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New Insight on the Performance of Equity Long/short Investment Styles

I. Introduction

The 4-factor Carhart model has been extensively used in the literature to evaluate fund performance. The applied research ranges from pure applications of the empirical model (e.g. Daniel, Grinblatt, Titman and Wermer, 1997; Chan, Chen and Lakonishok, 1999; Fama and French, 2010) to papers examining modified versions augmented with various factors: among others, the idiosyncratic risk or Amihud liquidity factor (e.g. Wagner and Winter, 2013) or the active peer group own outperformance (e.g., Hunter, Kandel, Kandel and Wermers, 2014). The Fama-French and Carhart factors have further been used to measure the market timing abilities of mutual funds (Angelidis, Giamouridis, and Tessaromatis, 2012). Banegas, Gillen, Timmermann and Wermers (2012) implement a conditional 4-factor model with state variables for conditioning exposures on macroeconomic information.

Regarding alternative funds, the nature of hedge fund practices and lack of transparency, i.e. the famous Long-Term Capital Management (LTCM) fiasco in 1998, has raised a set of concerns as to properly identify the hedge fund returns process and its underlying risk factors. Several extensions of the 4-factor Carhart model towards an asset-based model have been proposed in the literature: Fung and Hsieh (1997) develop a model with trading and location factors, Agarwal and Naik (2000, 2004) extend previous multifactor approach of hedge fund returns by introducing option-based factors, Fung and Hsieh (2004) propose a model with lookback straddles for capturing trend-following strategies in hedge funds. The Fung and Hsieh (2004) 7-factor model has been widely used as a reference in the literature for evaluating hedge funds performance (e.g., Ammann, Huber, and Schmid, 2011; Darolles and Mero, 2011; Joenväärä et al., 2014). Buraschi, Kosowski and Trojani (2013) add a correlation factor to account for the risk of unexpected changes in the correlation between pairwise securities. Recently, Hübner, Lambert and Papageorgiou (2015) have used option-implied moments for capturing hedge fund timing strategies.

However, contrary to other hedge funds strategies, Fung and Hsieh (2001) show that long-short equity funds do not exhibit strong exposures to option-like factors and do bear risks close to equity mutual funds. Long/short equity strategies indeed demonstrate significant exposure to the broad equity market, firm size and value stocks. Hasanhodsic and Lo (2007) indeed show that the long-short strategy can be cloned with liquid ETF instruments and that such replication offers very close performance. This is why (an extended form of) Fama and French three-factor model has usually been used to capture these sources of risk premia.

Issues around the relevance of the size or book-to-market factors have however been pointed out in the literature (e.g., among the most recent evidence work, Cremers, Petajisto and Zitzewitz, 2012; Fama and French, 2012, 2015; Hou, Xue and Zhang, 2015). Fama and French (2012) themselves illustrate the shortcomings of their risk factors model to price non-global investment funds with a tilt onto small value and growth stocks. Besides, Grullon and al. (2012) documented that strategies overexposed to growth stocks exhibit more sensitivity to the market volatility. To cure for the inefficiency of the *HML* factor, Fama and French (2015) have extended their seminal three-factor model into a five-asset pricing model. Asness et al. (2015) introduce a quality factor (*QMJ*) that is presumed to resurrect the size effects over time. The relevance of profitability and investment factors were already demonstrated in Chen and Zhang (2010).

Lambert, Fays and Hübner (2015) show that the Fama and French model does not need to be extended to five-, six- or seven-factor should the factors be correctly specified. The paper proposes an alternative specification of the size and book-to-market factors using a sequential sorting procedure[1]: the size factor (resp. value) can be defined as the average of the conditional size return spreads (resp. book-to-market return spreads) for different levels of momentum and book-to-market (resp. market

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capitalization). Such an alternative specification of Fama-French premiums might better disentangle hedge fund beta exposures from abnormal performance for most long-short portfolio strategies given their tilt toward small and value stocks. Davis (2001) indeed shows that the Fama and French (1993) *HML* factor hardly explains the performance of mutual funds, even the ones with a strong value tilt. This evidence is shared in Kothari and Warners (2001) who show misspecification of the 4-factor model for mutual funds with a style that differs from globally diversified funds.

Racicot and Théoret (2015) have recently applied the new 5-factor model developed by Fama and French (2015) on a set of hedge fund strategies. Contrary to Fama and French (2015), they show that the *HML* is not redundant for pricing alternative sources of risk for some investment styles[2]. The Fama and French profitability and investment factors do not subsume the entire pricing power of the value premium.

In the spirit of Racicot and Théoret (2015), we revisit the performance of equity long-short hedge funds with an updated version of the Fama and French model (2015). We evaluate the relevance of the sequential traditional risk factors, namely size, book-to-market of Lambert, Fays and Hübner (2015). Contrary to Racicot and Théoret who use lookback straddles of Fung and Hsieh (2004), we test the significance the higher co-moment factors developed by Lambert and Hübner (2013) for decomposing hedge fund performance. Racicot and Théoret (2015) indeed show weak significance of such option-based factors for pricing strategies such as long-short funds. Considering higher-moment rather than option-based factors reveals to capture part of the abnormal return of downside and extreme risk exposures taken by a fund manager indicating that this creation of alpha might be associated to alternative sources of risk instead of managerial skills.

Additionally, we demonstrate that not only long-short equity hedge funds are, to some extent, less exposed to small capitalisation stocks under the sequential framework, but they also prefer to capture a larger momentum premium in their strategies.

The remainder of the paper is structured as follows. Section 1 describes our hedge fund data and performs a Sharpe style analysis on individual hedge fund returns in order to sort them according to their investment styles. Section 2 compares the performance of style portfolios made of hedge funds using the augmented 5-factor Fama and French model (2014) with the alternative specification proposed in this paper. Section 3 performs a cross sectional analysis of the performance of individual hedge funds under both multifactor model specifications. Section 4 concludes.

II. Hedge Fund data

Net-of-fees returns on equity long-short hedge funds have been collected from Lipper/TASS database over the period July 1999 to October 2012. This database offers a global quantitative performance of the entire hedge fund industry with monthly and quarterly historical data of "*live*" and "*graveyard*" funds. It provides this distinction as it reports historical performance for funds that are no longer tracked due to diverse corporate events, i.e. merger, closure, liquidation, etc. From the 2719 funds available over July 1999 to October 2012, we are left with an average of 740 monthly hedge funds over our sample period considering the usual data retreatments for backfill bias and requiring a minimum of 36 monthly[3] rolling windows returns to perform Sharpe style analysis[4].

II.1. A. DEFINING HEDGE FUND INVESTMENT STYLES

In our attempt to classify the risk exposures of hedge fund managers into investment style, we replicate a three factor Fama and French (1993) model in which we substitute the Fama and French market, size and book-to-market returns with MSCI time-series. We expect to capture global asset-based exposures without endangering our subsequent regression-based analysis in which we directly apply the Fama and French size and value risk factors. This Sharpe style analysis performed on MSCI indices aims at providing better neutrality for comparing the specification errors between Fama and French factor models and our innovative sequential approach.

To proxy for the broad-based investment universe targeted by hedge fund managers, we use the MSCI World as a proxy for the market portfolio. To construct the size premium, we use the average spread return between the MSCI US Small cap and MSCI US Large cap indices. As for the value premium, we consider the average spread return between the MSCI US (Small, Mid, and Large cap) Value and Growth indices. Additionally, we augment this model with global exposures to the European and Emerging markets.

We perform the following Sharpe style analysis:

$$\begin{aligned} R_t^i = {} & \beta_1 \left[MSCI\ World_t - Rf_t \right] \\ & + \beta_2 MSCI\ US\ SMB_t \\ & + \beta_3\ MSCI\ US\ HML_t \\ & + \beta_4 \left[MSCI\ EU_t - Rf_t \right] \\ & + \beta_5 \left[MSCI\ EM_t - Rf_t \right] + e_t^i \end{aligned}$$

where R_t^i is the individual hedge fund return i at time t, Rf_t is the one-month Treasury bill rate from Ibbotson Associates, β_k is the unrestricted weight of the kth index, and where the sum of all weights is not restricted to sum to 1 as presented by Argawal and Nail (2000), e_t^i are the error terms specific to the individual hedge fund return i at time t.

We use a granular approach of the style analysis by revealing hedge funds' exposures on an individual basis. Such an application is somehow computer-based demanding since time-series for any security or fund are rarely composed of the same size, and hence should the model be adapted to 2719 different funds' returns time-series among our sample horizon. Besides, these 2719 funds represent both alive and dead funds meeting the constraint of a 36 monthly return period, constraint which is needed to perform one rolling Sharpe style analysis.

After retrieving the unconstrained weights for all funds, we proceed to standard 5x5 independent sort – i.e. Fama and French (1993) – on funds' size and value exposures. Similarly to their rebalancing procedure, we use the weights at the end of the month of June of year *t* to compute the five-by-five size and value characteristics from July *t* to June *t*+1.

II.2. DESCRIPTIVE STATISTICS

Table 1 describe hedge funds repartition into the five-by-five sorted portfolios.

We sub filter with a five-by-five ranking portfolios and make sure that portfolios are composed of ten long-short equity hedge funds (on average) at the starting point of our sample period[5].The reason leading to this heuristic constraint is that having fairly diversified portfolios average out the idiosyncratic noise of individual long-short hedge funds to get a much clearer view of the portfolio's sensitivity to the factors. Figure 1 depicts the percentage stock repartition among the twenty five portfolios.

From this classification methodology results Panel A (resp. Panel B) of Table 2 which reports the average weight (*t*-stat) exposures of our five factors model for each of the twenty five portfolios. To compute the respective *t*-stat of index weights attributed to each fund, we apply the Lobosco and DiBartelomeo (2002) methodology which multiplies the k^{th} index standard error of the style weight by the weight of this k^{th} index as follows,

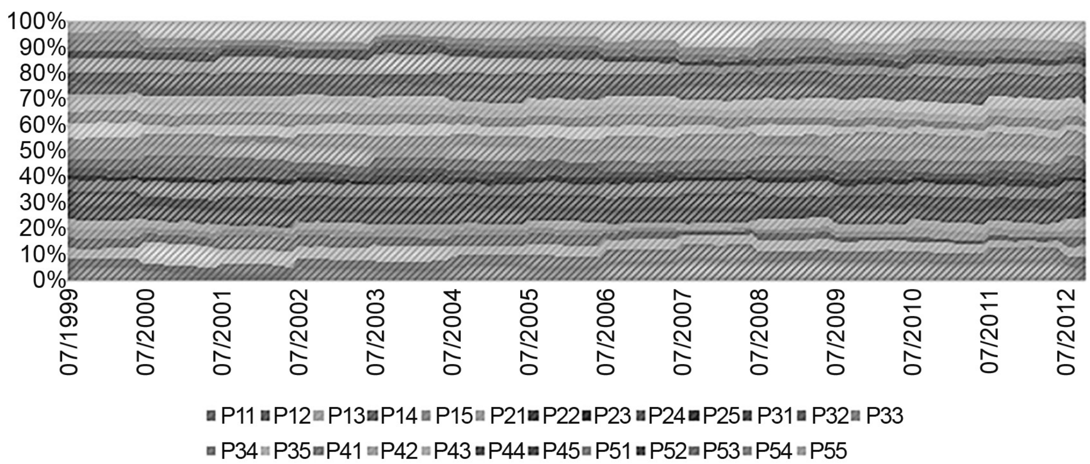
Table 1. Hedge Fund Distribution among the 5x5 Characteristics Portfolios

The table displays the hedge funds repartition after performing a Sharpe style analysis and sorting the funds into 5x5 portfolios according to their size and value exposures over July 1999-October 2012. Summary statistics are displayed (namely, the monthly average, minimum, maximum, and the standard deviation) for the 25 portfolios denoted P11 to P55: the number accounts respectively for their size and value exposures ranging from low (1), between the 20th and 40th percentile (2), medium (3), between the 60th and 80th percentile (4), and high (5).

	P11	P12	P13	P14	P15	P21	P22	P23	P24	P25	P31	P32	P33	P34	P35
Mean	43	35	30	22	16	21	37	39	36	17	21	30	34	37	25
Min	7	10	11	12	6	8	14	14	13	4	8	11	10	11	12
Max	83	66	49	34	38	43	68	68	55	36	36	60	59	72	45
S.D	25	17	8	7	7	10	14	14	13	8	7	14	13	17	7
	P41	P42	P43	P44	P45	P51	P52	P53	P54	P55	Total			Average / (σ)	
Mean	27	26	26	32	39	33	21	18	24	52	740			31 / (9)	
Min	12	12	4	9	12	14	9	3	9	11	286			11 / (3)	
Max	44	41	50	56	63	50	36	39	45	105	1121			55 / (17)	
S.D	9	7	14	14	15	10	7	10	12	24	263			13 / (5)	

Figure 1. Relative hedge fund distribution among the 5x5 Characteristics Portfolios

The figure displays the percentage of funds among the 5x5 characteristic-sorted portfolios over July 1999- October 2012. Rebalancing is made annually.



$$\lambda_k = \left(\frac{\sigma_i}{\sigma_k \sqrt{N - C - 1}}\right)^{-1}$$

where σ_i is the standard deviation of the error terms, e_t^i, specific to the individual hedge funds return i at time t, σ_k is the standard deviation of the error terms when the k^th index is regressed on the other indices left, N represents the number of observations used in the regression which amount to 36 in our framework, C accounts for the number of indices.

By construction, the portfolios' exposures on size and value factors tend to increase linearly with the ranking attributed to the five-by-five portfolios. Overall, significant exposures on size and value factors arise for portfolios with a low (1) or high (5) classification. These exposures are displayed in the Figure 2 for the different portfolios according to their size and value exposure levels.

Finally, we analyse historical patterns of these 25 equally weighted[6] portfolios with standard descriptive statistics reported in Table 3. Panel A displays monthly statistic measures: higher returns are reported for portfolios whose exposures load more on the size and value factors. Besides, gearing up the selection of funds with significant positive weights on size and value styles investments provides stronger risk/return trade-off as shown by an increasing Sharpe ratio with respect to the level exposures. Above all, 18 out of 25 portfolios provide a positive significant expected returns – with *t*-stats higher than 2. The 7 portfolio left with insignificant *t*-stats are the one scoring a negative level (short position) of either size or book-to-market ratio. Panel B also provides additional information on portfolios' risk with larger drawdown for portfolios showing significant negative exposures to the MSCI US SMB and MSCI US HML factors. Overall, portfolios with better risk-return trade-offs are the ones showing a high positive (and significant) exposures to either the size, value or both risk premiums while taking a short position on the European market as a hedging tool for overall market decorrelation.

Table 2. Average Sharpe Weights Style Analysis among the 5x5 Portfolios

The table displays the Sharpe style analysis for the 5x5 hedge fund portfolios sorted on their size and value exposures. Level (1), (2), (3), (4) and (5) respectively indicates a low (1), between the 20^th and 40^th percentile (2), medium (3), between the 60^th and 80^th percentile (4), and high (5) of funds' exposures to size and the book-to-market over July 1999-October 2012. Panel A reports the average weights in each portfolio and Panel B reports their respective t-stats.

Portfolio	MSCI WORLD	MSCI SMB	MSCI HML	MSCI EU	MSCI EM	MSCI WORLD	MSCI SMB	MSCI HML	MSCI EU	MSCI EM
	Panel A: Weights					Panel B: T-stat				
P11	17%	−32%	−76%	13%	17%	0,28	−1,15	−2,49	0,24	0,75
P12	18%	−19%	−25%	9%	11%	0,31	−0,92	−1,26	0,30	0,74
P13	18%	−17%	−7%	−2%	14%	0,31	−0,87	−0,38	0,05	0,82
P14	14%	−16%	11%	−4%	20%	0,25	−0,75	0,65	−0,03	1,09
P15	10%	−26%	49%	−10%	32%	0,09	−0,85	1,73	−0,13	1,42
P21	21%	0%	−66%	4%	14%	0,44	−0,02	−2,70	0,13	0,64
P22	4%	0%	−26%	12%	12%	0,11	−0,07	−1,64	0,44	0,82
P23	9%	1%	−6%	5%	8%	0,15	0,09	−0,50	0,36	0,78
P24	10%	1%	9%	3%	11%	0,29	0,13	0,61	0,13	0,77
P25	19%	0%	43%	−8%	26%	0,42	0,00	1,96	−0,13	1,29
P31	40%	13%	−65%	−3%	7%	0,81	0,64	−2,75	−0,18	0,38
P32	19%	12%	−26%	6%	7%	0,47	0,73	−1,45	0,19	0,48
P33	12%	11%	−7%	7%	6%	0,32	0,75	−0,52	0,29	0,44
P34	16%	11%	9%	0%	9%	0,48	0,77	0,62	0,01	0,67
P35	33%	15%	41%	−10%	17%	0,74	0,83	2,17	−0,26	1,04
P41	46%	29%	−68%	−12%	14%	0,91	1,29	−2,73	−0,30	0,54
P42	32%	29%	−26%	2%	4%	0,77	1,54	−1,44	0,02	0,26
P43	24%	25%	−8%	−2%	11%	0,60	1,42	−0,45	−0,04	0,66
P44	31%	28%	11%	−6%	11%	0,77	1,63	0,59	−0,21	0,73
P45	41%	28%	43%	−12%	18%	0,85	1,40	1,94	−0,33	0,96
P51	82%	71%	−72%	−29%	11%	1,22	2,34	−2,36	−0,55	0,34
P52	67%	67%	−26%	−19%	11%	1,20	2,56	−1,06	−0,36	0,38
P53	37%	62%	−8%	−9%	20%	0,83	2,54	−0,33	−0,21	0,71
P54	50%	59%	9%	−11%	12%	0,97	2,47	0,40	−0,27	0,67
P55	65%	75%	63%	−27%	24%	0,96	2,33	1,82	−0,51	0,94

Figure 2. Spider Charts of the Sharpe Weights According to the Size and Value Levels

he figure displays the Sharpe style analysis for the 5x5 characteristic-sorted portfolios Level (1), (2), (3), (4) and (5) respectively indicates a low (1), between the 20th and 40th percentile (2), medium (3), between the 60th and 80th percentile (4), and high (5) of funds' exposures to size and the book-to-market over July 1999-October 2012.

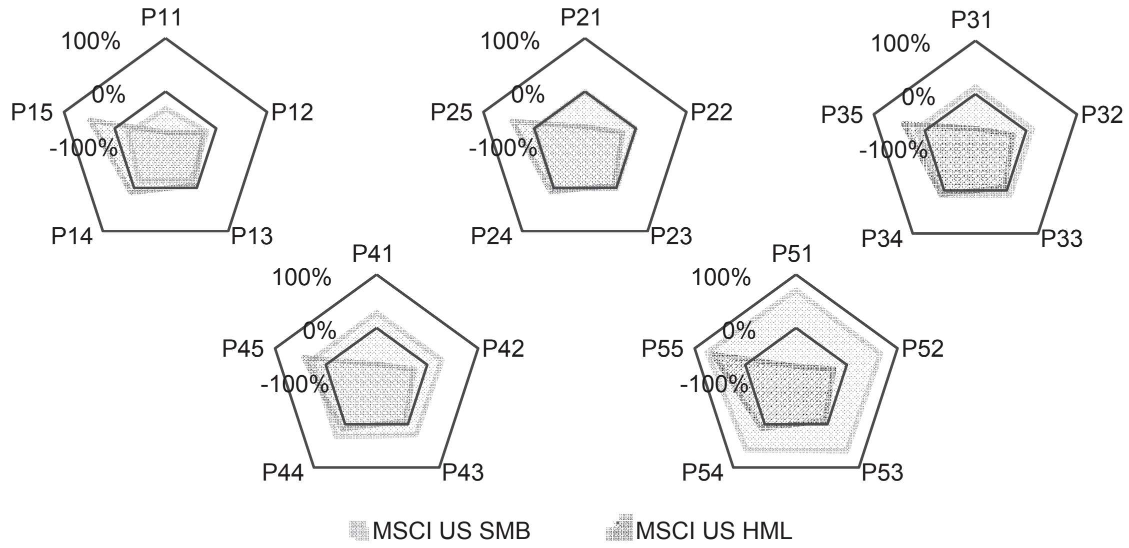


Table 3. Descriptive Statistics among the 5x5 Hedge Fund Style Portfolios

The table displays descriptive statistics for the 5x5 hedge fund portfolios sorted on their size and value exposures. Level (1), (2), (3), (4) and (5) respectively indicates a low (1), between the 20th and 40th percentile (2), medium (3), between the 60th and 80th percentile (4), and high (5) of funds' exposures to size and the book-to-market over July 1999-October 2012. The risk-free rate used to compute the Sharpe ratio is the one-month Treasury bill rate (from Ibbotson Associates) directly available from K. French's website. Panel A reports standard descriptive statistics based on the monthly returns, Panel B displays the mean, the standard deviation (S. D.), the annual Sharpe ratio and the maximum drawdown of the portfolio over the sample period. Figures are given in percentage.

	P11	P12	P13	P14	P15	P21	P22	P23	P24	P25	P31	P32	P33	P34	P35	P41	P42	P43	P44	P45	P51	P52	P53	P54	P55
Panel A: Monthly Descriptive Statistics																									
Mean	0,0	0,4	0,5	0,4	1,0	0,5	0,5	0,4	0,5	0,7	0,6	0,4	0,5	0,6	0,6	0,5	0,6	0,5	0,6	0,7	0,6	0,8	0,8	0,6	1,1
Min	−15,4	−6,8	−6,8	−5,3	−11,1	−15,7	−6,3	−8,0	−4,9	−5,2	−17,7	−7,9	−5,6	−5,2	−7,1	−13,1	−6,7	−7,7	−9,0	−10,0	−14,4	−9,9	−7,7	−9,3	−13,6
Max	16,8	12,0	4,8	5,9	13,0	23,1	9,6	5,3	4,6	7,9	32,8	11,9	10,0	7,0	5,4	22,4	15,3	13,2	8,9	8,0	26,8	18,5	11,7	15,6	11,5
S. D.	4,0	2,7	2,0	1,9	2,8	4,7	2,4	1,7	1,4	2,4	5,2	2,8	2,2	1,8	2,2	4,7	3,0	2,9	2,5	2,6	5,8	4,2	3,9	3,5	3,9
Skewness	0,0	0,6	−0,7	−0,4	0,7	0,8	0,3	−0,9	−0,6	0,1	1,9	0,1	1,0	−0,3	−0,5	0,8	1,0	0,6	−0,5	−0,6	0,7	0,3	0,1	0,2	−0,4
Kurtosis	3,7	3,5	1,4	0,8	4,6	6,0	2,7	4,4	1,5	0,4	12,5	2,9	4,8	1,5	0,6	4,9	5,0	3,8	2,5	1,7	3,1	1,8	−0,1	2,0	1,1
VaR (99%)	−11,0	−6,4	−5,3	−5,0	−4,3	−12,1	−5,9	−4,8	−3,6	−4,6	−12,0	−7,6	−4,2	−4,8	−5,0	−12,1	−5,8	−6,6	−7,7	−5,8	−14,0	−8,8	−7,2	−7,7	−9,0
Sharpe	0,0	0,1	0,1	0,1	0,3	0,1	0,1	0,1	0,2	0,2	0,1	0,1	0,1	0,2	0,2	0,1	0,1	0,1	0,2	0,2	0,1	0,1	0,2	0,1	0,2
T-stat	0,1	1,7	3,0	2,6	4,3	1,3	2,5	3,1	4,6	3,6	1,4	1,7	2,9	4,2	3,5	1,4	2,5	2,3	3,2	3,5	1,4	2,4	2,7	2,3	3,5
Obs.	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160
Panel B: Annually Descriptive Statistics																									
Mean	0,6	4,5	5,8	4,9	12,3	5,8	5,8	5,2	6,4	8,2	7,1	4,6	6,0	7,4	7,4	6,3	7,3	6,5	8,0	9,0	7,8	9,9	10,4	7,7	13,8
S. D.	14,0	9,4	6,9	6,7	9,8	16,4	8,3	5,9	4,9	8,2	17,9	9,6	7,5	6,3	7,5	16,1	10,4	10,1	8,7	9,0	20,1	14,4	13,4	12,0	13,4
Sharpe	−0,1	0,2	0,5	0,4	1,0	0,2	0,4	0,5	0,8	0,7	0,3	0,2	0,5	0,8	0,7	0,2	0,5	0,4	0,7	0,7	0,3	0,5	0,6	0,5	0,9
Max DD	−61	−34	−15	−21	−12	−51	−24	−18	−14	−25	−47	−29	−24	−16	−19	−50	−22	−21	−27	−24	−48	−32	−26	−30	−34

III. Performance Analysis of Hedge Fund Investment Styles

III.1. THE 5X5 SPECIFICATION ERROR MATRIX

In the quest of multifactor models parsimony to capture the variation of stocks and funds returns, Fama and French (2015) recently improved their cornerstone three-factor model to a five-factor model in which they augmented the size and value risk premiums with an investment (*CMA*) and a profitability (*RMW*) factor. The investment factor *CMA* (Conservative minus Aggressive) defines the return spread between firms that invest the least and the most. The profitability factor *RMW* (Robust minus Weak) represents the return spread between firms with the highest and the lowest operating profitability. Additionally, Asness et al. (2015) introduce a quality factor (*QMJ*) which is documented to resurrect the size effects over time.

Such an inflation of the number of variables needed to explain the cross-section of stock returns reveals concerns on the attempt of factor construction methodologies improvements. In Lambert, Fays and Hübner (2015), we propose an alternative factor construction to capture more accurately the return spread associated with the source of risk to be priced. Overall, we provide size and value factors with better balancing weights according to small/large value/growth portfolios as well as lower specification errors when pricing passive benchmark investment portfolios.

This factor construction procedure is similar to that of Lambert and Hübner (2013). To obtain the risk premium corresponding to dimension X, after sequentially controlling for dimensions Y and Z, the factor can be computed as:

$$X_{Y,Z,t} = \frac{1}{9}\left[\begin{array}{l}\sum_{b=H,M,L}\sum_{c=H,M,L} R_t\left(HX\middle|bY\middle|cZ\right) \\ -\sum_{b=H,M,L}\sum_{c=H,M,L} R_t\left(LX\middle|bY\middle|cZ\right)\end{array}\right]$$

where $R_t\left(aX|bY|cZ\right)$ represents the return of a portfolio of stocks ranked a on dimension X, among the basket of stocks ranked b on dimension Y, themselves among the basket of stocks ranked c on dimension Z. Dimensions X, Y and Z stand for size, book-to-market and momentum (in any order) while H, M and L stand for high, medium and low, respectively.

In contrast to an independent sorting, this sequential sorting ensures the same number of stocks in all 27 portfolios. All portfolios therefore provide the same level of diversification.

Ultimately, the rest of the paper performs a model-based comparison analysis between the new specification of the empirical CAPM provided by Fama and French (2015) and our alternative specification using a sequential sorting approach as to capture the long-short equity hedge funds' return variations. Namely, we consider the pricing properties of the original and sequential empirical CAPM augmented with the momentum factor of Carhart (1997) as well as the investment and profitability factors of Fama and French (2015) defined above. We also test the relevance of the quality factor defined by Asness et al. (2015). To this end, we illustrate in Tables 4 the pricing properties the two competing sets of factors by implementing a basic efficiency test similar to Cremers, Petajusto and Zitzewitz (2012) and Fama and French (2012, 2015). We evaluate the specification errors on a set of 5x5 unconstrained Sharpe styles hedge fund-sorted portfolio related to six regression models: Panel A performs a six-factor empirical CAPM using Fama and French value and size factors, Panel B performs a seven-factor empirical CAPM using Fama and French value and size factors, Panel C performs a six-factor empirical CAPM using sequential value and size factors, and Panel D performs a seven-factor empirical CAPM using sequential value and size factors. Table 4 reports the specifications errors, their respective *t*-statistics and *p*-values for the different models.[7]

Panels A and B which apply the empirical CAPM under the original Fama and French framework deliver significant specification errors (respective *p*-values are bolded). Under the six-factor empirical CAPM using Fama and French original factors, 21 out of 25 hedge fund style portfolios deliver specification errors at the 10% significance level. Adding the quality/junk factor of Asness et al. (2015), only two portfolios demonstrate insignificant specification alphas. Moving to Panel C, i.e. the six-factor empirical CAPM with the sequential substitutes of the size and value factors, only 12 out of the 25 style portfolios deliver significant specification errors at the 90% confidence level. Once the *QMJ* is introduced in the regression model, 21 out of 25 portfolios display significant alphas under the sequential framework which first indicates that *QMJ* introduces misspecification into the model (not only the alphas increase but the Schwarz criterion deteriorates) but also further emphasizes the robustness of our sequential factors with regard to Fama and French original specification. Our sequential factors are indeed able to mitigate part of the noise introduced by the *QMJ* factor.

As already discussed in the introduction, the nature of hedge fund strategies might introduce exposures to downside and extreme risks. Although long-short equity strategies have been shown to suffer less under those alternative risks (see supra), we control for these particular features of the hedge fund industry by augmenting the classical 4-factor Carhart (1997) model with the higher-moment factors developed by Lambert and Hübner (2013). Panel A of Table 5 performs the original Carhart model augmented with higher-moment factors under the Fama and French framework while Panel B considers the size and value factors under the sequential approach. The alphas delivered by the 25 portfolios sharply drop (even to negative values for the investment style tilted towards short positions of small caps and value stocks) when considering the downside and extreme risk exposures raised by hedge fund strategies. This indicates that part of the abnormal return of the funds might be associated to alternative sources of risk rather than managerial skills.

Table 4. Specification Errors (α) of the 25 Portfolios under the Original F&F and Sequential Framework

Table 4 exhibits specification errors (α) for the 25 portfolios produced by the extended empirical CAPM models. Panels A to D display the specification errors (α) for the 25 portfolios using the Fama and French (1993) approach as well as the respective *t*-statistics, *p*-values, and R^2-adjusted for a six-factor model, that is *RMff, SMBff, HMLff, UMDff, RMW* and *CMA*, as well as for a six factor model augmented with *QMJ* (seven factor model). *RMff, SMBff, HMLff, UMDff, RMW* and *CMA* time-series are available on K. French's library. *QMJ* (Quality minus Junk) is obtained from Asness et al. (2015). Panel A and B (resp. C and D) display the regression results for models using the Fama and French (resp. sequential) size and value factors for the period ranging over July 1999-October 2012.

	α_t					*t*-stat					*p*-value					R^2-adjusted				
B/M→	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Size↓																				
Panel A: Six-factor intercepts: *RM_{ff}, SMB_{ff}, HML_{ff}, UMD_{ff}, RMW*, and *CMA*																				
Low	0,14	0,30	0,23	0,14	0,65	0,80	2,39	1,90	1,13	3,20	0,43	0,02	0,06	0,26	0,00	0,76	0,70	0,50	0,42	0,29
2	0,52	0,31	0,19	0,21	0,20	2,99	3,09	2,21	2,33	1,30	0,00	0,00	0,03	0,02	0,19	0,82	0,76	0,65	0,41	0,42
3	0,36	0,23	0,28	0,32	0,32	1,87	2,21	2,45	3,32	2,65	0,06	0,03	0,02	0,00	0,01	0,81	0,80	0,60	0,59	0,58
4	0,45	0,39	0,34	0,32	0,27	2,60	3,10	2,86	2,38	1,97	0,01	0,00	0,00	0,02	0,05	0,81	0,76	0,77	0,61	0,60
High	0,38	0,53	0,55	0,25	1,62	1,81	2,83	2,65	1,48	2,49	0,07	0,01	0,01	0,14	0,01	0,82	0,72	0,61	0,66	0,14
Panel B: Seven-factor intercepts: *RM_{ff}, SMB_{ff}, HML_{ff}, UMD_{ff}, RMW, CMA*, and *QMJ*																				
Low	0,21	0,32	0,30	0,22	0,73	1,23	2,47	2,50	1,77	3,62	0,22	0,01	0,01	0,08	0,00	0,76	0,70	0,53	0,46	0,31
2	0,65	0,37	0,22	0,24	0,22	3,98	3,70	2,57	2,61	1,42	0,00	0,00	0,01	0,01	0,16	0,84	0,77	0,66	0,42	0,42
3	0,44	0,29	0,28	0,36	0,42	2,28	2,77	2,39	3,64	3,82	0,02	0,01	0,02	0,00	0,00	0,81	0,81	0,60	0,60	0,65
4	0,53	0,44	0,42	0,37	0,36	3,09	3,50	3,60	2,77	2,67	0,00	0,00	0,00	0,01	0,01	0,82	0,77	0,79	0,62	0,63
High	0,54	0,66	0,64	0,34	1,83	2,66	3,74	3,09	1,99	2,79	0,01	0,00	0,00	0,05	0,01	0,84	0,76	0,62	0,68	0,16
Panel C: Six-factor intercepts: *RM_{ff}, SMB′, HML′, UMD_{ff}, RMW*, and *CMA*																				
Low	0,09	0,24	0,20	0,00	0,54	0,53	1,92	1,64	0,00	2,54	0,60	0,06	0,10	1,00	0,01	0,76	0,71	0,49	0,46	0,25
2	0,40	0,25	0,12	0,16	0,05	2,34	2,48	1,34	1,64	0,30	0,02	0,01	0,18	0,10	0,77	0,83	0,77	0,66	0,38	0,40
3	0,25	0,16	0,15	0,21	0,23	1,34	1,49	1,37	2,26	1,90	0,18	0,14	0,17	0,03	0,06	0,82	0,81	0,65	0,63	0,59
4	0,41	0,31	0,26	0,15	0,13	2,33	2,51	2,18	1,10	0,87	0,02	0,01	0,03	0,27	0,39	0,81	0,77	0,78	0,63	0,55
High	0,30	0,44	0,50	0,16	1,43	1,39	2,36	2,34	0,93	2,12	0,17	0,02	0,02	0,35	0,04	0,82	0,73	0,60	0,66	0,13
Panel D: Seven-factor intercepts: *RM_{ff}, SMB′, HML′, UMD_{ff}, RMW, CMA*, and *QMJ*																				
Low	0,16	0,26	0,33	0,14	0,75	0,89	1,95	2,60	1,14	3,45	0,37	0,05	0,01	0,26	0,00	0,76	0,71	0,52	0,50	0,29
2	0,50	0,35	0,19	0,25	0,16	2,78	3,33	2,14	2,58	0,97	0,01	0,00	0,03	0,01	0,33	0,83	0,78	0,67	0,41	0,42
3	0,34	0,19	0,13	0,28	0,41	1,73	1,71	1,12	2,82	3,50	0,09	0,09	0,26	0,01	0,00	0,82	0,81	0,64	0,64	0,65
4	0,50	0,39	0,36	0,27	0,35	2,76	2,98	2,92	1,95	2,39	0,01	0,00	0,00	0,05	0,02	0,82	0,78	0,79	0,64	0,61
High	0,57	0,68	0,66	0,34	1,98	2,64	3,62	3,00	1,86	2,86	0,01	0,00	0,00	0,07	0,00	0,84	0,75	0,61	0,68	0,16

III.2. JOINT SIGNIFICANCE OF THE ALPHAS

Additionally, we use the Gibbons, Ross and Shanken (1989) (GRS) test on the joint significance of the estimated values for α_p across all hedge fund portfolios:

$$H_0 : \square_p = 0 \qquad \text{for } p = 1,\ldots,25$$

Following Gibbons, Ross and Shanken (1989), under the null hypothesis (H_0) that α_p is equal to 0 for all 25 (N) portfolios, the statistics $\left[T \Big/ \left(1+\overline{R'_F}\,\widehat{\Omega}^{-1}\,\overline{R_F}\right)\right]\alpha'_p \sum^{-1} \alpha_p$ follows a central F distribution with degrees of freedom N and (T-N-L), where $\overline{R_F}$ is a vector of sample means for the L factors ($\widetilde{R}_{Ft}$), $\widehat{\Omega}$ is the sample variance-covariance matrix for $\widetilde{R}_{Ft}$, Σ is the variance-covariance matrix of the residuals, $\widehat{\alpha}_p$ is a vector of the least squares estimates of the α_p across the N equations. We consider the case where L varies from 6 to 7 and N equals to 25 for the 25 independent hedge fund portfolios sorted on size and book-to-market. The F-statistics to test hypothesis are reported in Table 6.

Panel A of Table 6 shows the GRS test when using the set of Fama and French premiums, while Panel B performs the analysis under the sequential framework. Results indicate that the null hypothesis of all intercepts being jointly equal to zero is rejected with a confidence level of 95% under the original Fama and French definition of the size and value factors. Using the sequential premiums (Panel

Table 5. Specification Errors (α) of the 25 Portfolios under the Original F&F and Sequential Framework

Table 5 exhibits specification errors (α) for the 25 portfolios produced by the extended empirical CAPM models. Panels A and B display the specification errors (α) for the 25 portfolios as well as the respective *t*-statistics, *p*-values, and R²-adjusted for a six factor constituted of the Carhart four-factor model, that is RM_{ff}, SMB_{ff}, HML_{ff} and UMD_{ff} augmented with the co-skewness and co-kurtosis risk premiums. Panel A reports the results for the six factor model using the Fama and French size and value premiums. Panel B reports the results for the six factor model using sequential size and value premiums. The sample period range from July 1999-October 2012.

	α_t					*t*-stat					*p*-value					R²-adjusted				
B/M→	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
Size↓																				
	Panel A: Six-factor intercepts: *RM_{ff}, SMB_{ff}, HML_{ff}, UMD_{ff}, Co-Skewness*, and *Co-Kurtosis*																			
Low	−0,17	0,10	0,19	0,12	0,68	−0,99	0,81	1,67	1,00	3,53	0,32	0,42	**0,10**	0,32	**0,00**	0,72	0,68	0,49	0,43	0,29
2	0,20	0,21	0,13	0,21	0,29	1,14	2,16	1,63	2,48	1,97	0,26	**0,03**	0,11	**0,01**	0,05	0,78	0,75	0,65	0,43	0,40
3	0,07	0,10	0,20	0,30	0,34	0,35	0,89	1,84	3,34	3,00	0,73	0,37	0,07	**0,00**	**0,00**	0,78	0,77	0,59	0,61	0,59
4	0,16	0,26	0,22	0,28	0,31	0,88	2,16	1,92	2,26	2,34	0,38	**0,03**	0,06	**0,03**	**0,02**	0,78	0,75	0,75	0,62	0,59
High	0,12	0,37	0,45	0,18	1,30	0,54	2,05	2,27	1,10	2,10	0,59	**0,04**	**0,02**	0,28	**0,04**	0,79	0,71	0,60	0,66	0,13
	Panel B: Seven-factor intercepts: *RM_{ff}, SMB′, HML′, UMD_{ff}, Co-Skewness*, and *Co-Kurtosis*																			
Low	−0,23	0,07	0,18	0,08	0,64	−1,28	0,62	1,49	0,70	3,18	0,20	0,54	0,14	0,49	**0,00**	0,71	0,71	0,49	0,44	0,24
2	0,08	0,19	0,12	0,22	0,30	0,47	2,02	1,45	2,40	1,87	0,64	**0,05**	0,15	**0,02**	0,06	0,80	0,77	0,66	0,38	0,32
3	0,00	0,03	0,17	0,27	0,29	−0,01	0,33	1,63	3,13	2,54	0,99	0,74	0,10	**0,00**	**0,01**	0,82	0,80	0,65	0,65	0,59
4	0,11	0,23	0,18	0,25	0,29	0,62	2,02	1,63	2,00	1,98	0,54	**0,05**	0,11	**0,05**	**0,05**	0,79	0,78	0,78	0,63	0,53
High	0,06	0,32	0,42	0,16	1,35	0,27	1,80	2,06	0,96	2,13	0,79	0,07	**0,04**	0,34	**0,03**	0,81	0,73	0,60	0,66	0,13

Table 6. GRS tests on 25 Portfolios formed on Size and Book-to-market Exposures

This table presents the Gibbons-Ross-Shanken (GRS) statistics for testing whether the pricing errors of the 5x5 portfolio intercepts are jointly zero. *T* represents the amount of periods, N stands for the 25 regressions construct on the 5x5 portfolios formed on size and book-to-market Sharpe styles weights, *L* is the number of factors used in the regression. The GRS test follows then a central *F* distribution with degrees of freedom *N* and (T-N-L). Panel A shows the summary statistics using all the Fama and French premiums and the *QMJ* from Asness' library. Panel B substitutes the original F&F size and value by our sequential size and value premiums. Results displayed hereafter are given for a six factor model, that is RM_{ff}, SMB_{ff}, HML_{ff}, UMD_{ff}, *RMW* and *CMA*, as well as for a six-factor model augmented with *QMJ* (seven factor model) and finally for a six-factor constituted of the Carhart four-factor model augmented with the co-skewness and co-kurtosis. Tests are performed over the period ranging from July 1999 to October 2012.

Multi-Factor Model	T	N	L	*F*-GRS	*p*-value
Panel A : Fama and French Framework					
Six-factor intercepts	160	25	6	1,79	1,93%
Seven-factor intercepts	160	25	7	2,34	0,11%
Six-factor intercepts: Four-factor intercepts, Co-Skew. and Co-Kurt.	160	25	6	1,82	1,69%
Panel B : Sequential Framework					
Six-factor intercepts	160	25	6	1,59	4,95%
Seven-factor intercepts	160	25	7	2,07	0,48%
Six-factor intercepts: Four-factor intercepts, Co-Skew. and Co-Kurt.	160	25	6	1,67	3,44%

B), we observe reduced F-statistics under all multi-factor models. The GRS test of the joint significance of specification errors across hedge fund portfolios is barely rejected at the 5% significance level for a six-factor model composed of RM_{ff}, SMB_{ff}, HML_{ff}, UMD_{ff}, *RMW* and *CMA*. Besides, the 4-factor Carhart model augmented with higher-moment factors provide competitive results to the seven-factor model proposed by Asness et al. (2015).

IV. Cross-Sectional Performance Analysis of Individual Long-Short Hedge Funds

Given that hedge funds investment characteristics are known to be genuine and highly specific, we performed a cross-sectional analysis on each individual hedge fund composing the twenty five portfolios to enlighten their true exposures to size and value risk premiums. The following regression analysis results will only be based on a six multi-factor model, that is the recent Fama and French (2015) five-factor model augmented with a momentum factor. Section III indeed demonstrates the outperformance of the set of sequential in the new 5-factor Fama and French model (2015) augmented with the momentum factor and that the quality factor of Asness et al. (2015) incorporates more specification errors when pricing long-short equity hedge funds. We therefore check whether the results achieved above for the aggregate portfolios still hold on an individual basis.

Results on the average frequency of significant exposures[8] to the Fama and French (resp. sequential) factors are reported in Panel A (resp. Panel B) Table 7. We found higher frequencies of significant intercepts in all portfolios under the Fama and French than the sequential factor construction.

In Figure 3, we compare the distribution of significant alphas across the individual hedge funds constituting the twenty five portfolios between both frameworks – i.e. the Fama and French and sequential. Overall, we can first notice that amount of significant alphas tend to lower as we price funds with strong positive (or negative) exposures to the small caps and value stocks, second all the average frequencies of significant intercepts are lowered under the sequential (dark grey box plots) compared to the Fama and French (light grey box plots) framework.

Given that the sequential size and value deliver less specification errors (cf. Panel B of Table 7), these sequential size and value factors should return a corrected percentage of significant exposures to the size and value premiums for individual long-short hedge funds. Figure 4 exhibits the significant exposures to the size premium for individual hedge funds composing the 25 portfolios. As one could expect, long-short hedge funds with stronger exposures to the MSCI US SMB risk factor show on average a higher proportion of individual funds exposed to the Fama and French size factor (light grey box plots). However, the exposure to the size effect is oddly reduced under the sequential framework for the portfolios showing significant positive exposures (P51-P55) to the MSCI US SMB factor, we explain these results due to; first, a size premium only related to a "*turn-of-the-year*" effect under the sequential framework, and second, the overestimation of the size effect under the Fama and French methodology by evaluating small and intermediate capitalization

Table 7. Average Frequency of Significant Factor Exposures under the Fama and French and Sequential Frameworks

The table reports the mean frequency of individual hedge funds' significant exposures to risk factors as well as the intercept (α). The regression used is a six factor model that we applied for the period ranging from July 1999 to October 2012. The table display the frequency among the nine portfolios formed from the Sharpe weight styles sorted on size and value exposures. Panel A refers to the Fama and French framework and Panel B to the sequential approach for the five-factor Fama and French model augmented with the momentum factor. All figures are in percentage.

	P11	P12	P13	P14	P15	P21	P22	P23	P24	P25	P31	P32	P33	P34	P35	P41	P42	P43	P44	P45	P51	P52	P53	P54	P55
Panel A: Fama and French Framework																									
α	44	53	49	44	50	50	59	59	49	40	48	48	57	51	41	46	45	41	42	36	35	40	31	27	28
RM_{ff}	69	65	59	70	70	65	65	65	70	65	74	77	66	69	77	79	79	78	74	75	87	84	86	84	78
SMB_{ff}	19	20	19	25	27	27	27	23	36	31	42	37	37	41	34	53	52	47	48	44	61	68	70	63	52
HML_{ff}	28	21	20	24	31	25	20	19	26	40	27	20	25	33	45	26	17	30	37	52	22	23	34	40	54
UMD_{ff}	55	44	36	31	35	49	48	41	35	35	51	45	40	35	34	52	46	38	36	42	44	47	44	45	44
RMW_{ff}	32	22	19	20	21	38	27	20	22	19	43	26	22	21	30	44	25	25	22	23	44	35	29	27	29
CMA_{ff}	26	17	15	15	19	28	16	12	13	22	23	16	13	14	20	28	19	19	19	17	33	25	22	21	16
Panel B: Sequential Framework																									
α	38	45	44	39	41	48	52	50	44	35	42	44	49	44	35	39	39	33	32	34	32	36	28	23	25
RM_{ff}	72	67	64	71	69	71	72	67	74	68	79	79	71	75	80	85	83	79	78	80	89	86	89	88	79
SMB'	35	36	29	30	31	42	51	46	45	40	42	43	50	51	41	48	48	53	53	53	45	57	59	56	53
HML'	24	19	19	20	26	18	18	17	21	33	22	17	17	23	38	22	17	23	32	43	26	21	25	37	47
UMD_{ff}	57	44	37	31	37	54	50	45	36	39	55	49	41	37	37	56	47	44	39	43	46	48	44	45	49
RMW_{ff}	27	17	21	20	24	33	19	19	20	22	38	26	21	22	31	38	25	27	21	27	44	28	28	24	29
CMA_{ff}	30	21	15	19	25	34	20	14	20	26	30	17	16	19	30	32	24	25	25	24	38	36	30	26	23

Figure 3. Box Plots of the 25 Portfolios Frequencies for Significant Alphas

The figure display box plots of the frequency for individual hedge funds' significant alphas under a 90 percent confidence interval among the 25 portfolios. To compute the exposures, we performed regressions based analysis on all individual hedge funds composing each portfolios and display the ratio of hedge funds with a significant alphas over the number of hedge funds composing the portfolio. Box plots with a light grey colour refers to regressions using the size and value Fama and French factors, whereas dark grey colour refers to regressions using the sequential size and value factors.

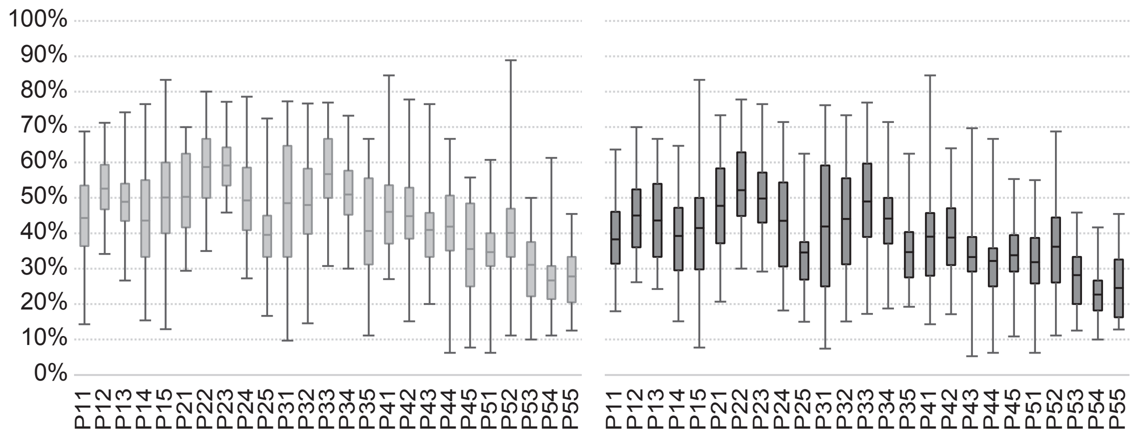
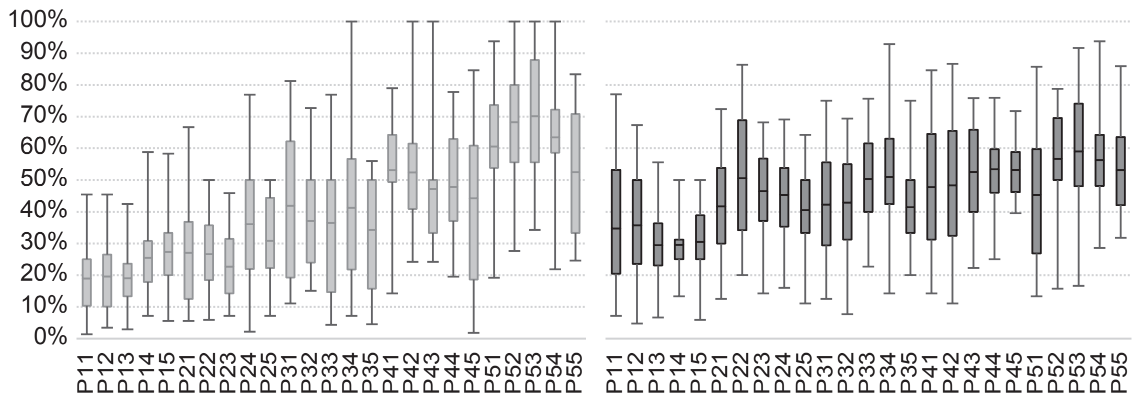


Figure 4. Box Plots of the 25 Portfolios Frequencies for Significant Size Exposures

The figure display box plots of the frequency for individual hedge funds' significant value exposures under a 90 percent confidence interval among the 25 portfolios. To compute the exposures, we performed regressions based analysis on all individual hedge funds composing each portfolios and display the ratio of hedge funds with a significant size exposure over the number of hedge funds composing the portfolio. Box plots with a light grey colour refers to regressions using the size and value Fama and French factors, whereas dark grey colour refers to regressions using the sequential size and value factors.

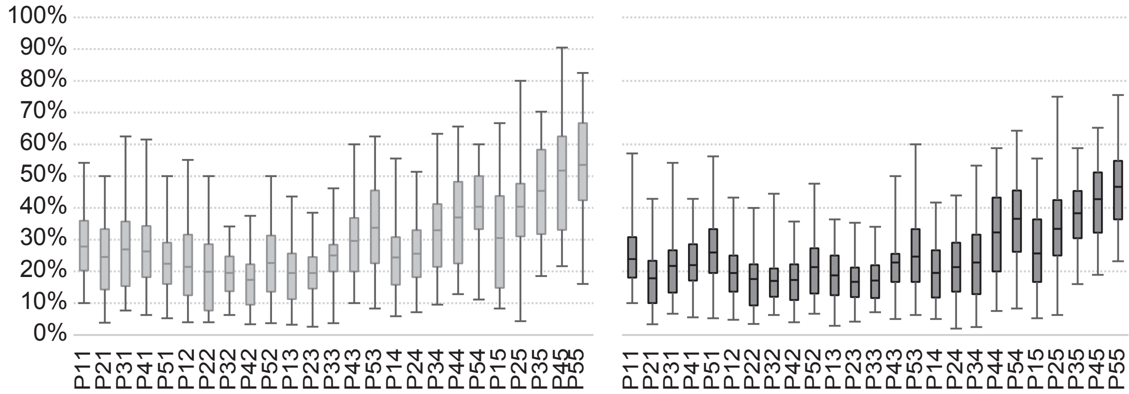


stocks as one common group, instead of basing calculations on the incremental return of pure small cap stocks. For this reason, Fama and French exposures to the size premium englobe a tilt towards medium capitalization stocks which, to some extent, biases the estimation of a true significant size premium only concentrated towards pure small capitalisation stocks. In fact, almost 80% of US stocks constitutes small capitalisations under the Fama and French methodology, whereas under the sequential framework is this amount set to 33% (Lambert, Fays and Hübner, 2015). Consequently, long-short equity hedge funds seem to be less exposed to small capitalisation stocks than expected but rather based their strategies upon higher momentum levels as reported in Panel B, Table 7.

Similarly, Figure 5 shows the amount of significant value exposures under both the Fama and French and

Figure 5. Box Plots of the 25 Portfolios Frequencies for Significant Value Exposures

The figure display box plots of the frequency for individual hedge funds' significant value exposures under a 90 percent confidence interval among the 25 portfolios. To compute the exposures, we performed regressions based analysis on all individual hedge funds composing each portfolios and display the ratio of hedge funds with a significant value exposures over the number of hedge funds composing the portfolio. Box plots with a light grey colour refers to regressions using the size and value Fama and French factors, whereas dark grey colour refers to regressions using the sequential size and value factors.



sequential framework. Globally, we prove that on one hand, under both frameworks the *HML* premium is not redundant next to the profitability and investment factors for long-short hedge fund equities. On the other hand, the sequential alternative of the value premium appears less prevalent for long-short equity hedge funds. This suggests that these long-short investment styles funds favour, to some extent, firms that invest less (*Conservative minus Aggressive)* over value stocks (cf. Table 7) given their similar characteristics of risks[9].

V. Concluding remarks

We perform a horse race between two specifications of the new CAPM empirical model defined by Fama and French (2015) for pricing equity long-short strategies. We show that the strong positive alphas delivered by a 5-factor Fama and French model (2015) augmented with a momentum factor and the quality factor of Asness et al. (2015) vanishes when the size and value factors are defined according to the sequential framework of Lambert, Fays and Hübner (2015). The sequential framework indeed delivers less pricing error when modelling the returns delivered by long-short equity. We also show that alphas sharply drop to negative values when considering the co-skewness and co-kurtosis factors of Lambert and Hübner (2013) which have also been defined using a sequential sorting of US stock returns. The fact that the significance of alphas are significantly reduced under the sequential framework of the 5-factor Fama and French (2015) model augmented with the momentum factor might be considered as an evidence of the completeness of the sequential approach for pricing risk factors. ■

1 Please refer to this paper for additional information about the methodology.
2 Please note that Fama and French acknowledge that the redundancy of the HML factor might be due to the sample period such that further studies are deserved to confirm this evidence.
3 We discard hedge funds reporting their performance only on quarterly basis.
4 We acknowledge that such retreatments might introduce sampling bias. According to the literature (e.g., Fung and Hsieh, 2000), this sampling bias is however rather small.
5 In the attempt to minimize the survivorship bias, we consider an horizon period for our analyzed sample posterior to 1994 period (Kelly and Hao, 2012). We also include "live" and "dead" funds in our sample.
6 The use of equal weights as a construction methodology for the portfolios lies in the attempt to avoid tilted return only towards large funds size.
7 Results of the Schwarz Bayesian Criterion (SBC) for information on models parsimony are available upon request.
8 Under a confidence interval of 90%.
9 HML and CMA are shown to share a common source of risk as documented in Lambert, Fays and Hübner (2015).

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