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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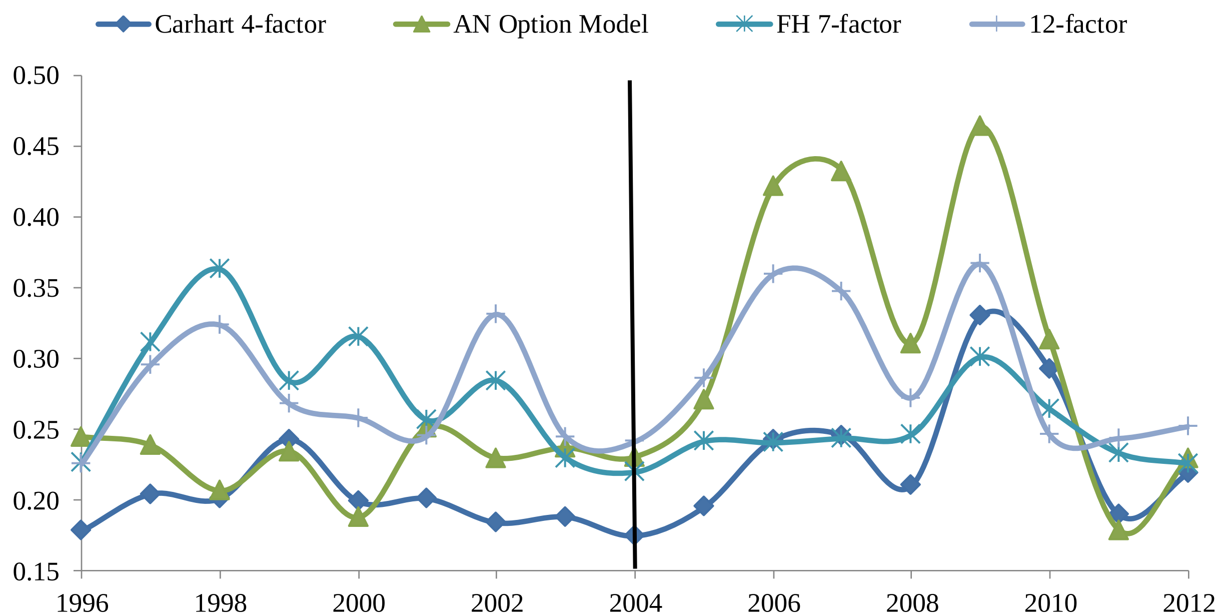
Figure IA.1 Trend in traditional and exotic risk exposures over time
The figure plots the average of absolute leverage-adjusted risk exposures over time. Leverage-adjusted risk exposure is calculated as the unadjusted risk exposure divided by the fund's leverage ratio. Each year, the average of the absolute 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

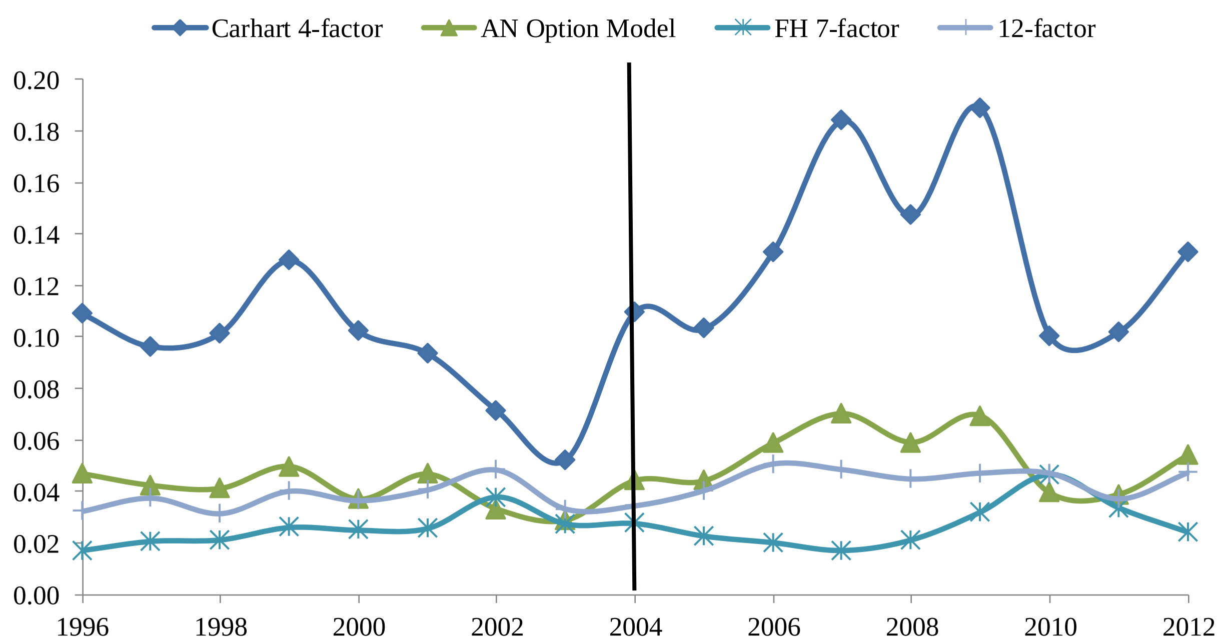


Table IA.1 Hedge fund flow-performance relation for low and high fee funds

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:

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

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.

	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)		
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