Original Article

The *q*-factor model and the redundancy of the value factor: An application to hedge funds

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ABSTRACT   We test the new Fama and French five-factor model on a sample of hedge fund strategies. This model embeds the *q*-factor asset pricing model which lies on the *CMA* and *RMW* factors. We find that the *HML* factor is not redundant for many strategies, as conjectured by Fama and French in their setting. *HML* seems to embed risk dimensions which are not included in the Fama and French new factors. In contrast to Fama and French, the α puzzle is robust to the addition of *CMA* and *RMW*. Furthermore, hedge funds seem to prefer, on the one hand, firms which invest a lot to firms which invest less, and, on the other hand, weak firms over robust ones. Finally, our results are not sensitive to the addition of the Fung and Hsieh seven-factor model. However, the explanatory power of the eleven-factor model is much higher for some hedge fund strategies involved in arbitrage.

INTRODUCTION

Fama and French (2015) have recently proposed an augmented version of their three-factor asset pricing model. They add two factors to their model: an investment factor and a profitability factor. These factors

are associated with the drivers of stocks prices in the q-factor asset pricing model or in the investment capital asset pricing model (ICAPM). They are thus well-known in the portfolio theory. For instance, Cochrane (1991) was the first to rely on the q-theory to price assets. Hou *et al* (2015) have also experimented with a new factor model that consists of a market factor, a size factor, an investment factor and a profitability factor – that is, return on equity. These factors are all the more relevant since they can capture the cyclical dimensions of the hedge fund behavior. Indeed, it has been established that this behavior is quite procyclical and very sensitive to macroeconomic shocks (for example, Racicot and Théoret, 2015, 2016). In complement to these previous articles, Fama and French (2015) study the relevance of CMA[1] and RMW[2] – respectively the investment and profitability factor – in their original three-factor asset pricing model.

More precisely, Fama and French (2015) intend to study the interactions of CMA and RMW with their original three-factor model. Actually, they find that their value factor (HML[3]) seems to become *redundant* for describing asset returns in the sense that RMW and especially CMA seem to capture all the risk dimensions of HML: when adding CMA and RMW in their asset pricing model, the factor loading of HML is no longer significant. Actually, firms whose stocks have a high book–to–market ratio tend to invest less and also to be less profitable. Alternatively, firms whose stocks have a low book–to–market ratio tend to invest aggressively and be profitable (Fama and French, 2015). The factor HML thus interacts with CMA and RMW, this interaction being so high in their sample that it seems to eliminate HML from the pricing model. However, as mentioned by Fama and French (2015), the redundancy of HML may be attributable to their sample and other studies must be achieved before arriving at this conclusion. According to Fama and French (2015): 'This result is so striking

we caution the reader that it may be specific to this sample'.

In this study, we apply the new Fama and French five-factor model to a sample of hedge fund strategies' returns. Our first contribution is to test the redundancy of the value factor (HML) when adding CMA and HML in the Fama and French three-factor model. In the hedge fund industry, the size factor (SMB) is also very important to explain returns. We must also consider the impact of the two new factors on the loading of SMB[4] since there are also interactions between size, investment and profitability. Our next contribution is to explore whether the introduction of the two new factors attenuates the alpha puzzle observed in the hedge fund industry. As assessed by Fama and French (2015), 'if an asset pricing model completely captures expected returns, the intercept is indistinguishable from zero'. If the α's of the hedge fund strategies are reduced in the five-factor model compared with the three-factor one, this will be an indication of the 'completeness' of the five-factor model.

Our empirical results show that the HML factor may be redundant for many strategies' returns but in several cases, the coefficient of HML remains significant when adding CMA and RMW. Hence, in contrast to Fama and French (2015) which seem to assess that HML is redundant when adding CMA and RMW, we cannot be so categorical regarding our sample of hedge funds' strategies. The impact of HML in the three-factor model is partly shared between CMA and RMW. It is difficult to establish that most of the impact of HML is absorbed by CMA, as suggested by Fama and French (2015). As the coefficient of HML is usually negative in our regressions, the coefficients of CMA and RMW are also negative. In our sample, hedge funds thus prefer aggressive firms over conservative ones and weak firms over robust ones. Hedge funds are thus in line with the Fama and French's (2015) new puzzle related to portfolios of small stocks whose returns behave like of firms that invest a lot despite

low profitability. However, according to the theory of implicit contracts in economics, firms may overinvest to relax their financing constraints[5] (for example, Fazarri *et al*, 1988; Thomas and Worrall, 2014). In this respect, the five-factor model does not mitigate the hedge funds' alpha puzzle: the α is insensitive to the two new factors. As a robustness check, we add to the five-factor model the seven factors proposed by Fung and Hsieh (1997, 2001, 2004) to price hedge funds' stocks. Our results are essentially unchanged.

This article is organized as follows. The next section discusses the Fama and French five-factor asset pricing model. In the subsequent section, we present our data and the stylized facts related to our study. In the penultimate section, we present our methodology and analyze our empirical results before concluding in the final section.

THE *Q*-FACTOR MODEL AND THE FAMA AND FRENCH FIVE-FACTOR MODEL

The first order condition of the *q*-factor model stipulates that firms will continue to invest until the marginal cost of investment is equal to its marginal benefit or Tobin's *q* (Tobin, 1969; Hou *et al*, 2015):

$$1 + a\frac{I_{it}}{A_{it}} = E_t[M_{t+1}\pi_{it+1}] \quad (1)$$

where I_{it} is the investment level of firm *i*; A_{it} is the level of firm's assets; $E_t[.]$ is the expectations operator conditional on the information set available at time *t*; M_{t+1} is the discount factor and π_{it+1} is the investment cash-flow. The LHS of (1) is the marginal cost of investment and its RHS, its marginal benefit of investment – that is, Tobin's *q* (1969).

Equation (1) may be rewritten as follows:

$$E[r_{it+1}] = \frac{E_t(\pi_{it+1})}{1 + a\frac{I_{it}}{A_{it}}} \quad (2)$$

According to equation (2), the stock expected return is related positively to its

expected profitability as measured by $E_t(\pi_{it+1})$ and negatively to its investment ratio, as measured by $(I_{it})/(A_{it})$. This is the essence of the *q*-factor model.

The Fama and French (2015) five-factor model adds to its three original factors the profitability and investment factors to capture the teaching of the *q*-factor model. It is formulated as follows:

$$R_{it} - r_{ft} = \alpha + \beta_1[R_{mt} - r_{ft}] + \beta_2 SMB_t + \beta_3 HML_t$$
$$+ \beta_4 CMA_t + \beta_5 RMW_t + \varepsilon_{it} \quad (3)$$

where R_{it} is the firm's stock return and r_{ft} is the risk-free rate; R_{mt} is the market portfolio return; *SMB* is a diversified portfolio which is long in small firms' stocks and short in big firms' stocks; *HML* is a diversified portfolio which is long in firms whose stocks have a high book–to-market ratio (that is, value stocks) and which is short in firms whose stocks have a low book-to-market ratio (that is, growth stocks); *CMA* is a diversified portfolio which is long in firms embedded with a low investment to assets ratio and short in firms with a high investment to assets ratio; ε_{it} is the innovation of the regression – its variance being associated with the idiosyncratic risk of strategy *i*. Finally, *RMW* is a diversified portfolio, which is long in firms with high profitability (in terms of net operating revenue to assets or *ROE*) and short in firms with low profitability. The addition of the *CMA* and *RMW* factors captures the two drivers of expected returns in the *q*-factor model (equation (2)).

The presence of the *SMB* factor in the return equation may be questionable since it is not a component of the *q*-factor model. But we must understand that the *CMA* and *RMW* factors are only proxies for the investment and profitability factors: they are measured with errors.[6] In this context, every factor which helps forecast returns has its place in the asset pricing equation. And since *SMB* remains a significant factor in the Fama and French's (2015) experiments even after adding *CMA* and *RMW* in the Fama and French (2015) experiments, it remains valuable to price assets.

In this respect, an empirical asset pricing kernel must span all the states of nature relevant for the estimation of a stock return. If *SMB* span dimensions of the state space not covered by *CMA* and *RMW*, it has a role to play in the return equation.[7]

Similarly to the market risk premium and *SMB*, the *CMA* and *RMW* factors command a positive premium. In this respect, given firm's profitability, a decrease in I_{it} in equation (2) leads to an increase in $E(r_{i,t+1})$. This relationship is well documented in the financial literature (for example, Hou *et al*, 2015; Fama and French, 2015). Fisher (1930) has established a negative relationship between return and investment – that is, the marginal productivity of capital schedule. Moreover, when the cost of capital as measured by r_i is high, the level of investment is low because a high cost of capital is associated with a low VAN, all else equal. There are thus many justifications to the negative relationship between expected return and the level of investment. The *CMA* factor captures this relationship. In other respects, according to equation (2), firms with high profitability provide higher expected returns than firms with low profitability. The *RMW* factor embeds this relationship.

Fama and French show that, at least at the theoretical level, the *CMA* and *RMW* factors substitute to the *HML* factor. To do so, they rewrite the seminal Miller and Modigliani (1961) equation in terms of the book-to-market ratio:

$$\frac{1}{book-to-market} = \frac{\sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - \Delta B_{t+\tau})}{(1+r)^{\tau}}}{B_t} \quad (4)$$

where $Y_{t+\tau}$ is earnings for period $t+\tau$; B_t is the equity book value; ΔB_t is the change in B_t,[8] and r is the expected stock return. According to equation (4), a higher book-to-market ratio implies a higher r. Moreover, a higher book-to-market entails a lower profitability $(Y_{t+\tau})$, all else equal. Finally, a higher book-to-market ratio is related to a lower level of investment. Therefore, *CMA* and *RMW* substitute to *HML*.

EMPIRICAL RESULTS

Data

The hedge fund strategies' returns are taken from the database managed by Greenwich Alternative Investment (GAI). GAI manages one of the oldest hedge fund databases, containing more than 13 500 records of hedge funds as of March 2010. Returns provided by the database are net of fees. The survivorship bias is accounted for in this database, as index returns for periods since 1994 include the defunct funds. The data set runs from January 1995 to September 2012, for a total of 213 observations. In addition to the weighted composite return, the database includes 9 return series of well-known hedge fund strategies. Finally, the Fama and French factors are drawn from French's database[9] and the Fung and Hsieh lookback straddles come from Hsieh's database.[10]

Stylized facts

Figure 1 provides the cross-correlations of the *CMA*, RMW and *HML* with the market return (*mkt*) and between themselves. The correlation of *CMA* and *RMW* with *mkt* is negative and high in absolute value at time *t*, and *RMW* is even correlated negatively with *mkt* at time *t+1*. *HML* is also negatively related to the *mkt* a time *t* but the correlation is positive and significant at time *t−1*. These factors thus tend to have a higher expected return when the market trends downward and vice versa when the market trends upward.

At time *t*, the correlation of *CMA* with *HML*, at 0.65, is higher than the correlation between *RMW* and *HML*, that is, 0.52, but the correlation between *RMW* and *HML* is much more persistent. This indicates that *RMW* and *HML* share common cycles. Overall, cross correlations show that the
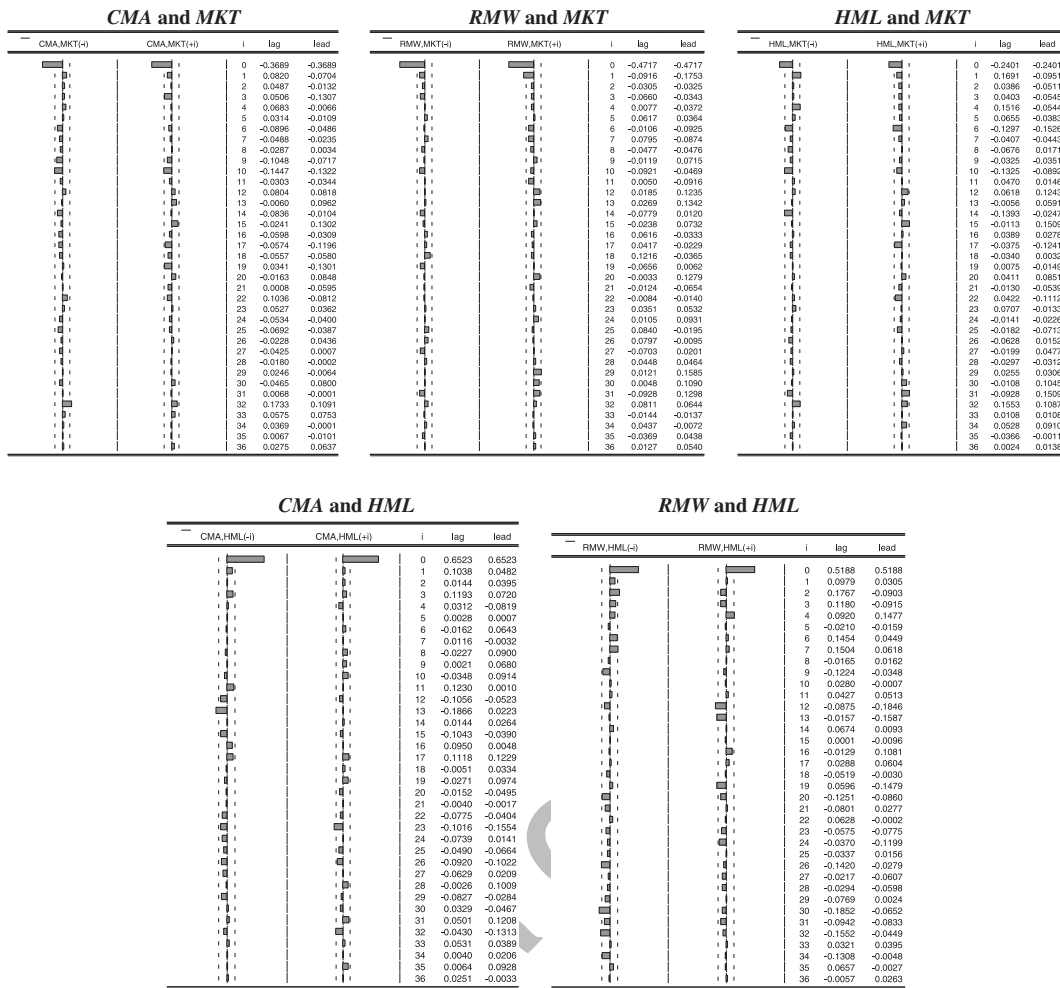
CMA and MKT

CMA,MKT(-i)	CMA,MKT(+i)	i	lag	lead
		0	-0.3689	-0.3689
		1	0.0820	-0.0704
		2	0.0487	-0.0132
		3	0.0506	-0.1307
		4	0.0683	-0.0066
		5	0.0314	-0.0109
		6	-0.0896	-0.0486
		7	-0.0488	-0.0235
		8	-0.0287	0.0034
		9	-0.1048	-0.0717
		10	-0.1447	-0.1322
		11	-0.0303	-0.0344
		12	0.0804	0.0818
		13	-0.0060	0.0962
		14	-0.0836	-0.0104
		15	-0.0241	0.1302
		16	-0.0598	-0.0309
		17	-0.0674	-0.1196
		18	-0.0557	-0.0580
		19	0.0341	-0.1301
		20	-0.0163	0.0848
		21	0.0008	-0.0595
		22	0.1036	-0.0812
		23	0.0527	0.0362
		24	-0.0534	-0.0400
		25	-0.0692	-0.0387
		26	-0.0228	0.0436
		27	-0.0425	0.0007
		28	-0.0180	-0.0002
		29	0.0246	-0.0064
		30	-0.0465	0.0800
		31	-0.0068	-0.0001
		32	0.1733	0.1091
		33	0.0575	0.0753
		34	0.0369	-0.0001
		35	0.0067	-0.0101
		36	0.0275	0.0637

RMW and MKT

RMW,MKT(-i)	RMW,MKT(+i)	i	lag	lead
		0	-0.4717	-0.4717
		1	-0.0916	-0.1753
		2	-0.0305	-0.0325
		3	-0.0660	-0.0343
		4	0.0077	-0.0372
		5	0.0617	0.0364
		6	-0.0106	-0.0925
		7	0.0795	-0.0874
		8	-0.0477	-0.0476
		9	-0.0119	0.0715
		10	-0.0921	-0.0469
		11	0.0050	-0.0916
		12	0.0185	0.1235
		13	0.0269	0.1342
		14	-0.0779	0.0120
		15	-0.0238	0.0732
		16	0.0616	-0.0333
		17	0.0417	-0.0229
		18	0.1216	-0.0365
		19	-0.0656	0.0062
		20	-0.0033	0.1279
		21	-0.0124	-0.0654
		22	-0.0084	-0.0140
		23	0.0351	0.0532
		24	0.0105	0.0931
		25	0.0840	-0.0195
		26	0.0797	-0.0095
		27	-0.0703	0.0201
		28	0.0448	0.0464
		29	0.0121	0.1585
		30	0.0048	0.1090
		31	-0.0928	0.1298
		32	0.0811	0.0644
		33	-0.0144	-0.0137
		34	0.0437	-0.0072
		35	-0.0369	0.0438
		36	0.0127	0.0540

HML and MKT

HML,MKT(-i)	HML,MKT(+i)	i	lag	lead
		0	-0.2401	-0.2401
		1	0.1691	-0.0951
		2	0.0386	-0.0511
		3	0.0403	-0.0545
		4	0.1516	-0.0544
		5	0.0655	-0.0383
		6	-0.1297	-0.1526
		7	-0.0407	-0.0443
		8	-0.0676	0.0171
		9	-0.0325	-0.0351
		10	-0.1325	-0.0892
		11	0.0470	0.0146
		12	0.0618	0.1243
		13	-0.0056	0.0591
		14	-0.1393	-0.0247
		15	-0.0113	0.1509
		16	0.0389	0.0278
		17	-0.0375	-0.1241
		18	-0.0340	0.0032
		19	0.0075	-0.0149
		20	0.0411	0.0851
		21	-0.0130	-0.0539
		22	0.0422	-0.1112
		23	0.0707	-0.0133
		24	-0.0141	-0.0226
		25	-0.0182	-0.0713
		26	-0.0628	0.0152
		27	-0.0199	0.0477
		28	-0.0297	-0.0312
		29	0.0255	0.0306
		30	-0.0108	0.1045
		31	-0.0928	0.1509
		32	0.1553	0.1087
		33	0.0108	0.0108
		34	0.0528	0.0910
		35	-0.0366	-0.0011
		36	0.0024	0.0138

CMA and HML

CMA,HML(-i)	CMA,HML(+i)	i	lag	lead
		0	0.6523	0.6523
		1	0.1038	0.0482
		2	0.0144	0.0395
		3	0.1193	0.0720
		4	0.0312	-0.0819
		5	0.0028	0.0007
		6	-0.0162	0.0643
		7	0.0116	-0.0032
		8	-0.0227	0.0900
		9	0.0021	0.0680
		10	-0.0348	0.0914
		11	0.1230	0.0010
		12	-0.1056	-0.0523
		13	-0.1866	0.0223
		14	0.0144	0.0264
		15	-0.1043	-0.0390
		16	0.0950	0.0048
		17	0.1118	0.1229
		18	-0.0051	0.0334
		19	-0.0271	0.0974
		20	-0.0152	-0.0495
		21	-0.0040	-0.0017
		22	-0.0775	-0.0404
		23	-0.1016	-0.1554
		24	-0.0739	0.0141
		25	-0.0490	-0.0664
		26	-0.0920	-0.1022
		27	-0.0629	0.0209
		28	-0.0026	0.1009
		29	-0.0827	-0.0284
		30	0.0329	-0.0467
		31	0.0501	0.1208
		32	-0.0430	-0.1313
		33	0.0531	0.0389
		34	0.0040	0.0206
		35	0.0064	0.0928
		36	0.0251	-0.0033

RMW and HML

RMW,HML(-i)	RMW,HML(+i)	i	lag	lead
		0	0.5188	0.5188
		1	0.0979	0.0305
		2	0.1767	-0.0903
		3	0.1180	-0.0915
		4	0.0920	0.1477
		5	-0.0210	-0.0159
		6	0.1454	0.0449
		7	0.1504	0.0618
		8	-0.0165	0.0162
		9	-0.1224	-0.0348
		10	0.0280	-0.0007
		11	0.0427	0.0513
		12	-0.0875	-0.1846
		13	-0.0157	-0.1587
		14	0.0674	0.0093
		15	0.0001	-0.0096
		16	-0.0129	0.1081
		17	0.0288	0.0604
		18	-0.0519	-0.0030
		19	0.0596	-0.1479
		20	-0.1251	-0.0860
		21	-0.0801	0.0277
		22	0.0628	-0.0002
		23	-0.0575	-0.0775
		24	-0.0370	-0.1199
		25	-0.0337	0.0156
		26	-0.1420	-0.0279
		27	-0.0217	-0.0607
		28	-0.0294	-0.0598
		29	-0.0769	0.0024
		30	-0.1852	-0.0652
		31	-0.0942	-0.0833
		32	-0.1552	-0.0449
		33	0.0321	0.0395
		34	-0.1308	-0.0048
		35	-0.0657	-0.0027
		36	-0.0057	0.0263

Figure 1: Cross-correlations between Fama and French's factors.
Notes: Each panel provides the correlations of the first factor with the lags and leads of the second factor. The confidence intervals of the correlations appear on the plots.

interactions between *RMW* and *CMA*, on the one hand, and *HML*, on the other hand, are high.

A look at the plot of orthonormal loadings of the Fama and French factors computed with the principal components analysis might help to see the links between them. According to Figure 2, *CMA* and *HML* are very close factors, which does not seem the case for *RMW*. Not surprisingly, *SMB* is close to the market factor.

Figure 3, which plots the spectra of the factors, gives a different picture. Spectral analysis is used to compare the dynamic aspects or cycles of the factors' time series. We have indicated the length of the cycles on the plots. The business cycle frequency corresponds to the shaded areas – that is, it is contained in the interval ranging from 18 months (six quarters) to 120 months (40 quarters) (DeJong and Dave, 2007). The spectra which are the most similar are those of *HML* and *RMW*. Both have a peak in the zone of the business cycle frequency and another at a cycle lasting 3.5 months. Similarly to the market factor, the spectrum of *CMA* is more akin to the one of a random variable.
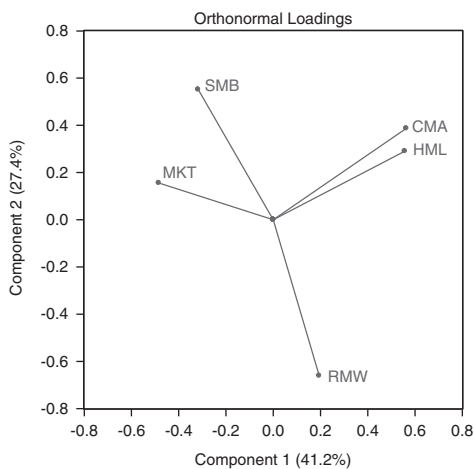
Figure 2: Factors' orthonormal loadings.
Notes: This plot is built with the two first components resulting from principal components analysis applied to the Fama and French's (2015) five factors.

We can get a better grasp of the links between the factors by running Granger causality tests (Table 1). The Granger test between *CMA* and *HML* is significant in both directions: *HML* Granger causes *CMA*, and *CMA* Granger causes *HML*, the latter test being more significant than the former. In other respects, *RMW* Granger causes *HML*, this test being more significant than for *CMA*. However, *HML* does not Granger causes *RMW*. Surprisingly, *SMB* Granger causes *CMA* and *RMW*, suggesting that the link between *SMB* and the two new factors is quite close. Size does impact investment and profitability.

Summarizing, it is difficult to assess *a priori* which of *CMA* or *RMW* is closest to *HML*. That depends on the framework we adopt. In a static framework, *CMA* seems closer to *HML* while in a dynamic one, *RMW* is closer. But regardless of the perspective, the links between these three factors are strong even if we can discard that *CMA* and *RMW* are perfect substitutes to *HML*. Consequently, the redundancy of *HML* is not established by the stylized facts.

Testing the redundancy of HML

To further investigate the issue related to the redundancy of *HML*, we first estimate the

Fama and French (1993) three-factor model with our sample of hedge fund strategies to measure the relative importance of this factor:

$$R_{it} - r_{ft} = \alpha + \beta_1 \left[R_{mt} - r_{ft} \right] + \beta_2 SMB_t + \beta_3 HML_t$$
$$+ \beta_4 ar(1) + \varepsilon_t \qquad (5)$$

We then estimate the five-factor model (equation (3)) with and without *HML* to see how the weight of *HML* is redistributed between *CMA* and *RMW*.

Before analyzing the results, note that we have included an *ar(1)* term in our estimation process to account for the autocorrelation of order 1 between returns. If markets are efficient, there should be no autocorrelation between returns because otherwise they become predictable. But in the hedge fund industry, autocorrelation may be because of return smoothing or to infrequent trading giving rise to illiquidity (Okunev and White, 2003; Pástor and Stambaugh, 2003; Getmansky *et al*, 2004; Chan *et al*, 2007; Brown *et al*, 2012; Chen and Tindall, 2012). This autocorrelation contributes to hide the effective risk in the hedge fund industry. Moreover, it gives rise to estimation biases if not accounted for. We rely on an *ar(1)* term to tackle autocorrelation created by return smoothing or illiquidity in our estimations (Okunev and White, 2003; Bali *et al*, 2014).[11]

Table 2 provides the estimation of equation (5) for the hedge funds' general index and for strategies. Note first that the explanatory power of the three-factor model is good for the general index and for many strategies – that is, long-short, growth, short-sellers and value index – the adjusted R^2 exceeding 0.75 in these cases. However for other strategies – futures, macro and equity market neutral – this model has a very low explanatory power. The adjusted R^2 seems co-linear to the market β: the higher the β of a strategy, the higher its R^2.

Most strategies display a significant *ar(1)* coefficient, which suggests illiquidity and return smoothing in the hedge fund industry. The coefficient of autocorrelation is also non-negligible for these strategies, ranging from
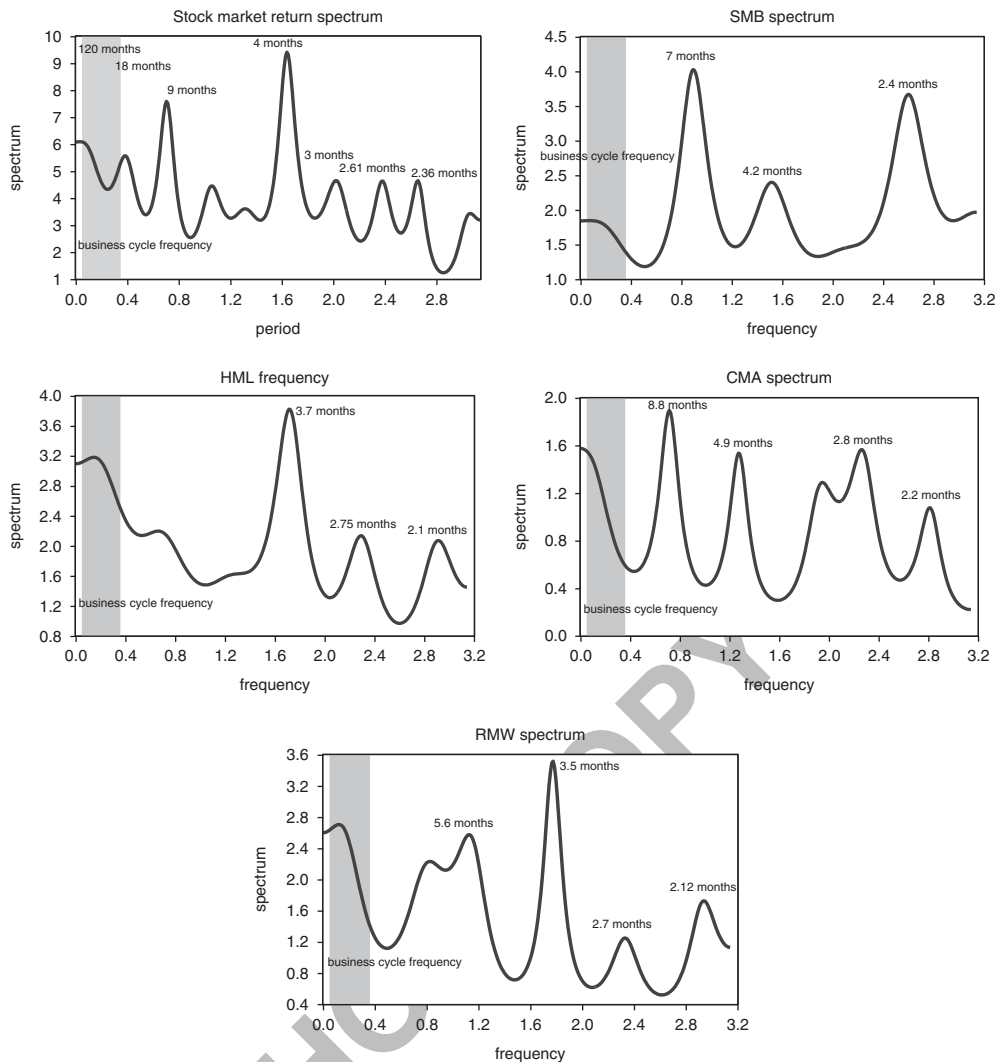
Figure 3: Spectra of Fama and French's factors.
Notes: These spectra are built using an AR(*p*) model. Specifically, the spectrum is a decomposition of the variance of a time series by frequency – the cycle frequency being low near the origin add increasing progressively till π. Comparisons of the height of the spectrum for alternative values of frequency indicate the relative importance of fluctuations at the chosen frequencies in influencing variance in the time series. A spectrum having a peak near the origin indicates that the series is very persistent through time: its autocorrelation function declines very slowly. A spectrum having a peak in the shaded area indicates that this time series has a cycle in the conventional business cycle frequency. A spectrum which shifts to the left through time indicates less volatility for the series, that is, a more stable series. Shaded areas correspond to the business cycle frequency, which is comprised between 6 and 40 quarters (DeJong and Dave, 2007).

0.14 for the market neutral strategy to 0.31 for the distressed securities strategy. Three strategies do not show any evidence of autocorrelation: macro, short-sellers and futures.

As expected, the β is generally low in the hedge fund industry, and usually much lower than the market portfolio β which is equal to one by definition. Over the whole sample period, it is equal to 0.29 for the general index with a maximum of 0.59 for the growth strategy. Note that short-sellers which are involved in a contrarian strategy with respect to the market display a $-\beta$ value (-0.80)

Table 1: Granger causality tests

Test	Statistics	
HML Granger causes (GC) CMA	F-statistic	1.72
	P-value	0.06*
CMA GC HML	F-statistic	1.93
	P-value	0.03**
HML GC RMW	F-statistic	1.21
	P-value	0.27
RMW GC HML	F-statistic	2.27
	P-value	0.01**
SMB GC CMA	F-statistic	2.51
	P-value	0.01**
CMA GC SMB	F-statistic	0.78
	P-value	0.66
SMB GC RMW	F-statistic	3.09
	P-value	0.01**
RMW GC SMB	F-statistic	1.46
	P-value	0.14

Notes: When the test accepts the hypothesis of causality, its *P*-value has one * if the test is significant at the 10% level and ** if the test is significant at the 5% level.

Table 2: The Fama and French three-factor model

	c	mkt_rf	SMB	HML	ar(1)	R^2/DW
gi	0.004	0.29	0.23	−0.12	0.22	0.76
	4.88	18.08	11.20	−5.66	3.15	2.00
ls	0.004	0.43	0.34	−0.15	0.30	0.82
	3.14	22.33	13.73	−5.75	4.59	2.04
macro	0.002	0.18	0.17	−0.15	0.02	0.15
	0.88	4.12	2.82	−2.52	0.34	1.98
gr	0.003	0.59	0.47	−0.37	0.18	0.80
	1.96	20.02	12.26	−8.98	2.65	2.05
ss	0.001	−0.80	−0.54	0.50	−0.01	0.78
	0.51	−19.4	−9.74	10.61	−0.09	2.00
fut	0.006	−0.06	−0.03	0.10	0.02	0.00
	2.65	−1.09	−0.04	1.35	0.32	1.95
vi	0.005	0.47	0.33	−0.11	0.27	0.82
	4.06	24.31	13.12	−4.36	3.98	1.99
ds	0.005	0.16	0.17	−0.03	0.31	0.44
	3.59	7.61	6.44	−1.23	4.71	2.04
ed	0.005	0.23	0.26	−0.05	0.25	0.66
	4.50	13.27	11.21	−1.98	3.72	2.04
emn	0.004	0.07	0.13	−0.03	0.14	0.22
	4.81	3.61	5.56	−1.57	2.01	2.03
oi	0.005	0.35	0.37	−0.23	0.21	0.67
	3.38	12.77	10.33	−5.95	3.14	2.06

Notes: gi is the return on the GAI general index. The list of the selected strategies is: ls (long-short); macro; gr (growth); ss (short-sellers); fut (futures); vi (value index); ds (distressed securities); ed (event driven); emn (equity market neutral); oi: opportunistic index. The *t* statistics are in italics and are HAC-adjusted. *mkt_rf* is the market risk premium. *ar(1)* is an autoregressive factor of order 1.

which is quite important in absolute value. Some strategies have a β close to 0, like futures (-0.06) and equity market neutral (0.07).

The second factor in importance which impacts hedge fund returns is *SMB*, its estimated coefficient being 0.23 for the general index. Except for short sellers, hedge funds generally prefer a positive exposure to the stocks of small firms over the stocks of big firms. Strategies with a higher β usually display a higher exposure to *SMB*. The negative exposure of short sellers to *SMB*, at -0.54, is once more quite high.

The factor which interests us in this study, *HML*, is also usually a significant factor for hedge fund strategies, albeit less important than *SMB*. Hedge funds usually short *HML*. They thus tend to prefer growth stocks over value stocks. For instance, the negative exposure of the general index to *HML* is equal to -0.12. Once more, the relative exposure of hedge fund strategies to *HML* is in ascending order of their exposures to the market return and *SMB*. In this respect, the exposures of the growth and opportunistic strategies are equal to -0.37 and -0.23, respectively. Since short–sellers follow a

contrarian strategy compared with the other ones,[12] its exposure to *HML*, at 0.50, is positive and high in absolute value. It is in line with its substantial negative exposure to the market and to *SMB*.

Table 3 provides the estimation of the complete Fama and French *five-factor model* (equation (3)) and the estimation of the corresponding *four-factor model* excluding *HML*. These estimations aim at testing, on the one hand, whether the impact of *HML* becomes redundant when including the two new factors *CMA* and *RMW*, and, on the other hand, at analyzing how the weight of *HML* is redistributed between *CMA* and *RMW* when omitting it from the five-factor equation. Fama and French (2015) found that *HML* has a tendency to become redundant when including *CMA* and *RMW* in their original three-factor model. They also suggest that the exposure to *HML* in their three-factor model will be mostly captured by *CMA*

Table 3: The Fama and French four-factor and five-factor model

	c	mkt_rf	SMB	HML	CMA	RMW	ar(1)	R^2/DW
gi	0.005	0.26	0.19	−0.03	−0.11	−0.13	0.24	0.71
	5.67	14.35	7.98	−1.15	−2.43	−3.45	3.60	1.97
	0.005	0.25	0.19	—	−0.14	−0.15	0.25	0.77
	5.84	14.53	7.89	—	−4.38	−4.78	3.74	1.97
ls	0.005	0.38	0.28	−0.02	−0.17	−0.17	0.34	0.83
	4.11	18.22	10.09	−0.57	−3.36	−4.02	5.21	2.01
	0.005	0.37	0.28	—	−0.20	−0.19	0.35	0.83
	4.20	18.69	10.16	—	−5.13	−5.12	5.30	2.01
macro	0.003	0.11	0.12	0.05	−0.34	−0.18	0.04	0.18
	1.72	2.27	1.78	0.56	−2.67	−1.78	0.62	1.98
	0.003	0.12	0.12	—	−0.29	−0.15	0.04	0.18
	1.65	2.49	1.84	—	−3.08	−1.96	0.54	1.98
gr	0.005	0.52	0.38	−0.19	−0.20	−0.28	0.18	0.82
	3.22	16.07	8.69	−3.18	−2.43	−4.18	2.57	2.02
	0.006	0.50	0.38	—	−0.38	−0.39	0.20	0.81
	3.59	15.46	8.31	—	−6.08	−6.71	2.96	2.02
ss	0.000	−0.77	−0.53	0.51	0.15	0.06	−0.01	0.78
	0.09	−16.10	−8.12	5.80	1.23	0.70	0.81	2.00
	−0.002	−0.69	−0.49	—	0.62	0.36	0.01	0.75
	−0.95	−13.92	−7.03	—	6.43	4.11	0.11	1.99
fut	0.006	−0.03	−0.01	0.02	0.16	0.01	0.02	0.00
	2.30	−0.61	−0.15	0.23	1.06	0.06	0.23	1.96
	0.006	−0.03	−0.01	—	0.19	0.02	0.01	0.00
	2.31	−0.57	−0.13	—	1.65	0.22	0.82	1.96
vi	0.006	0.43	0.30	0.01	−0.23	−0.11	0.34	0.84
	4.70	20.20	10.45	0.34	−4.28	−2.55	5.04	1.98
	0.006	0.43	0.30	—	−0.22	−0.11	0.33	0.84
	4.72	20.98	10.53	—	−5.50	−2.81	5.01	1.94
ds	0.006	0.13	0.14	0.03	−0.07	−0.12	0.31	0.45
	4.13	5.65	4.20	0.72	−1.17	−2.36	4.49	2.04
	0.006	0.14	0.14	—	−0.04	−0.10	0.32	0.45
	4.01	5.99	4.24	—	−0.97	−2.34	4.76	2.05
ed	0.005	0.22	0.21	−0.01	0.00	−0.12	0.24	0.67
	5.07	10.87	7.80	−0.19	−0.02	−3.02	3.55	2.03
	0.006	0.22	0.21	—	−0.01	−0.13	0.24	0.67
	5.17	11.22	7.83	—	−0.21	−3.68	3.54	2.03
emn	0.004	0.07	0.11	−0.06	0.08	−0.04	0.12	0.23
	4.64	3.32	3.94	−1.62	1.69	−0.98	1.78	2.02
	0.005	0.06	0.11	—	0.03	−0.08	0.13	0.24
	4.91	2.98	3.79	—	0.78	−2.17	1.94	2.03
oi	0.007	0.30	0.30	−0.10	−0.12	−0.22	0.22	0.69
	4.23	9.80	7.12	−1.79	−1.58	−3.48	3.26	2.04
	0.007	0.29	0.29	—	−0.22	−0.28	0.24	0.68
	4.44	9.61	6.96	—	−3.81	−5.18	3.52	2.04

Notes: For each strategy, we test the five-factor model including *HML* (first two rows) and the four-factor model excluding *HML* (last two rows). The *t*-statistics are in italics and are HAC-adjusted. See Table 2 for the list of the return variables.

than *RMW*. We now investigate if these results hold in the framework of our sample.

First, we observe that *HML* becomes usually redundant when introducing *CMA* and *RMW* in the factor model. It is the case for the general index and the following strategies: long-short, macro, value index, event driven strategies.[13] Note that the weight of *HML* in the three-factor model is shared between *CMA* and *RMW* and not exclusively by *CMA*. Moreover, the sum of the exposures to *CMA* and *RMW* is higher, in absolute value, than the exposure of hedge fund strategies' returns to *HML* in the three-factor model. However, for four strategies − that is, growth, short-sellers, equity market neutral and opportunistic index − *HML* remains significant when shifting from the

three-factor to the five-factor model. Excepting the equity market neutral strategy, the exposure of these strategies to *HML* is relatively high in the three-factor model. For instance, the exposure of the growth strategy to *HML* is equal to −0.37 in the three-factor model. It decreases (in absolute value) to −0.19 in the five-factor model, and the exposures to *CMA* and *RMW* are equal to −0.20 and −0.28, respectively. For one strategy – that is, the short sellers – the exposure to *HML* does not decrease when adding *CMA* and *RMW* to the set of factors. It remains at 0.50, significant at the 5 per cent level, and the *CMA* and *RMW* factors are not significant. When dropping *HML*, the coefficients of *CMA* and *RMW* are equal to 0.62 and 0.36, respectively, both significant at the 5 per cent level, suggesting again that *HML* may embed the impacts of *CMA* and *RMW* consistent with the Granger causality tests.

Except for short sellers which adopt a contrarian strategy, the exposures to *CMA* and *RMW* is negative for the hedge fund strategies. Therefore, hedge funds tend to prefer, on the one hand, firms which invest a lot to firms which invest less, and, on the other hand, weak firms to robust ones. These exposures parallel the hedge fund strategies' exposure to *HML* which is negative in our sample. However, as mentioned previously, *HML* firms tend to have a low investment ratio and tend to be less profitable. Thus, the positive link between *CMA* and *HML* is more obvious than the positive link between *RMW* and *HML*. *RMW* may embed risk dimensions which are not included in *HML*. For instance, the distressed strategy is neither sensitive to *HML* nor *CMA* but reacts negatively and significantly to *RMW*. Indeed, the distressed strategy is oriented toward the investment in stocks of weak firms which have a potential to recover.

In other respects, the five-factor model does not mitigate the hedge fund α puzzle. Shifting from the three to the five-factor model does not decrease the strategies' α: it

even increases for many of them. In this sense, for hedge funds, the five-factor model is not a 'more complete' model than the three-factor model.

Summarizing, consistent with the Fama and French's conjecture, our results show that for the majority of the strategies, the *CMA* and *RMW* factors substitute to *HML*. However, this is not always the case. When the *HML* coefficient is high and significant in the three-factor model, it tends to remain significant in the five-factor model even if the two factors associated with the q-factor model are also significant. When removing the *HML* factor in this situation, the exposures to *CMA* and *RMW* factors increases significantly in absolute value, which confirms the strong interaction between the three factors. Overall, consistent with the stylized facts, *HML* seems to embed information not contained in the other factors even if they are strongly interactive. In this respect, we cannot assess that *CMA* captures most of the weight of *HML* in the four-factor model – that is, which excludes *HML* – since *RMW* usually absorbs a non-negligible portion of the weight of *HML*.

Robustness check: An augmented version of the five-factor model encompassing the Fung and Hsieh empirical model

As a robustness check, we augment Fama and French's five factor model with the seven factors proposed by Fung and Hsieh (1997, 2001, 2004) to account for the dynamic dimensions of hedge fund strategies. These factors comprise five categories of straddle lookbacks, the change in the 10-year interest rate, and a change in the credit spread. The lookback straddles – which are especially useful to study the trend followers – are: the bond lookback, the stock lookback, the short–interest lookback, the currency lookback and the commodity lookback. Following the addition of these seven factors, our return

model takes the following form:

$$
\begin{aligned}
R_{it} - r_{ft} = {} & \alpha + \beta_1 \left(R_{mt} - r_{ft}\right) + \beta_2 \left(SMB\right)_t + \beta_3 \, CMA + \beta_4 \, RMW \\
& + \beta_5 \, bond\_look_t + \beta_6 \, stock\_look_t + \cdots \\
& + \beta_7 \, shortint\_look_t + \beta_8 \, currency\_look_t + \beta_9 \, commod\_look_t \\
& + \beta_{10} \, d(CredSpr_t) + \beta_{11} \, d(10Y_t) + \beta_{12} \, ar(1) + \varepsilon_t
\end{aligned} \tag{6}
$$

where $d(CredSpr)$ stands for the change in the credit spread – that is, the spread between the BBB and AAA US corporate bond yields; $d(10Y_t)$ in the change in the rate of the 10-year US federal government bond.

Table 4 provides the estimation of equation (6) for the hedge fund general index and strategies. While there was no obvious change in the adjusted R^2 when shifting from the three to four-factor model,[14] introducing the seven Fung and Hsieh factors in the estimation leads to increases in the adjusted R^2, which may be substantial for some strategies. For instance, while the four-factor model has no explanatory power for the futures strategy, the adjusted R^2 associated with the eleven-factor model is equal to 0.34 for this strategy. Option-like trading strategies thus play a great role for futures, all lookbacks being significant in its equation. The adjusted R^2 of the macro strategy also jumps from 0.15 to 0.30 when using the eleven-factor model rather than the four-factor one.

Adding the seven Fung and Hsieh factors has only a marginal impact on the estimation of the coefficients associated with the Fama and French four-factor model. The lookbacks impacting the most hedge fund strategies' returns are the short-interest, stock and currency lookbacks. The short-interest lookback affects significantly all strategies except short-sellers. The strategies have a negative exposure to this kind of lookback. Note that, with a correlation close to 0.70, the short interest lookback is the most related to the first principal component of the five Fung and Hsieh's lookbacks. This component has a $-\beta$ value (-0.10) and thus helps immunize against market risk. Our results thus suggest that the short–interest rate lookback plays a major role in the hedging operations of

hedge funds. The general index and many directional strategies – that is, long-short, macro and growth – have a positive and significant exposure to the stock lookback. Moreover, as expected, strategies more involved in arbitrage – that is, distressed, event-driven and equity market neutral – display a negative and significant exposure to the bond lookback. In addition to the general index, many strategies – that is, long-short, value index, distressed securities and event-driven – have a negative and significant exposure to the change in the credit spread.

Finally, the addition of the Fung and Hsieh's seven factors to the Fama and French's four-factor model does not help solve the hedge fund α puzzle. It even exacerbates it in many cases, the α being greater for many strategies. It seems that other factors must be considered to mitigate the puzzle.

CONCLUSION

To the best of our knowledge, this study is the first to transpose the *q*-factor model to hedge fund strategies. The advantage of this model is that it relies on a robust theoretical framework. We showed that it proves useful to better describe the hedge fund strategies. The new factors *CMA* and *RMW* are very significant for a majority of strategies. In our sample, hedge funds seem to prefer weak firms to robust ones, but also firms with a high investment ratio to firms with a low one. This selection is akin to the puzzle discovered by Fama and French (2015) in their experiments.

In contrast to Fama and French (2015) which seem to assess that *HML* is redundant when adding *CMA* and *RMW*, we cannot be

Table 4:   The Fama and French four-factor model augmented with the seven Fung and Hsieh factors

	GI	LS	MACRO	GR	SS	FUT	VI	DS	ED	EMN	OI
C	0.007	0.007	0.007	0.008	−0.002	0.008	0.007	0.006	0.006	0.005	0.009
	6.86	5.24	2.89	4.38	−0.87	3.04	5.35	5.33	6.81	4.85	4.78
MKT_RF	0.25	0.37	0.17	0.49	−0.70	0.08	0.42	0.12	0.20	0.04	0.28
	14.61	18.27	3.34	14.49	−12.89	1.42	20.3	5.05	10.26	2.05	8.89
SMB	0.19	0.28	0.15	0.37	−0.48	0.05	0.30	0.15	0.21	0.09	0.28
	8.09	10.13	2.17	8.02	−6.72	0.67	10.53	4.69	8.00	3.27	6.69
CMA	−0.18	−0.23	−0.32	−0.41	0.65	0.22	−0.25	−0.07	−0.04	0.00	−0.27
	−5.63	−6.11	−3.36	−6.57	6.55	2.22	−6.41	−1.52	−1.07	0.04	−4.62
RMW	−0.15	−0.19	−0.12	−0.40	0.40	0.06	−0.11	−0.07	−0.12	−0.08	−0.29
	−5.08	−5.35	−1.39	−6.89	4.48	0.67	−2.97	−1.84	−3.70	−2.34	−5.24
BOND_LOOKBACK	−0.003	−0.006	0.024	−0.010	0.023	0.046	0.001	−0.020	−0.017	−0.015	−0.016
	−0.66	−1.14	1.72	−1.08	1.53	3.05	0.1	−3.10	−3.14	−2.56	−1.84
STOCK_LOOKBACK	0.014	0.014	0.046	0.025	−0.008	0.038	0.007	0.001	0.011	0.001	0.012
	2.53	2.07	2.83	2.24	−0.44	2.21	1.04	0.10	1.78	0.15	1.22
SHORTINT_LOOKBACK	−0.013	−0.013	−0.021	−0.016	0.004	−0.021	−0.014	−0.006	−0.009	−0.009	−0.013
	−4.94	−4.23	−2.76	−3.04	0.46	−2.57	−4.33	−1.64	−3.17	−2.84	−2.74
CURRENCY_LOOKBACK	0.011	0.01	0.012	0.011	−0.017	0.048	0.01	0.002	0.005	0.007	0.017
	2.82	2.28	1.05	1.48	−1.39	3.94	2.11	0.37	1.06	1.46	2.38
COMMOD_LOOKBACK	0.008	0.004	0.031	0.005	0.012	0.074	−0.003	0.000	0.002	0.009	0.010
	1.66	0.76	2.07	0.48	0.74	4.6	−0.46	0.02	0.41	1.49	1.13
D(TAUX_10ANS)	0.002	0.003	0.006	−0.002	0.012	−0.007	0.002	0.009	0.002	0.001	0.004
	0.81	0.88	0.67	−0.28	1.32	−0.73	0.47	2.1	0.59	0.24	0.65
D(CREDIT_SPREAD)	−0.016	−0.014	−0.016	−0.011	−0.023	−0.017	−0.019	−0.042	−0.030	0.001	−0.013
	−2.64	−1.96	−0.99	−0.91	−1.35	−0.93	−2.6	−5.22	−4.46	0.19	−1.13
Observations	208	208	208	208	208	208	208	208	208	208	208
R^2	0.82	0.86	0.3	0.83	0.76	0.34	0.86	0.59	0.75	0.31	0.72
F-statistic	73.18	100.52	7.01	79.83	52.57	8.39	104.02	23.26	48.11	7.30	41.49
DW	2.01	2.06	2.01	2.04	2.00	2.00	2.01	2.04	2.02	2.04	2.05

Note: See Table 2 for the list of the return variables. The *t*-statistics are in italics and are HAC-adjusted.

so categorical regarding our sample of hedge funds' strategies. Consistent with Fama and French's (2015) conjecture, *HML* becomes redundant for many strategies when adding the two new factors. However, for some of them – especially when *HML* weights heavily in the three-factor model – *HML* coexists with *CMA* and *RMW*. *HML* thus seems to embed risk dimensions, which are not included in the Fama and French new factors.

In contrast to the study of Fama and French (2015) where the α tends to zero in their five-factor model, the addition of *CMA* and *RMW* does not solve the hedge fund α puzzle: α is robust to the inclusion of these factors. We also find that the Fung and Hsieh (1997, 2001, 2004) factors – which account for the option-like trading strategies followed by hedge funds – add more explanatory power to the hedge fund return model than the two new Fama and French factors.[15] But once more, the Fung and Hsieh factors do not solve the hedge fund α puzzle. They even exacerbate it.

ACKNOWLEDGEMENTS

NOTES

1. *CMA* is the abbreviation for 'conservative minus aggressive' – that is, a portfolio which is long in stocks of firms with a low ratio of investment to assets and short in stocks of firms with a high ratio of investment to assets.
2. *RMW* is the abbreviation for 'robust minus weak' – that is, a portfolio which is long in stocks of robust firms in terms of profitability and short in stocks of weak firms in terms of profitability.
3. *HML* is the abbreviation for 'high minus low' – that is, a portfolio which is long in stocks of firms having a high book-to-market ratio and short in stocks of firms having a low book-to-market ratio.
4. *SMB* is the abbreviation for 'small minus big' – that is, a portfolio which is long in stocks of small firms and long in stocks of big firms.
5. More precisely, firms overinvest when they are in financial distress and expect that projects with positive VAN may rescue them. By doing so, they expropriate their debt stakeholders.

6. Even if they consider that the factors of their model – including market risk premium, *SMB* and *HML* – are measured with errors, Hou *et al* (2015) and Fama and French (2015) do not 'instrument' factors to tackle the problem related to measurement errors. Their objective, as ours, is to study the interaction between factors. Replacing factors with instruments is inconsistent with this objective since it creates interactions *per se* which are not related to our goal. Moreover, introducing more factors – that is, *CMA* and *RMW* – in the original Fama and French three-factor model is a way to reduce the co-movement of the original three factors with the innovation of the empirical model, which creates the problem related to errors-in-variables. This interaction will be partly taken into account by *CMA* and *RMW*. It is precisely the object of our paper to study the interaction between old and new factors.
7. Note that Fama and French (2015) do not introduce the momentum factor (*UMD*) proposed by Carhart (1997) and the liquidity factor proposed by Pástor and Stambaugh (2003) in their new asset pricing model. They justify this omission by the fact that these two factors have regression slopes close to zero in their experiments so they decided to discard them. According to Fama and French (2015), these factors produce trivial changes in model performance.
8. Note that investment represents a decrease in the book value of equity (B_t) – that is, an expense or a negative cash-flow. Instead of putting ΔB in equation (4), Miller and Modigliani (1961) put I in their original equation – that is, equation (9) in their 1961 article.
9. The address of French's website is: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
10. The address of Hsieh database is: https://faculty.fuqua.duke.edu/~dah7/HFData.htm.
11. Note that there are more sophisticated ways to account for return smoothing. See Getmansky *et al* (2004) and Brown *et al* (2012).
12. Excepting the futures strategy.
13. Note that we list only the strategies which have a significant exposure to *HML* in the Fama and French three-factor model.
14. That is, the model including the market risk premium, *SMB, CMA* and *RMW*.
15. When excluding *HML*.

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