.8444***
Return vs 12-factor	4.8472***	0.7777***
CAPM vs FF3	4.8253***	0.8444***
CAPM vs Carhart4	5.2064***	0.8666***
CAPM vs AN	6.8718***	0.9111***
CAPM vs FH7	5.8715***	0.8666***
CAPM vs 12-factor	6.7442***	0.9111***
FF3 vs Carhart4	4.0391***	0.8222***
FF3 vs AN	4.8253***	0.8444***
FF3 vs FH7	5.2064***	0.8666***
FF3 vs 12-factor	6.8718***	0.9111***
Carhart4 vs AN	6.7442***	0.9111***
Carhart4 vs FH7	8.4369***	1.0000***
Carhart4 vs 12-factor	1.4698	0.6666***
AN vs FH7	3.0945*	0.8222***
AN vs 12-factor	4.0391***	0.8222***
FH7 vs 12-factor	5.2064***	0.8666***

Table IA.8 Controlling for backfilling bias (continued)

Panel B. Flow-performance relation: Traditional beta returns versus exotic beta returns

Risk Model	Traditional – Exotic	*p*-value
Carhart4	0.971	0.3651
AN	–1.530	0.0622
FH7	–5.389	0.0210
12-factor	–1.289	0.0198

Panel C. Persistence in hedge fund return components

	Carhart4			AN			FH7			12-factor		
	Alpha	Traditional Beta	Exotic Beta	Alpha	Traditional Beta	Exotic Beta	Alpha	Traditional Beta	Exotic Beta	Alpha	Traditional Beta	Exotic Beta
$Alpha_t$	0.038			–0.010			0.055			0.025		
	(0.381)			(0.765)			(0.020)			(0.339)		
Traditional $Beta_t$		–0.189			–0.120			–0.135			–0.079	
		(0.077)			(0.005)			(0.299)			(0.039)	
Exotic $Beta_t$			0.011			0.023			–0.070			–0.030
			(0.875)			(0.413)			(0.145)			(0.199)
Adj. R^2	0.189	0.503	0.207	0.160	0.340	0.170	0.150	0.514	0.163	0.145	0.257	0.116

Table IA.9 Alternative method to adjust for cross-sectional correlations in residuals
This table presents the findings from the alternative method of adjusting for the cross-sectional correlation in residuals by double clustering the standard errors at the fund and style × time levels. Panel A is analogous to Tables 4 and 5 and presents results from pairwise horserace between the different performance measures using the BvB approach and the BHO approach. Panel B is analogous to Table 7 and reports the differences in the investors' flow sensitivities to the returns from traditional betas and returns from exotic betas. Panel C is analogous to Table 8 and reports the persistence in alphas, returns from traditional betas, and returns from exotic betas.

Panel A. Hedge fund flow-performance risk model horserace

Panel A.1. Pairwise model comparison using the BvB approach

			Pairwise *t*-stats						
	b_1	Univ. t-stat	Return	CAPM	FF3	Carhart4	AN	FH7	12-factor
Return	0.216	11.10	0	–1.26	1.76	0.96	2.93	1.06	2.97
CAPM	0.223	14.11		0	5.21	3.50	6.37	2.74	4.35
FF3	0.180	9.05			0	–1.86	2.65	–0.21	2.81
Carhart4	0.196	13.53				0	5.65	0.58	3.75
AN	0.149	7.35					0	–1.68	1.80
FH7	0.184	12.33						0	3.68
12-factor	0.121	6.71							0

Panel A.2. Pairwise model comparison using the BHO approach

Risk Model	Sum of Difference	% of Diff >0
Return vs CAPM	–0.0080	0.4222***
Return vs FF3	2.4828**	0.7111***
Return vs Carhart4	3.5214***	0.7111***
Return vs AN	5.5565***	0.8666***
Return vs FH7	4.8932***	0.8666***
Return vs 12-factor	6.5622***	0.9777***
CAPM vs FF3	5.8006***	0.8222***
CAPM vs Carhart4	6.6316***	0.8666***
CAPM vs AN	7.6518***	0.9111***
CAPM vs FH7	7.0987***	0.9555***
CAPM vs 12-factor	8.3229***	1.0000***
FF3 vs Carhart4	5.7027***	0.7333***
FF3 vs AN	6.6599***	0.9777***
FF3 vs FH7	4.2522***	0.7555***
FF3 vs 12-factor	7.9765***	0.9555***
Carhart4 vs AN	5.9030***	0.8666***
Carhart4 vs FH7	2.5284***	0.7333***
Carhart4 vs 12-factor	7.5597***	0.9777***
AN vs FH7	–1.4180**	0.2888***
AN vs 12-factor	6.3603***	0.9777***
FH7 vs 12-factor	7.1989***	0.9777***

Table IA.9 (continued)

Panel B. Flow-performance relation: Traditional beta returns versus exotic beta returns

Risk Model	Traditional – Exotic	*p*-value
Carhart4	–0.653	0.6229
AN	–0.849	0.0417
FH7	–3.974	0.0068
12-factor	–1.171	0.0039

Panel C. Persistence in hedge fund return components

	Carhart4			AN			FH7			12-factor		
	Alpha	Traditional Beta	Exotic Beta	Alpha	Traditional Beta	Exotic Beta	Alpha	Traditional Beta	Exotic Beta	Alpha	Traditional Beta	Exotic Beta
Alpha_t	0.053			0.012			0.052			0.031		
	(0.021)			(0.471)			(0.006)			(0.058)		
$\text{Traditional Beta}_t$		–0.105			–0.066			–0.053			–0.043	
		(0.039)			(0.006)			(0.342)			(0.027)	
Exotic Beta_t			0.053			0.039			–0.055			–0.000
			(0.146)			(0.013)			(0.033)			(0.989)
Adj. R^2	0.180	0.433	0.177	0.159	0.280	0.146	0.151	0.456	0.142	0.142	0.202	0.106

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