Opening the black box: An analysis of equity hedge funds' performance

Istvan Nagy [a]

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Abstract

I analyze the performance of equity hedge fund managers by contrasting the returns explained by their 13F-reported holdings to their self-reported total returns. I find that a large majority of the funds fail to produce risk-adjusted performance over what is explained by their long positions when controlling for risk with conventional factor models conditioned on public information. A limited number of funds do, however, display especially good or especially bad performance. In the light of this result, I measure managers' stock picking ability in their long positions by conditioning their reported holding changes to publicly available information that is known to affect stock returns. I find that most managers do not display any significance of such a skill. Though, two small and equivalently-sized groups are particularly good, respectively particularly bad, at choosing stocks. These results are robust to various factor models and public information sets.

Keywords: Hedge Fund, Holdings, Stock Picking, Performance

JEL classification: G23, G29

[a] University of Neuchâtel, Pierre-à-Mazel 7, CH-2000 Neuchâtel, istvan.nagy@unine.ch, phone: +41(0)32 718 1372, fax: +41(0)32 718 14 01

1 Introduction

The hedge fund industry has, in the past, largely escaped the regulations that aim to protect individual investors by raising capital via private placement. Not surprisingly, the lack of transparency with regards to their characteristics and strategies is often advocated as the key variable that helps generating a positive risk adjusted return (alpha). Most hedge funds, in particular those specializing in equity, claim that releasing their holdings, even at low frequencies, could hurt their performance by revealing their strategy to the public and to competitors. Despite these concerns, since the 2008 financial turmoil, there has been a constant push toward greater transparency. Regardless of the holdings disclosure obligations already in place, and the strong resistance hedge funds have opposed,[2,3] both the European Community's Directive on Alternative Investment Managers and the SEC's Dodd-Frank Wall Street Reform and Consumer Protection Act, are currently being implemented.[4] These rapidly changing regulations underline the need for a better understanding of hedge funds' sources of performance and the information content of their disclosures. Indeed, if the information disclosed allows explaining a large fraction of performance by divulgating their investment strategies, the regulation could end up going against the interest of the investors whom it tries to protect. On the other hand, if these strategies are relatively naïve, investors could be paying fees for strategies they could have easily identified and implemented themselves.

Even though recent researches have established a link between secrecy and hedge fund performance,[5] as well as given an understanding of managers' skill inferred from their portfolio holdings,[6] the literature has yet paid little attention to what fraction of hedge fund

[2]See Agarwal, Fos and Jiang (2010, p.17).
[3]See for instance Sam Jones, *Hedge funds lobby SEC over secrecy rule,* Financial Times, 01/15/2012.
[4]See for instance Baptiste Aboulian, *MEP bites back at hedge fund lobby,* Financial Times, 04/22/2012.
[5]See for instance Agarwal, Jiang, Tang and Yang (2011) and Aragon, Hertzel and Shi (2011).
[6]See Griffin and Xu (2009).

performance is explained by their disclosed holdings. This paper answers this question and analyzes the performance generating ability of hedge fund managers in the light of the information contained in their mandatorily reported holdings.

Hedge fund disclosures may contain information that could allow opportunist followers to replicate a fund's investment strategy at a fraction of the cost, thereby allowing them to make short profits while arbitraging away the extra return of the strategy. Hasanhodzic and Lo (2007) show that the replication of hedge funds returns is feasible at a cost that does not exceed performance fees for some families of hedge funds. In fact Kat and Palaro (2006a, 2006b) confirm that, even voluntary reporting, such as being listed in a database, already facilitates hedge fund replication. Moreover, the fact that some funds require secrecy for part of their holdings[7] seems to indicate that at least some funds are worried about the information content of their disclosures; see for instance Agarwal et al. (2011) or Aragon et al. (2011). Though, as documented by Bacmann, Held, Jeanneret and Scholz (2008) among others, there are a number of hurdles to hedge fund replication which prevent the creation of exact clones. Additionally, the information disclosures being non-continuous and limited to certain types of positions, the difficulty in exactly matching hedge fund strategies seems to play in their favor.

On this ground, I argue that skilled hedge fund managers should be able to go beyond what their holding disclosures tell about their strategies and add value with interim trading and non-disclosed positions. In addition, given the fees they charge, they should be expected to display stock picking skills, even in their choice of long holdings. In this paper, I use two main methodologies to assess whether hedge fund managers fulfill these expectations. First, with the help of a number of factor models (some of them conditioned on public information), I measure the risk-adjusted performance equity focused hedge funds generate for their clients, in *total*, with their *visible* large long-only positions, and over these long-only positions

[7]Under specific circumstances holdings disclosures to the SEC can be delayed up to one year.

through *invisible* trading activity, short positions, and smaller positions. Using a dataset which combines monthly voluntarily disclosed returns with mandatorily reported quarterly holdings for 222 alternative investment firms (AIFs, hereafter), I show that most AIFs are unable to outperform their large long positions even though they engage in trading activities besides these positions. Concretely, while approximately one quarter of the AIFs is able to outperform in terms of *total* performance, only about three percent, manage to outperform their *visible* large long-only positions. I find that this performance has a concave relation with respect to size, thereby confirming previous studies. Interestingly, most AIFs appear to be heavily and positively exposed to market returns thereby not deserving the hedging component of "Equity Hedge". Somewhat reassuringly though, the proportion of managers underperforming in terms of total returns, and the proportion underperforming their long only positions stay limited to 3.13% and 6.25%. I also rule away the luck-only hypothesis. However, it remains that the vast majority of AIFs do not deliver any performance over their long holdings. Second, given the widespread inability to outperform *visible* long positions, I specifically measure the stock picking ability of equity hedge fund managers in the choice of these long positions by using a conditional weight-based measure. In particular, I condition the managers' holding changes on three different sets of public information and measure whether their choices are the result of superior stock picking skills or a mere inference from publicly available information. Analyzing returns and holdings changes obtained from the quarterly holdings of the AIFs, I find that most investment managers, about 80%, do not possess any stock picking skill. Though, there is a roughly similar proportion (about one tenth) of significantly skilled and significantly unskilled stock pickers. Also, consistently with Teo and Chung (2011), who show that hedge funds also influence analysts' recommendations and not only conversely, I find that conditioning AIFs' holdings on analyst data both influences the proportion of skilled and of unskilled stock pickers.

This paper contributes to the existing literature in three ways. First, by identifying an inability of most hedge funds to outperform their declared long positions, I rejoin the stream of research that advocates that most hedge fund performance does not stem from intricate risk exposures but only from secrecy about their long holdings, at least when it comes to the funds specialized in equity. Considering the current, regulatory-changing environment, this result seems to be worth considering by regulators when implementing new measures.

Second, I rejoin the existing literature by linking hedge fund performance with an easily identifiable fund-level characteristic. While I do not confirm all documented relations, there is a clear concave relation with respect to size. This underlines the importance of incorporating non-return information when making investment decisions.

Third, I am able to show that hedge funds' investment choices can most often be explained by public information and are not the result of any stock picking skill whatsoever. Though a small proportion of them appear to possess this kind of skill along with a similar proportion that have negative skill. In this vein, I rejoin Griffin and Xu (2009) who find limited evidence of superior skills as compared to mutual funds. I, however, depart from their results, since I find evidence of differential ability between hedge fund managers. Moreover, my results also contrast with the work of Ferson and Khang (2002), since the average level of stock picking ability I identify in hedge funds appears to be higher than what they find for mutual funds. When added to my previous finding, it appears, however, that hedge fund investors should be very careful when deciding with whom to invest since they might well end up paying important fees for no skill at all.

The rest of the paper is organized as follows. Section 2 summarizes the institutional situation faced by hedge funds. I discuss the choice of performance models in Section 3. The data and sample creation are detailed Section 4. Section 5 describes the estimations and presents my results. Section 6 concludes.

2 Institutional Setting

Until recently hedge fund regulation was loose with respect to what other institutional investors were facing. In the United States, however, hedge funds have long been constrained by some reporting requirements as stated in the Securities Exchange Act of 1934.[8] The basic reporting principle is stated in Section 13(f)(1): *Every institutional investment manager (…) which exercises investment discretion with respect to accounts holding equity securities (…) having an aggregate fair market value on the last trading day in any of the preceding twelve months of at least $100,000,000 (…) shall file reports with the Commission (…).* When considered in its integrality, the implication of Section 13(f) is that the SEC requires all institutional investment managers with at least USD 100 million under management to quarterly report their large long positions (over 200,000 USD or 10,000 shares) with a maximum delay of 45 days in so-called 13F forms. These filings must, among others, contain the CUSIP and the number of shares held in all the positions satisfying the above-mentioned constraints. Given the fact that institutional investors are generally long holders of large positions, the information contained in these forms can, up to some extent, allow linking the institutions' returns with the securities they hold. In a near future, the increased disclosure requirement coming with the implementation of the European Community's Directive on Alternative Investment Managers and the SEC's Dodd-Frank Wall Street Reform and

[8] http://www.sec.gov/about/laws/sea34.pdf

Consumer Protection Act should allow for more understanding of hedge funds' exposures and their sources of returns.[9]

Even though all institutional investors are subject to the 13F rule, in the context of hedge funds there is one particular family of funds that is more concerned since its members primarily invest in equity: equity hedge funds (EHFs, hereafter).[10] Of course, these funds do not only buy-and-hold large positions –they also hold smaller positions, short positions and exercise trading activities– but the 13F filings can at least describe one part of these funds' returns. In addition to this information, for the hedge funds which decide to voluntarily report their returns to publicly available databases, it is possible to obtain the total returns. Combining these returns with the 13F information permits estimating to what extent EHFs rely on their large long positions to generate performance and what comes from their hidden remaining positions and intra-quarter trading activity.

Hedge funds do, however, not directly report in the 13F forms, AIFs do. Concretely, a hedge fund is an investment vehicle detained by an AIF. In some cases the AIF and the fund can be a single and same entity, but it is not always the case. AIFs often possess and exercise management over several hedge funds (in the sample used in this study, AIFs consists of about two funds on average). SEC 13F forms are filled at the AIF level so that only the aggregate information about the holdings of all hedge funds managed by the firm is available, without any possibility to trace it back to a particular fund (unless the AIF only consists of a single fund). Fortunately, when hedge funds voluntarily report their returns to databases, they

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[9]Under the new SEC rules, investment firm with more than USD 150 million under management will have to fill the PF form. This Form requires them to report their AUM, leverage, the fund's five largest investors, gross and net performance for the fiscal year, the percentage of assets invested in certain strategies, the five counterparties to which they have the greatest credit exposures, and the percentage of transactions operated in regulated and OTC markets, among others. These forms shall however only be disseminated to governmental agencies and not to the public. The European Directive has similar requirements but applies them to all alternative investment managers marketing their product in the EU, regardless of their size. For more details, the rules US and European rules are available at http://www.sec.gov/rules/final/2011/ia-3308-formpf.pdf and at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2011:174:0001:0073:EN:PDF

[10]These funds are often also called Long/Short Equity.

also report the information about their parent AIF, thereby allowing the construction of a sample for the realization of the present study as I describe it in Section 4.

3 Performance Measurement for Equity Hedge Funds

Hedge funds performance measurement reposes on the mutual funds literature. I here first detail the similarities between these two investment fund families. Then, I build upon these similarities and propose a set of performance measurements models.

3.1 From Mutual Funds to Equity Hedge Funds

Because of a soft regulation, hedge funds are often advocated as very complicated investment vehicles that employ advanced investment strategies not applicable by other types of investment funds, but in fact they are not all that different from mutual funds. Indeed, while it is true that *in theory* hedge funds have almost unlimited latitude in their investment choices, *in practice* they do not. There are in fact a number of constraints that hedge funds have to comply with in order to be profitable and attract potential investors, and these constraints greatly limit the scope of their investment possibilities. For instance, hedge funds must follow their agreed-upon strategy since they are closely monitored by investors; see for instance Baquero and Verbeek (2009). Also, they need investment opportunities that are large enough, liquid enough, and predictable enough, to allow for a strategy to be implemented. Hence, while some funds invest in art[11] or bet on sport events,[12] and may be successful in doing so, these strategies cannot be implemented on a large scale by a large number of funds.

Given these constraints, most hedge funds end up being invested both in traditional financial assets and in *alternative* investments; see for instance Agarwal and Naik (2000) or Fung and Hsieh (2004b). Focusing on EHFs, funds that are specialized in equity, this

[11]See for instance Steve Johnson, *Hedge funds: Art fund draws up new model to adorn diversified portfolios,* Financial Times, 06/11/2007.

[12]See for instance Nathaniel Popper, *New hedge funds bet on sports, literally,* Los Angeles Times, 04/17/2010.

translates into portfolio returns that can be divided into two parts: a first, *visible* part that comes from long and large positions in securities that are observable from the 13F filings, and a second, *invisible* part that comes from small positions, short positions, and intra-quarter trading activity. The combination of these two parts forms the *total* performance of the fund. EHFs are in this sense, at least partially, mutual funds.

3.2 Choice of Performance Models

In view of the above, it is clear that the *visible* returns will behave differently from the *invisible* ones (while *total* performance will be a mixture between the two). In this vein, I first consider a number of typical mutual fund performance models to measure the performance of the *visible* part, namely the CAPM model of Jensen (1968), the model of Fama and French (1992), and the one of Carhart (1997). Even though these models have sometimes been shown to lack explicative power in certain contexts, they remain the pillars of the performance measurement literature and have the advantage of proposing readily replicable and easily interpretable factors.

Second, for the *invisible* and the *total* part, I follow Fung and Hsieh (2004a) who show that EHFs are mainly exposed to two factors: market and size spread. Based on this work I exclude the Fung and Hsieh (2001, 2002a, 2004b) seven factor model generally used in hedge fund performance measurements since it is better suited to advanced strategies than to EHFs. Following the work of Goetzmann, Ingersoll and Ivković (2000) who propose a factor that has option-like features for measuring daily timing, I also consider a version of the Carhart (1997) model augmented with this factor.

In a last step, since a number of papers in the hedge fund literature document dynamic exposures (see e.g. Patton and Ramadorai (2010), or Criton and Scaillet (2011)), I follow

Ferson and Harvey (1999)[13] and consider conditional versions of the models presented above. Indeed, these authors show that conditioning the models on publicly available information allows for dynamic exposures and better explicative power. However, given the short time series of hedge fund returns and because of the number of factors these models involve,[14] I do not consider any conditional version of the augmented Carhart (1997) since, under this specification, the number of funds analyzable would go down by almost thirty percent thus strongly biasing the sample toward surviving funds (funds with long-enough time series).

3.2.1 Choice of Stock Picking Measure

Given that the long portfolio holdings of my AIFs are know from the 13F filings, I can go beyond the return-based models introduced above and directly measure managers' stock picking ability from the stocks they hold. To this goal, a commonly used model is the one of Daniel, Grinblatt, Titman and Wermers (1997); see also Wermers (2000). This model however suffers from biases because the actual holdings are not observable in the months between reporting dates; see for instance Grinblatt and Titman (1993). Ferson and Khang (2002) propose an alternative model that conditions the performance measure on publicly available information to circumvent the interim trading bias mentioned above. Concretely, they introduce what they call the conditional weight-based measure (CWM hereafter), which in fact is a measure of the covariance between the portfolio weight changes and the subsequent returns conditioned on publicly available information. I detail these models and the corresponding variables in the coming Section

[13] Also see Ferson and Schadt (1996) or Ferson and Warther (1996).

[14] The number of factors in the conditional models = (original number of factors + 1) x (number of conditioning variables).

4 Data and Detailed Description of the Models

This section gives a detailed view of the data and models used in my analysis. First, I detail the return sets and holdings I use to estimate the performance of AIFs, along with the factors and the corresponding models introduced above. Second, I present the sample construction and the data sources. Third, I propose some descriptive statistics.

4.1 Returns, Holdings, Factors, and Models

4.1.1 AIFs' Returns and Holdings

For measuring the performance of AIFs, I use three sets of returns. Specifically, I first compute realized AIF monthly returns as the AUM-weighted average of each of their component hedge fund reported returns. This set of returns represents the *total* performance of AIFs, including all positions and trading activities. Second, I calculate the time series of monthly returns that an investor could obtain by mimicking the 13F holdings (rebalanced quarterly). Given the 13F reporting constraints detailed in the previous section, this set represents the *visible* returns from long and large positions only. Finally, I obtain the third set of *invisible* returns as the difference between the two previous ones. This final set measures the performance of holdings that do not appear on the 13F forms (small positions, short positions, and the trading activity –buy/sell order flow during the quarter–). To assess the stock picking ability of hedge fund managers, I use the same 13F filings as above. These filings allow me to combine the monthly returns of a portfolio rebalanced quarterly to the corresponding changes in portfolio weights. The stock picking ability is then measured on the long large positions of AIFs.

4.1.2 Models and Corresponding Factors

The models of Jensen (1968), Fama and French (1992), and Carhart (1997) I use to analyze the performance from *visible* returns are in fact extensions of one another, thus they can be written as follows:

$$(1)\ \underbrace{\underbrace{\underbrace{R_{i,t} = \alpha_i + \beta_{1,i}\left(R_{m,t} - R_{f,t}\right)}_{\text{Jensen (1968)}} + \beta_{2,i}SMB_t + \beta_{3,i}HML_t}_{\text{Fama and French (1992)}} + \beta_{4,i}WML_t}_{\text{Carhart (1997)}},$$

where α is the performance, $R_{m,t} - R_{f,t}$ is the market excess return, SMB_t equals small minus big, HML_t equals high minus low, WML_t is the 12x12 momentum.

The Fung and Hsieh (2004a) 2 factor model used to analyze *total* and *invisible* performance writes:

$$(2)\ R_{i,t} = \alpha_i + \beta_{1,i}SP500_t + \beta_{2,i}SizeSpread_t,$$

where $SP500_t$ is the monthly Standard & Poor's 500 return, and $SizeSpread_t$ is the monthly return on the portfolio long in the Russell 2000 and short on Standard & Poor's 500 return.

In the augmented model, the Goetzmann et al. (2000) timing factor, TF, simply comes as a 5th factor in the Carhart (1997) model presented above and computes as follows:

$$(3)\ TF_{m,t} = \left[\left(\prod_{\tau\in(\text{month } t)}^{t} \max\left\{1 + R_{m,\tau}, 1 + R_{f,\tau}\right\}\right) - 1\right] - R_{m,t},$$

where τ is a trading day belonging to month *t*, $R_{m,\tau}$ is the market return, and $R_{f,\tau}$ is the risk free rate. In this context, TF is equal to the value added by perfect daily market timing, per dollar of fund assets.

The Ferson and Harvey (1999) conditional models can be written in a general form as:

$$(4)\ R_{i,t} = \left(1 + \mathbf{z}_t\right)\alpha_i + \sum_{j=1}^{n}\left(F_{j,t} + F_{j,t}\mathbf{z}_t\right)\beta_{i,j},$$

where $F_{j,t}$ is the j^{th} factor of the base model under consideration and $\mathbf{z}_t = E(\mathbf{Z}_t) - \mathbf{Z}_t$ where $\mathbf{Z_t} = \{DY_t, CS_t, TS_t, TB_t\}$ is an information set where *DY* is the dividend yield on the S&P 500, *CS* is the credit spread defined as the month end-to-month end change in the difference between Moody's Baa yield and the Federal Reserve's ten year constant maturity yield, *TS* is the term spread (difference between the ten-year Treasury bond yield and the three-month Treasury Bill yield), and *TB* is the three-month Treasury bill.[15]

Finally, the Ferson and Khang (2002) conditional measure weight-based measure of stock picking writes as:

$$(5)\ CWM_{P,t} = E\left[\sum_{j=1}^{N_P}\left(w_{j,t} - w_{b,j,t,k}\right)\left(r_{j,t+1} - E\left(r_{j,t+1}|Z_t\right)\right)|Z_t\right],$$

where $CWM_{P,t}$ is the conditional weight-based measure, $N_{P,t}$ is the number of position in portfolio P at the time t, $w_{j,t}$ is the weight invested in stock *j* at t, $r_{j,t+1}$ is the observed return for stock j in the month beginning at t, $E\left(r_{j,t+1}|Z_t\right) = \mathbf{b_j Z_t}$ is the linear model that explains individual asset returns based on $\mathbf{Z_t}$, the information set, and $w_{b,j,t,k}$ is the benchmark weight for stock *j* at *t*. For computational details, please refer to Appendix A. To check whether the stock picking ability (if any) is the result of trading based on public information, I start with the standard information set from the asset pricing literature, $\mathbf{Z_t} = \{DY_t, CS_t, TS_t, TB_t\}$, previously described. In a second step, I sequentially add information that is publicly available and is known to affect stock prices. For a given firm, I first add the following corporate level variables: change in rating (if the firm has issued bonds), stock repurchase, SEO, and M&A (I discriminate between targets and acquirers). Finally, I also add changes in analysts' recommendations (computed over the last month) and earnings surprises. This allows isolating specific contributions of public information to the AIFs' performance. If the

[15] $E\left(\mathbf{Z}_t\right)$ is computed over *t-25 to t-1*, on a moving window basis.

manager has no inference beyond what can be inferred from publicly available information than the CWM is zero, otherwise it is positive if the inference was good and negative if it was bad.

4.2 Sample Construction and Data Sources

The nature of my estimations implies data gathering from several data sources. Mandatory reported 13F hedge fund holdings are from EDGAR. Hedge funds' voluntarily disclosed returns and characteristics are from TASS. Corporate events (SEO, repurchases, and M&A) are from SDC Platinum. Analysts' recommendations and earnings surprises are from I/B/E/S. The S&P 500 returns and dividend yields, as well as the returns on the Russell 2000 are obtained from Datastream. Stock returns, prices, and ratings (Standard & Poor's) are from CRSP. The yield on Moody's Baa, on the 10-Treasury, and on the three-month Treasury Bill are from the Federal Reserve's website.[16] The Carhart (1997) factors are from Kenneth French's website.[17] The Goetzmann et al. (2000) timing factor is calculated with the data presented above.

The sample period goes from January 1994 to the June 2011.[18] Table 1 details the number of funds and AIFs remaining in the sample after each step of the selection process described hereafter.

[INSERT TABLE 1 ABOUT HERE]

I start with the AIFs (available from TASS) that are only composed of EHFs, which report in USD,[19] and which provided their returns at least once in my date range, this represents 1,110 AIFs and 1,685 individual hedge funds. Importantly, not all of these AIFs report their

[16] http://www.federalreserve.gov/
[17] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
[18] TASS only came into operation in the mid 1990's making earlier data bias prone; see for instance Fung and Hsieh (2002b). Also, I/B/E/S and SDC Platinum are partially incomplete or imprecise prior to 1994; see for instance DellaVigna and Pollet (2009).
[19] This follows most existing literatures and allows to eliminate duplicate share classes in foreign currencies.

holdings to the SEC because they do not all meet the reporting requirements previously described. I thus download the list of all institutional investment managers that filled a 13F filing at least once during the sample period. These investment managers are not only hedge funds but can be any type of investment manager. I collect their names and hand-match them with my list of AIFs to obtain a sample of 268 investment firms. From these, I remove 5 AIFs that are large financial corporations that not only manage hedge funds, but also mutual funds and other investment vehicles. This intermediate sample consists of 263 AIFs.

However, since I need to compare TASS returns with 13F returns, I further remove the AIFs which manage funds that do not report their AUM (12 AIFs), thereby preventing me from computing their AUM-weighted share in the AIF's return.[20] I also remove the ones that do not have matching observation periods between 13F filings and TASS data (27 AIFs). Finally, I remove the AIFs whose funds only report quarterly returns to TASS (2 AIFs). I end up with a final sample of 222 AIFs and 493 individual hedge funds. These AIFs jointly represent about USD 345 billion of assets under management.

[INSERT TABLE 2 ABOUT HERE]

Table 2 reports the distribution of these 222 AIFs across the 17.5 years of my study. As we see, there is on average about 75 AIFs observed by year, while about 12 enter and 10 exit the sample each year. The peak number of AIFs is reached in 2005 (110) but remains high from 2001 to 2008. As one can expect, the highest number of exists happened in 2008 (29), with almost three times the average. The average attrition rate of 11.37 % is in line with previous studies; see for instance Liang (2000). Importantly this does not mean that more than one tenth of the AIFs go bankrupt ever year, but they leave the sample. This can happen for a number of reasons including bankruptcy, but also because the AIFs stopped reporting

[20]Some funds do not report their AUM on a monthly basis, but less frequently. Following Heaney (2008), for these funds I fill the gaps with a linear interpolation of the AUM between two reporting dates.

(voluntarily) to TASS, because it does not have anymore large enough long positions to report in 13F forms, because the AIF got smaller than the USD 100 million threshold, or because of a merger, among others.

I compute the AIFs' TASS-reported returns as the monthly AUM-weighted average of all the funds they manage. I also compute their monthly returns from their quarterly 13F stock holdings. Specifically, I assume the quantities reported for each stock (identified by its CUSIP) are held for one quarter starting from the reporting date[21] and calculate the portfolio return using stock prices from CRSP. I use unadjusted prices, taking into account the eventual splits (or reverse splits) and dividends. For a small subset of stocks which consist of over-the-counter securities, there is no data available from CRSP and I only have the quarterly prices reported in the 13F filings. I gauge the impact of these stocks on AIFs' returns by comparing the returns without these OTC positions to the returns obtained by including a linear interpolation of their quarterly prices and find almost no impact so that I do not consider these positions in the AIFs' final returns computation.

Finally, I construct the factors composing the public information sets $\mathbf{Z}_{j,t}$ as follows. Corporate events (SEO, repurchases, M&A target, and M&A acquirer) are dummy variables coded as one in the month where one of these events happened to the company under consideration and zero otherwise. Alphabetical ratings from Standard & Poor's are recoded numerically from 1 to 22 (22 being the best, AAA). If there is no rating for a given month the last available information is used and the rating change is computed as rating in *t* minus rating in *t-1*. Analyst recommendations, originally coded from 1 (strong buy) to 5 (strong sell), are recoded inversely to allow for easier interpretation (5=strong buy to 1=strong sell). If a

[21]One could argue that the stocks are not held from the reporting date on, but from the day after the previous reporting until the current reporting day in order to preserve secrecy. I mitigate this assumption by computing the correlation of returns between TASS and 13F under the two assumptions and testing whether they are significantly different from each other by converting them with Fisher's z-transformation and comparing the transformed values with the standard normal procedure (following Myers and Sirois (2004)). I find that the correlation with the first assumption is significantly higher than with the second, thereby mitigating this issue.

recommendation is missing, the last available observation is used and the recommendation change is computed as recommendation in *t* minus recommendation in *t-1*. At last, earnings surprises are coded as 1, 0, or -1 depending on the sign of the difference between actual EPS and average expected EPS for the months in which both actual and expected EPS are disclosed. In months with no disclosures, the variable takes a value of zero.

The sample suffers from a clear bias in terms of size, since funds only have to report to the SEC if they have more than USD 100 million under management *on average* during the preceding twelve months. The sample obtained is, however, free of survivorship bias, since all funds that have been active during the sample period are considered in the study.

4.3 Summary Statistics

Table 3 proposes summary statistics about the final sample used in this study and also contrasts it with the larger but not employable intermediate sample. The final sample consists of 14,710 AIF-month observations. The average AIF reports security holdings for a value of USD 1.553 billion. This number is, however driven by large big funds since the median fund only reports USD 149 million. The biggest and the smallest funds respectively detain more than USD 30 billion and less than USD 117 thousand in long security holdings.[22] This last number illustrates the legal requirements which states that AIFs have to report their holdings if, over the last twelve months, they exceeded USD 100 million *on average*. If we consider the returns, we first observe that the correlation between SEC 13F and TASS returns is at a level of 0.63,[23] indicating that the returns obtained from a quarterly rebalancing of AIFs' portfolios do not entirely explain the returns reported in TASS. In fact, the returns reported in TASS are higher on average (0.83% per month vs. 0.45%) thus showing that some AIFs are

[22]These numbers are calculated based on the last available SEC 13F filing for each reporting AIF, so that the reporting dates may not be the same for all of them, but they all appear only once in the computations.

[23]This number is computed as Pearson's correlation coefficient between the aggregated time series of returns of the 222 equity hedge AIFs from 13F and from TASS.

able to outperform their long positions, at least on a raw return basis. Interestingly, the median is higher in 13F returns (0.93% vs. 0.78%) which suggests that the higher return average in TASS is driven by a limited number of well performing AIFs as it is confirmed by the positive skewness (25.42). The kurtosis is also a little higher in TASS (0.80) than in the 13F (0.13) suggesting more peaked returns.

[INSERT TABLE 3 ABOUT HERE]

Contrasting the above with the intermediate sample we obviously see a large difference in the number AIF-month observations (10,718) since a large part of the sample reduction comes from unmatched observation dates. Considering the holdings and the returns information, the samples do, however, appear relatively similar. Indeed, the average holdings are different by a non significant (n. s.) USD 143 million, while the median is almost the same and the standard deviation changes by USD 293 million (relative change of about 5%). The minimum and maximum are the same, showing that both samples contain the same most extreme funds. The returns show a similar picture too. The mean return is different by a monthly (n. s.) 0.07%. The median is identical while the standard deviation changes by 0.04% (relative change of about 0.5%). The kurtosis changes very little, but the skewness is about 3 points smaller, which indicates a more centered distribution of the returns. Finally, the most extreme (minimum and maximum) returns change by about 12% each. All in all, this final sample looks representative of the intermediate sample.[24]

[INSERT TABLE 4 ABOUT HERE]

Table 4 reports further information about the AIF-month observations. The median AIF has 54 months of observations (66.26 for the average) but the variation is high since some AIFs only have 1 month of data while the highest number of observations is 210. The

[24]Importantly, the figures reported here concern the basic sample as obtained from the process explained above. The actual observations used in the analysis of part 2 may diverge slightly depending on the number of lags *k* used, the size of the *betas* estimation window for the *CWM*, or simply the number of factors used.

standard deviation is therefore a relatively high 50.81 months. The average stock holding period per AIF[25] ranges from a minimum of 4.7 months to a maximum of 52.52 with an average of 17.26 and a median of 15.22, so that, on average, an AIF tends to hold its positions for about one year and a half. The average number of stocks in portfolio is also varied. While the less diversified AIF holds an average of 2.21 stocks the most diversified one holds 1,166.88. The average and median AIFs respectively hold about 110 and 67 stocks in their portfolio.

[INSERT TABLE 5 ABOUT HERE]

Finally, Table 5 gives some stylized facts about the components of the information sets $\mathbf{Z}_{j,t}$ for the sample period. Information about the dividend yield, credit spread, term spread and Treasury bill would not be informative and is thus not reported in the table. Panel A shows information about the number of corporate and analyst related events across all stocks held in AIFs' portfolios. The variation between stocks is high. While most stocks do not encounter any rating change, SEO, or M&A event, some of them endure dozens. The picture is similar for the analyst related information variables. Minima are always zero while maxima can reach important numbers. This translates the fact that AIFs do not only invest in large, well-followed stocks, but are diversified over the entire stock universe. Panel B reports the distribution of these events across all years of the sample period. Although there are variations across years, there is no extreme year in which an event is dramatically numerous. It remains, however, that, with the exception of rating changes, the events tend to be more frequent in the earlier years of the sample. Expectedly, the year 2011 represents to smallest proportion in most events since our sample ends in June. Overall, the distribution of events appears to be relatively homogenous.

[25] The average number of stocks held by each AIF is computed as the average of the number of stocks they have in portfolio across all observation dates.

5 AIFs' Performance

This section reports my results about AIFs' performance. I first analyze their return-based performance. Second I investigate whether they truly exhibit skill. Third, I try to link their performance with firm-level characteristics. Finally, I analyze their stock picking skill based on their stock holdings.

5.1 AIFs' Return Analysis

5.1.1 Total Performance

I start by analyzing AIFs' performance in the light of their returns reported to TASS. These returns represent the *total* performance of the AIF including all positions and trading activities. I estimate the models previously presented, namely the unconditional and conditional versions of the Fung and Hsieh (2004a) 2 factor model and the augmented Carhart (1997) model, on each AIF's track record separately and collect the exposure to all factors as well as the remaining part, *alpha*. Table 6 reports the results.

[INSERT TABLE 6 ABOUT HERE]

Panel A presents the results for the unconditional and the conditional versions of the Fung and Hsieh (2004a) 2 factor model. For each factor, it reports the mean exposure across all AIFs, as well as the proportion of AIFs that have a significantly positive (or negative) exposure to that factor at the 5% level. Similarly, it also reports the proportion of AIFs with a significantly positive or negative alpha and its mean value. The exposures to the conditional factors are not reported since their interpretation makes limited sense; their use is simply indicated by "NO" or "YES". Notably, the results cannot be reported for all the 222 AIFs composing the sample, because some of them have time-series that are two short to estimate the model. The number of funds considered is indicated in the table.

Starting with the unconditional model we see that a little more than one fourth (26.51%) of the AIFs are able to outperform the model significantly while only 4.18% underperform significantly. The average monthly outperformance establishes at 0.30% per month, or about 3.7% per year. Interestingly, we see that a large proportion of AIFs (67.44%) are significantly long on the market while a small percentage (3.26%) is significantly short. This contrasts with the "Equity Hedge" denomination of this category of hedge funds, which appear to be more equity than hedge. The size spread also plays a role in the returns of 43.73% of the AIFs (42.80% long, 0.93% short). These figures confirm the findings of Fung and Hsieh (2004a) that EHFs are heavily loaded on these two factors.

If we switch to the conditional model the proportion of significantly outperforming AIFs reduces to 23.96% and the proportion of significantly underperforming ones goes down to 3.13%. This indicates that inference from publicly available information can explain, at least part of, some AIFs' returns. This is confirmed by the exposures on both S&P 500 and size spread. The proportion of AIFs significantly long on the market reduces to 51.56% while the exposure on size spread goes down to 37.50%. All in all, it appears that AIFs are using public information in their performance generating process since conditioning the model on these information variables helps better explaining AIFs' returns, as it is also confirmed by the higher adjusted R^2 (0.48 vs. 0.36) and the F-statistic (112.83 vs. 19.57).

Panel B reports the results for the augmented version of the Carhart (1997) model. As previously mentioned, I only report the unconditional version since conditioning the model amputates the sample from too many funds. We see that 23.30% of the AIFs are able to significantly outperform the model –while only about 3% underperform it significantly– by an average of 0.62% per month or 7.7% per annum. Expectedly from what we saw in Panel A, a large proportion of AIFs is significantly long on the market (64.56%) but only a small proportion is short (2.43%). Looking at the exposures on the other factors, the model appears to be better suited than the one of the Fung and Hsieh (2004a). Indeed, many AIFs (between about 30 to 40%) have significant exposures the SMB, HML, and WML. The timing factor, play a smaller role since about 5% of the AIFs show a significantly positive timing ability while approximately 13% have negative time skills. Nevertheless when we compare this model to the conditional Fung and Hsieh (2004a) we find a similar adjusted R^2 but a lower F-statistic. This rejoins the findings of Ferson and Harvey (1999) who show that mechanical trading based on public information is largely explicative of SMB and HML.

All in all, the conditional version of the augmented Fung and Hsieh (2004a) 2 factor model seems to be the most adequate to explain EHFs' returns because of its power and simplicity. Under this specification a little more than one fifth of the AIFs are able to outperform while only 3 percent underperform. Strikingly, this leaves about three in four AIFs which have neutral *total* performance and thus do not add any significant value to investors' portfolio.

5.1.2 Performance from Visible Positions

I now concentrate on the *visible* performance, so the one obtained from the returns computed from the holdings reported in AIFs' 13F filings. These filings only contain large long positions of AIFs' portfolio and therefore the returns computed thereof are not influenced by smaller positions, short positions or intra-quarter trading activity. Results are reported in Table 7.

[INSERT TABLE 7 ABOUT HERE]

Panel A shows the results for unconditional and the conditional versions of the Jensen (1968) CAPM model, while panel B shows the results for the two versions of the Carhart (1997) model.[26] Starting with the unconditional CAPM, we see that a simple model as this

[26] I do not report the results for the Fama and French (1992) model because it has a lower explicative power than the Carhart (1997).

one already has a high explanatory power with an adjusted R^2 of 0.64. In this context, 1.38% of the funds outperform the market while 7.37% underperform it significantly. Expectedly from long only positions, 98.61% of the funds are significantly long on the market while 0% is short. Switching to the conditional CAPM, the adjusted R^2 increases slightly to 0.66, this suggests that public information plays a role in the long investment choices of AIFs. This is verified by the changed exposures on the market, 76.96% are long, and 0.98% are short. The proportion of positive alpha AIFs establishes at 7.53% and the proportion of negative ones at 4.90%. This means, that public information is explicative of market returns and that at least some AIFs are able to exploit this information at their advantage.

Moving to Panel B, I directly start with the conditional version of the Carhart (1997) model since it has a better explanatory power than the unconditional one. Under this specification, 2.84% of the AIFs are able to provide a significantly positive alpha while 6.25% deliver a significantly negative one. The mean alpha is 0.43% per month or 5.3% per annum. A large majority of investment firms (88.06%) are significantly long on the market while none is short. The large number of AIFs exposed to the SMB, HML, and WML factors show that these traditional investment strategies still have the favor of fund managers in the choice of their long positions. If we compare these exposures the ones of the unconditional model we have again a confirmation that public information is explicative of the model's factors since for all factors the proportion of significantly exposed funds is lower in the conditional model.

All things considered, the conditional Carhart (1997) model appears to be well suited to explain the *visible* proportion of AIFs' returns. While most AIFs (about 91%) do not add value with their choice of large long holdings, about three percent appears to make judicious choices and is able to outperform significantly. Though, about twice as much significantly underperform with these holdings. This tends to indicate that EHFs mainly add value via short positions, small positions, or intra-quarter trading. I answer this question in the coming section.

5.1.3 Performance from Invisible Positions

So far, we saw that there are some AIFs which, in total, are able to outperform. We also saw that there are few AIFs that are able to do so with their choices of large long holdings. The question I answer here is which proportion of AIFs is able to outperform their large long holdings with the help of other position and intra-quarter trading, that is, with their *invisible* positions. The results are reported in Table 8. For brevity, I focus on the model with the highest explanatory power, the conditional Fung and Hsieh (2004a) 2 factor model.

[INSERT TABLE 8 ABOUT HERE]

Looking at the alpha it appears that, on average, AIFs destroy value with their *invisible* positions since the mean alpha is a negative -0.53% or -6.2% per annum. About 2.60% of them are able to significantly add value, but this only represents 5 managers out of the 192 considered for this analysis. On the contrary, only 10.94% (21 AIFs), significantly worsen their performance via their short and small positions or via their trading activity. This leaves an immense majority of the AIFs, more than 84% (166 AIFs out of 192), that are not able to add any significant value over their *visible* positions. So, while it appears that there is a small proportion of AIFs which are able to do better than their long only positions, most of them are not. This tends to indicated that all the sophisticated trading that hedge funds undertake (or at least pretend to undertake) mostly generate noise and often add little value. Also, given the ever-growing reporting requirements face by hedge funds, it seems that information about their long only position could well allow replicating the investment strategy of many of them. In the next section I go further in the analysis and try to identify the true proportions of outperforming AIFs, by disentangling it from good, and bad, luck.

5.2 Do AIF Managers Exhibit Skill?

As underlined in the pioneering work of Barras, Scaillet and Wermers (2010), hereafter BSW, in a regression setting, some proportion of entities are expected to be found to outperform solely by luck. In this section, I tackle this issue in two ways, first by following the Dempster, Laird and Rubin (1977) Expectation-Maximization algorithm as implemented by Chen, Cliff and Zhao (2012), hereafter CCZ, and second by implementing the BSW False Discovery Rate methodology. The former methodology diverges from the latter in several points, notably by not necessarily constraining the funds into three performance groups. Additionally, it allows extracting multiple distributions (performance groups) and their attributes from the empirical mixture of performance distributions observed. It also permits computing the proportion of managers that should fall in different performance groups, each defined by their own average performance and standard deviation. This methodology, however, suffers from a loss of information with respect to the one of BSW, by only taking into account the distribution of alphas and their standard errors, while BSW use all the information available in the returns and the benchmark factors. Since both methodologies return a proportion of AIFs that belong in a specific group, skilled, neutral, or unskilled, I contrast their results.

I apply both methodologies on the performance I obtained from my three sets of returns under the best fitting factor model for each, and force the classification to three groups: skilled (positive alpha), neutral (zero alpha), and unskilled (negative alpha). Following CCZ, I constrain the neutral group to have a 0 alpha. If their algorithm does not identify any negative alpha group, I limit their classification to two groups: good and neutral. Results are reported in Table 9.

[INSERT TABLE 9 ABOUT HERE]

The three panels A, B and C report the results for the *total* returns, the *visible* returns, and for the difference between the two, the *invisible* returns. The first column reports the average alpha, the second the standard deviation of the alpha, the third the probability to fall in each of the three (eventually two) performance groupings based on the CCZ technique, and the fourth the probability obtained with the BSW methodology. The numbers in parenthesis are bootstrapped standard errors for the parameters obtained from estimations of the algorithms over successive draws with replacement from the sample.

Looking at Panel A, we see a different picture from what could be expected from the previous analysis. As it appears, about 65.15% (respectively 49.41% under BSW) of AIFs are classified in the skilled category with an average alpha of 0.48% per month or 5.9% per year. Notably, the standard deviation of 0.54% signifies that some AIFs in this group do still provide a negative alpha but on average across all AIFs it is positive. Neutral AIFs represent 33.55% (resp. 33.85%) and also show a high variability of 4.18%. Finally, there is a proportion of 1.46% (resp. 16.74%) of the AIFs which are expected to fall in the unskilled group with an average alpha of -21.33% and standard deviation of 13.55%. As illustrated by this example, even though we can classify the AIFs into three performance groups, there is still a very high variation within them. Nevertheless, it is reassuring to find that most AIFs fall in the group that have a positive average alpha and this contrasts with the findings of the previous section. Contrasting the probabilities from both methodologies we see that they agree on the proportion of funds that are expected to be neutral, CCZ however, appears to be more generous since it provides a higher proportion of skilled along with a lower proportion of unskilled AIFs with respect to the ones from BSW. These results contrast with the ones from the work of Criton and Scaillet (2011) who find the 18.6%, 58.8%, 22.6% of skilled, neutral, and skilled funds among EHFs. The performance model, the period under consideration, and the sample they use are however different, which could explain these discrepancies.

If we switch to Panel B which reports the results for the *visible* returns, we see that 9.76% (resp. 0%) of the AIFs fall in the skilled group with an average monthly alpha 3.70% or 54% per year, though with a high monthly standard deviation of 19.48%. This means that while on average this grouping outperforms, this performance is likely driven by relatively extreme individuals. Since the CCZ algorithm did not return any unskilled group, the remaining 90.24% of the AIFs are classified as neutral. This grouping seems however relatively homogenous with a standard deviation of 1.14% per month. The BSW algorithm is not constrained by the number of groupings so that 96.61% appear to be neutral and 3.39% are unskilled. Again, CCZ appears to be more generous than BSW, even though the proportion of neutral funds is relatively close. So, these proportions tend to confirm that most AIFs are not able to outperform with their large positions only, while the proportion of outperforming ones ranges between zero and one tenth depending if we trust BSW or CCZ.[27]

Finally, looking at Panel C, we now turn to the analysis of the performance AIFs are able to generate over their large and long only positions through their *invisible* positions. A proportion of 28.43% (resp. 25.87%) of the AIFs are expected to be skilled, with a mean alpha of 1.19% per month, or 15.3% per year. The standard deviation is at 6.30%. Since the CCZ algorithm did not return any unskilled group, the remaining 71.57% fall in the neutral group with a standard deviation of alpha that establishes at 1.15%. Under BSW this proportion is of 72.93% while 1.20% falls in the unskilled group. In this situation, both methodologies reports almost equal results. These results tend to show that about one quarter

[27]The choice between these two methodologies (or another) is beyond the scope of this paper and is left for further research.

of the AIFs are skilled in their choice of *invisible* positions, while the remaining three quarters are neither good nor bad.

On the whole, these results tend to provide a more positive view about AIFs performance generating ability, both in terms of *total* performance, and in terms of *invisible* performance over their long only positions. Though, skill in the choice of *visible* large and long positions appears to be scarce. Nevertheless, these groupings at least discard the hypothesis that most AIFs with a positive alpha were only *lucky*, if anything, they tend to show than some good AIFs happened to be *unlucky*. Now that we know that at least some AIFs are able to provide investors with outperformance, it would be interesting to verify whether there are particular attributes that explain it. I tackle this issue in the next section.

5.3 Do AIF Characteristics Explain Alpha?

The literature reports a number of characteristics that influence hedge funds' performance. Getmansky (2012) identifies a concave relation with respect to size; also see Xiong, Idzorek, Chen and Ibbotson (2007). In the same vein, it has also been documented that younger funds tend to perform better, underlining a negative relation between age and performance; see for instance Boyson (2008) or Aggarwal and Jorion (2010). Deuskar, Wang, Wu and Nguyen (2011) find that funds from AIFs that manage fewer funds tend to perform better. Liang (1999), identifies a positive relation between the presence of share restrictions (lock up periods) and performance; also see Kazemi, Martin and Schneeweis (2003). Finally, Ramadorai and Streatfield (2011) detect a positive relation with respect to the level of incentive fees. Higher incentive fee funds perform better, though marginally.

I follow these authors and regress the cross-section of the alphas (I found in the previous section) on identifiable AIF characteristics. I estimate the following model:

(6) $Alpha_i = \beta_1 Size_i + \beta_2 Size_i^2 + \beta_3 Age_i + \beta_4 IncFee_i + \beta_5 Lock_i + \beta_6 NFunds_i + \beta_0 + \varepsilon$

where *Alpha* is the performance of each AIF as estimated by the conditional augmented Carhart (1997) model from the previous section, *Size* is the average size of the AIF during the period used to estimate its alpha, $Size^2$ is the square of *Size*, *Age* is the average age of all funds belonging to the AIF during the period used to estimate its alpha, *IncFee* is the average level of incentive fee across all funds belonging to the AIF, *Lock* is the average length of the lock up period across all funds managed by the AIF, *NFunds* is the average number of funds managed by the AIF during the period used to estimate its alpha, β_0 is simply a constant term, and ε is the error term.[28]

[INSERT TABLE 10 ABOUT HERE]

Table 10 reports the results for the alpha obtained from *total* returns, the *visible* returns, and from the *invisible* returns. Starting with the *total* alpha, we see that size is strongly and significantly positively linked with performance. Concurrently, squared size is significantly negatively linked with it. These two findings corroborate the literature detailed above, that performance is a concave function of size. At first performance increases in size before diseconomies of scale are more important that economies of scale and performance starts decreasing. The other four variables however contrast with previous literature since none of them appears to be significant. Looking at the alpha from *visible* positions, or from *invisible* positions none of the variables are significant. In other words, this means that while the size of the AIF has an influence on their *total* performance it does not have any particular influence on the performance of *visible* long only positions or on *invisible* trading activity and small or short positions. Noticeably, the adjusted R^2 is very low for all sets, which is however

[28] In unreported results, following the mutual fund literature, I also consider a model that includes the average management fee, and the average turnover across all funds managed by the AIF; see Ippolito (1989), Grinblatt and Titman (1994), Carhart (1997), Sirri and Tufano (1998), and Jan and Hung (2003). This model does however not return additional significant coefficients and does not either improve on the adjusted R-squared, nor on the F-statistic.

common for cross-sectional studies and translates an important variability between the entities analyzed; see for instance Pindyck and Rubinfeld (1998, p. 73-74).

Overall, it appears that the only hedge fund characteristic which is linked to performance is the size or the amount of assets under management. Interestingly though, and contrarily to the findings from the literature, the length of the lock up period does not significantly affect EHFs' performance. A potential explanation is that this particular category of hedge funds does not engage in trades that require such share restrictions to be successful.[29]

5.4 Do AIF Managers Possess Stock Picking Skills?

So far, we analyzed performance but did not tell much about the essence of this performance. Therefore, in the section, I follow Ferson and Khang (2002), and directly measure the stock picking ability of AIFs by conditioning their holding changes on a set of publicly available information.

5.4.1 Analysis of Stock Picking Conditioned on Public Information

Considering that a large part of AIFs are unable to outperform their long positions. I examine managers' stock picking ability as measured by the CWM computed with model (5). I directly use the AIFs' stock holdings obtained from their 13F filings. The lag, k, is equal to 3 months while the input betas are estimated over a 24-month moving window. Because of this, the measurement period is shortened by two years and is located between January 1996 and June 2011. The CWM is estimated AIF by AIF for all management firms which have a sufficient number of observations in the period mentioned. As illustrated in Panel A of Table 11, the mean CWM conditional on general factors (dividend yield, credit spread, size spread, and Treasury bill), establishes at a level of 0.16% per month or about 1.9% per annum.

[29] In an unreported robustness check, I verify this assumption by "unsmoothing" my returns with the Getmansky, Lo and Makarov (2004) methodology to remove the effect of illiquidity-induced serial correlation. The returns remain mostly unaffected, thereby confirming that EHFs do not generally engage in illiquid positions.

Approximately 7.8% of the managers show a significantly positive ability while about 11.1% have a significantly negative one. The remaining 81% have a neutral performance. This means that, when the information set is limited to general publicly available information, AIFs' stock picking ability does add some value *on average* but most AIFs do not. Moreover, there are more AIFs which destroy value than AIFs which create value with their stock picking. These findings contrast with the average CWM of 0.03% per quarter, or 0.12% per year, documented by Ferson and Khang (2002) in a sample of mutual funds. This suggests that, on average, hedge fund managers are better stock pickers than mutual fund managers. Their findings do no not however allow drawing conclusions about the proportion of significantly positive and negative stock pickers so we do not know the dispersion of stock picking ability in their sample.

[INSERT TABLE 11 ABOUT HERE]

Bigger information sets are better at explaining stock returns and could potentially allow managers to make a more advanced use of their information interpretation skills in their stock picking. Therefore, I now augment the information set to include corporate related factors which are changes in credit ratings, secondary offerings, mergers and acquisitions, and stock repurchases. Increasing the size of the information set does have some effect on the average CWM level which now increases to 0.37% per month or about 4.5% per year. Also, there are somewhat more managers with a positive ability (8.8%) and somewhat fewer managers with a significantly negative ability (9.7%). Nevertheless, the proportion of neutral managers still represents the vast majority.

Further augmenting the information set to now encompass analysts' related information, which are changes in analysts' recommendation and earnings surprises, adds some value. We see a decline in average CWM, to 0.01% per month or about 0.12% per year, which is now in line with the findings of Ferson and Khang (2002) for mutual funds. The proportion of significantly positive CWM increases slightly to reach a level of 9.8% but the proportion of significantly negative CWM goes back to more than 11%. So that, under this information set, in total, there is a slight decrease in the proportion of AIFs with a neutral stock picking ability. Based on this, it appears the performance of hedge fund managers needs to be measured over larger information set to reach similar conclusions as the ones about mutual fund managers. This suggests that the former are better at interpreting public information than the latter.

In a nutshell, we see that there is a non-negligible number of AIFs who show a significant and positive stock picking ability but that there is a similar (though somewhat higher) number of them who have a significantly negative ability. However, these AIFs represent a small fraction of the total number of managers, since a majority of them do not have any significant stock picking ability. Finally, we see that the choice of the information set matters because if it is not large enough, what should be interpreted as information contained in public information could be understood as stock picking skill. Also, adding analysts' information in top of the corporate related events both increases the proportion of outperforming and of underperforming managers. This last finding is in line with Teo and Chung (2011) who find that the analysts are actually often influenced by hedge fund holdings and not the other way around.

5.4.2 Proportion of Truly Good Stock Pickers

Following what I did in the previous sections, I apply the algorithm of CCZ and the one of BSW on my CWM estimates to gauge the true proportions of skilled, neutral, and unskilled AIFs in their stock picking. Results are exposed in Table 12.

[INSERT TABLE 12 ABOUT HERE]

Starting with the general information set in Panel A, the grouping appears very different from what would be expected from above. Indeed, the probability of having good stock picking ability established at 11.87% (resp. 11.64%) with a mean level of 1.97% per month or about 26% per year. The standard deviation is a relatively high 5.1%. The probability of being in the no stock picking ability group is at 33.9% (resp. 66.05%) and the low standard deviation at 0.16% indicates that the abilities are relatively close to zero for this group. Finally, there is large probability, 54.3% (resp. 22.31%) of having a negative stock picking ability with a mean CWM of -0.16% per month or -1.9% per year. Though the standard deviation of 0.69% indicates that even in this group there are AIFs which have a positive CWM. We see that the probabilities of being skilled are roughly equal under both the CCZ and the BSW estimation, however, this time BSW appears to be more clement with unskilled managers since it classifies half as many in this category as does the CCZ algorithm.

If we move to Panel B, the proportion of truly skilled AIFs decreases to 7.17% (resp. 8.99%) but the mean CWM of this group is now a relatively high 6.45% per month or 112% per year. Though, the standard deviation of 12.7% indicates that this value is driven by a number of exceptional performers. The probability of being neutral is at 41.02% (resp. 82.95%) with again a low standard deviation of 0.19% so the skills in this group stay close to zero. The probability of being unskilled is at 51.8% (resp. 8.06%) with an average CWM of -0.19% per month or about -2.3% per year. The standard deviation of 0.9% shows that some of the AIFs of this group can still have a positive CWM. Again, BSW is in line with CCZ concerning the skilled group, but dramatically differs in the unskilled one, since CCZ finds it more than 6 times more likely to be unskilled than BSW.

Finally, looking at Panel C, we see little change in the proportions (both for CCZ and BSW) even though there is an increase in the proportion of neutral AIFs to the expense of fewer bad AIFs under the CCZ measure. What changes though is the average CWM for the skilled ability group which establishes at 0.61% per month or 7.6% per year with a monthly standard deviation of 12.71%. This group therefore seems now even more composed of extreme performers that previously. The statistics for the other two groups remain stable. As previously, BSW is more clement than CCZ and classify almost five times less funds as unskilled.

Overall, the results are twofold. On the one hand, if we trust the CCZ technique, this last analysis sheds a different light on the previous findings about stock picking skill. While there seemed to be approximately the same proportion of skilled and unskilled stock picker AIFs, and a large proportion of neutral, the picture is now different. As it appears, around half of the AIFs fall in the unskilled group while no more than one tenth is in the skilled group. So, that a number of AIFs who showed a good or neutral ability must actually have been lucky, and should have been in the unskilled group. On the other hand, the BSW measure seems to be more in line with the findings of the previous section and finds a skill distribution which is more reassuring than the one of CCZ. Again, whether one decides to trust the CCZ or the BSW measure is beyond the scope of this research, it however appears that, at least for this measure of ability, the BSW methodology brings skill proportions that are more in line with what can be expected from the other results.

6 Discussion and Conclusion

This research contributes to the existing literature by offering a different methodology in assessing the “abnormal performance” of EHFs and by shedding a new light on the information content of SEC 13F disclosures. In a first step, I explicitly examine the performance that is not revealed by large long positions at the investment firm level and find that there are not many AIFs who are able to add value beyond their disclosed large long positions. In a second step, I apply a performance measure that was not previously used in the hedge fund literature. I show that most AIFs do not have any stock picking ability beyond what can be reach by inferring from easily collectable public information, thus positively contrasting with the findings in the mutual fund industry. All in all, these results lead to the conclusion that most EHFs are unable to add value by their trading activity, their short holdings, or their small positions. Moreover, it appears that even their choice of long large positions is most often not based on any particular stock picking skill. The implication for potential investors in EHFs is that it is necessary to carefully choose the manager they want to invest with since, while some of them do possess real stock picking skills, most of them do not. Finally, the implications for the regulators are twofold. One the one hand, since EHFs' holdings do indeed contain relevant information to replicate their performance, further divulgations might well end up allowing followers to arbitrage away any remaining performance. On the other hand, given the fact that most EHFs are not able to outperform, the limited reporting obligations they are subject to actually given them a convenient opportunity to hide the evidence about this lack of skill from the public. In this context, further divulgation requirements would certainly lead to a better efficiency in the markets by uncovering unskilled managers while allowing truly skilled ones to keep outperforming.

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Appendix A: Estimation of the CWM measure

I here give some computational details about the estimation of equation (5):

$$CWM_{P,t} = E\left[\sum_{j=1}^{N_P} \left(w_{j,t} - w_{b,j,t,k} \right) \left(r_{j,t+1} - E\left(r_{j,t+1} \middle| Z_t \right) \right) \middle| Z_t \right]$$

As underlined in Ferson and Khang (2002), the benchmark choice is open and can either accommodate the weights of an external index (in the case of an index tracking fund for instance) or be internalized based on the fund's previous holdings. Since hedge funds are assumed to be uncorrelated investments (see Brown, Goetzmann and Ibbotson (1999), Agarwal and Naik (2004), or Lhabitant (2006, page 25)), an external benchmark is inappropriate. I therefore follow Ferson and Khang (2002) and Grinblatt and Titman (1993), and define the benchmark weights as $w_{b,j,t,k} = w_{j,t-k} \prod_{\tau=t-k+1}^{t} \left(1 + r_{j\tau}\right) \big/ \left(1 + r_{P\tau}\right)$, where $r_{P\tau}$ is the buy-and-hold return on portfolio P using the weights in period τ. Given the quarterly disclosure requirements faced by EH funds, I set *k* to 3 months. For computation purposes I augment $\mathbf{Z}_t$ with a constant term. I follow the simple estimation procedure detailed in Wermers (2006, p. 227-228):

A) Estimation of the regression $r_{j,t+1} = \mathbf{b}'_j \mathbf{Z}_t + \varepsilon_{j,t+1}$, for each stock *j*, and storage of the coefficients $\hat{\mathbf{b}}_j$, I use an estimation window of 24 months (t-25 to t-1)[30]

B) With the coefficients obtained in A), estimation of the regression $\underbrace{\sum_{j=1}^{N_P} \left(w_{j,t} - w_{b,j,t,k} \right) \left(r_{j,t+1} - \hat{\mathbf{b}}'_j \mathbf{Z}_t \right)}_{\text{variable}} = CWM + \boldsymbol{\gamma}' \mathbf{z}_t + \varepsilon_{j,t+1}$ where *CWM* is the measure of the manager's ability and $\mathbf{z}_t = \mathbf{Z}_t - E(\mathbf{Z}_t)$ excluding the constant term. $E(\mathbf{Z}_t)$ is measured over (t-25 to t-1).

When the information set, $\mathbf{Z}_t$, is stock-dependent, the estimation of the *CWM* above has to be slightly modified by using the portfolios' benchmark-weighted exposures to the stock-specific information sets:

[30] Longer estimation windows allow for more precise estimates, but since exposures might change through time the betas obtained might not reflect the current exposure of the stock. In further robustness checks I will try to vary the size of this estimation window.

A) $r_{j,t+1} = \mathbf{b}'_j \mathbf{Z}_{j,t} + \varepsilon_{j,t+1}$

B) $\sum_{j=1}^{N_P} \left(w_{j,t} - w_{b,j,t,k} \right) \left(r_{j,t+1} - \hat{\mathbf{b}}'_j \mathbf{Z}_{j,t} \right) = CWM + \boldsymbol{\gamma}' \sum_{j=1}^{N_P} w_{b,j,t,k} \mathbf{z}_{j,t} + \varepsilon_{j,t+1}$

where $\mathbf{Z}_{j,t}$ and $\mathbf{z}_{j,t}$ are stock specific.[31]

[31] A more elegant solution would be to follow Bange, Khang and Miller (2003, p. 24) and assign a specific $\boldsymbol{\gamma}$ to each security, but since the portfolios generally consist of dozens or even hundreds of securities, the estimation would most often not be feasible.

Table 1: Sample Creation

This table reports the number of AIFs and the number of funds remaining after each step of the selection process. The two figures in bold represent the number of AIFs in the intermediate sample and in the final sample.

	Number of AIFs	Number of Funds
Equity Hedge Only	1,110	1,685
Matched in SEC – 13F	268	558
Hedge fund only	**263 (Intermediate Sample)**	552
Not missing AUM	251	532
Matching date between TASS & 13F	224	495
Reporting monthly	**222 (Final Sample)**	493

Table 2: Presence of AIFs by Year

This table details the number of AIFs present in the sample in each year. It also reports the number of AIFs entering and exiting the sample each year. Entries are calculated as the difference between the AIFs that were not present in the previous year and are present in the current year, and inversely for exits. Except for year 1994 where entries are calculated as the AIFs that were not present in January but appeared during the year, and exits are calculated as the AIFs that were present in January but disappeared during the year. The last column gives the attrition rate (Exits/AIFs in Database). The figures for 2011 only run until end of June.

Year	N AIFs in Database	N AIF Entries	N AIF Exists	Attrition Rate (%)
1994	24	6	2	8.33
1995	28	5	1	3.57
1996	34	7	1	2.94
1997	41	9	2	4.88
1998	58	18	1	1.72
1999	64	8	2	3.13
2000	82	20	2	2.44
2001	95	18	5	5.26
2002	101	20	14	13.86
2003	99	10	12	12.12
2004	109	19	9	8.26
2005	110	15	14	12.73
2006	107	13	16	14.95
2007	106	16	17	16.04
2008	93	16	29	31.18
2009	79	3	17	21.52
2010	71	3	11	15.49
2011 (until end of June)	61	6	16	26.23
Mean	75.67	11.78	9.5	11.37

Table 3: Sample Summary Statistics

This table gives summary statistics about the intermediate and the final sample as well as about the difference between the two. All holdings figures are from SEC 13F files, and reported at the last available observation date for each AIF. *(n. s.)* stands for "not significantly different from zero". The period covered is January 1994 to June 2011.

	Final Sample		**Intermediate Sample**	**Abs. Difference Between Samples**
Data Source	**SEC 13F**	**TASS**	**SEC 13F**	**SEC 13F**
Number of AIFs	222		263	41
Number of AIF-month obs.	14,710		25,428	10,718
Average total holdings (M $)	1,553		1,410	*(n. s.)* 143
Median total holdings (M $)	0.149		0.140	0.009
Total holdings std. dev. (M $)	4,324		4,031	293
Minimum total holdings (M $)	0.117		0.117	0
Maximum total holdings (M $)	30,713		30,713	0
Returns correlation(13F, TASS)	0.63		-	-
Average monthly return	0.45%	0.83%	0.38%	*(n. s.)* 0.07%
Median monthly return	0.93%	0.78%	0.93%	0.00%
Monthly returns std. dev.	7.72%	5.65%	7.68%	0.04%
Returns standardized kurtosis	0.13	0.80	0.20	0.07
Returns skewness	9.45	25.42	12.84	3.39
Minimum monthly return	-49.28%	-62.74%	-61.06%	11.78%
Maximum monthly return	131.96%	122.46%	143.90%	11.94%

Table 4: Holdings and Observations Summary Statistics

This table details statistics about the number of months of observations available for each AIF as well as information about the stock holing periods and the number of stocks in portfolio. Average stock holding periods for each AIF are computed as the average holding periods across all stocks they had in their portfolio. Average numbers of stocks for each AIF are computed as the average number of stocks they had in the portfolio across all observation dates. The Period covered is January 1994 to June 2011.

	Number of Months of Data	**Average Stock Holding Period**	**Average Number of Stocks in Portfolio**
Mean	66.26	17.26	110.27
Median	54	15.22	66.84
Standard Deviation	50.81	8.67	141.73
Minimum	1	4.70	2.21
Maximum	210	52.52	1,166.88

Table 5: Information Set Summary Statistics

This table gives stylized facts about the information sets. The seven columns relate the number of events linked to each stock, that is: rating changes, stock repurchases, secondary offerings, being an M&A acquirer, being an M&A target, change in analysts' recommendations, and earnings surprises. Panel A reports summary statistics about the entire sample period. Panel B presents the distribution of the number of events in each year of the sample. The period covered is January 1994 to June 2011.

	Rating Changes	**Repurchases**	**SEO**	**M&A Acquirer**	**M&A Target**	**Rec. Changes**	**Surprises**
Panel A: Events Linked to Each Stock from January 1994 to June 2011							
Mean	0.51	3.69	0.50	0.41	0.33	21.17	16.51
Median	0	2	0	0	0	8	9
StdDev	1.46	5.98	1.44	2.73	0.57	31.53	19.69
Min	0	0	0	0	0	0	0
Max	18	111	18	102	7	180	70
Panel B: Distribution of Events per Year (%)							
1994	2.77	5.60	9.39	7.77	3.95	4.65	4.97
1995	3.68	6.49	9.25	7.36	5.58	5.20	5.37
1996	3.53	7.93	11.00	7.92	6.30	5.61	5.92
1997	4.33	8.61	9.12	8.54	8.78	5.97	6.48
1998	6.21	9.79	11.62	8.62	9.24	6.32	6.55
1999	6.14	8.39	9.18	8.12	10.16	6.20	6.34
2000	6.30	6.10	4.90	6.18	8.66	6.09	5.92
2001	7.87	4.92	3.42	4.94	5.93	5.78	5.52
2002	7.93	4.12	2.23	4.43	3.90	6.38	5.18
2003	6.22	4.32	2.76	4.71	4.50	5.72	5.12
2004	4.61	4.57	3.22	4.56	4.19	5.58	5.40
2005	6.03	4.81	3.73	4.57	4.44	5.50	5.71
2006	5.72	5.05	3.41	5.08	5.60	5.76	5.85
2007	6.18	5.25	4.97	4.87	5.76	5.88	6.00
2008	7.36	4.54	4.95	4.03	3.84	6.31	5.88
2009	7.42	3.53	2.00	2.77	3.22	5.32	5.57
2010	5.16	3.83	2.57	3.44	3.93	5.15	5.54
2011	2.52	2.14	2.28	2.09	2.03	2.57	2.69
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 6: Total Performance

This table reports the results of AIF by AIF regression of total returns (TASS). The left-hand side presents the unconditional version of the model while the right-hand side presents the version conditioned on public information. Panel A reports the results for the Fung and Hsieh 2 factors specification and panel B reports the augmented Carhart specification. The first column (Mean level) presents the average exposure to a given factor. The other two columns report the proportion of AIFs with a significantly positive and a significantly negative exposure to the factor at the 5% level. The period covered is January 1994 to June 2011.

	Unconditional Model			**Conditional Model**		
	Mean level	**% positive at 5%**	**% negative at 5%**	**Mean level**	**% positive at 5%**	**% negative at 5%**
Panel A: Fung & Hsieh 2 Factor Model						
Alpha (%)	0.30	26.51	4.18	0.13	23.96	3.13
S&P 500	0.49	67.44	3.26	0.66	51.56	3.65
Size Spread	0.29	42.80	0.93	0.04	37.50	1.56
Conditional Factors		NO			YES	
Mean Adj. R^2		0.36			0.48	
Mean F-statistic		19.57			112.83	
N AIFs		215			192	
Panel B: Augmented Carhart Model						
Alpha (%)	0.62	23.30	2.91	–	–	–
Rm – Rf	0.41	64.56	2.43	–	–	–
SMB	0.22	32.52	1.46	–	–	–
HML	-0.02	20.87	17.48	–	–	–
WML	0.04	21.36	11.65	–	–	–
Timing Factor	-0.41	4.85	12.62	–	–	–
Conditional Factors		NO			–	
Mean Adj. R^2		0.48			–	
Mean F-statistic		20.91			–	
N AIFs		206			–	

Table 7: Performance from Visible Positions

This table reports the results of AIF by AIF regression of visible returns (13F). The left-hand side presents the unconditional version of the model while the right-hand side presents the version conditioned on public information. Panel A reports the results for the Jensen specification and panel B reports the augmented Carhart specification. The first column (Mean level) presents the average exposure to a given factor. The other two columns report the proportion of AIFs with a significantly positive and a significantly negative exposure to the factor at the 5% level. The period covered is January 1994 to June 2011.

	Unconditional Model			**Conditional Model**		
	Mean level	**% positive at 5%**	**% negative at 5%**	**Mean level**	**% positive at 5%**	**% negative at 5%**
Panel A: Jensen's CAPM Model						
Alpha (%)	0.00	1.38	7.37	0.64	7.53	4.90
Rm – Rf	1.23	98.61	0.00	0.69	76.96	0.98
Conditional Factors		NO			YES	
Mean Adj. R^2		0.64			0.66	
Mean F-statistic		88.54			185.98	
N AIFs		217			204	
Panel B: Carhart Model						
Alpha (%)	-0.23	1.40	10.70	0.43	2.84	6.25
Rm – Rf	1.15	93.02	0.00	1.11	88.06	0.00
SMB	0.33	48.84	3.72	0.04	36.36	2.84
HML	-0.01	21.40	19.07	0.16	15.91	10.23
WML	0.06	20.93	12.56	0.26	12.50	3.98
Conditional Factors		NO			YES	
Mean Adj. R^2		0.72			0.76	
Mean F-statistic		106.36			777.98	
N AIFs		215			176	

Table 8: Performance from Invisible Positions

This table reports the results of AIF by AIF regression of invisible returns (TASS-13F). The left-hand side presents the unconditional version of the model while the right-hand side presents the version conditioned on public information. Panel A reports the results for the Fung and Hsieh 2 factors specification and panel B reports the augmented Carhart specification. The first column (Mean level) presents the average exposure to a given factor. The other two columns report the proportion of AIFs with a significantly positive and a significantly negative exposure to the factor at the 5% level. The period covered is January 1994 to June 2011.

	Unconditional Model			**Conditional Model**		
	Mean level	**% positive at 5%**	**% negative at 5%**	**Mean level**	**% positive at 5%**	**% negative at 5%**
Panel A: Fung & Hsieh 2 Factor Model						
Alpha (%)	0.64	33.95	0.93	-0.53	2.60	10.94
S&P 500	-0.66	2.32	71.16	1.02	74.48	2.08
Size Spread	-0.31	2.79	42.32	0.50	55.21	1.56
Conditional Factors		NO			YES	
Mean Adj. R^2		0.41			0.69	
Mean F-statistic		28.14			260.94	
N AIFs		215			192	
Panel B: Augmented Carhart Model						
Alpha (%)	-0.03	13.11	4.85	–	–	–
Rm – Rf	-0.61	1.94	66.50	–	–	–
SMB	-0.17	2.91	30.01	–	–	–
HML	0.00	17.48	14.56	–	–	–
WML	0.01	16.50	13.11	–	–	–
Timing Factor	0.07	9.71	5.34	–	–	–
Conditional Factors		NO			–	
Mean Adj. R^2		0.48			–	
Mean F-statistic		29.62			–	
N AIFs		206			–	

Table 9: Alpha Grouping

This table reports the calculated probabilities, **π (CCZ)** using Chen et al. (2012) methodology, the corresponding average performance, **μ**, and the standard deviation, **σ**, for each grouping of AIFs: Skilled, Neutral, and Unskilled. The last column also reports the probability **π (BSW)** obtained from the Barras et al. (2010) methodology. Panel A reports the results for total performance (TASS) over the Fung & Hsieh 2 factor model, Panel B reports the results for the visible performance (13F) over the conditional Carhart (1997) model, and Panel C reports the results for the invisible performance (TASS-13F) over the Fung & Hsieh 2 factor model. The numbers in parenthesis are the corresponding bootstrapped standard errors obtained from successive draws with replacement. The period covered is January 1994 to June 2011.

	μ	**σ**	**π (CCZ)**	**π (BSW)**
Panel A: Total Performance				
Skilled (%)	0.48	0.54	65.15	49.41
	(0.01)	(0.01)	(1.11)	(3.64)
Neutral (%)	0.00	4.18	33.55	33.85
	(—)	(0.25)	(1.04)	(5.37)
Unskilled (%)	-21.33	13.55	1.30	16.74
	(2.94)	(0.64)	(1.69)	(4.82)
Panel B: Performance from Visible Positions				
Skilled (%)	3.70	19.48	9.76	0.00
	(0.66)	(1.07)	(0.47)	(3.77)
Neutral (%)	0.00	1.14	90.24	96.61
	(—)	(0.02)	(0.47)	(4.61)
Unskilled (%)	(—)	(—)	0.00	3.39
	(—)	(—)	(—)	(2.34)
Panel C: Performance from Invisible Positions				
Skilled (%)	1.19	6.30	28.43	25.87
	(0.12)	(0.12)	(0.71)	(3.29)
Neutral (%)	0.00	1.15	71.57	72.93
	(—)	(0.01)	(0.71)	(3.78)
Unskilled (%)	(—)	(—)	0.00	1.20
	(—)	(—)	(—)	(1.91)

Table 10: Alpha Explained by Fund Level Characteristics

This table reports regression estimates of the cross-section of alphas of AIFs. The alphas are computed over the Fung and Hsieh 2 factor model for the total and the invisible performance and over the conditional Carhart model for the visible performance. The first column reports the results for the total returns, the second for invisible performance, and the third for the visible performance. Numbers in parenthesis are the standard errors of the estimated coefficients. The significance levels are * 10%, ** 5%, and *** 1%. The period covered is January 1994 to June 2011.

	Total	**Visible**	**Invisible**
Size (in Billion)	2.22***	1.87	0.77
	(0.68)	(2.42)	(0.86)
$Size^2$	-0.54**	-0.29	-0.15
	(0.18)	(0.64)	(0.26)
Age	0.03	-0.05	-0.03
	(0.10)	(0.13)	(0.08)
Incentive Fee Level	0.00	-0.07	0.04
	(0.03)	(0.08)	(0.05)
Lock Up	0.84	-1.79	-0.12
	(0.79)	(1.23)	(0.75)
Number of Funds	-0.03	-0.15	-0.07
	(0.05)	(0.10)	(0.07)
Constant	-0.65	2.35	0.14
	(0.78)	(1.48)	(1.08)
Adj. R^2	2.21%	1.55%	0.56%
F-statistic	2.60	0.96	0.53
N AIFs	192	176	192

Table 11: CWM

This table reports the average CWM as well as the proportion of AIFs with a significantly positive and a significantly negative CWM estimated from the 13F holdings data. Panels A to C present the results conditioned on the three different sets of information. The number of lags, k, is 3. The CWM input betas are estimated over a moving 24-month period. The period covered is January 1996 to June 2011.

	Mean level	**% positive at 5%**	**% negative at 5%**
Panel A: Information Set = General Factors			
CWM (%)	0.16	7.83	11.06
Mean Adj. R^2		0.06	
N AIFs		217	
Panel B: Information Set = General & Corporate Level Factors			
CWM (%)	0.37	8.76	9.68
Mean Adj. R^2		0.07	
N AIFs		217	
Panel C: Information Set = General, Corporate Level, & Analyst Factors			
CWM (%)	0.01	9.77	11.16
Mean Adj. R^2		0.06	
N AIFs		215	

Table 12: CWM Grouping

This table reports the calculated probabilities, **π (CCZ)** following Chen et al. (2012), the corresponding average CWM, **μ**, and the standard deviation, **σ**, for each grouping of AIFs: Skilled, Neutral, and Unskilled. The last column reports the probability ***π*** **(BSW)** following Barras et al. (2010). Panels A to C present the results conditioned on the three sets of information. The numbers in parenthesis are the corresponding bootstrapped standard errors obtained from successive draws with replacement. The period is January 1996 to June 2011.

	μ	**σ**	**π (CCZ)**	**π (BSW)**
Panel A: Information Set = General Factors				
Skilled (%)	1.97	5.11	11.87	11.64
	(0.18)	(0.15)	(0.48)	(2.76)
Neutral (%)	0.00	0.16	33.85	66.05
	(—)	(0.00)	(0.93)	(9.02)
Unskilled (%)	-0.16	0.69	54.29	22.31
	(0.01)	(0.02)	(0.89)	(8.16)
Panel B: Information Set = General & Corporate Level Factors				
Skilled (%)	6.45	12.71	7.17	8.99
	(0.51)	(0.54)	(0.32)	(4.33)
Neutral (%)	0.00	0.19	41.02	82.95
	(—)	(0.00)	(0.92)	(5.21)
Unskilled (%)	-0.19	0.90	51.81	8.06
	(0.01)	(0.02)	(0.94)	(2.57)
Panel C: Information Set = General, Corporate Level, & Analyst Factors				
Good (%)	0.61	16.19	6.89	7.48
	(0.60)	(1.07)	(0.58)	(3.55)
Neutral (%)	0.00	0.23	48.06	82.41
	(—)	(0.01)	(1.73)	(3.66)
Unskilled (%)	-0.11	1.29	45.05	10.11
	(0.03)	(0.09)	(1.34)	(1.55)