A Sheep in Wolf's Clothing?

A Comparative Analysis of Alternative Mutual Funds and Hedge Funds

Paolo Frazzarin[a] and Jorge Lobo[b,*]

ABSTRACT

This paper analyzes to which extent alternative mutual funds emulate hedge fund strategies and what are the performance drivers for this category of funds. We use a two-step regression process for our analysis and find that alternative mutual funds differ from hedge funds on three main fronts: they fail to generate alpha, they do not share the same factor exposures, and their returns are impacted in a different way by fund-specific features. The findings contain relevant implications for investors, who should not fall into the trap of considering the two asset classes as perfect substitutes.

Keywords: Alternative Investments, Alternative Mutual Funds, 1940 Investment Company Act, Hedge Funds, Factor Analysis

JEL Classification: G11, G12, G23

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[a] Student of MSc in Finance at Stockholm School of Economics. E-mail: 40521@student.hhs.se

[b] Student of MSc in Finance at Stockholm School of Economics. E-mail: 40516@student.hhs.se

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1. Introduction

Alternative mutual funds (AMFs) have grown impressively in size and prominence during the years following the financial crisis. These funds implement an array of different hedge fund strategies within a mutual fund structure compliant with the 1940s Investment Company Act. Despite their recent growth, it is still unclear whether they really deliver the best of both worlds: uncorrelated returns and alpha like hedge funds (HFs), together with transparency and liquidity like traditional mutual funds (TMFs), (Meder, 2012). Clarifying this idea is of uttermost importance for investors, who should not regard AMFs as perfect substitutes for HFs without first considering their intrinsic characteristics. The goal of this paper is to assess whether the strategies employed by AMFs are comparable in terms of absolute performance and factor exposures to those of HFs, and whether the determinants of performance and incentives of AMF vehicles are more similar to those of HFs or TMFs. We manage to obtain data on 8 different investment sub-strategies and we then use a two-step regression process for the analysis. First, AMF returns are regressed on factor models and HF indices to assess the absolute performance and the degree of strategy replication. Second, the alpha obtained in the first step is regressed on several micro fund variables to assess performance drivers and incentives. Our sample of 620 AMFs segregated by investment strategy allows us to deepen the analysis conducted by previous studies, which are constrained by sample size, and to better determine the degree of replication of different HF styles.

This paper finds that AMFs fail to generate alpha across all the eight different strategies, while all but one HF strategies show positive significant alpha. AMFs also show meaningful differences in implementation of investment strategies compared to HFs, since factor exposures within the same investment strategies vary significantly. Furthermore, the degree of common variation between AMFs and their matching HF indices is relatively low. This difference in implementation is greater the higher the complexity of the investment strategy that AMFs try to replicate, pointing to regulation as being an important drag for AMFs. The paper also shows that AMFs fail to achieve performance persistence, in a similar way to TMFs. Finally, we identify several determinants of performance in AMFs, some of which fail to match those identified for other kinds of investment vehicles. Age and manager tenure affect performance negatively, in line with what is shown in the literature for HFs and opposite to some of the findings for TMFs. Flows have a positive effect on performance, a finding that we explain on the basis that AMFs benefit from flows when they are small, as they are able to implement a wider array of strategies, but suffer from them once they reach a critical size. This intuition is confirmed by our finding that strategies with greater capacity constraints show lower positive flow coefficients. Turnover also has a positive effect on performance, something that for TMFs has not always been proven to hold.

We believe that the analysis can shed value on this increasingly important asset class and describe it well in terms of its intrinsic characteristics: risk, return and similitudes to both HFs and TMFs.

The paper is structured in several sections. Section 2 provides a background on the academic literature regarding AMFs and discusses how this paper relates to it. Section 3 describes the sources of data and the process of gathering and cleaning them. Section 4 describes the methodology used in the paper and the choice of variables. Section 5 analyzes the results and comments on the findings, while section 6 concludes and summarizes all key findings and their practical relevance. The paper is complemented by a reference and an appendix section.

2. Literature Review

TMFs and HFs present differences in terms of investment strategies, investor bases and the type of regulation that they are subject to. In the US, for instance, while the Securities Act of 1933 and the Securities Exchange Act of 1934 apply to both, it is only mutual funds that comply with the Investment Company Act of 1940. The reason for this is that HFs are structured as a limited partnership. As a result, they need to remain private, and are restricted in terms of soliciting and marketing to be able to enjoy lower investment restrictions. The 1940 Investment Company Act poses constraints and requires compliance in the fields of leverage, short-sales, liquidity, diversification and transparency.

While TMFs and HFs have traditionally remained isolated from each other, some managers started to blur the line between them by implementing alternative investment strategies compliant with the ’40 Act mutual fund regulation. The first family of AMFs was launched by Stanley Druckenmiller in association with Dreyfus Corporation in 1986, known as “Strategic Funds” (Dreyfus, 2015). This series of AMFs employed index futures, options, short selling, and other hedging techniques previously attributed solely to HFs. In order to be categorized as mutual funds, AMFs need to comply with rules derived from the 1940 Investment Company Act.

The evolution of this nascent asset class was slow until the 1997 repeal of the short-short rule, which previously required that mutual funds derive less than 30% of their gross income from the sale of securities held for less than 3 months (Bae & Yi, 2008). The repeal originated a new wave of AMFs, which started using a wider array of investment strategies than before, due to the greater flexibility allowed. Still nowadays, the size of AMFs relative to the overall United States TMF and HF industries remains small with $300bn of assets under management by mid- 2014, representing just 2% and 12% of the overall mutual fund and HF industries respectively (Deutsche Bank, 2014; Barclays, 2014; BarclayHedge, 2015). However, it is not the absolute size but rather the relative growth of these numbers from 2008 that really stands out. Following the financial crisis in 2008, the AMF industry has experienced a 38% compound annual growth rate (CAGR), compared to 9% and 13% CAGRs for overall mutual funds and HFs respectively (ICI, 2014).

This recent surge in volumes derives from both demand and supply factors. On the demand side, following the 2008 financial crisis, institutional investors in HFs prefer investment products with greater liquidity (Meder, 2012). Likewise, retail investors might now gain access to alternative investment strategies due to the lower minimum investment requirements of AMFs. These investment vehicles may prove to be good diversification tools as well as return enhancers in a portfolio thanks to the exposure to alternative risk premia (SEI, 2013). On the supply side, the creation of AMFs provides HF managers the opportunity to gather new assets from current investors in HFs and potentially new investor bases (SEI, 2013). This is especially interesting given the slowdown of asset growth in the HF industry (Deutsche Bank, 2014).

A new field in the literature on asset management has flourished with the growth of AMFs: several research papers have been written to examine the performance and characteristics of this new asset class. Below we present the most relevant contributions.

The first strand of literature on the topic explores the performance of this asset class during different time periods, focusing mainly on the presence of alpha. Kanuri & McLeod (2014) find in a sample of 318 AMFs, comprising 9 different investment strategies, that the greatest share of funds record negative alpha in both positive and negative market backdrops. The paper also shows that return persistence is not present within the sample and that managers do not succeed in timing the market. Huang & Wang (2013) explore the performance of 80 equity AMFs during the 2007 financial crisis. The paper concludes that most AMFs perform better than a long only equity index during that period, but that they fail to deliver any abnormal performance. The reason the authors find for this phenomenon, is that outperformance from short positions is not sufficiently large to offset the underperformance from long positions. Badrinath & Gubellini (2011) study the performance of 110 long short, market-neutral and bear alternative equity mutual funds via multi-factor and conditional CAPM models. The paper finds that Long/Short Equity funds show little difference compared to Long-only mutual funds, that market neutral funds have small loadings on risk factors and show insignificant alphas, and that bear funds record negative alphas.

A second strand of the literature is the one that studies not only the performance of AMFs, but also the determinants of their performance and their resemblance to their sibling asset classes, i.e. TMFs and HFs. The greatest contribution on this front so far is the paper by Agarwal, Boyson & Naik (2009), which not only runs a factor analysis on funds, but also studies some of the fund features and incentives behind excess returns. The paper concludes from a sample of 52 funds that “hedged mutual funds”, as the paper calls AMFs, outperform TMFs and underperform HFs in terms of performance. The underperformance with respect to HFs is attributed to skill, strategy and regulation. The regulation hypothesis claims that hedged mutual funds, once controlling for fund characteristics and differences in risk and past performance, still underperform HFs because of the heavier regulation that affects mutual funds. The strategy hypothesis deals with HFs’ ability to profit from short as well as from long positions. Finally the skill hypothesis claims that managers of hedged mutual funds who come from the HF industry outperform their peers. All three hypotheses are proven to hold in the sample. The methodology used in the paper involves a two-pass regression. In the first-pass regression, both Fung-Hsieh seven-factor and Carhart four-factor models are used to collect the alphas, while the second-pass regression regresses the alphas on explanatory variables to assess the validity of the skill, strategy and regulation hypotheses. The limitations of their analysis include the reduced sample size (52), a sample period (1994-2004) that excludes the recent wave of AMFs openings, and the difficulty to dig deeper into the drivers of HFs outperformance with regards to AMFs due to their different contract features. Most importantly, the paper fails to obtain inferences based on different AMF investment strategies, a tool that might circumvent the challenges posed by contract feature heterogeneity in comparing HFs and AMFs. Specifically, the paper uses only control dummies to differentiate the performance of HFs and AMFs, and it attributes this difference entirely to regulation, without investigating the issue any further. We believe that a comparison across strategies can help assess the impact of regulation on performance through an analysis of relative performance divergence and factor replication.

In the same line of research, Busack, Drobetz, & Tille (2014) transpose the analysis to UCITS funds (the European equivalent of AMFs in the United States) and study their limitations due to regulation in the European Union. The authors compare the performance of 1082 alternative UCITS funds to that of HFs and divide both types of funds according to their investment style to study the differential in factor loadings. The paper uses both a regression based on the Fung-Hsieh model and a simple regression on the returns of the matching HF indices (HFR). The authors show that UCITS funds perform in a similar way to HF indices in terms of raw returns, but, surprisingly, they outperform HFs in terms of risk-adjusted returns, thus providing a better risk-return profile to investors. However, UCITS funds show lower exposure to risk factors than HFs and have mostly insignificant absolute returns across strategies, pointing to UCITS funds and HFs pursuing different strategies and hence being different asset classes. These results must be interpreted with caution due to the representativeness issues derived from using a single HF index as a proxy for overall HF performance. Despite this fact, the paper provides important information on the performance of alternative UCITS funds and introduces the methodology of simple regressions of matched strategies.

3. Data Selection

a. Data Gathering

i. Alternative Mutual Funds

The process that we employ to create AMF samples for each strategy is formed by several steps in order to assure the correct categorization of AMFs within each category and the maximum number of funds.

The primary source of data for AMFs in this study is the CRSP Survivor Bias Free database, which is widely used for gathering TMF data in financial empirical studies. This database includes all existing and defunct funds, avoiding the upward performance bias derived from just including surviving funds in the sample. In order to look for mutual funds deploying some kind of alternative strategy in their investment mandate, we download the whole database dating back to the first available date in CRSP and then sort the funds by Lipper objective code to just include alternative strategies. The corresponding code names employed in this paper and the ones that are used to differentiate between alternative strategies are: LSE, ACF, AMS, AGM, MFF, EMN, AED, DSB, and ABR, described in **Table 1**. Existence of duplicates is reviewed via the single NASDAQ code for each fund and duplicates are removed if present.

Once the preliminary sample is obtained from CRSP, a second search is performed using Morningstar. Morningstar provides a categorization of mutual funds for different strategies. We select the existing funds under the labels Long/Short Equity, Nontraditional Bond, Multi-alternative, World Allocation, Managed Futures, Equity Market Neutral and Bear Market. We then double check overlaps between CRSP and Morningstar prior to merging the two samples.

A third search is then performed via the website (Alternative Strategy Partners, LLC, 2015), which includes a list of AMFs categorized by strategy. AMFs that are not present in neither CRSP nor Morningstar are thus added to our sample.

As a consistency check, all AMFs selected using the procedure mentioned above are reviewed individually using their corresponding prospectuses to assess whether the categorization published by the data providers is in line with the Principal Investment Strategies published by the portfolio managers. As a matter of fact, there exists a number of AMFs that are assigned to other categories and some that are dropped from the sample altogether after reviewing the prospectuses. Very common reassignments are the ones between Equity Long/Short and Equity Market Neutral, and the ones between Multi-strategy and Global Macro.

As a result of the process above, we obtain a set of eight different sub samples, each of them corresponding to a different alternative investment strategy. This paper covers Equity Long/Short, Equity Market Neutral, Alternative Fixed Income, Global Macro, Multi-strategy, Managed Futures, Event-driven and Dedicated Short-bias.

Once the sub samples are created, the data are downloaded from Bloomberg. The data include the time series of performance and assets under management for each individual AMF within our sample, together with descriptive fund data for the second-pass regression, including fund inception date, turnover, expense ratio, minimum investment, load, management fee and fund manager start date. In addition to that, we create dummy variables from information in fund prospectuses regarding bank Managed Funds, whether the fund features an institutional share class and whether it features a retail share class.

ii. Hedge Funds

With AMFs being the core part of the analysis, the paper employs a representative sample of HFs obtained via indices of HF indices as a benchmark for comparison. The reason for using this procedure, outlined in Amenc, Martellini, & Vaissié (2003), is to avoid population misrepresentation due to heterogeneity in terms of fund inclusion among different HF indices.

Most HF indices feed from their own HF databases by using different selection criteria and calculation methods. There exists an extensive literature covering the problem of HF database and benchmark heterogeneity, which argues that it is hard to obtain a full picture of actual HF performance from a single database. Agarwal, Fos, & Jiang (2012) touch upon this point when they use 5 different HF databases (CISDM, HFR, MSCI, TASS and EUREKA) to construct their sample, as just 21% of HFs are covered by 2 or more databases. This means that in their paper 79% of HFs in the sample are present in just one database. The main factor behind biased HF samples comes from the fact that HFs raise from both institutions and high net worth individuals capital via private placement. As there exists no disclosure requirements for such investment vehicles, reporting data to databases is merely discretionary. Furthermore, databases have different criteria for inclusion in terms of minimum size, track record, defunct funds and openness to new investments. This results in great performance divergence in indices when compared to each other. Amenc, Martellini, & Vaissié (2003) report divergence in returns ranging from a minimum of 2.71% to a maximum 22.04% the maximum for indices covering the same investment strategy. Fung & Hsieh (2004) also explore differences between different HF indices, and find a correlation coefficient of 0.76 between the HFRI and CTI Indices, due to different computation methods and different underlying pools of HFs.

One solution to this problem is using common variation across HF Indices to proxy the overall movement of HFs as a whole. As outlined in Amenc, Martellini, & Vaissié (2003) there exist potentially two ways to implement this method; one is by computing an equally weighted index of all competing HF indices, the other is by using Principal Component Analysis (PCA) to refine the logic of the equally weighted portfolio to create a one dimensional vector comprising most of the variation within each strategy. The logic behind the PCA method is that any common variation in a set of variables can be described as a linear combination of a set of implicit, orthogonal and unobserved factors. The first factor carries the greatest part of the variation, normally leaving the rest to be redundant.

EDHEC Risk Institute provides monthly time series of PCA indices of HF indices tracking specific investment strategies. The paper matches each one of these indices to the strategies present in the AMFs sample. **Table 1** outlines the matching procedure for each of the strategies.

Table 1: Matching of Hedge Fund Indices and AMFs

Edhec Hedge Fund Indices	Alternative Mutual Funds Sample	Lipper objective code	Morningstar categories
Equity Long/Short	Equity Long/Short	LSE & ABR*	Long/Short Equity
Fixed Income Arbitrage	Alternative Credit	ACF	Nontraditional bond
Funds of Funds	Multi Strategy	AMS	Multialternative
Global Macro	Global Macro	AGM	World Allocation
CTA Global	Managed Futures	MFF	Managed Futures
Equity Market Neutral	Equity Market Neutral	EMN & ABR*	Equity Market Neutral
Event Driven	Event Driven	AED	
Short Selling	Short Bias	DSB	Bear Market

*ABR comprises Absolute Return funds. Some were included in either Equity Long/Short or Equity Market Neutral after revising the corresponding prospectuses

iii. Risk Factors

We obtain monthly return data for the trend following factors in the Fung-Hsieh model from David Hsieh's website (Hsieh, 2012), where he provides them and explains how to form the remaining four factors. The market factor is the total return series for the S&P500, the size spread is the Russell 2000 total return index minus the S&P500 total return index, the bond market factor is simply the 10 year bond US Treasury yield, and the credit spread factor is the Moody's Baa index yield minus the yield of the 10 year US Treasury.

Regarding the factors for the Carhart model, we obtain them from Kenneth French's website (French, 2015).

b. Data Description

i. Alternative Mutual Funds

Our original sample of AMFs includes 620 unique funds and spans between 1997 and 2014. **Table 2** shows the number of active AMFs by year in the sample. One can observe a substantial increase in the number of funds starting from the years after the 2008-2009 crisis, with the largest growth occurring in Multi-strategy and Alternative Credit funds.

Table 2: Active AMFs by Year

	Long/Short Equity	Eq. Market Neutral	Multistrategy	Alt. Credit	Global Macro	Managed Futures	Event Driven	Short Bias	Total
1997	1	0	1	2	3	0	1	1	9
1998	3	2	1	2	3	0	1	1	13
1999	4	3	1	2	3	0	1	1	15
2000	7	4	1	2	4	0	1	2	21
2001	10	4	1	2	4	0	2	2	25
2002	12	5	2	2	5	0	2	2	30
2003	14	6	2	2	6	0	3	2	35
2004	17	7	3	4	6	0	3	2	42
2005	22	11	6	6	9	0	3	2	59
2006	34	14	7	9	11	0	3	2	80
2007	45	15	8	10	14	0	3	2	97
2008	56	20	20	16	16	0	3	3	134
2009	67	22	28	22	17	1	4	2	163
2010	85	28	38	29	28	6	7	2	223
2011	100	34	57	42	44	16	8	2	303
2012	120	37	80	50	61	37	9	3	397
2013	143	42	102	73	77	44	17	3	501
2014	148	43	109	107	80	46	19	5	557

All AMFs with lives shorter than 24 months are excluded from the final sample to avoid multi-period sampling bias and to ensure representativeness in the regression results, in line with the methodology used in Ackermann, McEnally, & Ravenscraft (1999). **Table 3** outlines the sample's descriptive characteristics broken down by strategy. Return and volatility are measured as the average of all annual measures.

Table 3: Summary Statistics of AMFs

	Long/Short Equity	Eq. Mkt Neutral	Multistrategy	Alt. Credit	Global Macro	Managed Futures	Event Driven	Short Bias	Whole Sample
Annual return	2.95%	2.66%	3.64%	1.98%	2.49%	4.70%	1.56%	-20.63%	2.69%
Annual Volatility	5.25%	3.03%	2.93%	0.98%	3.33%	5.64%	2.56%	9.67%	3.63%
Sharpe Ratio	0.38	0.57	0.92	1.07	0.47	0.67	0.24	-2.23	0.48
Skewness	-0.50	-0.33	-0.51	0.80	-0.92	0.30	-0.34	0.02	-0.24
Excess Kurtosis	104.02	53.79	64.38	310.51	117.95	26.79	189.04	59.22	126.45
Max Drawdown	21.86%	12.49%	10.70%	6.62%	15.04%	1.85%	11.91%	57.24%	13.80%
Calmar Ratio	0.42	1.39	0.72	1.04	0.39	9.28	0.29	-0.48	1.41
99% daily VaR	-4.94%	-2.49%	-2.35%	-1.17%	-3.28%	-2.75%	-2.61%	-6.69%	-3.14%

From our summary statistics we see that all the AMF strategies provide a positive expected return except for Short-bias. The best performing strategy in our sample period is Managed Futures, with an average return of 4.7% per year. The high expected returns comes however with high volatility, which is second only to Short-bias funds. The best risk-return profile as measured by the Sharpe ratio is Alternative Credit. Alternative Credit is also one of the few strategies to show positive skewness; most strategies, and in particular Global Macro, have a negative skew, meaning that they are prone to large negative outcomes, and positive excess kurtosis, pointing to non-normality of returns.

We then look at some measures of risk of left-tail events. First of all we report the maximum drawdown and we see that Short-bias records the largest among the strategies, followed by Long/Short Equity. Once we adjust the drawdown for expected returns, thus obtaining the Calmar ratio, we see that Managed Futures offer the highest expected returns per maximum drawdown. Finally, we include the 99% daily value-at-risk, calculated using simple historical simulation. We see that once again it is Short-bias funds that have the most extreme VaR, followed by Long/Short Equity funds.

Table 4: Fund Characteristics of AMFs

	Long/Short Equity	Eq. Market Neutral	Multi-Strategy	Global Macro	Whole sample
Fund Turnover	317%	377%	175%	120%	247%
Total Assets (MSUD)	580.9	318.3	572.1	1811.4	820.7
Front Load	0.6%	0.4%	0.5%	0.5%	0.5%
Back Load	0.1%	0.0%	0.0%	0.1%	0.1%
Deferred Load	0.1%	0.0%	0.0%	0.1%	0.1%
Early Withdraw Fee	0.6%	0.4%	0.6%	0.4%	0.5%
Management Fee	1.1%	1.0%	0.8%	0.8%	0.9%
12b_1 Fee	7.1%	7.3%	7.1%	5.3%	6.7%
Expense Ratio	1.7%	1.8%	1.7%	1.2%	1.6%
Min. Investment (USD)	855,114	6,530,117	2,549,928	4,769,152	3,676,078
Manager Tenure (years)	2.8	2.6	4.2	5.2	3.7
Load & Other fees (dummy)	40%	25%	34%	31%	32%
Fund age (years)	4.7	5.8	3.9	5.2	4.9
Bank managed (dummy)	8%	11%	16%	5%	10%
Institutional (dummy)	81%	89%	83%	86%	85%
Retail (dummy)	95%	81%	85%	83%	86%

Table 4 (cont.): Fund Characteristics of AMFs

	Alt. Credit	Managed Futures	Event Driven	Short Bias	Whole sample
Fund Turnover	303%	116%	163%	126%	247%
Total Assets (MSUD)	1363.9	307.3	670.2	75.3	820.7
Front Load	0.3%	0.2%	0.0%	1.0%	0.5%
Back Load	0.1%	0.0%	0.0%	0.2%	0.1%
Deferred Load	0.1%	0.0%	0.0%	0.2%	0.1%
Early Withdraw Fee	0.4%	0.6%	0.8%	0.8%	0.5%
Management Fee	0.7%	0.7%	0.8%	1.0%	0.9%
12b_1 Fee	2.4%	1.1%	0.0%	5.0%	6.7%
Expense Ratio	1.1%	1.8%	1.4%	1.9%	1.6%
Min. Investment (USD)	8,976,778	1,111,716	575,316	381,000	3,676,078
Manager Tenure (years)	6.2	3.5	5.9	8.0	3.7
Load & Other fees (dummy)	20%	58%	32%	33%	32%
Fund age (years)	6.3	3.2	4.5	7.8	4.9
Bank managed (dummy)	12%	8%	0%	0%	10%
Institutional (dummy)	96%	94%	100%	83%	85%
Retail (dummy)	90%	83%	79%	83%	86%

As seen in **Table 4**, Equity Market-Neutral together with Long/Short Equity funds have the highest fund annual turnover among the fund strategies. The average minimum investment in AMFs is above $ 3 million, which is a fairly high figure even considering the fact that we consider the institutional share class to compute this statistic. The average AMF has an average age of 5.2 years, and an average manager tenure of 4.8 years. Short-bias funds and Alternative Credit funds tend to have the longest life and the longest manager tenure, whereas Managed Futures funds have a relatively low average age. Long/Short Equity and Equity Market Neutral funds have the shortest average manager tenure in the sample. Only 8% of the AMFs are managed by banks, with the largest proportion within Multi-strategy. Most of the funds in our sample offer both a retail and an institutional share class. What we can infer from the high minimum investment[1] is that the institutional share classes try to target the very wealthiest and largest investors.

ii. Hedge Funds

In a similar way to AMFs, we analyze the risk-return profiles of the different HF indices.

Table 5: Summary Statistics of EDHEC Hedge Fund Indices

	Equity Long/Short	Equity Market Neutral	Funds of Funds	Fixed Income Arbitrage	Global Macro	CTA Global	Event Driven	Short Selling	Whole Sample
Annual return	8.52%	6.24%	6.00%	5.81%	7.67%	6.29%	8.65%	-0.25%	6.12%
Annual Volatility	7.32%	2.91%	5.71%	4.33%	5.37%	8.27%	6.03%	17.32%	7.16%
Sharpe Ratio	1.15	2.11	1.03	1.32	1.41	0.75	1.42	-0.02	1.14
Skewness	-0.42	-2.39	-0.41	-3.92	0.91	0.17	-1.56	0.74	-0.86
Excess Kurtosis	1.30	16.16	3.90	24.70	2.39	-0.10	5.59	2.95	7.11
Max Drawdown	13.22%	8.19%	12.04%	10.53%	9.79%	11.54%	11.91%	30.51%	13.47%
Calmar Ratio	0.64	0.76	0.50	0.55	0.78	0.54	0.73	-0.01	0.56
99% daily VaR	-6.75%	-5.87%	-6.18%	-8.67%	-3.13%	-5.43%	-8.86%	-13.40%	-7.29%

Looking at HF indices in **Table 5**, we see that the strategy that, on average, has guaranteed the best return is Event-driven, followed closely by Equity Long/Short. Once again, HFs that focus on short selling, achieve negative expected returns and do so with a very high annual volatility (about 17%). In contrast with the case of AMFs, it is not Alternative Credit (here approximated by Fixed Income Arbitrage) that has the lowest volatility, but Equity Market Neutral. Overall, we can see that HFs seem to outperform AMFs in terms of expected returns, even though this comes at the cost of a slightly higher volatility.

In terms of risk-adjusted performance, Equity Market Neutral shows the highest Sharpe ratio, followed by Event-driven, in which case it is high returns that make up for an also high volatility. We would like to also point out the fact that the Sharpe ratio becomes very unreliable for strategies like Short-bias, where the high standard deviation in the denominator dampens the effect of negative expected returns in the numerator.

Most HF strategies have negative skewness, with the most extreme value being fixed income arbitrage. Short selling, CTA Global and Global Macro show positive skewness. It is striking to notice that fixed income arbitrage funds feature large negative skewness, whereas their matched Alternative Credit AMFs show the largest positive skewness in the AMF sample.

All strategies except for CTA Global have a positive excess kurtosis. In general, we see that the values for kurtosis are substantially lower for HFs than for AMFs, something that might point to return distributions with fatter tails in the latter category.

Looking at measures of left-tail risk, we see that the different strategies have a fairly homogeneous profile in terms of maximum drawdown and Calmar ratio, with the negative

[1] James & Karceski (2006) report an average of $471,869 to $565,190, depending on the sample length, for institutional funds.

exception being short selling funds. In terms of the 99% historical daily VaR, Global Macro and CTA Global funds are the best performers, with tail losses of about 3% and 5% respectively. As for volatility, we ascertain that HF strategies tend to have, on average, a higher value-at-risk than their AMF counterparts.

Overall, from our summary statistics it emerges that HFs outperform AMFs both in terms of raw and risk-adjusted returns. However, HFs face higher volatility and VaR levels. On a strategy by strategy basis, the biggest difference in raw performance comes in Short Selling and Event-driven funds, 20% and 7% respectively.

4. Methodology

a. First-pass Regression

As explained in the Introduction, the first task in our analysis is to investigate whether strategies employed by AMFs are similar in terms of absolute performance and factor exposure to strategies employed by HFs. In order to analyze this proposition we need to look at both alpha generation and risk factor loadings to have a clear view on what are the return drivers for AMFs and what are the strategies that share similar exposures with HFs.

This paper makes use of two widely used factor models in finance as a tool to inspect the return drivers of AMFs and HFs: The Fung-Hsieh model and the Carhart model. In order to perform the analysis, the paper follows the methodology employed in Agarwal, Boyson, & Naik (2009), by which we individually regress each AMF on each of the two factor models to obtain individual factor exposures and alpha coefficients. We then average regression coefficients across funds pertaining to each specific investment strategy. In this way, we obtain 8 different averages of coefficients for each of the 2 regression models.

The most widely used and accepted factor model for HFs was developed by Fung & Hsieh (2004). The main innovation compared to previous factor models that tended to focus on TMFs is that, alongside factors based on the equity and bond markets, Fung & Hsieh (2004) use factors built based on the returns of look-back straddles, i.e. dynamically-managed option strategies developed on the currency, bond and commodity markets. While we expect a better performance of the Fung-Hsieh model in explaining overall returns in our analysis due to the non-traditional nature of the funds being analyzed, the Carhart model can still be useful in identifying AMFs that behave more like TMFs. The Carhart model (Carhart, 1997) applies the Fama-French three-factor model (Fama & French, 1992) to equity TMFs and adds to it the cross-sectional momentum factor developed by Jegadeesh & Titman (1993), and defined as the spread in the returns of the stocks with the best and the worst returns in the previous eleven months, with a one month lag.

The Fung-Hsieh model is designed to model HF returns directly, hence we would expect better explanatory power in modeling alternative investment strategies. For this reason, while it is true that both models will be used in the analysis, greater emphasis will be put on the Fung-

Hsieh model for the main intuition. The first two factors, equity market risk and size spread are included to model equity strategies, the bond market factor and the credit spread factor are included to model fixed income strategies, while the remaining three factors represent look-back straddles on bonds, currencies and commodities, included to measure trend following strategies in the mentioned asset classes. The specification of the model is outlined in ***Equation 1***.

Equation 1: Fung-Hsieh 7 Factor model

$$RET_{i,t} = \alpha + \beta_1 * S\&P_{i,t} + \beta_2 * SC - LC_{i,t} + \beta_3 * 10Y_{i,t} + \beta_4 * CredSpr_{i,t} + \beta_5 * BdOpt_{i,t} + \beta_6 * FxOpt_{i,t} + \beta_7 * ComOpt_{i,t} + \psi_{i,t}$$

The Carhart model, on the other hand, includes equity market, size, value and momentum factors. The specification of the Carhart model is outlined in ***Equation 2***.

Equation 2: Carhart 4 Factor model

$$RET_{i,t} = \alpha + \beta_1 * RMRF_{i,t} + \beta_2 * SMB_{i,t} + \beta_3 * HML_{i,t} + \beta_4 * PR1YR_{i,t} + \psi_{i,t}$$

On top of that, we add another approach by which we not only compare AMFs and HFs via factor models, but we also regress individual AMFs on the HF index matching their investment strategy. This additional model specification is outlined in ***Equation 3***.

Equation 3: Matched Hedge Fund Index model

$$RET_{i,t} = \alpha + \beta * HF\ Index_{i,t} + \psi_{i,t}$$

We collect the average coefficients as in the factor model regressions and inspect coefficient of determination and regression coefficients to assess similarities. In theory, one would expect to find that AMFs implementing the same strategy as the index have a significant factor loading on the HF index and a coefficient of determination close to 1. A similar approach is used in Busack, Drobetz, & Tille (2014), but in that case the analysis focuses on UCITS and employs just HFR indices, incurring in the HF representativeness issues described in our Data selection section[2].

For all three regressions, the paper computes coefficients using returns both net and gross of fees[3] for AMFs. However, we just report results for net returns in the main body of the paper.

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[2] HFRI and HFRX indices used in (Busack, Drobetz, & Tille, 2014) are calculated from the HFR database. This database contains just 10.2% of existing Hedge Funds, according to (Agarwal, Boyson, & Naik, 2009). Moreover, HFR indices require minimum Assets under Management of USD50 million for inclusion, together with monthly/quarterly rebalancing frequency and different weighting schemes.

[3] Gross return regressions are reported in the appendix, with gross return series calculated as the net return series plus 1/12 of the annual expense ratio as it is the procedure in (Gaspar, Massa, & Matos, 2006).

The reason for this choice is that most HF indices capture HF performance net of fees, hence the comparison requires net returns also for AMFs.

Standard errors for average coefficients within each strategy are calculated using a bootstrap procedure with 10,000 replications[4], sampling from the corresponding funds in the strategy, (Agarwal, Boyson, & Naik, 2009). As an example to illustrate this procedure, in the Long/Short strategy sample, for the S&P factor in the Fung-Hsieh model, 10,000 standard errors will be picked randomly from any of the funds' coefficients to get a representative standard error measure. This standard error is then used to compute the test statistic and to determine the statistical significance. The use of bootstrapped standard errors in regression analysis and finance literature is widespread. The main reason for it is that in linear regression analysis of small samples, bootstrapped measures provide more accurate confidence intervals than the ones provided by asymptotic closed form estimates, as shown in Gonçalves & White (2005).

Finally, to test whether the difference in factor exposures and in alphas between AMFs and HFs is significantly different from zero, we run a Student's t-test for the difference of means. We use the standard errors that we computed as described above for the calculation of the t-statistic. We report the coefficient of the difference of means and look at its statistical significance. We run the test for all different specifications, i.e. net and gross returns for the Fung-Hsieh and Carhart models, although we focus our attention on net returns and on the Fung-Hsieh model, for the sake of comparability with the HF indices.

Once we obtain the results from the three models, we carry out a strategy by strategy comparison of the findings as a way to assess the impact of regulation on performance divergence between HFs and AMFs. If regulation were the main factor constraining strategy replication, as suggested by Agarwal, Boyson, and Naik (2009), it would then follow that AMFs pursuing a less sophisticated investment strategy would fare better in replicating their HF counterparts. A "simpler strategy" in our case refers to a narrow set of sub-strategies within the investment strategy, a narrow use of asset classes, and an easy access to the securities needed to implement the strategy. An example will illustrate our intuition clearly. Equity Long/Short employs two different sub-strategies (directional and pairs trading), uses just one asset class, and its access to stocks should be relatively straightforward. On the other hand, Global Macro funds face potential unlimited sub-strategies depending on the macroeconomic shift they want to capitalize on, tap potentially all different asset classes, and access to investment tools to implement the strategy might not be that easy due to the global nature of the strategy and the availability and liquidity of them. As a result, one would expect the Equity Long/Short strategy to fare better in replication terms than the Global Macro strategy. This idea could then be exported to the rest of investment strategies being analyzed in this paper. We would define as simple strategies Equity Long/Short,

[4] The original paper by Agarwal, Boyson, & Naik (2009) uses 1,000 replications. Increasing the number of replications, in our case, improves precision without a substantial increase in computation time.

equity Short-bias and Alternative Credit. All the rest we consider as more challenging to implement. Please refer to **Table 12** in the appendix for an explanation of the strategies.

b. Second-pass Regression

As explained in the Introduction, the second task in our analysis is to determine whether determinants of performance and incentives of AMF vehicles are more similar to those of HFs or TMFs.

In order to address this issue, we develop a second-pass regression based on the variables used in Agarwal, Boyson, & Naik (2009), complemented with 6 additional variables that represent salient features in TMF literature and contribute to explain TMF performance. These additional variables are both dummies (institutional targeted, retail targeted, bank managed and load & other fees) and level variables (manager tenure and management fee).

In line with Agarwal, Boyson, & Naik (2009), we also add year-dummy variables to account for time fixed effects and use a two-year lag in past performance. In terms of the year dummy variables, they are included to avoid distortion of the regression results caused by special conditions within a specific year. However, they are kept unreported for the sake of conciseness, in line with Agarwal, Boyson, & Naik (2009), as we assume that their coefficients would not add much value to our analysis. In using a two-year lag in past performance, we avoid having any overlap between dependent and independent variables. This comes with the cost of requiring the existence, and hence the survival, of any specific AMF for four years, something that might reduce substantially our sample size. The gains from avoiding the overlap include reducing the misstatement in the standard errors and dealing with the risk of cross-sectional autocorrelation among funds residuals (Agarwal, Boyson, & Naik, 2009). All the variables except past performance have a one-year lag: this is because, intuitively, present performance is expected to be influenced by fund characteristics in the previous year. Age is measured as the natural logarithm of the fund's age expressed in years, and calculated as time from the inception date[5]. Size is calculated as the natural logarithm of assets under management. Contrary to the methodology in Agarwal, Boyson, & Naik (2009), we do not take into account the level of the load because, in our sample, the level of this fee tends to be quite homogeneous across the AMFs that have it, and we believe it is more sensible to differentiate between the funds that apply this charge and those that do not[6].

[5] In the mutual fund industry, different share classes might have different launch dates at which they become available. In our case, we are considering the longest living institutional share class since we are interested in the fund and its strategy as a whole rather than in the different contractual specifications of share classes.

[6] According to Gil-Bazo & Ruiz-Verdù (2009), looking just at the expense ratio, one might overlook the different components of the costs borne by the investor in the fund. Therefore, it might be advisable to control for funds that charge a load.

We collect yearly alphas obtained from the first-pass regression and then use them as dependent variables in our second-pass regression, as indicators of performance. We regress them on the factors included in our second-pass regression model, as illustrated in ***Equation 4***.

Equation 4: Second-pass Regression model

$$\begin{aligned} Perf_{i,t} = \beta_0 + \beta_1 Perf_{i,t-2} + \beta_2 Size_{i,t-1} + \beta_3 Age_{i,t-1} + \beta_4 ExpenseRatio_{i,t-1} + \beta_5 Flow_{i,t-1} \\ + \beta_6 Tenure_{i,t-1} + \beta_7 Min.Inv._i + \beta_8 Insti_i + \beta_9 Retail_i \\ + \beta_{10} BankManaged_i + \beta_{11} Turnover_{i,t-1} + \beta_{12} Load\&Other_i \\ + \beta_{13} Mgmt\ Fee_i + \sum_{t=1}^{T} \beta_{14}\, I(Year_t) + \psi_{i,t} \end{aligned}$$

Where T is the number of years for which we have data on the specific strategy and *Perf* is the first-pass alpha coefficient. As a robustness check we then run the same regression using gross returns instead of alpha as the dependent variable in order to see whether there exists a large difference between the two performance measures.

As in the first-pass regression, we estimate the standard errors for the coefficients using bootstrapping with 10,000 replications: for some of the regressions, the sample size is still quite small, and this makes the traditional regression standard errors unreliable. Moreover, bootstrapping allows us to take into account the potential non-normality of returns. We look at the bootstrapped standard errors to compute the p-values and to test for the significance of the coefficients.

Given the low number of observations for certain AMFs, the coefficient of determination might be a bad measure for the appropriateness of the model. We believe however that at this stage, it is not the size of the R^2 coefficient that matters for our analysis, but rather to see whether certain specific features of the funds have an impact on performance. Therefore we think that a good way to understand the goodness of fit of our model is to look at the unexplained part of the variation in the dependent variable. As a result, in order to assess whether this model specification is suitable for our purposes, we look at both the size and the significance of the regression intercept[7].

In addition to the second-pass regression, we run an additional test that has been present in both the HF and the TMF literature: we look at the determinants of fund flows. In our paper flows are measured as explained in ***Equation 5***.

[7] While adding variables to the original model of Agarwal, Boyson, & Naik (2009), we look at whether these additions subtract too much variation to the dependent variable by changing the significance and size of previously found coefficients. We thus ascertain that our model does not suffer from multi-collinearity and improves the explanatory power of Agarwal, Boyson, & Naik (2009).

Equation 5: Flows calculation

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}}$$

Where TNA are the fund total net assets in dollar value and R is the return of the fund between t-1 and t (Sirri & Tufano, 1998).

The intuition for this is developed by Berk & Green (2004), who build a model to justify the interaction between performance, flows and size. The authors show that the underperformance with respect to the benchmark characterizing TMFs is not necessarily due to the lack of skill, but rather to the fact that managers accept new inflows into their funds – and, given the decreasing returns to scale, accept to lower their return – up to the point to which the returns are still attractive to investors.

The model we use to analyze these determinants is outlined in ***Equation 6***.

Equation 6: Flows Regression on potential determinants

$$\begin{aligned} Flow_{i,t} = \beta_0 &+ \beta_1 Perf_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Age_{i,t-1} + \beta_4 ExpenseRatio_{i,t-1} \\ &+ \beta_5 Flow_{i,t-1} + \beta_6 Tenure_{i,t-1} + \beta_7 Min.Inv._i + \beta_8 Insti_i + \beta_9 Retail_i \\ &+ \beta_{10} BankManaged_i + \beta_{11} Turnover_{i,t-1} + \beta_{12} Load\&Other_i \\ &+ \beta_{13} Mgmt\ Fee_i + \sum_{t=1}^{T} \beta_{14}\, I(Year_t) + \psi_{i,t} \end{aligned}$$

We use performance with one year lag because we do not have the overlap issue anymore and we believe, given what has been found in the previous literature, that it is performance in the previous year that should influence current flows. We define two specifications of the model, following the insight of James & Karceski (2006): in one regression we define past performance as the lagged alpha, whereas in the other we define performance as the lagged gross return. In this way we can see whether the two measures have a different impact on flows, and potentially infer whether one or the other is more relevant for investors in AMFs for their investment choices.

We include the same variables as in the performance regression in order to see whether they also have a significant impact on flows. In particular, we are interested in studying the performance-flow relation, and in which way one variable influences the other. A large part of the manager compensation in mutual funds comes from the management fee, which is based on the size of the assets under management. This, together with the fact that almost none of the AMFs in the sample charges a performance fee, means that attracting new flows can be as much of a motivation for AMF and TMF managers as achieving a high return. Therefore, we believe that it is of great interest to see to which extent the same incentive variables can explain performance and flows.

We include a control for lagged flows in order to investigate whether current flows are in any way dependent on past flows, i.e. whether there is any sort of flow momentum.

i. Motivation for the Selection of Variables

In the following paragraphs we explain in detail the variables that we include in the second-pass and the flow regressions. We illustrate the formal rationale for doing so, based on the findings of the previous literature. In particular, Agarwal, Boyson, & Naik (2009) use past performance, size, age, expenses, flows, turnover and load mainly as controls, without focusing on the implications of the coefficients they find. We believe that, given the interplays that have been found in the literature, as well as the differences highlighted between HFs and TMFs regarding some of these features, it would be informative to analyze in which way these variables affect performance and flows.

The fact that increasing size erodes fund return is confirmed in the empirical literature by Chen, Hong, Huang, & Kubik (2004) for TMFs and by Ammann & Moerth (2005) for HFs; in both cases the main reason found by the authors is capacity constraints that are implicit in the strategies implemented. Li, Zhang, & Zhao (2011), on the other hand, find that additional capital flows into HFs do not seem to lower subsequent returns by the same amount as in TMFs: the authors find a positive impact of flows on performance. The "diseconomies of scale" that characterize TMF investing are also behind the lack of persistence in performance (Berk & Green, 2004): investors pour money in the best performing funds, forcing them to lower their returns and to shift down in the performance quantiles.

Indeed, TMFs do not exhibit a high degree of performance persistence, as shown by Carhart (1997) and confirmed by Bollen & Busse (2005), who point that persistence can be seen only over very short time periods. HFs, on the other hand, while having different incentives and facing, perhaps, different capacity constraints, do not show a very different behavior in terms of performance persistence. Boyson (2008) shows that HF performance persistence follows the implication of the Berk & Green model, and that a substantial degree of persistence can be found only among relatively small and young HFs.

Regarding the impact of age and manager tenure Boyson (2003) shows that older HFs tend to underperform younger ones and attributes this result to the career concerns of fund managers. TMFs show, according to Boyson (2003) the opposite pattern, since risk-taking increases with age, mainly due to the different compensation mechanisms and the less important role of reputation. HF managers have a salary that is based on the performance and the size of the fund, whereas TMF managers lack the performance-linked element of compensation. By including a variable that measures for how long a manager has been active at a specific fund, we want to see whether having a long-standing manager detracts from the fund's performance as seen by, for example, Boyson (2003), or whether it is a positive factor, as in Chevalier & Ellison (1999b).

We consider then the impact of the size of the minimum investment required, as in James & Karceski (2006). Minimum investment can be seen, according to James & Karceski (2006) as a proxy for investor oversight, which in turn can be an incentive on performance. From the same paper, and along the lines of investor oversight, we also take the idea of including dummy variables describing whether the fund is offered in retail and/or institutional share classes. In this way, we want to control for the possibility that there exist two different markets for AMFs, where the institutional market is the one in which funds actively compete based on alpha, as confirmed by Del Guercio & Reuter (2014). We create the dummy by looking through the prospectuses of the AMFs in the sample and examining all the available share classes. Finally, we create a dummy describing whether the fund is managed by a bank or not, with banks being defined as any of private, commercial or investment banks. The idea is that bank managed funds might pursue objectives other than the maximization of excess returns to investors, and might be used as a way to retain customers to other services offered by the banking concern.

On top of the above-mentioned variables, we also want to control for additional features that have been deemed relevant in the TMFs literature. In particular, we look at turnover defined as the lower between the value of securities purchased and the value of securities sold by the fund over the last twelve months in proportion to the net asset value. In the TMFs literature[8], fund turnover has sometimes been used as an approximation for unobserved actions by fund managers (Cremers & Petajisto, 2009). James & Karceski (2006) show that turnover seems to be significant in explaining higher risk-adjusted returns, suggesting that funds that trade more are more likely to generate excess returns. Day, Wang, & Xu (2001), on the other hand, find a negative impact of turnover on performance.

We also want to assess the impact of different fees, hence we include a level measure of management fee. Indeed, it is within management fees that we see the most variation, and we believe that looking at the level might be more insightful. Gil-Bazo & Ruiz-Verdù (2009) look at the relation between fees and performance in TMFs. In a market made of rational individuals, since TMFs provide portfolio management services, it should be that the funds that are the best at providing those services are the ones that receive the highest compensation. However the fee-performance relation appears to be negative: an increase in fees seems to be detrimental for performance. Their findings confirm what already shown by Carhart (1997). We believe that expense ratio and management fee are not perfect substitutes as explanatory variables[9]: including

[8] Hedge funds tend not to disclose their asset turnover to data providers, making it hard to conduct research on this measure, as pointed out by Agarwal, Boyson, & Naik (2009)

[9] The fact that only about a third of the funds in our sample charge a load or other fees, as can be seen in the data description, also supports the choice to create a dummy.

management fee adds a dimension that looks more closely at management incentives, because it tells how much the management company will receive in percentage of assets under management. The expense ratio can sometimes be a bad approximation for this, since it is generally less stable and might be a better fit to explain all the fees together, rather than just the management fee. As pointed out by Sirri & Tufano (1998), fund managers tend to dedicate the fee inflow from load and other fees to marketing and sales efforts.

Regarding the drivers of flows, the literature looks primarily at the impact of past performance, and controls for size and age (Li, Zhang, & Zhao, 2011). We want however to dig deeper into the determinants of flows and therefore we look also at manager tenure, following the insights developed by Chevalier & Ellison (1999), who look at manager age and tenure. In particular, we have reasons to believe that investors might not only look at the age of the fund, but also at the manager's: if AMFs try to replicate HFs as closely as possible, the manager should play a larger role than in TMFs (Li, Zhang, & Zhao, 2011). In addition to that, we believe that by looking at the share class variables (institutional and retail), at the minimum investment and at whether the fund is managed by a bank concern; we could derive some information on what are the features of AMFs that attract investors, and on which kind of public has been pouring money into this relatively new asset class. Controlling for expense ratio and fees can show us whether what has been found by Sirri & Tufano (1998) for TMFs holds also for AMFs, i.e. that consumers are fee sensitive and that low-fee funds grow faster in terms of Assets under Management. Finally, we control for turnover in order to assess whether there exists any relation between manager's activism and flows in the fund.

We expect AMFs, which by definition are a blend of a TMF contract structure and HF strategies, to share some of the explanatory factors of performance and flows with these two other asset classes. However, we do not expect AMFs to have some specific features that separate them from all other investment vehicles, since it might be the case that AMFs try to cater to different categories of investors, compete based on different characteristics and have different performance drivers. Accordingly, we believe that it is also crucial to analyze what are the main factors that influence flows into AMFs; hence, we could perhaps learn more about investor preferences and better understand whether the growth of this new asset class has been driven by fundamental features that determine its strength, such as performance, or whether it has been driven mainly by external unobservable factors.

5. Results

a. First-pass regression

6. We present the results from our first-pass regression. **Table 6** shows the regression coefficients from the Fung-Hsieh model, whereas **Table 7** shows the regression coefficients from the Carhart model. Both tables are divided in two panels to show the results for AMFs and HF indices. **Table 8** presents the results of the regression of AMFs on their reference HF indices. Please refer to

Table 12 in the Appendix, in which we describe the strategies analyzed and the expected factor exposures, for a comparison of the results. We complement the section with explanations of the relevant findings and their practical significance.

Table 6: First-pass Regression using the Fung-Hsieh model

	Intercept	Equity Market	Equity Size	Bond Market	Credit Spread	Bond Option	Currency Option	Commodity Option	Adjusted R2
Panel A: Alternative 40 Act Mutual Funds									
Equity Long/Short	0.000	**0.431*** **	0.012	-0.029	-0.077	-0.006	0.002	-0.007	0.626
Equity Market Neutral	0.000	**0.112** **	0.006	-0.006	-0.020	-0.004	0.000	0.000	0.355
Multi Strategy	0.000	**0.247*** **	-0.015	-0.067	-0.088	-0.004	0.005	-0.006	0.573
Alternative Credit	0.002	**0.083** **	**0.068* **	**-0.123*** **	**-0.149*** **	-0.014	0.004	-0.005	0.469
Global Macro	-0.001	**0.339*** **	0.011	**-0.120*** **	-0.127	-0.008	-0.005	-0.009	0.573
Managed Futures	0.000	**0.216*** **	**-0.298*** **	-0.015	0.027	0.003	0.043	-0.003	0.423
Event Driven	0.001	**0.182*** **	0.060	-0.011	-0.010	-0.004	-0.001	-0.009	0.512
Short Bias	-0.011	**-0.767*** **	-0.160	**0.197** **	**0.292*** **	0.014	-0.003	0.004	0.714
Whole sample	0.000	**0.278*** **	-0.020	-0.047	-0.076	-0.005	0.005	-0.006	0.547
Panel B: Matched EDHEC Hedge Fund Indices									
Equity Long/Short	**0.005*** **	**0.266*** **	**0.155*** **	**-0.055* **	**-0.155*** **	-0.005	0.004	0.002	0.647
Equity Market Neutral	**0.004*** **	**0.057*** **	**0.045*** **	-0.007	**-0.058*** **	**-0.012*** **	**0.008*** **	0.000	0.345
Funds of Funds	**0.004*** **	**0.149*** **	**0.095*** **	**-0.065** **	**-0.193*** **	-0.007	0.007	0.004	0.465
Fixed Income Arbitrage	**0.004*** **	0.024	**0.027*** **	**-0.138*** **	**-0.278*** **	-0.008	**-0.007* **	0.004	0.435
Global Macro	**0.006*** **	**0.122*** **	**0.049* **	**-0.078** **	**-0.146*** **	0.000	**0.019*** **	**0.012* **	0.267
CTA Global	0.001	**0.230*** **	**-0.243** **	-0.028	-0.025	0.028	**0.031** **	0.010	0.307
Event Driven	**0.006*** **	**0.182*** **	**0.104*** **	**-0.062*** **	**-0.213*** **	**-0.018*** **	0.005	-0.004	0.663
Short Selling	**0.004* **	**-0.650*** **	**-0.383*** **	-0.002	0.115	0.011	-0.008	0.004	0.589
Index average	**0.005*** **	**0.023* **	0.006	**-0.060*** **	**-0.132*** **	-0.001	**0.009*** **	0.006	0.171

Notes: Regression results for Fung Hsieh 7 factor model using net returns for all funds and hedge fund indices. Tests for significance use a standard error computed from a bootstrapping procedure with 10,000 replications. *, **, and *** stand for significant at the 90%, 95% and 99% confidence level respectively. Reported coefficients comprise the average coefficients among all funds within each strategy.

Table 7: First-pass Regression using the Carhart model

	Intercept	Equity Market	Size	Value	Momentum	Adjusted R2
Panel A: Alternative 40 Act Mutual Funds						
Equity Long/Short	-0.002	**0.587*** **	-0.005	0.000	-0.005	0.667
Equity Market Neutral	0.000	**0.148** **	-0.003	-0.014	0.016	0.328
Multi Strategy	-0.002	**0.336*** **	-0.058	-0.027	-0.020	0.563
Alternative Credit	0.001	**0.149*** **	-0.037	0.037	-0.036	0.343
Global Macro	-0.003	**0.459*** **	-0.048	0.004	-0.019	0.530
Managed Futures	-0.004	**0.304*** **	**-0.414*** **	**-0.347*** **	0.031	0.294
Event Driven	0.000	**0.243*** **	0.051	0.023	-0.015	0.508
Short Bias	-0.007	**-1.009*** **	-0.031	0.036	0.062	0.737
Full sample	-0.002	**0.381*** **	-0.056	-0.028	-0.008	0.525
Panel B: Matched EDHEC Hedge Fund Indices						
Equity Long/Short	**0.005*** **	**0.362*** **	**0.136*** **	-0.004	**0.050*** **	0.761
Equity Market Neutral	**0.004*** **	**0.090*** **	**0.036** **	**0.045*** **	**0.045*** **	0.292
Funds of Funds	**0.003*** **	**0.234*** **	**0.106*** **	-0.023	**0.067*** **	0.579
Fixed Income Arbitrage	**0.004*** **	**0.086*** **	**0.045* **	**0.067** **	-0.007	0.141
Global Macro	**0.005*** **	**0.173*** **	**0.048* **	0.001	**0.068*** **	0.307
CTA Global	-0.001	**0.246*** **	**-0.370*** **	-0.058	0.055	0.217
Event Driven	**0.005*** **	**0.267*** **	**0.131*** **	**0.069*** **	0.009	0.628
Short Selling	**0.004*** **	**-0.796*** **	**-0.327*** **	**0.286*** **	-0.007	0.829
Index Average	**0.004*** **	**0.054*** **	0.019	**0.062*** **	**0.040*** **	0.116

Notes: Regression results for Carhart 4 factor model using net returns for all funds and hedge fund indices. Tests for significance use a standard error computed from a bootstrapping procedure with 10,000 replications. *, **, and *** stand for significant at the 90%, 95% and 99% confidence level respectively. Reported coefficients comprise the average coefficients among all funds within each strategy.

Table 8: First-pass Regression using the Matched Hedge Fund Index model

	Intercept	Hedge Fund Index	Adjusted R2
Panel A: Alternative 40 Act Mutual Funds			
Equity Long/Short	-0.002	**1.143*** **	0.524
Equity Market Neutral	-0.001	0.709	0.168
Multi Strategy	0.000	**0.974*** **	0.458
Alternative Credit	-0.002	**1.023*** **	0.389
Global Macro	-0.001	**1.238*** **	0.302
Managed Futures	-0.001	**0.815** **	0.462
Event Driven	-0.001	**0.666*** **	0.450
Short Bias	-0.008	**1.122*** **	0.598
Whole Sample	-0.001	**1.436*** **	0.225

Notes: Regression results for the hedge fund index regressions using net returns for all funds and hedge fund indices. Tests for significance use a standard error computed from a bootstrapping procedure with 10,000 replications. *, **, and *** stand for significant at the 90%, 95% and 99% confidence level respectively. Reported coefficients comprise the average coefficients among all funds within each strategy.

i. Long/Short Equity

Long/Short Equity funds tend to have a directional and positive exposure to the stock market. However, the correlation with the market tends to be smaller than for traditional Long-only equity funds[10] as a result of the short portion of the portfolio. Also derived from the spread plays used by these funds, one would expect to find positive exposures to equity risk factors such as size, value or momentum, which represent zero cost portfolios following similar rationale to that of pairs trading and provide risk premia. As a result of the reasons stated above, one would expect Long/Short Equity funds to show positive market beta but lower than 1, and significant positive coefficients in some of the equity risk factors in the Fung-Hsieh and Carhart models. Moreover, because the strategy is purely focused on equities, the Carhart model might fit this investment category better than the Fung-Hsieh model, as the latter also includes factors directed towards explaining other asset classes.

AMFs in the category show a significant, positive and lower than 1 coefficient for the market factor, in line with expectations. However, they fail to show any other significant coefficients, contrary to what had been postulated and pointing to a simplistic approach to equity investing. This contrasts with the matched HF index, which shows positive significant exposure to size and momentum in the Carhart model; and positive significant exposure to size and negative significant exposure to fixed income factors in the Fung-Hsieh model. Furthermore, it features a lower coefficient on the stock market, pointing perhaps to a greater use of short positions or pairs trading. While the positive exposure to equity risk factors points to a more elaborate strategy of HFs with greater use of pairs trading to extract risk premia, the negative exposure to the bond market factor might imply high leverage of the fund, and the negative exposure to the credit spread might imply greater skew towards riskier stocks or distressed firms. If we then look at how similarly AMFs behave with regards to the HF index, we can see that our sample of AMFs only shares 0.52 of variation with the former, while the rest is left unexplained. However, the coefficient on the HF index is positive significant and close to 1, still pointing to a close similarity between the two categories.

Another main difference is that AMFs in the category fail to show any positive significant alpha in either model, something that HFs do in both.

ii. Equity Market Neutral

It is logical to assume that Equity Market Neutral funds should exhibit a very small market coefficient and a wider array of exposures to other risk factors in the models. Following the same logic of pairs trading and zero cost portfolios, one would expect Equity Market Neutral funds to

[10] Carhart (1997) shows in his results exposures to the stock market greater than 0.86 for all traditional long only equity funds in its sample.

exploit risk premia to an even larger extent than Long/Short Equity, as the latter can also derive returns from directional investments. Adding to this, it might also be the case that Equity Market Neutral funds use derivatives to hedge, such as options or swaps, which could result in some factor exposure to either fixed income or option factors in the Fung-Hsieh model.

We observe from our results that, first of all, both AMFs and HFs deploying this strategy deliver on their main investment goal; i.e. show an equity market coefficient next to 0. HFs, however, do a slightly better job on minimizing stock market correlation, as the factor exposure is closer to zero. While both positive coefficients on the market are significant, their economic significance is negligible. For a 10% market movement, AMFs and HFs show a 1% and 0.5% movement respectively. Also, a very apparent trend, and one that is also present for Long/Short Equity funds is that AMFs fail to show any other significant factor exposure or alpha. HFs, however, show positive significant alpha, hence fulfilling our intuition that they derive returns from unexplained sources. Adding to this, HFs also show positive significant exposures to all the remaining equity factors in the Carhart model, pointing to HFs using factors that are less correlated with the market to extract risk premia. In the Fung-Hsieh model for HFs, it is also interesting to find negative coefficients on the credit spread, pointing most likely to investments in risky companies; and on the bond option factor, maybe derived from derivative positions held by the fund or plainly by the fact that volatility in fixed income markets impacts negatively the returns of HFs in this family. A positive significant coefficient on the FX option factor points to Equity Market Neutral HFs profiting from volatility in currency markets, most likely due to the opening of potential pair trades. Exposures to options could also be justified as a way of converting cash flows to different currencies or rates with the purpose of maintaining an overall market neutral position. Despite the statistical significance of the coefficients for options, their magnitude is quite small in both the Fung-Hsieh model and the Carhart model.

In terms of relative similitude, this strategy is the single one in which the regression of AMFs on the index delivers a non-significant coefficient on the HF index, together with the lowest explanatory power. This highlights that investors should be well aware that Equity Market Neutral AMFs face some relevant constraints in implementation. Despite following in theory the same investment strategies, the two type of funds do not share the same risk exposures.

iii. Multi-strategy

For the Multi-strategy category, one could expect many different significant factor loadings as funds obtain exposure to a wide set of investment strategies. This investment approach is similar to the fund of funds procedure, and this motivates us to match this family of AMFs to the fund of HFs index[11]. While the approach to investment is similar in terms of multiple allocation to

[11] Please refer to **Table 12** for further information on the Multi-strategy approach

different alternative strategies, the set of chosen strategies within each fund might change, hence making it more difficult to extract general inferences from this sub-sample compared to the other sub-samples that follow a narrower investment strategy.

Our sample of AMFs shows slightly disappointing results; the funds in the sample fail to deliver any alpha and just show a positive significant coefficient on the stock market factor in both model specifications. HFs, on the other hand, do provide alpha and access to size, bond market, and credit spread factors in the Fung-Hsieh model; and size and momentum in the Carhart model. This, in principle, points to a weak implementation of this investment strategy, which fails to provide exposure to many return drivers that the underlying investment strategies exploit. An alternative explanation could be that the factors to which each AMF has exposure might vary quite a lot from one fund to the other, driving non-shared coefficients to insignificant territory. A very good candidate to be explained by this phenomenon is the bond market factor of the Fung-Hsieh model with a 0.16 p-value. While many Multi-strategy funds will follow some kind of fixed income strategy, some others might have just exposure to equity or equity and FX as an example. On the HF side, fund of HFs might share trends of allocation to the same type of HFs, then showing more significant coefficients. In any case, an element that cannot be argued away is the fact that Multi-strategy AMFs are not able to deliver absolute returns.

With regards to the regression of the AMF sample on the HF index, we find a significant coefficient very close to 1, still with a coefficient of determination smaller than 0.5. This could well be interpreted as proof that while AMFs within this investment strategy behave similarly to HFs, they fail to provide the extra 50% of variation that is probably most value-creating.

iv. Alternative Credit

The main expectation for this category is a better fit of the Fung-Hsieh model, as the Carhart model does not include risk factors designed for fixed income assets. In the Fung-Hsieh model, it is also expected to find significant exposures to fixed income factors and perhaps to option factors as a result of the use of derivatives within these funds. Our first expectation is fulfilled for our AMF sample, with the Fung-Hsieh model performing better in explaining results. This difference between models is even more punctuated in the case of HFs. With regards to coefficients, our AMF sample shows positive significant coefficients on the stock market and the size factor, and negative significant coefficients on the bond and credit spread factors. While the equity factors are significant, their magnitude is small, pointing to little economic meaning. The negative bond coefficient means that funds are short the bond yield, hence long the bond price and positive fixed income correlation. The negative credit spread coefficient points to a skew of investment strategies towards riskier fixed income assets, which would suffer in case the credit spread widened. It is, up to some extent, surprising not to find some significant exposure to the option factors in the Fung-Hsieh model, as the derivatives strategies explained in **Table 12** should have some impact on them.

HFs, on the other hand, do not have a significant factor exposure on the stock market, but they have exposure to size, bond, and credit spread factors in the same direction as AMFs. The credit spread coefficient is even greater in absolute terms, probably showing a riskier portfolio of names chosen by HFs for their investment strategies. Adding to these factor exposures, HFs also have a negative significant coefficient on the FX option factor, which probably points to some derivative use for currency hedge of cash flows or to investments in fixed income instruments denominated in different currencies. However, the coefficient is very small in economic terms. Moving onto the Carhart model, the value factor is also present in HFs, hence tapping another risk premium source.

In the regression of our AMF sample on the HF index, we identify a positive significant coefficient close to 1 with a coefficient of determination around 0.4. This shows that the underlying strategies of both AMFs and HFs look alike up to some extent, while again, there exists a sizable portion of non-shared variation. This variation might be the determinant behind the fact that HFs show alpha in both model specifications while AMFs do not.

v. Global Macro

Based on the nature of this investment strategy, one would expect to find several significant factor exposures in both models, first because of the use of many different asset classes for the implementation of the strategy, and second due to the use of derivatives in order to hedge some exposures, such as currencies or rates, in global trades. The commodity option factor is expected to be significant as currencies play a big role in macroeconomic shifts and the Global Macro investment strategy profits from an increase in volatility, which should be captured by the option like factors in the Fung-Hsieh model. Also, the Global Macro investment strategy tends to feature a small correlation with overall equity markets, hence we would expect a low equity market factor coefficient.

What we observe in our AMFs sample is a very simplistic approach to investing. In the Fung-Hsieh model we just observe significant coefficients for the stock market and the bond market factors, which are reasonable as we explained before due to the different asset classes Global Macro funds invest in. However, we would expect additional factor loadings on the rest of risk factors. As for the Carhart model, just the stock market factor is significant, leaving out many other return generating strategies. Adding to this, alpha is not significant for this strategy either in any model specification.

The weak investment routine used by AMFs in this strategy becomes magnified when looking at our results for HFs. Alpha is first of all present and positive, and just the bond option factor is non-significant in the Fung-Hsieh model. This wide array of coefficients is exactly what we hypothesized that the strategy should show. As for the Carhart model, just the value factor is non-significant, with the rest of factors showing positive coefficients for extracting the risk premia.

The regression of AMFs on the HF index shows a positive significant coefficient greater than 1, probably due to the higher exposure of AMFs to the stock market factor. The coefficient of determination is low, pointing to quite some divergence in implementation between AMFs and HFs.

vi. Managed Futures

We would expect Managed Futures funds to show exposure to the equity market, and to the three factors designed for trend following in the Fung-Hsieh model. The reason for this is that this type of funds implement their strategies across asset classes in commodity, interest rate, equity and currency markets via futures contracts.

For our AMF sample, we see that CTAs show a positive coefficient on the equity market, which might be justified by AMFs implementing trend following strategies in the asset class[12]. Furthermore, we also observe a negative loading on the size and value factors. While on the one hand one might expect to see stronger trends on small stocks, on the other hand, it makes sense to see a negative size coefficient since futures contracts are easily available mostly for large companies, whose stocks also tend to be more liquid and faster in reacting to new information releases (Cenesizoglu, 2011). As for the coefficient on value, the negative sign probably results from the implementation route of AMFs: these funds make a heavier use of futures on indices, and stock indices tend to have a growth bias (EDHEC, 2015). It is highly surprising the fact that we fail to find any significance neither in any of the option-like factors present in the Fung-Hsieh model used for trend following strategies nor in the momentum factor in the Carhart model. This clearly shows that Managed Futures AMFs fail to closely replicate the strategies originally implemented by HFs and fail to show the same option-like return profiles that characterize HFs. A reason for it might lie in the restrictions in the structure of the 40's Act funds, which limit leverage to 1.33x in terms of cash borrowing and state that funds need to maintain a diversified portfolio of positions, in which no single asset should constitute more than 5% of the whole portfolio (Barclays, 2014). The requirements of the 40's Act fund have been addressed in the Managed Futures sub-strategy by creating a standard framework of 25% allocation into a sub-adviser responsible for performing the trading and a 75% that the fund keeps in fixed income assets. While in theory the leverage undertaken by the sub-adviser should be able to obtain a 100% level, it might be restrained up to some extent due to the format as opposed to a HF that

[12] The positive coefficient might well be justified by the fact that equity markets tend to perform positively over the long term (BlackRock, 2014), hence the cumulative combination of trend following positions should be positive as the investment strategy would tap upward movements with greater frequency.

might have no restriction in terms of format. Please refer to **Table 12** for an explanation of the format employed by AMFs with regards to Managed Futures.

In terms of our HF regressions, it is surprising to observe that Managed Futures is the single category within HFs in our study that fails to deliver any alpha. Non-generation of alpha is also the case for AMFs in this investment strategy. However, we observe a positive significant factor exposure on the FX option factor in the Fung-Hsieh model and the momentum factor in the Carhart model, pointing to better implementation or higher use of trend following strategies within HFs than for AMFs. The negative significant coefficient on the size factor is also present, probably due to the same reasons as in the case of AMFs.

The regression of AMFs on the HF index shows a positive significant and close to 1 coefficient, with a relatively large coefficient of determination, around 0.5, showing that strategies do look alike up to some extent, although they still do not share a sizable part of co-movement.

vii. Event-driven

As a result of the relatively broad set of sub-strategies comprised within the Event-driven strategy, we would expect a representative fund following this strategy to show a range of significant coefficients across equities, fixed income and even options, the latter being a result of convertible arbitrage. Hence, we would expect the Fung-Hsieh model to provide us with greater explanatory power, as it uses as explanatory variables factors other than equity related.

Looking at our sample of AMFs, we fail to confirm our expectations, as the equity market is the only significant factor. This points to the fact that Event-driven AMFs do not pursue a rich set of sub-strategies and most likely pursue a merger arbitrage approach, neglecting the rest of the sub-strategies (**Table 12**). The equity coefficient is positive but smaller than 1, corresponding quite well with the merger arbitrage approach, which hedges its outright position but still shows some long exposure to equity markets due to its dependence on positive market backdrops for closing of deals.

The HF regression on the factors do show the coefficients we hypothesized. Furthermore, both models record a very good explanatory power, with the Fung-Hsieh model performing better. First of all, alpha is positive and significant, as opposed to AMFs. Second of all, we observe positive equity market and size factors, the size factor probably explaining the HFs' pursuance of the activist stance strategy. With regards to bond market and credit spread coefficients, both are negative and significant. This could be expected due to implementation of capital structure arbitrage, convertible arbitrage, and distressed securities arbitrage. Furthermore, when the credit spread is reduced, implying better market conditions and more risk seeking by investors, these funds perform better, as their distressed securities holdings increase in value. Interesting as well is the negative exposure to the bond option factor, probably derived from the option component of the convertible arbitrage strategy or the option like payoff derived from investing in distressed securities, which features a small downside, capped at zero when the company defaults, and a very high unlimited upside linked to the recovery of the subject company. If we now move to the Carhart model, we observe that for HFs, equity and alpha are significant as in the case of the Fung-Hsieh model. Adding to this, the value and size factors record positive significant coefficients. The positive size coefficient probably relates to the activist stance strategy, in which funds focus their investment strategies toward smaller companies. With regards to value, this coefficient would most likely derive from investing in companies with low book to market ratios, as it is the case of distressed securities.

The AMF regression on the HF index shows a positive significant coefficient, which is closer to 0.5 than to 1, probably due to the lack of sub-strategies in the AMFs that are actually present in HFs.

viii. Short-bias

For Short-bias, we expect a negative exposure on the equity market, together with some potential factor loadings on the other equity risk factors implicitly derived from individual shorts of stocks.

Before examining the results, we must first disclose that the size of the sample for this specific strategy is the smallest in comparison to all the other alternative strategies we explore. This, is a consequence of the overall negative performance that funds pursuing this strategy have recorded over time. Despite this inconvenience, we find interesting results. First of all, the coefficients of determination from both models prove to be the best across all other strategies. This can be attributed to two potential factors: a lower variability in implementation across funds due to lower number of funds being included in the sample, and/or a very straightforward loading on the equity factor, which explains most of the variation. The second hypothesis might be more realistic given that the equity loading is in both models close to -1. This is what one could expect from these funds and points to the fact that the pursued strategies deliver what they actually promise. We find interesting negative correlation with the bond market factor and positive correlation with the credit spread factor for the Fung-Hsieh model (positive coefficient in bond market yields actually points to negative correlation between bond prices and fund returns). These two factor exposures might derive from the implicit nature of the funds, which profit from stress in financial markets, coinciding with higher risk premium demanded by investors for holding longer and riskier bonds.

Contrary to our AMFs sample, we identify positive alpha for the Fung-Hsieh and Carhart models in HFs. This is fairly interesting to find, as the average return of the strategy for HFs is actually negative. However, it has been argued that despite the negative absolute returns achieved by Short-bias funds, these funds tend to deliver consistent alpha (i.e. they lose less than what would be expected to lose in following such a strategy) (Holt, 2007). Apart from that, we can observe that the strategies pursued by HFs within dedicated Short-bias seem to be more elaborate, with a wider array of significant coefficients. We first observe that the size factor is significant and negative in both specifications. This is explained by the fact that HFs decide to target smaller companies in order to short their stocks. This might be reasonable as stocks for large market capitalization stocks tend to suffer from more momentum driven buying pressure or simply because HFs can have access to stock lending in smaller companies. With regards to the value factor, it makes perfect sense that we obtain a positive coefficient, due to the fact that HFs will tend to short stocks with low book to market ratio, or overvalued stocks. No exposure to this factor in our sample of AMFs might point to a more systematic exposure to the whole market, rather than performing a company-by-company analysis to choose underperformers. This, in our opinion, adds less value to investors as it fails to provide exposure to return factors and could be easily replicated by taking short positions in stock indices or long positions in inverse ETFs.

In terms of the regression on the HF index, we can identify that the coefficient is positive and significant, and close to 1. So, looking also at the 0.6 coefficient of determination, we can conclude that our sample does replicate quite closely the strategies that dedicated Short-bias HFs carry out, with some room for difference probably due to short selling limitations stated in the 40's Act. In particular, the extra cost borne by AMFs due to performing the short selling via tri-party agreement with segregated assets to cover the positions (**Table 12**), might limit the degree to which leverage can be obtained via outright shorts.

ix. Summary

Across strategies we identify several traits of AMFs that ought to be summarized on a general note. As an anticipation of the subsequent explanations, we find that alpha is not significant in AMFs, contrary to HFs. Furthermore, we find that the set of factor exposures is narrower in the case of AMFs and that divergence in factor exposures is greatest for investment strategies that are more complex in implementation.

First of all, within our AMF sample we fail to find any significant alpha in any of the investment strategies for the two models that the paper employs. This is further confirmed by a difference of means t-test[13], which shows that the overall difference in alpha between AMFs and HFs is significant for the Fung-Hsieh model. Furthermore, the test shows significant differences in all the Fung-Hsieh model factors, among which, the equity market factor is greatest in economic terms, and shows that AMFs tend to tap this kind of systematic risk more often than HFs to derive returns. It is a proof of divergence from HFs, which record positive significant alpha for all strategies but Managed Futures. The absence of alpha in AMFs and the difference in absolute performance versus HFs is in line with the findings in Agarwal, Boyson, & Naik (2009).

[13] Please refer to **Table 16** and **Table 17** in the Appendix for results on the test for differences of means.

Second, our analysis of risk factor loadings suggests greater simplicity in the strategies implemented by AMFs compared to HFs'. As an example, for AMFs, Multi-strategy, Equity Market Neutral and Event-driven strategies just show a significant exposure to the equity market factor while the corresponding strategies in the HF Indices show at least four different factor exposures in the Fung-Hsieh model. On the same front, it is quite illustrative to observe that only Managed Futures AMFs show exposure to more than just the equity market factor in the Carhart model, illustrating that the greatest part of AMFs fail to tap non-directional risk premium factors in that model. On the replication side, the regressions of AMFs on their corresponding HF indices show quite low coefficients of determination, pointing to the fact that AMFs and HFs differ significantly. The highest R^2 coefficients in the regressions on HF indices are recorded for Short-bias and Long/Short Equity, around 0.5. Coincidentally, these two are the strategies that are theoretically least complex in implementation. All other strategies perform poorly in terms of coefficient of determination, with even Equity Market Neutral recording a non-significant coefficient with its own HF index. One would expect the coefficient of determination to be in the vicinity of 1 as strategies should be similar and variation should be explained by the HF index. However, these coefficients of determination are slightly higher than those obtained in Busack, Drobetz, & Tille (2014), for the case of UCITS funds regressions on HFR indices.

Third, we confirm that strategies that are more complex in implementation achieve poorer factor replication in terms of both factor loadings and coefficients of determination. Strategy simplicity is assessed based on our framework outlined in the methodology section. For instance, while the Event-driven strategy employs many sub-strategies, might need to use different asset classes within a capital structure, and might face difficulties in accessing securities of companies subject to corporate events; Managed Futures implement just one main sub-strategy, can implement it in just one asset class if needed, and will use liquid and easy-to-access securities to profit from price movements. On top of this, Managed Futures funds also have easier access to shorting, as they do not outright short but rather short futures contracts that require lower margins[14]. In our sample we observe that underperformance and strategy replication divergence are more marked for Event-driven than for Managed Futures AMFs. Another example of a complex strategy that fails to be replicated is Global Macro. We use these findings as proof that the restrictions imposed by the 1940's Act regulation on leverage, short positions, liquidity, diversification and transparency, put a drag on the performance of AMFs. This inference is subject to the assumption that manager skills are homogeneous between HFs and AMFs.

All these findings lead us to conclude that even though AMFs claim to implement HF strategies, they are clearly inferior in both performance and elaboration of the investment

[14] In the US, Regulation T (Federal Reserve Board, 2015) requires a margin of 150% for outright short equity positions. On the other hand, the Chicago Mercantile Exchange (CME), one of the largest futures exchanges, requires margins spanning from 2% to 9% for positions in equity futures contracts (CME Group, 2015).

strategies. Moreover, investment strategies implemented within the mutual fund wrapping tend to perform worse and very differently to what the original strategy within HFs would. This motivates us to pinpoint the importance of segregating AMFs and HFs into two different asset class realms, each offering different features and return patterns. Furthermore, it must be noted that replication differs between strategies, and that the comparison between AMFs and HFs should not be carried out on a general but rather on a strategy-specific basis.

b. Second-pass regression

Table 9 presents the results of the second-pass regression outlined in the methodology section using alphas collected from the Fung-Hsieh model. With this regression we look into the determinants of alpha. We comment the results on a strategy-by-strategy basis and conclude with a summary of general findings and consequent inferences.

Table 9: Second-pass Regression

	Intercept	Past Performance	Size	Age	Expense Ratio	Flow	Manager Tenure	Min. Investment	Institutional	Retail	Bank Managed	Turnover	Load and other fees	Mgmt Fee
Long/Short Eq.	0.00001	**-0.00124*****	**-0.00285***	-0.00097	**0.00004***	**0.00376****	0.00067	0.00016	0.00001	0.00001	**0.00000***	**0.00030****	-0.00001	0.00002
Eq. Mkt Neutral	0.00002	-0.00056	0.00032	**-0.00964*****	0.00004	**0.00303***	**-0.00311****	0.00024	0.00002	0.00002	0.00000	-0.00004	0.00000	0.00002
Multistrategy	-0.00003	0.00001	0.00098	**-0.00339****	-0.00004	**0.00137***	-0.00098	-0.00007	-0.00003	-0.00003	0.00000	-0.00006	0.00000	-0.00003
Alt. Credit	0.00006	**-0.00099****	-0.00302	**-0.00284*****	0.00001	**0.00328***	-0.00167	**0.00031***	0.00006	0.00005	0.00001	**0.00061****	0.00004	0.00005
Global Macro	**0.00006***	0.00036	-0.00086	0.00035	0.00006	0.00145	**-0.00582***	0.00041	0.00004	0.00005	0.00000	0.00017	**0.00001****	**0.00006***
Managed Futures	0.00002	-0.00014	0.00278	0.00258	-0.00006	0.00389	0.00241	0.00044	0.00002	0.00003	-0.00001	-0.00006	0.00002	0.00003
Event Driven	0.00002	-0.00027	-0.00328	-0.00064	0.00003	-0.00018	-0.00065	0.00021	0.00002	0.00002	0.00000	**0.00014*****	**0.00000***	0.00002
Short bias	-0.00042	-0.00145	0.00122	**-0.01561****	-0.00074	0.00877	**-0.01571****	-0.00544	-0.00043	-0.00042	0.00000	0.00006	-0.00033	-0.00051
Full Sample	0.00001	**-0.00055*****	**-0.00107***	**-0.00205*****	0.00001	**0.00274*****	**-0.00127****	0.00014	0.00001	0.00001	0.00000	**0.00019*****	0.00000	0.00002

The table shows the results of the regression:

$$PERF_{i,t} = \beta_0 + \beta_1 PERF_{i,t-2} + \beta_2 SIZE_{i,t-1} + \beta_3 AGE_{i,t-1} + \beta_4 EXPENSE_{i,t-1} + \beta_5 FLOW_{i,t-1} + \beta_6 TENURE_{i,t-1} + \beta_7 Min.Inv._i + \beta_8 Insti_i + \beta_9 Retail_i + \beta_{10} BankManaged_i + \beta_{11} Turnover_{i,t-1} + \beta_{12} Load\&Other_i + \beta_{13} MGMT\ Fee_i + \sum_{t=1}^{T} \beta_{14}\, I(YEAR_t) + \psi_{i,t}$$

In this regression we use the alphas obtained by running the Fung-Hsieh model as the performance measure. Tests for significance use a standard error computed from a bootstrapping procedure with 10,000 replications. *, **, and *** stand for significant at the 90%, 95% and 99% confidence level respectively. Reported coefficients comprise the average coefficients among all funds within each strategy.

i. Long/Short Equity

The variable that appears to be most significant for Long/Short Equity is lagged performance. This coefficient is negative, meaning that AMFs that did well in the past, and generated positive alphas, tend to underperform in the following years. This finding is interesting because it shows how, among Long/Short Equity funds, persistence in alphas is very low.

Lagged flows also appear to be significant and show a positive coefficient: this means that a fund that has received positive inflows in the previous period is more likely to outperform. In light of the previous literature, the result seems counterintuitive: funds that grow in size should experience decreasing returns to scale. Indeed, if we look at the coefficient for log size, the value is negative and significant. However, the explanation for flows can come from the fact that these funds, being relatively young, have not yet reached their critical size (Getmansky, 2012). Therefore, new fund inflows would be spent in new, profitable, investment opportunities, rather than going to scale up existing strategies that then experience decreasing returns.

Surprisingly, the coefficient on the expense ratio is positive and significant at 90% level. This means that funds with higher expenses seem to outperform. Perhaps, if one assumes that part of the costs covered by the expense ratio are actually investments in more skilled managers and better infrastructures, which might be key for this style, it is justifiable that higher expenses lead to better performance. Of the additional variables that we have added to the model, turnover appears to be significant and shows a positive coefficient. On the one hand, a manager can destroy large parts of the returns by trading too much. On the other hand, in order to generate alpha, a manager needs to rotate the portfolio in order to profit from changing market conditions, and a higher turnover can be correlated with better performance, as it seems to be the case for AMFs. Perhaps, given the short-term nature of the Long/Short Equity strategies (e.g. pair trades), managers who are faster at rotating the portfolio into new bets are also the ones who can reap higher excess returns.

ii. Equity Market Neutral

In the second-pass regression for the Equity Market Neutral AMFs, the three main significant variables seem to be Fund Age, Flows and Manager Tenure.

Age is significant at 99% level and appears with a negative coefficient. This means that AMFs that have been on the market for longer tend to generate lower alphas compared to younger peers. An explanation to this phenomenon might be that older funds might tend to engage in the so-called style drift. This means that, in order to avoid the decreasing returns to scale that come with a larger size, managers start to implement strategies that are outside of their areas of expertise, thereby generating lower excess returns (Frumkin & Vandegrift, 2009). Another explanation, as we have seen in the literature, might come from higher career concerns and lower incentives to take risks for older managers, who, on average, are more likely to work for older funds (Boyson, 2003).

Flows are significant at 95% level and positive. AMFs that experienced higher inflows in the previous year, show a higher excess return in the current period. Once again this might be due to the fact that managers receiving new flows are able to invest them in new strategies that can still guarantee increasing returns. In this case, the size factor does not appear to be significant, but one might infer that, with an average size of $318million, Equity Market Neutral AMFs do not, on average, reach the critical size after which returns diminish drastically.

Finally, among the variables we have added to the regression, Manager Tenure appears to be significant and negative. As some papers show, young, newly hired managers tend to perform better than their older peers (Li, Zhang, & Zhao, 2011), meaning that, at least in our Equity Market Neutral sample, keeping the same manager for a long period of time would be detrimental to returns.

iii. Multi-strategy

The two main factors that are significant for Multi-strategy AMFs are Age and Flows.

Age has a negative coefficient. As for other strategies, older funds seem to perform worse, in terms of excess returns.

Flows appear with a positive coefficient: once again, funds that have received positive flows in the previous year seem to outperform, suggesting the fact that managers tend to invest these funds on new opportunities rather than just scaling up existing strategies and thus facing decreasing returns.

Contrary to other strategies we would expect Multi-strategy funds to benefit from a larger fund size, since, by definition, this style tries to gain exposure to several different sources of return. In our regression we see a positive but insignificant coefficient, which fails to confirm this intuition.

iv. Alternative Credit

The second-pass results of Alternative Credit AMFs show several significant coefficients. Age is significant and comes with a negative sign, as in other strategies. Once again, older funds tend to underperform in terms of alpha.

Flows are significant at the 90% level and appear with a positive sign, pointing to the fact that AMFs that receive positive investment flows tend to outperform in the following year, perhaps due to the ability to invest in new strategies.

Past performance is significant at the 95% level and comes with a negative coefficient, showing that there is no medium term persistence in alpha for Alternative Credit funds. At the opposite, AMFs that performed well in the past show weaker performance later on.

Among the variables that we have added to the base model, Turnover appears to be the most significant. This variable appears with a positive, although economically small coefficient. It might be that, in a similar way to Long/Short Equity funds, Alternative Credit funds that see a large rotation in the asset portfolio are able to generate more alpha, meaning that an active management approach is rewarded.

Finally, contrary to other strategies, here we see that Minimum Investment is significant and has a positive coefficient. As shown in the literature by James & Karceski (2006), TMFs with higher minimum investment might try to target more sophisticated investors, and thus have a stronger incentive to generate alpha. We can thus infer that, contrary to other strategies, within Alternative Credit, the fact of having a higher entry threshold motivates funds to focus more on creating alpha.

v. Global Macro

The most significant result for Global Macro AMFs is that Manager Tenure appears to be significant and has a negative coefficient. As for other strategies, it seems to be detrimental to the fund's performance to keep a manager for a long period of time.

It is surprising to see that for Global Macro funds, both management fee and load and other fees are positive significant, although with small coefficients. This might mean that within this particular style, more expensive funds actually add value for the investor.

Contrary to other strategies, we do not see any significant coefficient on neither Flows nor Size meaning that the magnitude and the growth of assets under management might be less important of an incentive in this strategy. More importantly, many year dummies have significant positive or negative coefficients. This, in itself, can be an interesting finding: rather than being the specific features of the manager or of the funds, especially in terms of incentives, that are relevant in the generation of alpha, it is the specific time at which we look at the fund that has a substantial impact. It might therefore be the case that funds within this specific strategy show similar return patterns in specific years, perhaps due to broader market conditions[15].

Finally we would like to stress the fact that Global Macro is the only case for which we see a positive and significant intercept, meaning that the explanatory power of the fund features is lower for this style.

vi. Managed Futures

We do not manage to see any significant coefficient in the second-pass regression for Managed Futures AMFs, perhaps due to the short track record of the funds within this style. This kind of

[15] Casano, J., CAIA (2010) shows that returns in Global Macro funds are driven by macroeconomic themes rather than by fundamental analysis. Schneeweis, Kazemi, & Martin (2002) deal with the "vintage year effect" and show that funds launched in different market environments have different subsequent performance. In their sample, they find that this effect is relevant for Global Macro funds.

strategy is relatively new in the world of AMFs, and it is hard to find funds with a long track record.

In many respects, Managed Futures HFs have features that make them ideal to study, because of their asymmetrical payoff profile and their divergent risk style. Looking at the results of the first-pass regression, AMFs implementing this strategy fail to gain exposure to the risk factors that are typical of Managed Futures HFs. Therefore it is probably not surprising to find that even the factors behind their generation of alpha do not correspond to what is usually found in the HF literature. In particular it has been shown that CTAs have a relative strong persistence in performance (Molyboga, M., 2014), something that we fail to trace in our sample of Managed Futures AMFs.

vii. Event-driven

Event-driven AMFs show few significant coefficients in the second-pass regression. Among the most interesting findings is the positive significant coefficient on Turnover. This result points to the fact that Event-driven strategies benefit, in terms of alpha generation, from rotating the assets in the portfolio. Intuitively, these funds take bets on the outcome of a specific event, and therefore have no reason to keep on being invested in a specific asset once the event is either triggered or called off. Most likely, managers with higher turnover are those who manage to spread their bets in the best way.

viii. Short-bias

For Short-bias AMFs, Age appears to be significant and to have a negative sign. The coefficient is also economically significant. Thinking about the average performance of this strategy, it seems clear that the few funds in the sample have been doing poorly over the sample period. What is surprising though is that the older the funds become, the more they tend to generate a negative alpha. Apparently, even though the competition is low because of the low expected returns, and only a few funds manage to survive, these funds face the same issue as the ones in other strategies, i.e. Age being detrimental on risk-adjusted performance.

Manager Tenure is also significant and negative: indeed for most Short-bias funds this variable tends to be very close to the age of the fund, contrary to what happens for other strategies. Results for both Age and Manager Tenure are in any case in line with those found for other strategies.

ix. Summary

Overall, we see that there exists substantial variation in the drivers of alpha across the different strategies. However, we are able to identify four factors that are often significant throughout strategies, in particular age, manager tenure, flows, and turnover.

As an anticipation of the subsequent explanations, we find similarities between AMFs and TMFs with regards to the lack of performance persistence. The similarities between AMFs and HFs include the negative impact of age and manager tenure, and the positive impact of flows on performance. With regards to turnover, while the evidence is mixed for TMFs, HFs do not report such a measure and hence the outright comparison is challenging. However, the expectation would be that HFs would require a high turnover due to implementation of their investment strategies, and that turnover would potentially contribute to their performance.

First of all, we observe very weak evidence of performance persistence across strategies: in most cases coefficients are negative and/or insignificant, pointing to no persistence in the generation of alpha. We believe that our results already manage to point to a key feature of AMFs. In similar fashion to TMFs, AMFs do not show elements of performance persistence. Thus our paper confirms the findings of Kanuri & McLeod (2014) for TMFs. The literature on HF performance persistence, on the other hand, still has mixed results (Boyson N. , 2008; Agarwal & Naik, 2000).

Second, older AMFs perform on average worse than younger ones, and coefficients on Age tend to be significant and sizeable in magnitude. This goes hand in hand with manager tenure, which also appears as significant and shows also a negative coefficient. This is to be expected as the two factors are interlinked. In this sense, AMFs seem to resemble more to HFs and to mirror the findings of Boyson (2003). Our data do not allow us to assess to which extent this feature might be due to managers' career concerns. However, since AMFs try to target the traditional public of HFs up to some extent, reputation might be a key driver behind the incentive not to assume more risk in the fund. AMF managers do not usually have their own wealth invested in the fund, and, at least in our sample, are not compensated based on performance, pointing to lower incentive alignment than in the case of HFs. Our results seem however to go against what has been found about TMFs, and in particular by Chevalier & Ellison (1999) on the increased boldness of older managers.

In addition, for many strategies Flow is significant and appears to have a positive impact on performance. It seems therefore that, on average, AMFs that receive a larger inflow of capital in a given year tend to do better in the following year. This could mean that the positive flow of money is invested in profitable opportunities rather than being put into the existing strategies that the funds have in place and that tend to have decreasing returns, as described by Berk & Green (2004) for the case of TMFs. Furthermore, we notice that those strategies that intuitively have lower capacity constraints, such as Alternative Credit and Long/Short Equity, are the ones that benefit the most from flows. This result might seem to be hard to reconcile with the fact that larger funds tend to underperform (Berk & Green, 2004). However, the fact that, except for Long/Short Equity funds, we do not find a significantly negative coefficient on size, corroborates the meaning of our results.

Additionally, looking at the aggregate sample we see that Turnover has a positive and significant impact on performance. The literature on TMFs finds mixed results on the issue, for example Cremers & Petajisto (2009) find a positive impact whereas Day, Wang, & Xu (2001) find a negative one, but we hypothesize that the managers of AMFs, having to pursue more dynamic strategies than their TMF counterparts, are rewarded, in terms of better performance, for more frequent changes in the portfolio composition.

In our regression we do not find a strong evidence for the impact of Minimum Investment, Institutional or Retail classes, and Bank Managed on the generation of alpha. Perhaps, contrary to the study of James & Karceski (2006), our sample is more homogeneous, especially in terms of minimum investment and of target category of investors. Moreover, the evidence in terms of underperformance by bank-managed funds is somewhat blurred. Frye (2001) for instance, finds that among bond funds, bank-managed ones might be, on average, more conservative, but do not show a substantial underperformance.

c. Flow Regression

Table 10 and **Table 11** present the results of the second-pass regression for flows. We briefly discuss in the section the value adding findings obtained from this complementary model.

Table 10: Flow Regression –Alpha from the Fung-Hsieh model as explanatory variable

	Intercept	Past Performance	Size	Age	Expense Ratio	Past Flows	Manager Tenure	Min. Investment	Institutional	Retail	Bank Managed	Turnover	Load and other fees	Mgmt Fee
Long/Short Equity	0.363	0.119	-2.084	-1.621	0.507	**-0.122*** **	-0.080	6.176	0.363	0.363	4.068	17.103	0.361	0.399
Eq. Market Neutral	0.000	0.012	**0.250** **	**-0.576** **	-0.001	**-0.242*** **	-0.162	-0.001	0.000	0.000	-8.104	0.001	0.000	0.000
Multistrategy	**0.006***	**-0.066** **	-0.321	**-0.699***	0.008	**-0.252*** **	**-0.313** **	**0.059** **	0.005	0.005	0.004	**0.065***	0.003	0.001
Alt. Credit	0.010	-0.020	**-0.897** **	0.236	0.006	**-0.202*** **	-0.242	0.049	0.010	0.009	5.062	**0.090*** **	0.007	0.006
Global Macro	0.029	-0.168	3.695	-0.002	0.017	5.442	1.829	0.327	**0.029***	0.006	1.856	0.285	0.005	0.022
Managed Futures	0.033	-0.023	0.132	-0.233	0.054	-0.243	-0.222	0.389	0.033	0.032	0.001	0.014	0.031	0.012
Event-Driven	0.000	0.400	7.122	-14.060	0.001	**-0.308** **	-14.060	0.004	0.000	0.000	0.000	0.026	4.587	0.000
Short Bias	0.023	**0.051***	2.622	-1.082	0.056	-0.040	-1.082	0.165	0.004	0.023	0.000	0.111	0.018	0.021
Whole Sample	0.132	-0.025	-0.101	**-1.041** **	0.181	0.660	-0.184	2.186	0.132	0.128	**0.001***	5.852	0.127	0.140

Table 11: Flow Regression – Raw returns as explanatory variable

	Intercept	Past Performance	Size	Age	Expense Ratio	Past Flows	Manager Tenure	Min. Investment	Institutional	Retail	Bank Managed	Turnover	Load and other fees	Mgmt Fee
Long/Short Equity	0.363	0.019	-2.089	-1.622	0.507	**-0.124*** **	-0.079	6.176	0.363	0.363	4.110	17.103	0.361	0.399
Eq. Market Neutral	0.000	0.006	**0.250** **	**-0.576** **	-0.001	**-0.242*** **	-0.162	0.000	0.000	0.000	-7.717	0.001	0.000	0.000
Multistrategy	**0.006***	0.078	-0.323	**-0.692***	0.008	**-0.251*** **	**-0.312** **	**0.059** **	0.005	0.005	0.004	**0.065***	0.003	0.001
Alt. Credit	0.010	-0.189	**-0.898** **	0.2335	0.006	**-0.201*** **	-0.242	0.049	0.010	0.009	5.060	**0.090*** **	0.007	0.006
Global Macro	0.029	-0.343	3.691	-0.001	0.017	5.439	1.8285	0.328	0.030	0.006	1.859	0.287	0.005	0.022
Managed Futures	0.033	-0.012	0.132	-0.234	0.054	-0.243	-0.222	0.389	0.033	0.032	0.001	0.014	0.031	0.012
Event-Driven	0.000	-0.558	7.110	-14.05	0.001	**-0.308** **	-14.050	0.004	0.000	0.000	0.000	0.026	4.630	0.000
Short Bias	0.022	-0.756	2.578	-1.065	0.055	-0.047	-1.065	0.164	0.004	0.022	0.000	0.108	0.018	0.021
Whole Sample	0.132	-0.038	-0.101	**-1.039** **	0.181	0.660	-0.184	2.186	0.132	0.128	**0.001***	5.852	0.127	0.140

The table shows the results of the regression:

$$Flow_{i,t} = \beta_0 + \beta_1 Perf_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Age_{i,t-1} + \beta_4 Expense_{i,t-1} + \beta_5 Flow_{i,t-1} + \beta_6 Tenure_{i,t-1} + \beta_7 Min.Inv._i + \beta_8 Insti_i + \beta_9 Retail_i + \beta_{10} BankManaged_i + \beta_{11} Turnover_{i,t-1} + \beta_{12} Load\&Other_i + \beta_{13} Mgmt\ Fee_i + \sum_{t=1}^{T} \beta_{14}\, I(YEAR_t) + \psi_{i,t}$$

Table 10 uses the alpha resulting from the Fung -Hsieh first-pass regression using net returns, whereas **Table 11** uses raw returns as a measure of lagged performance.

As an anticipation of the subsequent explanations, we find that contrary to both TMFs and HFs, performance is not a determinant of flows for AMFs. However, it is mostly past flows that determine lower flows in the future and year dummies that carry most explanatory power in the model.

In a different way from HFs and TMFs, past performance is a very weak and only sporadically significant determinant of fund flows for AMFs. We express past performance as both lagged raw returns and lagged alpha, and we use a one-year lag, since it can be assumed that it is last year's winners that should attract the most flows. Only when we use past alpha and only for Short-bias funds we see a significant positive impact on flows.

On the other hand, we observe that the most consistent determinant of performance is past flows. Surprisingly, however, the coefficient is in most cases negative. This means that AMFs that managed to attract substantial positive flows in the previous year will attract lower inflows in the current year.

Other variables have, in turn, a mixed impact on flows, and we see very much variation across strategies in terms of which factors are significant and with which sign they appear. For example, Size is significant in two cases, but while for Alternative Credit funds it has a negative impact, for Equity Market Neutral it has a positive influence. This might be due to the different optimal size that different strategies might have for their funds: Equity Market Neutral might require a larger size, so that investors are not afraid of seeing their returns decrease because of the larger scale.

For most AMFs, control variables on some of the years (coefficients not shown) are significant, pointing to significant time fixed effects. It might be that flows into AMFs are determined more by general moves in the market or yearly trends rather than by the features of the individual funds. Investors might flock to AMFs within a particular style when they feel that the strategy might be rewarded in the future, and given the insignificant coefficients on past performance, the signal for investors to move into a certain strategy does not seem to come from past return information. This phenomenon can be seen in particular for Global Macro funds, for which we found that also in the performance regression year controls were significant. This finding is interesting because it sheds light on a peculiar feature of AMFs: contrary to TMFs, it is not only the best performing funds - based on past returns - that receive capital inflows. Therefore, although we are conscious that the issue would need to be investigated further, we believe that our results show some evidence that the extraordinary growth of AMFs has not been driven in a specific way by some funds delivering exceptional returns. It might rather be that a combination of demand and supply effects has determined an increase in popularity of this relatively new asset class, as mentioned in the literature review.

One interesting consequence of these findings might be that investors in AMFs do not pay much attention to past performance: it might be that AMFs are perceived as a hedging tool in the portfolio, so that they do not need to deliver outstanding results, but rather to offer a complementary risk-return profile to the rest of the portfolio, as suggested by Principal Management Corporation (2014). On the other hand, one might say the same about HFs, even though HF flows are in fact performance-sensitive (Agarwal, Daniel, & Naik, 2009).

d. Robustness Checks

In order to assess whether our model is adequate and whether our results are robust across different model specifications, we run a series of checks.

First of all, for the first-pass analysis, while we just report in the main body the results of the regressions using net returns for AMFs, we also perform the same analysis using gross returns, as in Gaspar, Massa, & Matos (2006). The difference between the two methods lies in the alpha and is very small, leaving all our inferences unchanged.

We also change the input to our second-pass regression: instead of using the Fung-Hsieh model to obtain the alpha, we run a regression that uses the Carhart model. Second, we also try using alphas from gross return regressions of both models. Finally, we run the model using raw yearly net returns instead of alphas to see whether the first-pass regression fails to retain some interesting features of the funds' returns.

As an additional check for the interpretation of coefficients in the first-pass regression, we perform a test for differences of mean coefficients between AMFs and HFs, which confirms mostly the same findings obtained from the regressions.

For all the model specifications we report the bootstrapped standard errors computed using 10,000 bootstrap replications.

i. Test for Differences of Means

The test for differences of means provides information as to whether coefficients of the Fung-Hsieh and Carhart models present statistically significant differences between AMFs and HFs. The use we give it in our paper is for verification of the results obtained in the first-pass regressions. **Table 16** and **Table 17** for the tests are shown in the Appendix section.

The main focus of our attention in this analysis is on alpha, which proves to be significantly different in a full sample basis for both models. Moreover, we can observe that the equity market exposure is significantly higher for AMFs, and that all three remaining factors in the Carhart model are significantly lower for AMFs, confirming our findings in the regression that AMFs fail to tap risk premium factors. In terms of the factors in the Fung-Hsieh model, we can observe that all factors in a full sample basis are significantly different, further confirming the proposed divergence in strategy implementation.

ii. The Carhart Model

Using the Carhart model to compute alphas (**Table 18** in the appendix) rather than the Fung-Hsieh model, we do not observe substantial differences in the coefficients.

For Multi-strategy AMFs, the Carhart model shows also significant coefficients in Manager Tenure, Turnover, Minimum investment and Other Fees, all with negative sign. Of these we would like to attract the attention on Tenure, which, as for other strategies, impacts negatively performance, suggesting that keeping the same manager for long can be detrimental. Surprisingly, a higher turnover seems to affect negatively performance, meaning that, within this strategy, rotating the assets in the portfolio is not rewarding for a manager.

For Short-bias AMFs, in the Carhart model, a whole range of other variables shows significant coefficients, perhaps due to the worse performance of the Carhart model in the first-pass regression, which leaves a larger unexplained part of the performance. We believe, however, that given the small number of funds pursuing this strategy in our sample, the results using both the Fung-Hsieh and the Carhart model to compute alpha have to be considered very cautiously.

Alongside these differences we notice that the Carhart model gives relatively higher coefficient of Flows and relatively lower ones on Size and Age. However, in terms of significant coefficients, we believe that the differences are minimal, and that therefore the robustness check confirms the findings of our main model.

iii. Gross Returns

If we use gross instead of net returns to generate the first-pass alphas (**Table 20** in the appendix) we do not find substantial differences in the second-pass coefficients. In general we notice that gross returns allow us to detect more significant coefficients, and to increase the degree of significance of those that were already significant in the main model. One exception is Global Macro AMFs, for which the model with gross returns detects several more significant variables, in particular the dummies that identify Institutional and Retail Funds. Given the fact that the sign of the coefficients does not change across the two specifications, and looking at the magnitude of the coefficients, we believe that the economic significance of the differences is limited. If we compare the coefficients for the Carhart model (**Table 21** in the appendix), the differences are even smaller between net and gross returns. The interpretation of the results therefore does not change.

iv. Raw Returns

By using raw returns as the dependent variable in the second-pass regression we notice some differences in the coefficients. Intuitively, if we treat the explanatory variables included in our regression as incentives that motivate the manager to deliver performance, it is not unexpected that the incentives to generate alpha differ from the incentives to generate raw returns.

The only result that stands out from this regression is the change in the sign of the coefficient on Flow. If before, in most cases, Flow had a positive and sometimes significant coefficient, here, most often, this variable shows a negative coefficient, which is quite often significant. The evidence that one can gather from this result is that an increase in flows into a specific fund determines, in the following year, a higher risk-adjusted return, as expressed by the Fung-Hsieh model alpha, but a lower raw return, everything else being equal.

The lower raw return can be explained by simple economic intuition. As in Berk & Green (2004), we can assume that managers face decreasing returns to scale and that it is inevitable, as the size of the fund increases, to report lower absolute returns. The positive effect on alpha, however, is more surprising. We might attempt to explain it by assuming that, in a similar way to HFs, AMFs tend to compete based on the excess returns that they deliver, rather than on the basis of their raw returns. Therefore, in order to attract investors while facing lower returns to scale, the managers of these funds have the incentive to generate above-benchmark returns.

7. Conclusion

In our study, we investigate whether AMFs manage to deliver returns in line with HF strategies and replicate the performance and risk exposure of HFs. Previous studies have focused mainly on AMFs as a whole (Agarwal, Boyson, & Naik, 2009), rendering the interpretation of risk factor exposures uninformative. We add a new layer of analysis by breaking down the regressions to a strategy-by-strategy basis and by comparing AMFs with their corresponding HF indices. Other papers have adopted a similar approach, but without exploring the differences of risk factors or the determinants of performance (Busack, Drobetz, & Tille, 2014).

We not only find that AMFs do not manage to achieve a significantly positive alpha, i.e. show weak of asset selection and market timing skills, but also that they do not achieve the same factor exposures as HFs of the same style do. This difference is greater the higher the complexity of the strategy subject to implementation, and we hypothesize, given our results, that this could be a consequence of regulation, under the assumption of homogeneous manager skills between HFs and AMFs.

We also look at the impact of manager and fund characteristics on the performance of AMFs and we conclude that, in this respect, AMFs constitute an asset class of their own that blends features of HFs and TMFs. Looking at the features of the AMFs, we are able to identify four factors that are significant for most strategies: age, manager tenure, flows and turnover. In terms of their impact on performance we find commonalities and differences with both TMFs and HFs. As expected, performance persistence is low for AMFs, pointing to the lack of a consistent effect of skills in the generation of alpha. Older AMFs, as well as AMFs with older managers, tend to underperform. In addition, AMFs with higher annual turnover generate a higher alpha, confirming the hypothesis that AMFs that rotate their portfolio more often are better at mimicking dynamic HF strategies. Alpha seems to be positively affected by flows, contrary to what happens for raw returns.

Finally, by looking at the determinants of flows, we find that neither lagged raw returns nor lagged alpha have a significant impact on fund flows. Given the significance of some year dummy variables, we might assume that flows are in part determined by time-specific factors, such as, perhaps, market conditions, that make it more attractive to invest in a certain kind of AMFs. This phenomenon might be justified by the fact that AMFs are selected as diversifiers in investors' portfolio, so that the effect on mitigating portfolio volatility is more relevant than performance itself.

To sum up, we see that AMFs, while being an interesting and growing asset class, do not manage yet to deliver the same risk-adjusted performance as HFs do, nor do they achieve the same risk exposures. Therefore we believe that investors willing to gain exposure to HF styles should evaluate carefully whether to use AMFs as a perfect substitute to HFs, taking into account their intrinsic differences as asset classes.

One needs to be aware that AMFs are a growing asset class, so the findings in this paper should be interpreted as an assessment of the current state of the industry. Moreover, our study is limited to US-based, 40's Act-compliant AMFs, and interesting results could probably be found by considering their European counterparts, UCITS-compliant AMFs. The quality of our analysis relies fundamentally on the factor models being used when comparing AMFs and HFs. The comparison would benefit from the refinement of such models, perhaps through the inclusion of strategy-specific factors. Furthermore, the analysis of determinants of performance would benefit from the development of a specific variable capturing the impact of regulation, something that could be derived from condensing AMF and HF micro data into one proxy variable. The same reasoning could be extended to other incentives, such as fees.

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9. Appendix

Table 12: Explanation of Alternative Investment Strategies

	Role in the Portfolio	Strategy Description	Return Drivers	Financial Instruments Used	Expected Factor Exposures
Long/Short Equity	Return Enhancer	• Outright long (short) undervalued (overvalued) stocks • Pairs trading: offseting positions in two stocks	• Correction in price of mispriced stocks • Convergence (divergence) of stock prices	• Outright stocks • ETFs and ETNs • Stock derivatives	• Minor equity market exposure (FH-C) • Potential size and value exposures (C)
Equity Market Neutral	Risk Reducer / Diversifier	• Minimize the exposure to equity markets • Achieve absolute returns by tapping other risk factors	• Uncorrelated markets driven by fundamentals • Stock picking	• Outright stocks • ETFs and ETNs • Stock derivatives	• Minimal equity exposure (FH-C) • Potential size, value and momentum exposures (C) • Hedging could result in fixed income and option exposures (FH)
Multistrategy	Risk Reducer / Diversifier	• Quasi-fund-of-funds approach • Implementation of several alternative strategies	• Ability to shift stategies depending on market opportunities should guarantee returns in different market environments • Low correlation among strategies	• ETFs and ETNs • Allocation to funds-of-funds	Exposures across asset classes, potentially significant in all the analyzed risk factors (FH-C)
Alternative Credit	Diversifier	• Unconstrained fixed income investment • Use of short positions and derivatives • Relative Value • Dynamic duration targeting	• Fixed income risk premia (credit, duration, etc.) • Credit picking - Spread plays • Dynamic duration might reduce interest rate risk	• Exotic fixed income instruments (e.g. ABSs, leveraged loans) • Synthetic credit exposures through CDSs • Swaps • Derivatives on fixed income	• Fixed income (FH) • Low explanatory power of Carhart model • Bond and FX option factors from the use of derivatives (FH)
Global Macro	Diversifier	• Top-down approach across geographies and asset classes • Investments based on macroeconomic views • Directional trades, carry trades and mean reversion	• Mispricing and effetct of geopolitical and macroeconomic events • Tends to perform well in adverse markets for stocks and bonds	• Unconstrained: long and short positions in any kind of asset and derivative contract	Wide range of exposures including especially: • FX options (FH) • Bond and commodity options due to role of rates and commodities in macroeconomic shifts (FH) • Low correlation with equities (FH-C)
Managed Futures	Diversifier	• Also known as Commodity Trading Advisors (CTAs) • Exploit movements in assets without trying to identify any fundamental price • Trend following • Use of signals based on price movements	• Low correlation with traditional asset classes and strategies • Benefit from formation of strong trends in the market	• Derivatives on different asset classes (stocks, currencies, commodities, fixed income, etc.)	• FX, commodity and bond option factors (FH) • Cross-sectional momentum (C)
Event Driven	Return Enhancer	• **Merger arbitrage**: pairs trades on M&A targets and acquirers • **Capital structure arbitrage**: take opposite positions in securities of the same company at different layers of the capital structure • **Convertible arbitrage**: exploit mispricings between convertible debt instruments and underlying equity • **Distressed securities**: investing in securities of distressed or bankrupt companies • **Activist stance**: taking a sizable stake in a company and exert influence in strategic decisions	• Success/failure of corporate events • Unjustified in terms of voting rights, dividends or interest payments, liquidation preference, liquidity, etc • Mispricing of convertible securities • Mispricing of distressed securities due to illiquity, low analyst coverage, legal restrictions • Implementation of corporate actions that boost the stock price	• Common and preferred stock • Equity derivatives • Bonds and fixed income derivatives • Convertible bonds	Depending on the sub-strategy pursued: • Relative equity exposure (FH-C) • Different exposures to equity as well as fixed income factors • Substantial credit and minor equity exposure • Substantial credit exposure • Equity and size exposure, since small firms are easier to take over
Short Bias	Diversifier	• Short overvalued stocks • Try to obtain negative correlation with the equity market as a whole	• Adverse equity markets • Convergence of prices to (lower) fundamental value	• Outright short positions in stocks • ETFs and ETNs on individual stocks/sectors on on the market as a whole • Stock derivatives	• Negative equity market exposure (FH-C) • Potentially size and value exposures (C)

Notes: FH indicates the Fung and Hsieh model, C indicates the Carhart model. Sources: (Fung & Hsieh, 1997), (Fung & Hsieh, 2002), (Busack, Drobetz, & Tille, 2014) (Principal Management Corporation, 2014) and fund prospectuses used for information on strategy implementation.

Table 13: First-pass Regression using the Fung-Hsieh model and Gross Returns

	Intercept	Equity Market	Equity Size	Bond Market	Credit Spread	Bond Option	Currency Option	Commodity Option	Adjusted R2
Panel A: Alternative 40 Act Mutual Funds									
Equity Long/Short	0.001	**0.431*****	0.012	-0.029	-0.077	-0.006	0.002	-0.007	0.626
Equity Market Neutral	0.001	**0.112****	0.006	-0.006	-0.020	-0.004	0.000	0.000	0.355
Multi Strategy	0.001	**0.247*****	-0.015	-0.067	-0.088	-0.004	0.005	-0.006	0.573
Alternative Credit	0.003	**0.083****	**0.068***	**-0.123*****	**-0.149*****	-0.014	0.004	-0.005	0.469
Global Macro	0.000	**0.339*****	0.011	**-0.120*****	-0.127	-0.008	-0.005	-0.009	0.573
Managed Futures	0.001	**0.216*****	**-0.298*****	-0.015	0.027	0.003	0.043	-0.003	0.423
Event Driven	0.002	**0.182*****	0.060	-0.011	-0.010	-0.004	-0.001	-0.009	0.512
Short Bias	-0.010	**-0.767*****	-0.160	**0.197****	**0.292*****	0.014	-0.003	0.004	0.714
Whole Sample	0.001	**0.278*****	-0.020	-0.047	-0.076	-0.005	0.005	-0.006	0.547

Notes: Regression results for Fung Hsieh 7 factor model using net returns for all funds and hedge fund indices. Tests for significance use a standard error computed from a bootstrapping procedure with 10,000 replications. *, **, and *** stand for significant at the 90%, 95% and 99% confidence level respectively. Reported coefficients comprise the average coefficients among all funds within each strategy.

Table 14: First-pass Regression using the Carhart model and Gross Returns

	Intercept	Equity Market	Size	Value	Momentum	Adjusted R2
Panel A: Alternative 40 Act Mutual Funds						
Equity Long/Short	-0.001	**0.587*** **	-0.005	0.000	-0.005	0.667
Equity Market Neutral	0.001	**0.148** **	-0.003	-0.014	0.016	0.328
Multi Strategy	0.000	**0.336*** **	-0.058	-0.027	-0.020	0.563
Alternative Credit	0.002	**0.149*** **	-0.037	0.037	-0.036	0.343
Global Macro	-0.002	**0.459*** **	-0.048	0.004	-0.019	0.530
Managed Futures	-0.003	**0.304*** **	**-0.414*** **	**-0.347*** **	0.031	0.294
Event Driven	0.001	**0.243*** **	0.051	0.023	-0.015	0.508
Short Bias	-0.005	**-1.009*** **	-0.031	0.036	0.062	0.737
Whole Sample	0.000	**0.381*** **	-0.056	-0.028	-0.008	0.525

Notes: Regression results for Carhart 4 factor model using net returns for all funds and hedge fund indices. Tests for significance use a standard error computed from a bootstrapping procedure with 10,000 replications. *, **, and *** stand for significant at the 90%, 95% and 99% confidence level respectively. Reported coefficients comprise the average coefficients among all funds within each strategy.

Table 15: First-pass Regression using the Matched Hedge Fund Index model and Gross Returns

	Intercept	Hedge Fund Index	Adjusted R2
Panel A: Alternative 40 Act Mutual Funds			
Equity Long/Short	-0.001	**1.143*** **	0.524
Equity Market Neutral	0.000	0.709	0.168
Multi Strategy	0.001	**0.974*** **	0.458
Alternative Credit	-0.001	**1.023*** **	0.389
Global Macro	0.000	**1.238*** **	0.302
Managed Futures	0.001	**0.815** **	0.462
Event Driven	0.000	**0.666*** **	0.450
Short Bias	-0.007	**1.122*** **	0.598
Whole Sample	0.001	**1.436*** **	0.225

Notes: Regression results for the hedge fund index regressions using net returns for all funds and hedge fund indices. Tests for significance use a standard error computed from a bootstrapping procedure with 10,000 replications. *, **, and *** stand for significant at the 90%, 95% and 99% confidence level respectively. Reported coefficients comprise the average coefficients among all funds within each strategy.

Table 16: Test for Differences of Means using the Fung-Hsieh model

	Alpha	Equity Market	Size	Bond Market	Credit Spread	Option Bonds	Option FX	Option Commodities
Long/Short Equity	**-0.005***	**0.164*****	**-0.143*****	**0.026*****	**0.078*****	-0.001	-0.002	**-0.009*****
Eq. Market Neutral	-0.004	**0.055*****	**-0.039*****	0.000	**0.038*****	**0.007*****	**-0.008*****	0.000
Multistrategy	-0.004	**0.097*****	**-0.111*****	-0.002	**0.105*****	0.003	-0.001	**-0.010*****
Alt. Credit	-0.003	**0.059*****	**0.041*****	**0.014*****	**0.129*****	**-0.006***	**0.010*****	**-0.009*****
Global Macro	-0.007	**0.217*****	**-0.038*****	**-0.042*****	**0.019****	**-0.009*****	**-0.024*****	**-0.022*****
Managed Futures	-0.001	-0.014	**-0.055*****	0.013	**0.052*****	**-0.025*****	**0.012***	**-0.013****
Event-Driven	-0.005	0.000	**-0.044*****	**0.052*****	**0.204*****	**0.013*****	**-0.006*****	**-0.005*****
Short Bias	**-0.015***	**-0.116*****	**0.223*****	**0.199*****	**0.176*****	0.003	0.006	0.000
Whole Sample	**-0.005*****	**0.253*****	**-0.018*****	**0.023*****	**0.055*****	**-0.005*****	**-0.004*****	**-0.012*****

Table 17: Test for Differences of Means using the Carhart model

	Alpha	Equity market	SMB	HML	Momentum
Long/Short Equity	-0.007	**0.225*****	**-0.141*****	**0.004**	**-0.055*****
Eq. Market Neutral	-0.004	**0.058*****	**-0.039*****	**-0.059*****	**-0.029*****
Multistrategy	-0.005	**0.103*****	**-0.164*****	-0.004	**-0.086*****
Alt. Credit	-0.003	**0.063*****	**-0.082*****	**-0.030*****	**-0.030*****
Global Macro	-0.008	**0.286*****	**-0.096*****	0.003	**-0.087*****
Managed Futures	-0.003	**0.058*****	**-0.044****	**-0.289*****	-0.024
Event-Driven	-0.005	**-0.024*****	**-0.079*****	**-0.046*****	**-0.024*****
Short Bias	-0.011	**-0.212*****	**0.296*****	**-0.250*****	**0.070*****
Whole Sample	**-0.006*****	**0.326*****	**-0.074*****	**-0.090*****	**-0.049*****

Tables 16 and 17 show the difference in the coefficients of the first-pass regression between alternative mutual fund strategies and their hedge fund indices counterparts. We see that although the difference in alpha is significant only on an aggregate level, this difference is still negative throughout all strategies. Moreover, most of the differences in factor loadings are significant in both the Fung-Hsieh and Carhart models. In particular we see that alternative mutual funds tend to have a higher equity market exposure (except for Short-bias funds), and a lower exposure to the option factors, as well as to momentum, pointing to a substantially different risk profile.

Table 18: Second-pass Regression using Alphas from the Carhart model

	Intercept	Past Performance	Size	Age	Expense Ratio	Flow	Manager Tenure	Min. Investment	Institutional	Retail	Bank Managed	Turnover	Load and other fees	Mgmt Fee
Long/Short Eq.	-0.00002	**-0.00104*** **	**-0.00218***	-0.00132	**-0.00001**	**0.00621*** **	-0.00006	-0.00012	-0.00001	-0.00002	**0.00000**	**-0.00010**	-0.00002	-0.00002
Eq. Mkt Neutral	0.00000	-0.00018	0.00074	**-0.00871*** **	0.00000	**0.00352***	**-0.00222***	0.00004	0.00000	0.00000	0.00000	-0.00005	0.00000	0.00001
Multistrategy	-0.00012	-0.00016	0.00050	**-0.00597*** **	-0.00017	**0.00209** **	**-0.00170** **	**-0.00035** **	-0.00012	-0.00011	-0.00001	**-0.00033*** **	**-0.00002***	-0.00009
Alt. Credit	0.00005	**-0.00139** **	**-0.00483** **	**-0.00382** **	0.00001	**0.00908*** **	**-0.00271***	**0.00028***	0.00005	0.00005	0.00001	**0.00059***	0.00004	0.00005
Global Macro	0.00006	0.00005	-0.00201	0.00007	0.00008	0.00103	**-0.00571** **	0.00035	0.00003	0.00006	0.00000	-0.00037	**0.00000**	**0.00007**
Managed Futures	-0.00032	-0.00004	-0.00055	0.00023	-0.00057	0.00326	0.00045	-0.00353	-0.00029	-0.00027	-0.00007	-0.00070	-0.00018	-0.00006
Event Driven	0.00001	-0.00022	-0.00342	-0.00057	0.00001	-0.00040	-0.00059	0.00007	0.00001	0.00001	0.00000	**0.00010** **	**0.00000***	0.00001
Short bias	**-0.00060*** **	**-0.00255***	0.00318	**-0.00556** **	**-0.00124** **	0.00120	**-0.00562** **	**-0.00595** **	**-0.00037***	**-0.00060*** **	0.00000	-0.00133	**-0.00043***	**-0.00065*** **
Whole Sample	**-0.00004** **	**-0.00058*** **	**-0.00155*** **	**-0.00300*** **	**-0.00007** **	**0.00438*** **	**-0.00187*** **	**-0.00034** **	**-0.00004** **	**-0.00004** **	-0.00001*	**-0.00014** **	**-0.00002** **	-0.00001

In this table we show the results of the second-pass regression when we use the Carhart model to estimate the alphas that we use as dependent variable.
The results confirm what we have found with our main model. Flow seems to have a positive impact, which is significant for the first four strategies, whereas age and Management Tenure have a negative and mostly significant impact. Once again we see that Past Performance comes with a negative coefficient in most cases and is sometimes significant, pointing to low persistence. Finally, Turnover is significant, but contrary to the main model, comes sometimes with a negative coefficient, giving a more blurred evidence.

Table 19: Second-pass Regression using Raw Returns

	Intercept	Past Performance	Size	Age	Expense Ratio	Flow	Manager Tenure	Min. Investment	Institutional	Retail	Bank Managed	Turnover	Load and other fees	Mgmt Fee
Long/Short Equity	0.00003	-0.00036	**0.00436***	-0.00193	0.00003	**-0.01528*** **	**0.00137**	0.00023	**0.00002***	0.00003	0.00000	**0.00041*** **	0.00001	0.00002
Eq. Market Neutral	-0.00001	-0.00004	-0.00093	-0.00263	-0.00002	0.00261	-0.00044	-0.00015	-0.00001	-0.00001	-0.00001	0.00016	-0.00001	0.00000
Multistrategy	0.00010	0.00017	-0.00189	0.00162	0.00012	**-0.00461***	**-0.00356** **	**0.00034***	0.00009	0.00009	0.00002	**0.00045*** **	**0.00001***	0.00007
Alt. Credit	0.00006	-0.00018	-0.00058	**-0.01111*** **	**0.00001***	-0.00947**	**-0.00798*** **	0.00018	0.00006	0.00006	0.00001	**0.00037*** **	0.00005	0.00006
Global Macro	**0.00005** **	-0.00035	-0.00258	-0.00255	0.00004	**-0.00956** **	0.00428	**0.00044***	**0.00005** **	0.00004	0.00000	**0.00058*** **	0.00001	0.00004
Managed Futures	0.00016	0.00001	-0.00211	0.00638	0.00017	-0.00427	0.00506	0.00196	0.00018	0.00010	0.00005	0.00020	0.00003	0.00005
Event-Driven	0.00002	-0.00172	0.00146	**-0.00738** **	0.00003	-0.01186	**-0.00791** **	0.00023	0.00002	0.00002	0.00000	**0.00019** **	0.00000	0.00002
Short Bias	-0.00083	**-0.01106***	-0.00020	0.03689	-0.00211	-0.03356	0.02267	-0.00866	-0.00024	-0.00083	0.00000	-0.00361	**-0.00111***	-0.00078
Whole Sample	**0.00005*** **	-0.00031	0.00044	-0.00161	0.00003	**-0.00925*** **	-0.00011	**0.00029** **	**0.00005*** **	**0.00004***	**0.00001** **	**0.00036*** **	0.00000	**0.00003***

In this table we show the results for the second-pass regression when we use raw returns as the dependent variable instead of alpha. That is to test the goodness of our two-pass procedure. We see that most of the previous findings are confirmed including the positive impact of Turnover, and the negative impact of Age and Manager Tenure. A puzzling effect shown by this specification is the significant negative impact of Flows on performance. We also find that, at least for certain strategies, the "Investor Monitoring" variables are significant, although the evidence is too weak to generalize any result.

Table 20: Second-pass Regression using the Fung-Hsieh model and Gross Returns

	Intercept	Past Performance	Size	Age	Expense Ratio	Flow	Manager Tenure	Min. Investment	Institutional	Retail	Bank Managed	Turnover	Load and other fees	Mgmt Fee
Long/Short Eq.	0.00001	-0.00135***	-0.00158	-0.00034	0.00004**	0.00233	-0.00147	0.00018	0.00001	0.00001	0.00000*	0.00044***	-0.00001	-0.00032
Eq. Mkt Neutral	0.00004	-0.00077	0.00049	-0.01040***	0.00009	0.00324*	-0.00316**	0.00042	0.00004	0.00004	0.00001	0.00007	0.00000	0.00003
Multistrategy	0.00001	-0.00006	0.00125*	-0.00357***	0.00002	0.00127*	-0.00103	0.00009	0.00001	0.00000	0.00001	0.00009	0.00001	0.00000
Alt. Credit	0.00006*	-0.00109**	-0.00335*	-0.00309***	0.00002*	0.00372**	-0.00179	0.00036**	0.00006*	0.00006	0.00001	0.00077***	0.00004	0.00005
Global Macro	0.00008**	0.00033	-0.00081	0.00029	0.00008*	0.00197	-0.00628*	0.00060**	0.00005*	0.00006*	0.00000	0.00037	0.00001**	0.00008**
Managed Futures	0.00009	-0.00009	0.00271	0.00263	0.00010	0.00393	0.00246	0.00122	0.00008	0.00009	0.00000	0.00010	0.00007	0.00007
Event Driven	0.00003	-0.00066*	-0.00348	-0.00142	0.00005	0.00124	-0.00097	0.00040	0.00003	0.00003	0.00000	0.00020***	0.00000*	0.00004
Short bias	-0.00029	-0.00137	0.00130	-0.01542**	-0.00047	0.00878	-0.01551**	-0.00433	-0.00037	-0.00029	0.00000	0.00044	-0.00024	-0.00038
Whole Sample	0.00003***	-0.00058***	-0.00105*	-0.00213***	0.00004***	0.00288***	-0.00137**	0.00028***	0.00002**	0.00003***	0.00000	0.00028***	0.00001	0.00003***

Table 21: Second-pass Regression using the Carhart model and Gross Returns

	Intercept	Past Performance	Size	Age	Expense Ratio	Flow	Manager Tenure	Min. Investment	Institutional	Retail	Bank Managed	Turnover	Load and other fees	Mgmt Fee
Long/Short Eq.	0.00000	-0.00041*	0.00125*	-0.00143**	0.00000	0.00027	-0.00030	0.00002	0.00000	0.00000	0.00000	0.00003	0.00000	0.00000
Eq. Mkt Neutral	0.00002	-0.00025	0.00077	-0.00903***	0.00005	0.00364**	-0.00221*	0.00023	0.00002	0.00002	0.00000	0.00008	0.00000	0.00002
Multistrategy	-0.00008	-0.00019	0.00072	-0.00623***	-0.00010	0.00199**	-0.00169**	-0.00019*	-0.00008	-0.00008	-0.00001	-0.00018*	-0.00001*	-0.00006
Alt. Credit	0.00006*	-0.00149**	0.00496**	-0.00420**	0.00002	0.00923***	-0.00297**	0.00033**	0.00006*	0.00006	0.00001	0.00072**	0.00004	0.00005
Global Macro	0.00008	-0.00004	-0.00199	-0.00001	0.00010	0.00195	-0.00645**	0.00057	0.00005	0.00007	0.00000	-0.00016	0.00000	0.00009
Managed Futures	-0.00024	-0.00005	-0.00058	0.00030	-0.00041	0.00329	0.00051	-0.00274	-0.00023	-0.00021	-0.00006	-0.00054	-0.00013	-0.00001
Event Driven	0.00002	-0.00027	-0.00328	-0.00064	0.00003	-0.00018	-0.00065	0.00021	0.00002	0.00002	0.00000	0.00014***	0.00000*	0.00002
Short bias	-0.00047***	-0.00255*	0.00326	-0.00537**	-0.00097**	0.00121	-0.00542**	-0.00483**	-0.00031*	-0.00047***	0.00000	-0.00095	-0.00035*	-0.00051**
Whole Sample	-0.00002	-0.00042***	-0.00033	-0.00307***	-0.00004	0.00245***	-0.00199***	-0.00014	-0.00002	-0.00001	0.00000	0.00000	-0.00001	0.00001

Table 20 shows the results of the second-pass regression when we use gross returns to run the Fung -Hsieh model to generate the alphas that we use as dependent variables, whereas **Table 21** shows the same results obtained when using gross returns and the Carhart model. In both cases we see that the key findings of our main specification are not altered by the use of these different models. Specifically, Age and Manager Tenure have a negative and often significant effect on alpha, whereas Flow and Turnover mainly have a positive impact.