Timing is Money:

The Factor Timing Ability of Hedge Fund Managers

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ABSTRACT

This paper studies the level, determinants, and persistence of the factor timing ability of hedge fund managers. We find strong evidence in favor of factor timing ability at the aggregate level, although we find ample variation in timing skills across investment styles and factors at the fund level. Our cross-sectional analysis shows that better factor timing skills are related to funds that are younger, smaller, have higher incentive fees, have a smaller restriction period, and make use of leverage. An out-of-sample test shows that factor timing is persistent. Specifically, the top factor timing funds outperform the bottom factor timing funds with a significant 1% per annum. This constitutes 13% of the overall performance persistence in hedge funds. The findings are robust to the use of an alternative model, alternative factors, and controlling for the use of derivatives, public information, and fund size.

JEL-codes: G23, G11

Keywords: Hedge funds, market timing, factor investing, factor timing

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1. Introduction

Performance of the top hedge funds is persistent and cannot be explained by luck or sample variability (Kosowski, Naik and Teo, 2007). These findings are consistent with Jagannathan, Malakhov and Novikov (2010), who find that a portfolio of the top 33% of funds ranked on historical alpha *t*-statistics maintained its alpha in an out-of-sample test. Furthermore, they find little evidence for performance persistence among inferior funds, which support the interpretation that top funds have superior managerial talent and skills. In contrast to the results in hedge funds, Pastor and Stambaugh (2002) find that for the majority alphas of equity mutual funds are negative. The difference in performance (persistence) between hedge funds and mutual funds might be explained by the incentive fees for hedge fund managers, which enables hedge funds to attract more talented and skilled managers. Another possible explanation for the difference in performance can be related to the fact that hedge funds are less strictly regulated and therefore are more flexible to engage in, for example, short selling and leverage, and are better positioned to adjust their beta exposures to forecasts. The latter can be referred to as the timing ability of fund managers. In this paper, we study the extent of factor timing by hedge funds, its determinants, as well as its persistence.

It is well known that hedge funds employ dynamic strategies and have time-varying beta exposures on factors; see Fung and Hsieh (1997). Several studies followed examining the drivers of these dynamics. Patton and Ramadorai (2010) find that managers condition exposures on leverage, carry trade, as well as equity markets conditions. Fung et al. (2008) use a continuous rolling regression approach and find significant time variation in betas. Bollen and Whaley (2009) on the other hand study whether there are discrete changes in factor loadings. Schauten, Willemstein, and Zwinkels (2015) study whether the dynamic factor loadings can be explained by positive feedback dynamics.

We extend the literature in three important ways by combining factor investing with dynamic strategies. First, Chen and Liang (2007), among others, have shown that hedge funds possess market timing skills. Our study extends their paper and investigates whether hedge fund managers are able to time the Fung-Hsieh (2004) factors. Second, we examine the determinants of the timing ability of hedge fund managers. Ackermann et al (1999) and Liang (1999) find that hedge funds' fee structure is a determinant of their performance. We extend their line of thinking and look into the cross-sectional determinants of factor timing skills. Finally, this study also tests whether factor timing skills can be a useful tool for investors to select hedge funds. Although results vary, a majority of studies finds a certain level of performance persistence for hedge funds; see e.g. Agarwal and Naik (2000). We extend this line of research by examining whether the performance persistence in hedge funds can be explained by persistence in market timing skills.

Our final data sample from Lipper TASS contains 3,124 hedge funds spread over nine investment styles over the period January 1994 to April 2014. We use the factor model of Fung and

Hsieh (2004) to examine the factor timing skills of hedge fund managers at both an aggregate level and an individual fund level. The timing measure we employ is an extension of the famous Treynor and Mazuy (1966) measure.

Our main findings are as follows. At the aggregate level we find that hedge fund managers do possess factor timing skills, consistent with existing studies looking at market timing skills (Agarwal and Naik, 2000). We find especially strong timing skills for the market, size, and bond factors. Interestingly, we find substantially negative timing for the Emerging Markets factor. This might be caused by herding behavior of institutional investors in emerging markets, possibly due to information asymmetry (see Chloe, Kho, and Stulz, 1999).

At the individual level, the results suggest that funds with different investment styles show ample variation in timing skills on the different factors. The timing skills, though, appear not to be directly related to the style. Global macro funds, funds of funds, and long short equity funds show relatively more significant timing skills on the market factor than the funds of the other investment styles. Regarding the size factor, we find relatively more timing skills in convertible arbitrage funds, event driven funds, emerging market funds, and multi-strategy funds. Furthermore, only convertible arbitrage funds show evidence of emerging market factor timing skills. Finally, emerging market funds show the highest percentage of funds with timing skills on the credit-spread factor.

The results on the determinants of the factor timing ability of hedge fund managers suggest that better factor timing skills are related to funds that are younger, smaller, have higher incentive fees, have a shorter restriction period, and make use of leverage. There is, however, again quite some variation over the factors. For example, age and incentive fees are positively related to timing skills for the market and size factors.

Finally, we find that the factor timing skills of hedge fund managers have a certain degree of persistence. Whereas a long-short strategy based on the Fung-Hsieh alpha yields 7.2% annually, we find a significant out-of-sample alpha of almost 1% annually in the spread between the best and worst factor timing funds. In other words, approximately 13% of hedge fund outperformance is driven by factor timing, suggesting that the remaining 87% is driven by asset selection skills.

We run a series of additional tests to check the robustness of our results. We use a bootstrap analysis to distinguish factor timing skills that are based on actual skills from the ones that are based on random variation or luck. Furthermore, the findings are robust to the model, alternative factors, derivatives, public information, and fund size.

The remainder of this paper is structured as follows. We review the existing literature in Section 2. Section 3 describes the data and methodology that we use to estimate the factor timing ability of the hedge funds. Section 4 presents the results of the factor timing ability of funds. Section 5 studies the cross-sectional determinants of factor timing ability. Section 6 looks further into the persistence in the timing ability of funds. In section 7, we check the robustness of our results and Section 8, finally, concludes.

2. Literature review

2.1 Factor investing

Where traditional investing implies portfolio diversification at the assets-class levels, factor-based investing is building on the arbitrage portfolio theory (Ross, 1976) and involves identifying compensated factor exposures and constructing a portfolio by allocation to these factors. As such, factor investors are not attempting to maximize alpha, but to harvest factor premia. Through the years, many factors have been analyzed in academic literature and the most well-known factors are the market factor, the value factor, the size factor, the momentum factor, the volatility factor, the credit factor and the term factor; see Fama and French (2015). The most commonly used multifactor-model by practitioners and academics to evaluate hedge fund performances is the Fung-Hsieh eight-factor model (Fung and Hsieh, 2004).

Factor-based investing is an existing concept in the finance literature, but new interest started with the study of Ang, Goetzman and Schaeffer (2009). The Norwegian government initiated this study to analyze the underperformance of the active management of the Norwegian Government Pension Funds during the credit crunch in 2008. The results indicate that a large proportion of the performance can be explained by the exposure to systematic factors, and that factors earn a premium over the long run. Therefore, the advice to the Norwegian Government Pension Funds is to use factor based investing for asset allocation and portfolio construction. This advice is enforced by the fact that the correlation between factors is relatively low (Bhansali, 2011; Ilmanen and Kizer, 2012).

Ilmanen, and Kizer (2012) show that a portfolio constructed with a factor based strategy can improve the returns of well diversified portfolios. Similar studies show that for a diverse range of portfolio configurations the returns can be improved by using portfolios constructed with a factor-based strategy. Bender, Briand, Nielsen, and Stefek (2010) provide evidence that a traditional portfolio with a 60/40 allocation to equity and bonds has a similar return as an equally weighted risk premium portfolio but the annual volatility in the portfolio is much lower, illustrating the diversification potential. Bird, Liem and Thorp (2013) find similar results for alternative portfolios and Bender, Hammond and Mok (2014) demonstrate that in portfolios of active managers factor exposures play a critical role in explaining the fund performance. They show that up to 80% of alpha can be explained by the exposure to common factors.

2.2 Timing ability of fund managers

According to Fama (1972), fund manager skills can be subdivided into two parts: selectivity and market timing. Selectivity explains the ability to select the best performing stocks on a certain risk level and market timing is the ability to forecast the market movements and adjust the market exposure to this superior information. Both Fung and Hsieh (1997) and Agarwal and Naik (2004) demonstrate that hedge funds employ dynamic trading strategies, have time varying beta exposures, and generate option-like returns. Moreover, hedge funds are less strictly regulated and therefore more flexible to engage in short selling, derivatives, and leverage. The combination of these qualities makes hedge funds potentially better suited for factor timing than for example mutual funds.

Treynor and Mazuy (1966) were the first to develop a method to measure the timing ability of fund managers. Their method implies that market timing ability results in a convex relation between fund returns and the market factor. The reasoning behind this is that when a forecast shows a positive (negative) market movement, the fund manager will increase (decrease) the fund's exposure to the market factor. Treynor and Mazuy (1966) use their measure to study the market timing ability of 57 mutual fund managers and find little evidence for market timing skills. The method of Treynor and Mazuy (1966) is extended by Jensen (1972) and Pfleiderer and Bhattacharya (1983). Building on the work of Jensen (1972), Pfleiderer and Bhattacharya (1983) develop a simple regression method to measure the timing ability of fund managers. Their technique extends the CAPM with a quadratic term of the excess return on the market portfolio. Merton (1981) presents an alternative option-based framework, which enables him to separate the added value of the selection skills and the market timing skills without assuming a CAPM framework. Merton shows that the value created by timing skills can be linked to the value of free options on the market index. Henriksson (1984) develops both parametric and nonparametric statistical procedures based on the model of Merton and Henriksson (1981) and uses this model to test the forecasting skills of mutual fund managers. Similar to Treynor and Mazuy (1966), the results show that there is little evidence for timing skills among mutual fund managers. In fact, Henriksson finds that 62% of mutual funds studied have negative timing values, which can be interpreted as fund managers mistiming the market.

To explain the findings of negative market timing Jagannathan and Korajczyk (1986) link the findings in previous literature of negative timing skills to the proportion of option-like securities in portfolios of mutual funds. They show that the use of options can cause spurious timing results. Other studies control for public information to explain the findings of negative timing skills (Becker, Ferson, Myers and Schill, 1999; Ferson and Schadt, 1996). Ferson and Schadt (1996) find relative more positive and less negative timing results compared to findings in previous literature when the Treynor-Mazuy (1966) model is extended with the use of conditioning public information. Bollen and Busse (2001) provide evidence for a large proportion of mutual funds with market timing abilities. In contrast to previous literature they make use of daily returns instead of monthly returns, which increases their statistical power. Goetzmann, Ingersoll, and Ivkovic (2000) also made use of daily returns but did not find significant evidence for market timing abilities among mutual fund managers. Frijns, Gilbert, and Zwinkels (2016) show that mutual fund managers adjust factor exposures to past returns rather than future returns.

Although hedge funds have a higher potential for market timing than mutual funds, empirical results vary. Fung, Xu and Yau (2002) demonstrate that global equity-based hedge funds do not show global equity market timing skills. Chen (2007) examines the timing ability of hedge funds on their focus market, which depends on the investment category and looks at differences per investment category. They use a conditional Treynor-Mazuy (1966) model to control for the influence of public information. The results show that fund managers of the styles convertible arbitrage, global macro, managed futures and long-short equity have timing abilities on their focus market and the result are robust to the use of options. These results are consistent with the results of Chen and Liang (2007), who investigate the market and volatility timing ability of hedge funds that describe themselves as market timers. They also use a conditional Treynor-Mazuy (1966) model and the results show significant evidence for market timing and volatility timing abilities of hedge funds managers. In addition, Cao, Chen, Liang and Lo (2013) test whether hedge funds can time market liquidity and demonstrate that hedge fund managers do possess liquidity timing skills. The liquidity timing skill is persistent over time and can be an explanation for hedge fund alpha. Li and Shawky (2014) investigate the market timing abilities of long short equity hedge fund managers during periods of crisis. They use a semiparametric panel data estimator for more accuracy in evaluating risks in short periods. They find that 17% of the 2,697 funds in their sample possess market timing skills and that the top market timers outperform the bad market timers with an alpha of 150 basis points per year. Schauten, Willemstein, and Zwinkels (2015) find that overall hedge fund do possess some timing skills, without conditioning on the style, based on a time-varying parameter approached.

We extend the literature by investigating whether hedge fund managers are able to time the Fung-Hsieh (2004) factors. It therefore provides a broader image of the timing skills of hedge fund managers than the studies focusing on one particular style. Furthermore, this study examines the cross-sectional and investment style differences related to the factor timing ability of hedge fund managers. Finally, we extend the literature by examining the persistence of timing ability and the potential this yields for fund selection.

2.3 Hypotheses

Based on the findings in the literature review we formulate the following hypotheses:

Hypothesis 1: Hedge fund managers possess factor timing skills.

Hedge funds are less strictly regulated and therefore are more flexible to engage in short selling, leverage and are better positioned to adjust their beta exposures to forecasts, which can be referred as the timing ability of fund managers. Combining these aspects with the growing interest among practitioners and academics in factor investing, we expect that hedge fund managers successfully time the Fung-Hsieh (2004) factors.

Hypothesis 2: The factor timing ability on individual factors differs over the investment strategies.

Hedge funds are typically classified into different investment styles. They therefore have expertise in different types of asset classes or factors. Therefore, we expect that the funds in the different investment categories time different factors.

Hypothesis 3: The timing ability of hedge funds is related to more flexibility, experience, skill and commitment of the managers.

For the analysis on the determinants of factor timing ability, we base our hypothesis on the differences between mutual funds and hedge funds (Pastor and Stambaugh, 2002). Hence, we expect that more flexible hedge fund managers are superior in factor timing. Flexibility is related to fund age, size, and use of leverage. Furthermore, we expect that more experienced fund managers possess more factor timing skills. Next, we expect that funds with higher skilled managers have better factor timing skills. Attracting skilled fund managers is related to higher incentive fees and the use of a high water mark. Finally, we expect that fund managers that are more committed to the fund, as proxied by personal capital in the fund, are more suited to successfully perform factor timing.

Hypothesis 4: The factor timing ability of hedge fund managers is persistent.

The existing literature shows that hedge fund performance shows a certain degree of persistence (Agarwal and Naik, 2000). Performance is driven by either stock selection skills or timing skills (Fama, 1972). If the persistence in performance is indeed driven by timing skills, this should be reflected by persistence in timing ability.

3. Data and Methodology

3.1 Data

The hedge fund data is obtained from the Lipper TASS database, which is widely used in the hedge fund literature. The database contains time series of monthly hedge fund returns from November 1977 until present, but until 1994 it does not retain dead funds. Fung and Hsieh (2002) address several biases in hedge fund data, including the survivorship bias, the backfilling bias and the selection bias. To minimize the survivorship bias data, we use monthly data from January 1994 to April 2014, including the dead funds. Following the existing hedge fund literature, we remove the first 18 months for every hedge fund to control for the backfilling bias and only include funds with a minimum of 36 monthly returns, a minimum of average assets under management of $10 million, and funds that report monthly net-of-fee excess US dollar returns. Next, we winsorize the top and bottom 1% of all returns to minimize the influence of outliers.

Hedge funds are categorized by their investment styles and the Lipper TASS database classifies hedge funds in 11 investment categories: long short equity, convertible arbitrage, event driven, global macro, fund of funds, fixed income arbitrage, emerging market, equity market neutral, managed futures, dedicated short bias, and multi-strategy. This study will focus on equity-oriented strategies. Therefore, the fixed income arbitrage and the managed futures strategies will be excluded from the sample.

We use the Fung-Hsieh (2004) eight-factor model as the benchmark, because this model is the most widely used model among academics and practitioners to evaluate hedge fund performances. The model includes an equity market factor, a size factor, a bond market factor, a credit-spread factor, three trend-following factors for bonds, currencies, and commodities, and an emerging market factor. For robustness, we will study the stability of our results for this choice by removing and including additional factors.

The data for the trend-following factors is obtained from the website of David Hsieh[3]. The data for the equity market factor, size factor, value factor and momentum factor is obtained from the Center for Research in Security Prices (CRSP) database. For the emerging market index factor we use the MSCI emerging market index monthly total return and this time series is obtained through Thomson Reuters Datastream. For the bond market factor we use the monthly change in the ten year Treasury constant maturity yield. For the credit-spread factor we use the monthly change in the Moody's Baa yield less the 10 year Treasury constant maturity yield. Both time-series for the ten-year Treasury constant maturity yield and for the Moody's Baa yield are obtained from the Federal Reserve Board database[4].

The final data sample contains 3,124 funds over the period from January 1994 to April 2014. From the 3,124 funds in the data sample, 2,132 are dead and 992 are still alive in 2014. The data sample includes 965 funds of funds and 2,195 funds in nine style categories. Panel A of Table 1 reports the monthly returns of the funds per investment style in the final sample. The average monthly return of all funds is 0.64%, which adds to 7.72% annually with a monthly standard deviation of 3.82%. The minimum and maximum monthly return of the total sample are -19.50% and 20.63%, respectively. Funds of funds have lower average returns (4.88% annually) than hedge funds (8.95% annually). These findings are consistent with the findings of Hsieh and Fung (2001) and can be explained by the fact that funds of funds are more diversified and charge operating expenses and management fees on top of the expenses and fees charged by the hedge funds in which they invest. Moreover, funds of funds seem to hold more cash than hedge funds to prevent liquidity problems when investors redeem their shares. All hedge fund return distributions are leptokurtic and most of the funds have negative skewness. This is consistent with the findings in Brooks and Kat (2001) and especially true for convertible arbitrage index.

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[3] The data of the trend-following factors are available from http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls

[4] Data are downloaded from the Federal Reserve Board website: www.federalreserve.gov/releases/H15/data.htm

Panel B of Table 1 summarizes the descriptive statistics of the eight factors of the Fung and Hsieh (2004) model and Panel C of Table 1 reports the summary statistics for the four Carhart (1997) factors from January 1994 to April 2014.

Panel D summarizes the control variables including the Pastor and Stambaugh liquidity factor, the Chicago Board Options Exchange volatility index (VIX), the 3-month treasury T-bill rate, the term spread between the 10-year and tree-month treasury bonds, the quality spread between the Moody's BAA- and AAA- rated corporate bonds and the dividend yield of the S&P 500.

< INSERT TABLE 1 HERE >

The hedge fund characteristics for the funds in the data sample are also obtained from the Lipper TASS database. Table 2 summarizes the fund characteristics. The average fund age in the data sample is 7.30 years, the shortest lifetime in the data sample is 3 years[5] and the longest lifetime of a fund is 19.67 years. The average fund size is 188.65 million dollars in average assets under management, with a minimum of 10.02 million dollars and a maximum of 16,146.56 million dollars. The average minimum requirement is 0.96 million dollars, ranging from zero to 50 million dollars. The average management fee of funds in the data sample is 1.39% of the assets under management. The management fees percentages vary between zero and 4.80%.

The incentive fee is on average 15.28% of the fund profits and 65.05% of the funds use a high water mark. The incentive fees percentages vary between zero and 50%. Among the funds in the data sample, 55.12% use leverage, 18.96% use derivatives, 33.23% of the managers have personal capital invested in the fund, 16.01% are open to public, and 94.14% employs effective auditing. The average redemption period of the funds in the data sample is 42.86 days with a maximum of 365 days. The average lockup period among the funds is 3.92 days with a maximum of 90 days and the average pay out period is 17.99 days with a maximum of 640 days.

< INSERT TABLE 2 HERE >

3.2 Methodology

To measure the factor timing ability of hedge fund managers, we build on the framework of Treynor and Mazuy (1966). The framework of Treynor and Mazuy (1966) is based on the capital asset pricing model, which explains that fund manager portfolio returns follow the process presented in Equation (1):

[5] Due to the 18 month minimum that we impose

$$R_{i,t+1} = \alpha_i + \beta_{i,t} * MKT_{t+1} + \varepsilon_{it+1} \quad \mathrm{t} = 0, \ldots, T-1, \tag{1}$$

where $R_{i,t+1}$ is the return for fund i in excess of the risk-free rate and MKT_{t+1} is the market return in excess of the risk-free rate. The idea behind the framework of Treynor and Mazuy (1966) is that the fund manager of fund i will adjust the $\beta_{i,t}$ in month t +1 on forecasted market movements. A first-order Taylor series expansion is used to express market beta as a linear function of the forecast of the market returns.

$$\beta_{i,t} = \beta_i + \gamma_i(MKT_{t+1}|I_t), \tag{2}$$

where γ_i is the coefficient that captures the timing skill and (MKT_{t+1}) is the manager's forecast of the market return given the information set *I* in period *t*. Substituting Equation (2) in Equation (1) results in the Treynor-Mazuy (1966) market-timing model:

$$R_{i,t+1} = \alpha_i + \beta_i * MKT_{t+1} + \gamma_i * MKT_{t+1}^2 + \varepsilon_{it+1} \quad \mathrm{t} = 0, \ldots, T-1, \tag{3}$$

We focus on the factor timing skills of hedge fund managers. Factor timing is the skill of a fund manager to adjust the factor exposure for a specific factor based on a forecast of the specific factor condition. This paper is focused on the factor timing of the Fung and Hsieh (2004):

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{ij} f_{j,t+1} + \varepsilon_{it+1} \tag{4}$$

where $f_{j,t+1}$ represents the eight-factors of the Fund-Hsieh factor model: $f_{1,t+1}$ is an equity market factor (MKT), $f_{2,t+1}$ is a size factor (SMB), $f_{3,t+1}$is the monthly change in the yield of the ten-year treasury (YLDCH), $f_{4,t+1}$ is the monthly change in the spread between Moody's Baa bond and the ten-year treasury yields (BAAMSTY), $f_{5,6,7,t+1}$ are three trend-following factors for bonds (PTFSBD), currencies (PTFSFX), and commodities (PTFSCOM) and $f_{8,t+1}$ is the emerging market index factor (EM).

Following the timing literature we use a first-order Taylor series expansion to express the factor beta as a linear function of the forecast of the factor return. The linear form for every factor is presented in Equations (5) to (12).

$$\beta_{1i,t} = \beta_{1i} + \gamma_{1i}(MKT_{t+1}) \tag{5}$$
$$\beta_{2i,t} = \beta_{2i} + \gamma_{2i}(SMB_{t+1}) \tag{6}$$
$$\beta_{2i,t} = \beta_{3i} + \gamma_{3i}(YLDCHG_{t+1}) \tag{7}$$
$$\beta_{2i,t} = \beta_{4i} + \gamma_{4i}(BAAMTSY_{t+1}) \tag{8}$$

$$\beta_{2i,t} = \beta_{5i} + \gamma_{5i}(PTFSBD_{t+1}) \tag{9}$$

$$\beta_{2i,t} = \beta_{6i} + \gamma_{6i}(PTFSFX_{t+1}) \tag{10}$$

$$\beta_{2i,t} = \beta_{7i} + \gamma_{7i}(PTFSCOM_{t+1}) \tag{11}$$

$$\beta_{2i,t} = \beta_{8i} + \gamma_{8i}(EMRF_{t+1}) \tag{12}$$

Substituting Equations (5)-(12) in Equation (4) results in the factor timing model that we use to estimate the factor timing ability of hedge funds:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} f_{j,t+1}^2 + \varepsilon_{it+1} \ , \tag{13}$$

where $\gamma_{i,k}$ denotes the exposure to the quadratic form of the factors and therefore captures the factor timing skill of the hedge fund manager for factor k.

4. Factor Timing Ability

4.1 Equally weighted fund portfolios

Table 3 presents the estimation results of the Fung-Hsieh eight-factor model (2004) estimated on equally weighted portfolios of fund per investment style and combined. The alpha is positive and significant for all portfolios, except for the dedicated short bias funds. The exposure to the market is significantly positive for the all funds portfolio and for all style portfolios, except for the dedicated short bias and emerging markets portfolio. The exposure to the size factor is significantly positive at the 1% level for the all funds portfolio. The event driven and long short equity funds show significant positive exposure and the dedicated short bias funds show significant negative exposure to the size factor at the 1% level. The exposure to the bond market factor is negative but insignificant for the all funds portfolio and only significant but negative for convertible arbitrage and dedicated short bias funds. Next, the exposure to the credit-spread factor is negative for all investment style portfolios and significant at the 1% level for most of the portfolios except for the dedicated short bias, equity market neutral, global macro and long short equity funds. The exposure to the trend-following bond factor is insignificant for the all funds portfolio and for all investment style portfolios except for the event driven fund portfolio (negative). The exposure to the trend-following currency factor is positive significant at the 1% level for most of the investment style portfolios except for the convertible arbitrage, dedicated short bias, and multi-strategy fund portfolios. The exposure to the trend-following commodity factor is positive insignificant for the all funds portfolio and also insignificant for all investment style portfolios. Finally, the exposure to the emerging market factor is positive significant for the all funds portfolio and positive significant for most of the investment styles at the 1% level.

Only the dedicated short bias portfolio has a negative insignificant exposure and the equity market neutral portfolio has a positive insignificant exposure to the emerging market factor.

< INSERT TABLE 3 HERE >

Table 4 reports the analysis on the factor timing skills at an aggregate level. Table 4 shows that the all funds portfolio has positive significant timing skills on the market factor and size factor at the 1% level, negative significant timing coefficients for the bond market factor at the 1% level and on the emerging market factor at the 5% level. Note, however, that negative timing skills for the bond factor are in fact positive for the fund if the fund has a net long exposure to the bond market because the bond factor is denominated in yields (changes). Interestingly, the results show that the different investment styles show various timing skills on different factors. None of the investments style portfolios show significant positive timing skills on the credit-spread factor and on the trend-following factors. Only the fund of funds portfolio demonstrates significant negative timing of the trend-following currency factor.

The portfolio of the convertible arbitrage funds only shows significant positive timing skills on the size factor at the 1% level. The dedicated short bias fund portfolio is the only investment style portfolio that demonstrates significant positive exposure to the emerging market factor and negative exposure to the credit-spread factor. Furthermore, the dedicated short bias fund portfolio shows positive exposures when the other investment style portfolios show negative exposures and vice versa to most of the timing factors. This might indicate that the dedicated short bias funds are a good hedge to the other investment style funds. The portfolio of event driven funds only shows significant negative exposure to the bond market factor at the 1% level. The portfolio that consists of emerging markets funds shows significant positive timing skills on the size factor at the 1% level and significant negative exposure to the bond market timing factor and emerging market timing factor at the 1% level. This result is in contrast with the expectation that emerging markets funds are experts in investing in emerging markets and therefore are expected to be also experts in timing the emerging market factor.

The results show no evidence for significant timing skills in the portfolio that consists of equity market neutral funds, but the portfolio has no significant negative timing coefficients either. This result can be related to the aim of equity market neutral funds to neutralize risks. The portfolio of global macro funds only has significant positive timing skills on the market factor and a significant negative exposure to the bond market timing factor at the 5% level. This is in accordance with the strategy of these funds to exploit market trends by using their expertise on analyzing macroeconomic trends.

The portfolio that consists of funds of funds shows the most significant exposure to the timing factors. The portfolio demonstrates significant positive timing skills on the market factor and on the size factor at the 1% and 5% level respectively. Moreover, the portfolio shows negative exposure to the bond market, the trend-following currency and the emerging market factor at the 1% level and significant negative exposure to the trend-following commodity factor at the 10% level. These findings are in accordance with the goal of fund of funds to invest in other hedge funds and therefore make use of many different strategies. The long short equity style portfolio has only significant positive timing skills on the market factor at the 5% level and significant negative exposure to the trend-following currency factor. The significant market timing skills can be explained by their expertise on forecasting and investing in the equity market. The portfolio with the multi strategy funds shows significant positive timing skills on the market and size factor at the 1% level. The exposure to the other timing factors is negative but insignificant at the 5% level. Like fund of funds, multi strategy funds make use of multiple strategies and therefore are supposed to have exposure to more timing factors then other hedge funds and this is supported by the results.

< INSERT TABLE 4 HERE >

In summary, the results on the aggregate level suggest that almost all investment style portfolios have positive alphas and that hedge fund managers typically possess factor timing skills based on our measure. This result confirms our hypothesis 1. Furthermore, the results on the aggregate level support our hypothesis 2 that funds with different investment styles show different timing skills on the individual factors. The timing skills, though, appear not to be related to their investment style. The differences in factor timing skills among the different investment styles are further examined in the analysis at the individual level in Section 4.2.

4.2 Individual funds

Table 5 presents the distribution of *t*-statistics for the timing coefficients per factor at the individual fund level for all funds. Firstly, Table 5 shows that there is relatively more positive exposure to the market, size and credit-spread timing factors and relatively more negative exposure to the bond market, the three trend-following and the emerging market timing factors. Secondly, Table 5 shows the percentage of funds with *t*-statistics exceeding the indicated values. 35% of the funds show positive market timing skills and 10% of the funds exhibit negative market timing. Furthermore, 46% of the funds possess size factor timing skills and 9% of the funds show negative size factor timing. In contrast to the market and size factor, the results show relatively fewer funds with significant positive timing skills than significant negative timing on the bond market, the trend-following currency, and the emerging market factor with 11% and 65%, 7% and 38%, and 10% and 52%, respectively. The difference between the percentage of funds with significant positive skills and negative timing for the credit spread, the trend-following bond and commodity factor is less explicit.

< INSERT TABLE 5 HERE >

Table A.1 (see Appendix A) presents the distribution of *t*-statistics for the timing coefficients per factor at the individual fund level for each investment style. For conciseness, we only discuss the results that are meaningful and which are divergent from the results in Table 5. First, the convertible arbitrage funds in Panel A show more positive timing on the market and size factor than all styles combined, but none of these funds show significant timing skills on the trend-following commodity factor. Moreover, 36% of the convertible arbitrage funds have a negative exposure to the trend-following commodity factor and 12% has a significant negative exposure to this factor at the 5% level. Another major deviation is that a higher percentage of the convertible arbitrage funds possess significant emerging market timing skills than the combination of all funds, 38% and 9% respectively.

In Panel B the dedicated short bias funds show a lot of deviation in comparison to all funds. For example, the percentage of funds with significant market timing skill is smaller than the percentage of funds with significant negative exposure to the market timing factor. In total there is more negative than positive market timing, 48% and 10% respectively. In contrast to all funds combined, the dedicated short bias funds show for the credit-spread and trend-following currency factor more negative than positive exposure and more positive than negative timing on the trend-following commodity and emerging market factors. The deviation from the other funds can perhaps be explained by their aim to profit from declining markets. In other words, dedicated short bias funds try to time against other factor timers.

Panel D shows that 98% of the emerging market funds possess significant timing skills on the size factor. Like the equally weighted analysis, this analysis shows that emerging market funds have more negative than positive exposure to the emerging market-timing factor. This is against the expectation that these funds are experts in timing the emerging market factor.

Panel F shows a higher percentage of funds of funds with significant market timing skills than for all funds combined. Furthermore, the percentage of fund of funds with significant negative exposure to the bond market, the trend-following currency and the emerging market factor is much higher than for all funds combined. The event driven, the long short equity and the multi strategy funds show similar results as the combination of all fund styles. The equity market neutral and global macro funds show smaller percentages of funds with significant positive or negative exposure to the factors than for all funds[6].

[6] One could argue that Fund of funds do not attempt to time factors, but investment styles instead. We test this by running the same type of analyses using style indices rather than factors as explanatory variables. In unreported results, we find limited evidence for style timing by fund of funds. Specifically, we only find significant negative timing for the Convertible Arbitrage and Equity Market Neutral styles.

5. Determinants of Factor Timing Ability

After having established that funds possess a certain degree of factor timing ability in Section 4, we now turn to the question which fund characteristics are related to timing ability. We quantify timing ability by means of the t-statistic of the factor timing coefficient. We take the t-statistic rather than the coefficient itself, because the magnitude of the coefficient is conditional on the order of magnitude of the factor itself. Table 6 shows the results of the analysis of the relation between several fund characteristics and the *t*-statistics of the factor timing coefficients for the individual funds. The included characteristics are the fund age, the fund size, the minimum required investment, the management fees, the incentive fees, the restriction period, the lockup period and the use of a high water mark, leverage, derivatives, personal capital, effective auditing and the option for the fund to be open to public.

< INSERT TABLE 6 HERE >

Focusing on the average timing skills over the factors first, the results in Table 6 demonstrate that better timing skills are related to funds that are younger, smaller, have higher incentive fees, make use of leverage, and have a smaller restriction period.

Interestingly, the results show ample variation in the relation between the fund characteristics and the individual timing factors. The positive significant relation with the fund age, the fund size, and the negative significant relation with the incentive fees and the restriction period explain the market timing skills. The latter three are in contrast with the findings on the average factor timing skill. The positive relation with timing the market could be explained by the fact that older and larger funds are more experienced. The only significant effect on the size factor timing skill is the positive effect of the fund age, which also can be related to experience. The bond market timing ability is explained by a significant negative relation with the fund age, the fund size, and the restriction period, and by a significant positive relation with the incentive fees and the open to public dummy. These findings are in accordance with the findings of the cross-sectional analysis of the average factor timing skill and are explained by the inverse relation between the factor (in yields) and bond prices.

Furthermore, the results show a significant positive relation between the credit-spread factor timing skill and the management fees, the high water mark and the audit dummy and a negative relation with the incentive fees and the personal capital dummy. Possibly the negative effect of the incentive fees and the personal capital dummy is compensated by the positive effect of the management fee and the high water mark to attract skilled managers. A significant negative relation with the fund age and the minimum required investment and a significant positive effect of the management fees, the leverage dummy and the restriction period can explain the trend-following bond factor timing skill. The trend-following currency factor timing ability has a significant negative relation with the variables fund age, the fund size and the management fees and a significant positive relation with the minimum required investment, the incentive fees and the dummy open to public. The trend-following commodity factor timing skill can be explained by a significant positive influence of the incentive fees and a significant negative relation with the management fees and the high water mark dummy. Finally, the results for the emerging market factor timing skill show a significant positive relation with the minimum required investment, the incentive fees and the personal capital. We find a significant negative relation between the emerging market factor timing skill and the fund age, the fund size, the high water mark, the restriction period and the dummy for effective auditing.

Table B.1 (Appendix B) shows the results of the analysis of the cross-sectional relation between the fund characteristics and the average *t*-statistics of the timing coefficients for the individual funds per investment style. The results show some variation in the relation between the different investment styles and the fund characteristics. None of the fund characteristics have a significant influence on the factor timing ability of convertible arbitrage funds, dedicated bias funds, and long short equity funds. For event driven funds the results demonstrate a significantly negative relation between the factor timing ability and the minimum investment requirement at the 5% level and a significantly positive relation with the incentive fees and the leverage dummy at the 1% level. A significantly negative relation at the 1% level with the fund size and the management fees explains the factor timing skill of emerging market funds. The factor timing ability of equity market neutral funds is significantly positive related to the personal capital of a fund manager invested in the fund. The results on factor timing ability of the funds of funds are similar to the results when all styles are combined. A significantly negative relation with the fund age at the 1% level explains the factor timing skill of global macro funds. For multi-strategy funds we find a significantly negative relation with the fund size at the 1% level.

Overall, the cross-sectional analysis demonstrates that the factor timing skills on the individual factors show a lot of variation in the relation with fund characteristics. This is also the case for the different investment styles. For the average factor timing skill and the combined investment styles, we find that funds that are younger, smaller, have higher incentive fees, have a smaller restriction period and that make use of leverage possess better timing skills. This might be because these funds are more flexible to engage in factor timing strategies due to the younger and smaller environment. A longer restriction period is associated with more flexibility, whereas a shorter restriction period is preferable for investors. Thereby, funds with smaller restriction periods can theoretically attract more investors, which in turn can result in attracting higher skilled managers. Furthermore, higher incentive fees are related to the ability of a fund to attract more skilled managers. These results partly confirm hypothesis 3. Moreover, the findings that smaller funds and funds with smaller restriction periods possess better factor timing skills are in accordance with the expectation that more flexible funds have better factor timing skills. The results also confirm the expectation that a more skilled fund manager, which is proxied by the incentive fee, has better factor timing skills. The results do not confirm our expectation that more experienced and committed fund managers, proxied by personal capital, have better timing skills.

6. Persistence in Factor Timing

Market timing is mechanically related to (static) alpha within the Treynor-Masuy framework in an in-sample setting. Although this is less obvious in our multi-factor setting due to cross-correlations between factors, we also find a positive relation between the average timing ability of funds and in-sample alpha[7]. Question is, however, whether the timing ability is persistent. Therefore, we perform an out-of-sample performance test by looking into the persistence of factor timing ability. As a benchmark, we start by studying the performance persistence in our database based on the Fung-Hsieh alpha. For each month and fund, we estimate the factor model (without timing) based on a lookback period of 36 months starting in January 1997. Then, we sort the funds for every month in deciles based on their Fung-Hsieh alpha and create portfolios for every month per decile. Next, we hold the portfolios for 1 month and calculate the portfolio returns. Finally, we use the portfolio return time series for each holding period and decile to estimate the eight-factor alpha.

Subsequently, we do an out-of-sample analysis based on the timing ability of fund managers. For each month and fund, we estimate the factor timing model based on a lookback period of 36 months starting in January 1997 with the factor timing model of Equation (13), and calculate the average t-value of the factor timing coefficients γ. Then, we sort the funds for every month in deciles based on their average factor timing t-value and create portfolios for every month per decile. Next, we calculate the portfolio returns. Finally, we use the portfolio return time series for each decile to estimate the eight-factor alpha.

The benchmark results, based on the Fung-Hsieh alpha, are presented in Table 7.

< INSERT TABLE 7 HERE >

Table 7 shows that the 10-1 spread portfolios yield positive significant returns for all holding periods. For the 1-month holding period, the spread portfolios yields a significant 0.60% per month.. These results confirm the findings of Kosowski, Naik, and Teo (2007) that there is indeed performance persistence for hedge funds.

The results for the persistence in factor timing are presented in Table 8.

< INSERT TABLE 8 HERE >

[7] The average t-value of the γ's in Equation (13) has a positive and significant correlation with the Fungh-Hsieh alpha (t = 3.30).

The last column presents the spread portfolio consisting of the spread between the top and bottom factor timing portfolios and demonstrate that top factor timing portfolios deliver higher alphas than the bottom factor timing portfolios. For the 1-month holding period, the spread portfolio shows a significant positive alpha of 0.08% per month (*t*-statistic 4.33), which is equal to 0.96% annually. This implies that the performance persistence of hedge funds at the 1-month horizon that we find in Table 7 can be explained for 13.3% (=0.08 / 0.601) by factor timing skills, suggesting that the remaining 86.7% is explained by stock picking skills.

In summary, the results on the analysis of the economic value of factor timing show that top factor timing funds outperform the bottom factor timing funds and earn significant alpha. Therefore, it can be concluded that factor timing skills of a hedge fund manager is persistent and as a result add significant value for investors, confirming our hypothesis 4.

7. Robustness Checks

7.1 Bootstrap p-values

We use a bootstrap analysis to test whether the timing skills are based on random variation or on actual skills. Following Kosowski, Timmermann, White, and Wermers (2006), we use a bootstrap procedure for statistical inferences to distinguish whether the factor timing skills are actual skills or pure luck. The bootstrap procedure has five steps.

1. Estimated per fund the factor timing model and store the estimated coefficients and the time-series of residuals $\{\varepsilon_{\mathrm{it}}\}$.
2. Calculate "pseudo" fund returns using the stored coefficients and randomly resampled residuals (with replacement). The "pseudo" fund returns were generated under the null hypothesis of no timing ability, so the coefficients for factor timing were set to be zero.
3. Estimate the factor timing model but now with the "pseudo" fund returns. Store the bootstrapped factor timing coefficients and the t-statistics. The estimated factor timing coefficients are representing sampling variation, because the factor timing coefficients of the "pseudo" funds are zero by construction.
4. Repeat the first three steps for 1,000 iterations.
5. Calculate the bootstrapped p-value following Equation (14):

$$p = \frac{1}{B}\sum_{b=1}^{B} I(t_{i,s}^{b} > t_{\gamma i}), \tag{14}$$

where $t_{i,s}^{b}$ is the bootstrapped *t*-statistic per fund and iteration, $t_{\gamma i}$ is the *t*-statistic per fund. I is one if $t_{i,s}^{b} > t_{\gamma i}$ and zero otherwise. The p-value of the bootstrapped t-statistic is equal to proportion of the bootstrapped *t*-statistics that are higher than the actual *t*-statistic. The results of the bootstrap analysis are presented in Table 9 and show the *t*-statistics of the factor timing coefficients for the funds at the extreme percentiles per factor. For every fund at the extreme percentiles Table 9 shows a corresponding *p*-value calculated with the bootstrap procedure. For the market timing factor, the top extreme percentiles 90%, 95%, 97%, 99% and the top fund show bootstrap *p*-values close to zero with *t*-statistics of 2.05, 2.64, 2.78, 3.25 and 4.59 respectively. For the negative extreme percentiles, only the 1% and the bottom fund, with respectively *t*-statistics of -3.00 and 4.78 show *p*-values close to zero. This indicates that the top 10% of the funds sorted on market timing factor *t*-statistics possess timing skills, which are not due to random variation or luck. The results for the size-timing factor show similar results as the market-timing factor.

For the positive extreme percentiles with *t*-statistics of 2.36 or higher, the calculated *p*-values are close to zero and for the negative extreme percentiles only the bottom fund demonstrates a *p*-value close to zero. This suggests strong evidence for size factor timing skills that are actually based on skills. The bond market and emerging market show for all *t*-statistics in the negative extreme percentiles *p*-values smaller than 0.05 and only for the *t*-statistics in the 99% percentile and the top fund *p*-values smaller than 0.05. This implies weak evidence for actual timing skills on the bond market and emerging market factor, but strong evidence for negative timing on these factors not based on random variation. For the credit-spread and the three trend-following factors, we find *p*-values smaller than 0.05 in the bottom, 1%, 3% and 5% percentiles and in the 97%, 99% and top percentiles. This suggests evidence that negative timing and positive factor timing skills can be distinguished from luck on the credit-spread and the three trend-following factors.

< INSERT TABLE 9 HERE >

7.2 Choice of factor model

The top half of Table 10 presents the distribution of *t*-statistics for the timing coefficients per factor per individual fund estimated with a Treynor-Mazuy (1966) model using the Carhart four-factor model rather than the Fung-Hsieh eight factor model. In contrast to the results in Table 5 based on the Fung-Hsieh (2004) eight-factors, the results show a higher percentage of funds with negative than positive market timing, and 20% of the funds show significant negative market timing at the 5% level. Furthermore, there is a less explicit difference between percentage of funds with positive and negative exposure to the size-timing factor than the results of the Fung-Hsieh (2004) based model in Table 5 show. In addition, there are more funds with a positive than negative exposure to the value- and momentum-timing factor. Of all funds 18% and 14% show timing skills on the value and momentum factor, respectively. These results show evidence for factor timing in hedge funds, which is in accordance with the results using the Fung-Hsieh (2004) eight-factor based model. The differences in exposure to the market and size factor between the two models can be explained by the shortcoming of the Carhart four-factor based model to capture nonlinear relation with the asset market.

The bottom part of Table 10 presents results of an extension of the Fung-Hsieh eight factor model, namely including the Betting-Against-Beta factor (BaB) of Frazini and Pedersen (2014) as well as the Global Carry Factor (GCF) of Koijen, Moskowitz, Pedersen, and Vrugt (2015). The results give a qualitatively similar image as for the benchmark factor model as well as for the reduced factor model.

< INSERT TABLE 10 HERE >

7.3 Public information

Ferson and Schadt (1996) show that spurious timing can occur when a fund manager adjusts the fund exposure based on public information. This kind of timing cannot be attributed to a talent or skill of a manager and therefore we have to control for this kind of factor timing. To control for spurious factor timing skills based on public information, we use a model including lagged instruments following the model of Ferson and Schadt (1996):

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 + \sum_{l=1}^{L} \delta_{i,l} z_{l,t} MKT_{t+1} + \varepsilon_{it} \quad , \qquad (15)$$

where $z_{l,t}$ denotes the four lagged instruments. Following Chen and Liang (2007), we use the three-month T-bill yield, the term premium, quality spread and the dividend yield of the S&P 500 index as lagged instruments.

Table 11 shows the distribution of *t*-statistics for the timing coefficients per factor per individual fund controlling for public information. The results show that our findings are robust for spurious timing based on public information, because there are no major differences between the funds timing skills when controlling for public information or when we do not control for public information.

< INSERT TABLE 11 HERE >

7.4 Use of derivatives

Jagannathan and Korajczyk (1986) show that spurious market timing can be caused by the use of derivatives in mutual funds. Table 12 presents the distribution of *t*-statistics for the timing coefficients per factor for funds that are using derivatives and do not use derivatives. The results show that our findings are robust for the use of derivatives. There are no major differences between the percentages of funds with factor timing skills between the funds using derivatives (Panel A) and the funds that are not using derivatives (Panel B).

< INSERT TABLE 12 HERE >

7.5 The Effect of Fund Size

Following the credit crunch of 2008, the government of the United States signed the Dodd-Frank act in 2010 to reform the financial system and to increase the financial stability of the United States. The Dodd-Frank act introduces a required registration for hedge funds with assets under management of more than 150 million dollars. The increasing regulation on large hedge funds can affect the factor timing ability of these funds. Therefore, Table 13 presents the distribution of *t*-statistics for the timing coefficients per factor controlling for fund size. The results show no major differences between funds with assets under management smaller than 50 million dollars (Panel A), larger than 50 million dollars and smaller than 150 million dollars (Panel B) and funds with assets under management larger than 150 million dollars (Panel C). The large funds in Panel C only show relatively more funds with positive exposure to the market and size timing factor and relatively more funds with more negative exposure to the trend-following currency and emerging market factor.

< INSERT TABLE 13 HERE >

7.6 Controlling for volatility and liquidity timing

Cao et al. (2013) demonstrate that hedge funds have volatility timing and liquidity timing skills. To control for the volatility timing and liquidity timing skills, we extend the Treynor-Mazuy (1966) model following the model of Busse (1999) and Cao et al. (2013):

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 + \delta_1 MKT_{t+1}\left(\sigma_{m,t+1} - \overline{\sigma_m}\right) + \delta_1 MKT_{t+1}\left(L_{m,t+1} - \overline{L_m}\right) + \varepsilon_{it+1}, \quad (16)$$

where $\sigma_{m,t+1}$ represents the market volatility, which is demeaned with the average market volatility of the total time series ($\overline{\sigma_m}$). $L_{m,t+1}$ denotes the market liquidity factor, which is demeaned with the average market liquidity of the total time series ($\overline{L_m}$). These factors are demeaned with the time series average of the specific factors for ease of use.

Table 14 demonstrates the results of the individual factor timing skills of hedge funds when controlling for market volatility timing and market liquidity timing. The results show that 31% of the funds demonstrate significant market volatility timing skills at the 5% level. Furthermore, there is less strong evidence for market liquidity timing skills, 5% of the funds show significant timing skills at the

5% level. These results indicate that our findings on the factor timing ability are robust to controlling for market volatility timing skills and market liquidity timing skills.

< INSERT TABLE 14 HERE >

8. Conclusion

This study examines whether hedge fund managers have factor timing skills on the factors of the Fung and Hsieh (2004) model. Using a data sample of 3,124 funds from January 1994 to April 2014, we examine the factor timing ability of hedge fund managers, the determinants of timing ability, as well as the persistence in timing ability.

The results at both the aggregate and the individual level suggest that hedge fund managers do possess factor timing skills. Additionally, the results on the analysis of the different investment styles suggest that funds with different investment styles show a lot of variation in timing skills on the individual factors. The results on the cross-sectional analysis of the factor timing ability of hedge fund managers suggest that better factor timing skills are related to funds that are younger, smaller, have higher incentive fees, have a smaller restriction period and make use of leverage. The analysis of the persistence in the factor timing skills suggests that the top factor timing funds outperform the bottom factor timing funds with a significant alpha of 0.96% annually. This implies that the factor timing skills of hedge fund managers add value for investors.

Finally, the findings in this study are robust to the use of an alternative factor model, public information, derivatives, and alternative factors including the market volatility factor and the market liquidity factor. Additionally, we find similar results when controlling for fund size. We confirm through a bootstrap analysis that the results are not driven by statistical noise.

To conclude, for the first time in the timing literature this study presents broad and strong evidence for the factor timing skills of hedge fund managers and explains the factor timing skills by several fund characteristics. A better understanding of the factor timing skills of hedge fund managers is important for investors to make a better investment decision and important for the managers self to learn from.

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Appendices

Appendix A. The distribution of factor timing skills per style

Table A.1: Distribution of the *t*-statistics for the timing coefficients per factor for each investment style.
This table presents the distribution of *t*-statistics for the timing coefficients per factor at the individual fund level for each investment style. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} f_{j,t+1}{}^2 \ \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\boldsymbol{\gamma_{i,k}}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors with two lags. The number in the table shows the percentage of funds with *t*-statistics of the factor timing coefficients exceeding the indicated values. The percentages are presented per timing factor and for the average of the timing factors. The different panels show the factor timing skills per investments style including convertible arbitrage funds, dedicated short bias funds, event driven funds, emerging market funds, equity market neutral funds, funds of funds, global macro funds, long short equity funds and multi-strategy funds.

Panel A: Convertible arbitrage

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	1	2	4	15	11	4	7	30
SMB	0	0	1	23	19	13	1	55
YLDCHG	13	19	23	10	8	4	55	22
BAAMTSY	7	9	12	5	4	3	28	12
PTFSBD	4	4	5	16	9	4	13	29
PTFSFX	1	4	12	2	0	0	17	2
PTFSCOM	6	12	18	0	0	0	36	0
EM	2	3	4	16	14	8	9	38
Average	4.25	6.63	9.88	10.88	8.13	4.50	20.75	23.50

Panel B: Dedicated short bias

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	16	16	16	5	5	0	48	10
SMB	0	0	0	21	5	0	0	26
YLDCHG	0	0	5	16	5	0	5	21
BAAMTSY	5	11	11	5	5	0	27	10
PTFSBD	11	11	11	5	0	0	33	5
PTFSFX	0	5	5	0	0	0	10	0
PTFSCOM	0	5	16	5	5	0	21	10
EM	0	0	5	0	0	0	5	0
Average	4.00	6.00	8.63	7.13	3.13	0.00	18.625	10.25

Panel C: Event driven

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	4	5	8	6	4	3	17	13
SMB	2	4	6	21	17	14	12	52
YLDCHG	20	25	29	4	2	1	74	7
BAAMTSY	4	8	12	13	9	4	24	26
PTFSBD	4	9	13	5	1	1	26	7
PTFSFX	6	14	17	5	3	2	37	10
PTFSCOM	2	3	5	5	3	2	10	10
EM	5	10	15	3	1	1	30	5
Average	5.88	9.75	13.13	7.75	5.00	3.50	28.75	16.25

Table A.1 (continued**)**

Panel D: Emerging market

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	2	5	6	19	14	9	13	42
SMB	0	0	1	42	33	23	1	98
YLDCHG	19	26	32	3	2	1	77	6
BAAMTSY	4	5	8	22	17	10	17	49
PTFSBD	4	6	10	8	4	2	20	14
PTFSFX	5	10	15	4	2	1	30	7
PTFSCOM	2	3	5	8	6	4	10	18
EM	19	23	29	8	5	3	71	16
Average	6.88	9.75	13.25	14.25	10.38	6.63	29.875	31.25

Panel E: Equity market neutral

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	4	6	10	14	9	6	20	29
SMB	7	7	9	13	10	6	23	29
YLDCHG	5	8	13	12	7	7	26	26
BAAMTSY	3	5	6	11	10	9	14	30
PTFSBD	7	10	16	2	1	0	33	3
PTFSFX	2	5	12	9	5	3	19	17
PTFSCOM	2	3	7	5	3	3	12	11
EM	6	11	16	10	3	1	33	14
Average	4.50	6.88	11.13	9.50	6.00	4.38	22.5	19.88

Panel F: Fund of fund

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	1	2	3	22	14	9	6	45
SMB	1	3	4	18	13	9	8	40
YLDCHG	26	33	40	2	1	1	99	4
BAAMTSY	4	6	8	12	7	3	18	22
PTFSBD	4	6	10	6	3	1	20	10
PTFSFX	11	17	24	2	2	1	52	5
PTFSCOM	2	4	7	2	1	0	13	3
EM	20	28	37	2	1	1	85	4
Average	8.63	12.38	16.63	8.25	5.25	3.13	37.625	16.63

Panel G: Global macro

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	1	3	5	22	16	8	9	46
SMB	2	2	5	12	8	5	9	25
YLDCHG	6	12	15	8	5	3	33	16
BAAMTSY	3	6	12	10	6	2	21	18
PTFSBD	2	4	5	10	6	2	11	18
PTFSFX	4	8	17	7	4	2	29	13
PTFSCOM	2	5	8	5	5	1	15	11
EM	8	11	15	4	3	3	34	10
Average	3.50	6.38	10.25	9.75	6.63	3.25	20.125	19.63

Table A.1 (continued**)**

				Panel H: Long short equity				
Variables	**t≤-2,326**	**t≤-1,960**	**t≤-1,645**	**t≥1,645**	**t≥1,960**	**t≥2,326**	**Total negative**	**Total positive**
MKT	2	3	4	16	10	6	9	32
SMB	2	4	6	17	13	8	12	38
YLDCHG	9	13	17	8	5	3	39	16
BAAMTSY	5	7	10	13	9	5	22	27
PTFSBD	4	8	13	8	4	2	25	14
PTFSFX	7	11	17	3	2	1	35	6
PTFSCOM	4	5	9	5	4	2	18	11
EM	8	11	16	7	4	3	35	14
Average	5.13	7.75	11.50	9.63	6.38	3.75	24.375	19.75
				Panel I: Multi strategy				
Variables	**t≤-2,326**	**t≤-1,960**	**t≤-1,645**	**t≥1,645**	**t≥1,960**	**t≥2,326**	**Total negative**	**Total positive**
MKT	2	2	3	15	11	7	7	33
SMB	1	1	3	24	18	14	5	56
YLDCHG	14	18	25	5	3	1	57	9
BAAMTSY	4	6	8	11	6	4	18	21
PTFSBD	3	5	8	4	2	2	16	8
PTFSFX	3	7	15	6	5	2	25	13
PTFSCOM	4	9	11	1	0	0	24	1
EM	10	13	20	7	4	0	43	11
Average	5.13	7.63	11.63	9.13	6.13	3.75	24.375	19.00

Appendix B. The fund characteristics of the factor timing funds per style

Table B.1: Cross-sectional analysis timing ability per investment style.

This table presents the cross-sectional analysis of the factor timing skills of hedge fund managers per investment style. The dependent variable is the average *t*-statistic of the factor timing skill coefficient. We estimate the following model per factor:

$$t-\text{statistic}_i = \alpha_0 + \beta_1 Log(Age)_i + \beta_2 Log(Size)_i + \beta_3 Ln(MinInv)_i + \beta_4 MFee_i + \beta_5 IFee_i + \beta_6 High\ water\ mark_i + \beta_7 Leverage_i + \beta_8 Derivatives_i + \beta_9 Personal\ capital_i + \beta_{10} Lockup\ period_i + \beta_{11} Restriction\ period_i + \beta_{12} Open\ to\ public_i + \beta_{13} Audit_i + \xi_i$$

Where the independent variables are the fund age, measured by the months operating, the fund size measured by the average assets under management, the minimum investment in dollars, the management fee and the incentive fee in percentage, the lockup period in months, the restriction period in days and the dummy variables for the use of a high water mark, leverage, derivatives, personal capital, open to public and effective auditing. The robust standard errors are presented in the parentheses. Significance is represented by *** (1% level), ** (5% level), * (10% level).

Variables	CA	DSB	ED	EM	EMN	FOF	GM	LSE	MS
Log (age)	0.011	0.408	0.030	-0.110	-0.018	-0.193***	-0.194***	-0.048	-0.025
	(0.095)	(0.260)	(0.059)	(0.076)	(0.089)	(0.035)	(0.068)	(0.030)	(0.062)
Log (size)	0.008	0.100	-0.020	-0.076***	0.018	-0.032**	-0.010	0.018	-0.086***
	(0.033)	(0.095)	(0.022)	(0.029)	(0.031)	(0.013)	(0.019)	(0.012)	(0.030)
Ln (min. inv.)	-0.006	0.574	-0.083**	0.027	0.018	0.007	-0.043*	-0.012	0.042**
	(0.040)	(0.583)	(0.032)	(0.021)	(0.034)	(0.007)	(0.024)	(0.014)	(0.020)
Management fee	9.250	-32.328	1.150	-26.737***	7.127	2.413	-10.813*	-1.734	4.722
	(8.941)	(15.512)	(5.795)	(7.839)	(8.456)	(2.368)	(5.923)	(3.288)	(4.103)
Incentive fee	0.045	4.759	1.374***	-0.144	-0.442	0.625**	-0.318	0.032	0.384
	(1.292)	(14.694)	(0.514)	(0.592)	(0.441)	(0.244)	(0.465)	(0.276)	(0.660)
High water mark dummy	-0.078	0.210	0.016	-0.051	0.135	-0.027	0.071	0.009	0.059
	(0.103)	(0.742)	(0.064)	(0.075)	(0.097)	(0.034)	(0.085)	(0.035)	(0.087)
Leverage dummy	0.106	-0.031	0.187***	-0.113	0.012	0.023	0.072	0.005	0.142
	(0.115)	(0.223)	(0.060)	(0.070)	(0.095)	(0.034)	(0.092)	(0.030)	(0.108)
Derivatives dummy	-0.106	-	0.047	0.116	-0.036	-0.077*	0.113	-0.054	0.028
	(0.101)	-	(0.074)	(0.082)	(0.157)	(0.041)	(0.070)	(0.039)	(0.065)
Personal capital dummy	0.007	0.514	-0.088*	0.063	0.194**	0.011	-0.058	0.023	-0.118*
	(0.077)	(0.584)	(0.053)	(0.068)	(0.080)	(0.037)	(0.064)	(0.028)	(0.067)
Lockup period	0.002	-0.024	-0.001	-0.003	-0.012	-0.002	-0.001	-0.002	-0.000
	(0.006)	(0.028)	(0.003)	(0.003)	(0.009)	(0.002)	(0.005)	(0.002)	(0.003)
Restriction period	-0.000	0.003	0.001	-0.002**	0.000	-0.001***	0.001	0.000	-0.000
	(0.001)	(0.008)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Open to public	-0.218**	-0.122	0.065	0.101	0.092	0.070**	0.081	0.011	-0.051
	(0.085)	(0.996)	(0.070)	(0.081)	(0.103)	(0.035)	(0.062)	(0.040)	(0.080)
Audit	0.220	-	0.165	0.087	0.041	-0.065	0.154	0.043	0.029
	(0.187)	-	(0.116)	(0.196)	(0.093)	(0.054)	(0.364)	(0.055)	(0.084)
Constant	-0.410	-11.726	0.584	2.022***	-0.732	1.091***	1.458***	-0.073	0.819
	(0.815)	(10.902)	(0.490)	(0.554)	(0.702)	(0.259)	(0.499)	(0.272)	(0.571)
Observations	103	15	264	229	122	661	116	829	143
Adj. R-squared	0.087	0.909	0.133	0.181	0.123	0.125	0.238	0.012	0.172

Tables and Figures

Table 1: Descriptive statistics

This table presents the descriptive statistics for the data sample. The sample period is from January 1994 to April 2014. Panel A reports the average monthly returns on all funds, hedge funds, funds of funds and for each investment category. The returns are in percentage per month. The column Funds resemble the amount of funds for each investment category and N is the number of observations per investment category. Panel B shows the summary statistics for the Fung-Hsieh risk factors including: the Fama and French equity market factor (MKT), the Fama and French size factor (SMB), the monthly change in the yield of the ten-year treasury (YLDCHG), the monthly change in the spread between Moody's Baa bond and the ten-year treasury yields (BAAMSTY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and the emerging market index (EM). Panel C presents the summary statistics for the Carhart four-factors including: the Fama and French equity market factor (MKT), the Fama and French size factor (SMB), the Fama and French value factor (HML) and the Fama and French momentum factor (MOM). Panel D shows the summary statistics for the control variables including: the Pastor and Stambaugh liquidity factor, the Chicago Board Options Exchange volatility index (VIX), the 3-month treasury T-bill rate, the term spread between the 10-year and tree-month treasury bonds, the quality spread between the Moody's BAA- and AAA- rated corporate bonds and the dividend yield of the S&P 500

Panel A: Hedge funds per investment style

Variables	Funds	N	Mean	Median	Std. Dev.	Min.	Max.	Skewness	Kurtosis
Convertible arbitrage	112	9,951	0.60	0.71	2.91	-13.75	10.53	-1.21	11.31
Dedicated short bias	19	1,465	0.07	0.04	6.26	-16.18	20.63	0.33	4.11
Emerging market	277	24,224	0.84	0.83	5.92	-19.50	19.80	-0.15	5.48
Equity market neutral	147	11,986	0.54	0.50	2.13	-6.56	7.20	-0.10	5.09
Event driven	312	29,240	0.73	0.76	2.57	-9.28	9.12	-0.48	6.77
Fund of funds	965	82,580	0.41	0.57	2.42	-8.66	8.22	-0.51	6.24
Global macro	130	10,889	0.74	0.51	4.00	-11.04	14.25	0.39	4.97
Long short equity	980	87,068	0.80	0.76	4.70	-14.72	16.62	0.03	5.39
Multi strategy	182	16,137	0.68	0.72	3.12	-11.13	11.82	-0.18	6.96
All funds	3,124	273,540	0.64	0.66	3.82	-19.50	20.63	-0.02	7.96

Panel B: Fung-Hsieh risk factors

Variables	N	Mean	Median	Std. Dev.	Min.	Max.	Skewness	Kurtosis
MKT	244	0.61	1.33	4.50	-17.23	11.35	-0.73	4.09
SMB	244	0.19	-0.09	3.43	-16.40	22.02	0.88	11.38
YLDCHG	244	-0.01	-0.03	0.23	-1.11	0.65	-0.20	4.62
BAAMTSY	244	0.00	-0.01	0.19	-0.99	1.45	1.27	18.70
PTFSBD	244	-1.64	-4.14	15.36	-26.63	68.86	1.39	5.52
PTFSFX	244	-1.03	-5.29	19.27	-30.13	90.27	1.36	5.64
PTFSCOM	244	-0.46	-3.05	14.02	-24.65	64.75	1.10	4.82
EM	244	0.48	0.54	7.02	-29.34	22.48	-0.49	4.78

Panel C: Carhart four-factor risk factors

Variables	N	Mean	Median	Std. Dev.	Min.	Max.	Skewness	Kurtosis
MKT	244	0.61	1.33	4.50	-17.23	11.35	-0.73	4.09
SMB	244	0.19	-0.09	3.43	-16.40	22.02	0.88	11.38
HML	244	0.25	0.25	3.25	-12.61	13.88	0.03	6.03
MOM	244	0.44	0.52	5.26	-34.72	18.39	-1.58	13.39

Panel D: Control variables

Variable	N	Mean	Median	Std. Dev.	Min.	Max.	Skewness	Kurtosis
Liquidity factor	244	-2.67	-1.64	7.20	-33.37	20.10	-1.06	5.93
VIX	244	5.98	5.60	2.36	2.98	19.78	1.89	9.08
3 Month T-bill rate	244	0.00	0.20	2.15	-2.77	3.39	-0.05	1.35
Term spread	244	0.00	-0.03	1.18	-2.43	1.96	-0.14	1.87
Quality spread	244	0.00	-0.11	0.45	-0.42	2.41	2.95	13.88
Dividend yield S&P 500	244	0.00	-0.08	0.48	-0.79	1.70	0.84	3.91

Table 2: Summary statistics hedge fund characteristics

This table presents the summary statistics of the hedge fund characteristics of the fund in the data sample. The sample period is from January 1994 to April 2014. The characteristics included are fund age, measured by the months operating, the fund size measured by the average assets under management, the minimum investment in dollars, the management fee and the incentive fee in percentage, the lockup period in months, the restriction period in days and the dummy variables for the use of a high water mark, leverage, derivatives, personal capital, open to public and effective auditing.

Variables	N	Mean	Median	Std. Dev.	Min.	Max.
Age	3,124	7.30	6.08	3.69	3.00	19.67
Size	3,124	188.65	66.76	484.02	10.02	16,146.56
Minimum investment	3,108	0.96	0.50	2.24	0	50
Management fee	2,939	1.39%	1.50%	0.52%	0%	4.80%
Incentive fee	2,937	15.28%	20%	7.67%	0%	50%
High water mark	3,122	65.05%	100%	47.69%	0%	100%
Leverage	3,124	55.12%	100%	49.74%	0%	100%
Derivatives	2,506	18.95%	0%	39.20%	0%	100%
Personal capital	3,124	33.23%	0%	47.11%	0%	100%
Open to public	3,124	16.01%	0%	36.67%	0%	100%
Audit	3,124	94.14%	100%	23.49%	0%	100%
Redemption period	3,124	42.86	30	30.56	0	365
Lock up period	3,124	3.92	0	7.28	0	90
Pay out period	3,124	17.99	14	22.66	0	640

Table 3: Performance analysis of the equally weighted fund portfolios per style

This table presents the coefficients for equally weighted fund portfolios per investment style. For each portfolio, we estimate the following Fung-Hsieh factor model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{ij} f_{j,t+1} + \varepsilon_{it}$$

Where the dependent variable is the excess return for equally weighted portfolios based on all funds and per investment style. The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The investments styles included are convertible arbitrage (CA) funds, dedicated short bias (DSB) funds, event driven (ED) funds, emerging market funds (EM), equity market neutral (EMN) funds, funds of funds (FOF), global macro (GM) funds, long short equity (LSE) funds and multi-strategy (MS) funds. The sample period is from January 1994 to April 2014. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors. The standard errors are presented in the parentheses. Significance is represented by *** (1% level), ** (5% level), * (10% level).

Variables	All funds	CA	DSB	ED	EM	EMN	FOF	GM	LSE	MS
MKT	0.165***	0.067**	-0.828***	0.119***	-0.015	0.048***	0.080***	0.070*	0.347***	0.098***
	(0.021)	(0.030)	(0.071)	(0.019)	(0.052)	(0.016)	(0.026)	(0.037)	(0.031)	(0.018)
SMB	0.077***	0.029	-0.384***	0.046***	0.056	-0.000	0.040*	-0.011	0.170***	0.031
	(0.018)	(0.024)	(0.059)	(0.017)	(0.040)	(0.011)	(0.023)	(0.034)	(0.024)	(0.020)
YLDCHG	-0.066	-1.372***	-2.083**	0.026	0.211	-0.125	-0.381	-1.086*	0.335	0.055
	(0.325)	(0.399)	(0.867)	(0.312)	(0.758)	(0.210)	(0.411)	(0.598)	(0.373)	(0.264)
BAAMTSY	-1.837***	-4.685***	-1.680	-2.718***	-2.629***	-0.493*	-2.335***	-1.043	-0.913	-1.829***
	(0.482)	(0.544)	(1.545)	(0.337)	(0.899)	(0.281)	(0.540)	(0.996)	(0.625)	(0.361)
PTFSBD	-0.004	-0.005	0.002	-0.014***	-0.010	-0.004*	-0.002	-0.003	-0.002	-0.005
	(0.004)	(0.005)	(0.013)	(0.004)	(0.009)	(0.003)	(0.005)	(0.007)	(0.005)	(0.004)
PTFSFX	0.009***	-0.006	-0.010	0.009***	0.012*	0.004**	0.012***	0.033***	0.008**	0.005
	(0.003)	(0.004)	(0.009)	(0.003)	(0.006)	(0.002)	(0.004)	(0.007)	(0.004)	(0.003)
PTFSCOM	0.003	-0.008	0.003	-0.006*	0.000	0.002	0.011*	0.010	0.002	-0.001
	(0.004)	(0.007)	(0.016)	(0.004)	(0.008)	(0.003)	(0.005)	(0.008)	(0.005)	(0.005)
EM	0.089***	0.060***	-0.005	0.044***	0.440***	0.004	0.086***	0.078***	0.058***	0.069***
	(0.015)	(0.018)	(0.037)	(0.013)	(0.037)	(0.010)	(0.018)	(0.020)	(0.022)	(0.014)
Alpha	0.004***	0.004***	0.002	0.004***	0.004***	0.004***	0.002***	0.005***	0.004***	0.005***
	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R-Squared	0.772	0.549	0.732	0.662	0.797	0.153	0.588	0.297	0.805	0.679

Table 4: Factor timing coefficients equally weighted fund portfolios per style

This table presents the factor timing coefficients for equally weighted fund portfolios per investment style. For each portfolio, we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 \ \ \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. The investments styles included are convertible arbitrage (CA) funds, dedicated short bias (DSB) funds, event driven (ED) funds, emerging market funds (EM), equity market neutral (EMN) funds, funds of funds (FOF), global macro (GM) funds, long short equity (LSE) funds and multi-strategy (MS) funds. The sample period is from January 1994 to April 2014. The sample period is from January 1994 to April 2014. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors with two lags. The standard errors are presented in the parentheses. Significance is represented by *** (1% level), ** (5% level), * (10% level).

Variables	All funds	CA	DSB	ED	EM	EMN	FOF	GM	LSE	MS
MKT	0.158***	0.060**	-0.836***	0.109***	-0.042	0.047***	0.065***	0.065*	0.346***	0.090***
	(0.020)	(0.028)	(0.068)	(0.021)	(0.045)	(0.016)	(0.021)	(0.035)	(0.029)	(0.017)
SMB	0.067***	0.009	-0.387***	0.040*	0.026	-0.001	0.039**	-0.007	0.161***	0.021
	(0.017)	(0.029)	(0.070)	(0.022)	(0.043)	(0.013)	(0.019)	(0.037)	(0.024)	(0.015)
YLDCHG	-0.190	-1.251***	-1.284*	-0.030	0.000	-0.233	-0.559*	-1.435***	0.084	-0.023
	(0.289)	(0.442)	(0.764)	(0.283)	(0.605)	(0.202)	(0.314)	(0.508)	(0.365)	(0.286)
BAAMTSY	-2.078***	-4.817***	-0.515	-2.740***	-3.013***	-0.685***	-2.489***	-1.491*	-1.425**	-2.053***
	(0.458)	(0.559)	(1.286)	(0.339)	(0.763)	(0.250)	(0.514)	(0.800)	(0.574)	(0.351)
PTFSBD	0.002	-0.008	-0.008	-0.006	-0.000	-0.001	0.007	0.002	0.005	0.000
	(0.005)	(0.007)	(0.017)	(0.005)	(0.010)	(0.004)	(0.006)	(0.008)	(0.007)	(0.005)
PTFSFX	0.011***	-0.006	-0.013	0.007*	0.016*	0.004*	0.019***	0.034***	0.013**	0.009***
	(0.004)	(0.005)	(0.012)	(0.004)	(0.008)	(0.002)	(0.004)	(0.007)	(0.005)	(0.003)
PTFSCOM	0.006	-0.006	0.008	-0.006	0.010	0.002	0.017***	0.019**	0.003	0.001
	(0.004)	(0.007)	(0.017)	(0.005)	(0.010)	(0.003)	(0.005)	(0.008)	(0.006)	(0.005)
EM	0.098***	0.065***	-0.019	0.052***	0.468***	0.006	0.102***	0.089***	0.064***	0.078***
	(0.015)	(0.018)	(0.033)	(0.014)	(0.030)	(0.011)	(0.014)	(0.020)	(0.022)	(0.013)
MKT²	0.545**	0.493	-1.239	-0.045	0.928*	0.317	0.824***	0.949**	0.692**	0.561***
	(0.240)	(0.444)	(0.807)	(0.240)	(0.540)	(0.208)	(0.255)	(0.439)	(0.332)	(0.175)
SMB²	0.315***	0.466***	0.066	0.205	0.949***	0.006	0.228**	-0.021	0.282*	0.362***
	(0.089)	(0.173)	(0.417)	(0.136)	(0.260)	(0.064)	(0.092)	(0.203)	(0.152)	(0.082)
YLDCHG²	-149.928***	56.042	139.014	-194.057***	-328.736***	-30.938	-281.949***	-174.183**	-109.965*	-109.233*
	(43.940)	(100.978)	(115.569)	(40.797)	(83.594)	(41.546)	(52.494)	(71.572)	(65.885)	(61.583)
BAAMYSY²	31.934	-106.947*	-377.577***	17.622	134.314	28.860	41.903	77.851	59.094	-16.717
	(70.119)	(60.151)	(78.356)	(53.542)	(103.566)	(30.021)	(78.006)	(123.201)	(77.175)	(60.782)
PTFSBD²	-0.012	-0.014	0.001	-0.005	0.002	-0.016	-0.014	-0.012	-0.031	-0.026*
	(0.015)	(0.029)	(0.051)	(0.019)	(0.028)	(0.011)	(0.016)	(0.027)	(0.020)	(0.015)
PTFSFX²	-0.011	0.002	0.026	0.011	-0.016	-0.005	-0.035***	-0.014	-0.024**	-0.024*
	(0.010)	(0.014)	(0.035)	(0.014)	(0.021)	(0.006)	(0.013)	(0.027)	(0.011)	(0.013)
PTFSCOM²	-0.010	-0.008	-0.048	0.011	-0.028	0.002	-0.025*	-0.040	-0.004	-0.007
	(0.013)	(0.030)	(0.058)	(0.015)	(0.025)	(0.009)	(0.015)	(0.029)	(0.016)	(0.013)
EM²	-0.219**	0.049	0.621***	-0.122	-0.626***	-0.096	-0.355***	-0.252*	-0.123	-0.076
	(0.095)	(0.140)	(0.232)	(0.082)	(0.224)	(0.069)	(0.097)	(0.139)	(0.147)	(0.082)
Constant	0.005***	0.002	0.002	0.005***	0.007***	0.004***	0.005***	0.007***	0.005***	0.006***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Adj. R-Squared	0.781	0.551	0.738	0.678	0.818	0.151	0.646	0.305	0.812	0.703

Table 5: Distribution of factor timing coefficients for individual funds per factor

This table presents the distribution of t-statistics for the timing coefficients per factor per individual fund. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 \; \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. The sample period is from January 1994 to April 2014. The Newey-west t-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors with two lags. The number in the table shows the percentage of funds with t-statistics of the factor timing coefficients exceeding the indicated values. The percentages are presented per timing factor and for the average of the timing factors.

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	2	3	5	17	11	7	10	35
SMB	2	3	4	20	15	11	9	46
YLDCHG	16	22	27	6	3	2	65	11
BAAMTSY	4	6	9	13	9	5	19	27
PTFSBD	4	7	11	7	4	2	22	13
PTFSFX	7	12	19	4	2	1	38	7
PTFSCOM	3	5	8	4	3	1	16	8
EM	12	17	23	5	3	2	52	10
Average	6.25	9.38	13.25	9.50	6.25	3.88	28.88	19.63

Table 6: Cross-sectional analysis of the factor timing skills of hedge fund managers

This table presents the cross-sectional analysis of the factor timing skills of hedge fund managers. The dependent variable is the t-statistic of the factor timing skill coefficient. We estimate the following model per factor:

$$t-\text{statistic}_i = \alpha_0 + \beta_1 Log(Age)_i + \beta_2 Log(Size)_i + \beta_3 Ln(MinInv)_i + \beta_4 MFee_i + \beta_5 IFee_i + \beta_6 High\ water\ mark_i + \beta_7 Leverage_i + \beta_8 Derivatives_i + \beta_9 Personal\ capital_i + \beta_{10} Lockup\ period_i + \beta_{11} Restriction\ period_i + \beta_{12} Open\ to\ public_i + \beta_{13} Audit_i + \xi_i$$

Where the independent variables are the fund age, measured by the months operating, the fund size measured by the average assets under management, the minimum investment in dollars, the management fee and the incentive fee in percentage, the lockup period in months, the restriction period in days and the dummy variables for the use of a high water mark, leverage, derivatives, personal capital, open to public and effective auditing. The robust standard errors are presented in the parentheses. Significance is represented by *** (1% level), ** (5% level), * (10% level).

Variables	MKT^2	SMB^2	$YLDCHG^2$	$BAAMYSY^2$	$PTFSBD^2$	$PTFSFX^2$	$PTFSCOM^2$	EM^2	Average
Log (age)	0.419***	0.285***	-0.380***	0.037	-0.310***	-0.270***	-0.074	-0.205***	-0.062***
	(0.047)	(0.062)	(0.063)	(0.058)	(0.046)	(0.047)	(0.045)	(0.052)	(0.016)
Log (size)	0.062***	0.056**	-0.174***	0.013	-0.003	-0.082***	-0.007	-0.064***	-0.025***
	(0.020)	(0.025)	(0.029)	(0.025)	(0.020)	(0.021)	(0.019)	(0.024)	(0.007)
Ln (min inv.)	-0.030*	-0.011	0.024	-0.025	-0.048***	0.032*	0.016	0.065***	0.003
	(0.016)	(0.021)	(0.024)	(0.018)	(0.015)	(0.017)	(0.015)	(0.022)	(0.005)
Management fee	-6.253	-2.918	7.633	13.320**	10.568**	-8.904**	-16.214***	-0.679	-0.431
	(4.642)	(6.623)	(6.233)	(5.272)	(4.468)	(4.492)	(4.375)	(5.445)	(1.581)
Incentive fee	-1.557***	-0.917*	5.261***	-0.942**	-0.611	1.496***	1.018***	4.654***	1.050***
	(0.379)	(0.484)	(0.521)	(0.424)	(0.373)	(0.372)	(0.327)	(0.450)	(0.128)
High water mark dummy	0.096*	0.001	-0.118	0.261***	0.087	0.050	-0.120**	-0.282***	-0.003
	(0.058)	(0.082)	(0.079)	(0.065)	(0.058)	(0.057)	(0.053)	(0.064)	(0.020)
Leverage dummy	0.094*	0.047	-0.050	0.119*	0.153***	0.018	-0.016	-0.038	0.041**
	(0.056)	(0.071)	(0.077)	(0.065)	(0.055)	(0.056)	(0.049)	(0.064)	(0.019)
Derivatives dummy	0.027	0.102	-0.103	-0.101	-0.063	-0.089	0.084	-0.024	-0.021
	(0.066)	(0.081)	(0.088)	(0.078)	(0.065)	(0.069)	(0.063)	(0.076)	(0.022)
Personal capital dummy	-0.021	0.014	0.051	-0.121**	-0.072	-0.028	0.005	0.124**	-0.006
	(0.052)	(0.066)	(0.070)	(0.061)	(0.051)	(0.052)	(0.047)	(0.059)	(0.018)
Lockup Period	-0.003	-0.001	-0.003	-0.003	-0.002	0.001	-0.005	0.002	-0.002*
	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.001)
Restriction period	-0.001**	0.001	-0.007***	0.001	0.001*	-0.000	-0.001	-0.002**	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Open to public	-0.092	-0.022	0.213**	-0.042	-0.037	0.197***	0.040	0.078	0.042*
	(0.066)	(0.078)	(0.089)	(0.077)	(0.063)	(0.067)	(0.059)	(0.075)	(0.022)
Audit	0.134	0.183	-0.200	0.450***	-0.059	0.121	-0.017	-0.376***	0.030
	(0.105)	(0.119)	(0.140)	(0.137)	(0.112)	(0.106)	(0.106)	(0.113)	(0.034)
Constant	-2.078***	-1.727***	3.632***	-0.711	1.800***	1.523***	0.285	0.582	0.413***
	(0.432)	(0.527)	(0.606)	(0.508)	(0.421)	(0.437)	(0.394)	(0.521)	(0.145)
Adj. R-squared	0.052	0.020	0.121	0.023	0.036	0.041	0.016	0.081	0.065

Table 7: Performance Persistence

This table presents an out-of-sample performance test. For each month and fund, we estimate the following factor timing model based on a rolling sample period of 36 months starting in January 1997:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). Then, we sort the funds for every month in deciles based on their estimated α and create portfolios for every month per decile. Next, we hold the portfolios for one month and calculate the portfolio returns. Finally, we use the portfolio return time series for each holding period and decile to estimate the following Fung and Hsieh eight-factor model. This table presents the alphas and the *t*-statistics per decile. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors.

1	2	3	4	5	6	7	8	9	10	10 - 1
-0.044	0.012	0.078	0.112	0.143	0.195	0.227	0.302	0.382	0.557	0.601
(-0.478)	(0.202)	(1.177)	(1.827)	(2.429)	(3.177)	(3.464)	(4.404)	(4.340)	(4.875)	(4.806)

Table 8: Economic value of factor timing skills of hedge fund managers.

This table presents an out-of-sample performance test. For each month and fund, we estimate the average factor timing coefficients based on a lookback period of 36 months starting in January 1997 with the following factor timing model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 \ \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. Then, we sort the funds for every month in deciles based on their average factor timing ability and create portfolios for every month per decile. Next, we hold the portfolios for one month and calculate the portfolio returns. Finally, we use the portfolio return time series for each holding period and decile to estimate the following Fung and Hsieh eight-factor model, which is the similar to the factor timing model but without the quadratic forms of the risk factors. This table presents the alphas and the *t*-statistics per decile. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors.

1	2	3	4	5	6	7	8	9	10	10 - 1
0.28	0.29	0.30	0.30	0.30	0.31	0.33	0.37	0.36	0.36	0.08
(16.32)	(15.36)	(18.98)	(19.16)	(19.75)	(19.73)	(22.02)	(21.56)	(23.72)	(27.19)	(4.33)

Table 9: Bootstrap analysis of the factor timing skill for the individual hedge funds.

This table presents the results of the bootstrap analysis of the factor timing skill for the individual hedge funds. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^{2} \;\; \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. The sample period is from January 1994 to April 2014. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors. This table shows per factor the *t*-statistics of the factor timing coefficients and the *p*-values from the bootstrap analysis for the extreme percentiles. For the bootstrap procedure, the number of iterations is 1,000.

		Negative extreme percentiles					**Positive extreme percentiles**				
Variables		**Bottom**	**1%**	**3%**	**5%**	**10%**	**90%**	**95%**	**97%**	**99%**	**Top**
MKT	*t*-statistic	-4.78	-3.00	-1.97	-1.61	-1.13	2.05	2.64	2.78	3.25	4.59
	p-value	0.000	0.002	0.079	0.07	0.175	0.052	0.014	0.014	0.004	0.000
SMB	*t*-statistic	-8.74	-2.69	-1.92	-1.54	-1.02	2.36	3.20	3.49	4.62	11.21
	p-value	0.000	0.050	0.139	0.068	0.227	0.013	0.031	0.017	0.005	0.000
YLDCHG	*t*-statistic	-10.68	-5.63	-4.31	-3.87	-2.95	1.19	1.83	2.09	2.69	4.65
	p-value	0.000	0.001	0.012	0.003	0.014	0.129	0.115	0.06	0.034	0.002
BAAMYSY	*t*-statistic	-6.75	-3.53	-2.54	-2.19	-1.56	1.84	2.47	2.65	3.42	5.80
	p-value	0.000	0.004	0.013	0.034	0.131	0.116	0.037	0.045	0.007	0.000
PTFSBD	*t*-statistic	-5.11	-3.11	-2.53	-2.21	-1.70	1.37	1.89	2.043	2.55	4.28
	p-value	0.000	0.007	0.017	0.03	0.063	0.092	0.072	0.035	0.026	0.001
PTFSFX	*t*-statistic	-5.00	-3.28	-2.86	-2.55	-2.10	1.02	1.61	1.77	2.35	3.73
	p-value	0.002	0.007	0.007	0.029	0.027	0.175	0.061	0.043	0.03	0.003
PTFSCOM	*t*-statistic	-4.37	-2.83	-2.27	-1.89	-1.53	1.15	1.67	1.87	2.51	4.79
	p-value	0.000	0.009	0.034	0.085	0.098	0.143	0.085	0.047	0.015	0.000
EM	*t*-statistic	-6.98	-4.38	-3.49	-3.14	-2.67	1.11	1.79	1.88	1.96	5.02
	p-value	0.000	0.000	0.001	0.007	0.035	0.131	0.057	0.054	0.078	0.000
Average	*t*-statistic	-1.92	-1.16	-0.94	-0.81	-0.63	0.36	0.59	0.65	0.85	1.35
	p-value	0.000	0.001	0.001	-0.038	0.058	0.114	0.067	0.019	0.015	0.002

Table 10: Choice of Factors.

This table presents the distribution of *t*-statistics for the factor timing coefficients per individual fund. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 \;\; \varepsilon_{it}$$

The included independent variables in Panel A are the Carhart four-factors including: an equity market factor (MKT), a size factor (SMB), a value factor (HML) and a momentum factor (MOM). The variables included in Panel B are the Fung-Hsieh eight factor model, as well as the Betting against Beta (BaB) and Global Carry (GCF) factors. The models also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors. The number in the table shows the percentage of funds with *t*-statistics of the factor timing coefficients exceeding the indicated values. The percentages are presented per timing factor and for the average of the timing factors.

All	**t≤-2,326**	**t≤-1,960**	**t≤-1,645**	**t≥1,645**	**t≥1,282**	**t≥2,326**	**Total negative**	**Total positive**
				Panel A: Reduced Factor Model				
MKT	16%	20%	24%	9%	12%	4%	60%	25%
SMB	4%	7%	10%	15%	21%	8%	21%	44%
HML	9%	11%	13%	23%	30%	13%	33%	66%
MOM	3%	5%	7%	21%	30%	9%	15%	60%
Average	8%	11%	14%	17%	23%	9%	32%	49%
				Panel B: Extended Factor Model				
MKT2	4%	2%	1%	11%	18%	24%	7%	53%
SMB2	4%	3%	1%	9%	14%	20%	8%	43%
YLDCHG2	20%	15%	11%	3%	5%	7%	45%	15%
BAAMYSY2	8%	5%	3%	4%	7%	10%	17%	21%
PTFSBD2	10%	7%	5%	2%	3%	5%	22%	10%
PTFSFX2	16%	10%	5%	1%	2%	3%	31%	6%
PTFSCOM2	7%	4%	2%	1%	2%	4%	13%	8%
EM2	18%	12%	8%	2%	3%	6%	39%	11%
BaB2	17%	11%	7%	3%	4%	7%	35%	14%
GCF2	8%	5%	3%	3%	5%	9%	16%	17%
Average	11%	7%	5%	4%	6%	10%	23%	20%

Table 11: Controlling for public information.

This table presents the distribution of *t*-statistics for the timing coefficients per factor per individual fund controlling for public information. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J}\beta_{i,j}f_{j,t+1} + \sum_{k=1}^{K}\gamma_{i,k}{f_{j,t+1}}^2 + \sum_{l=1}^{L}\delta_{i,l}z_{l,t}MKT_{t+1} + \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. To control for public information four lagged instruments are included and $z_{l,t}$ denotes these four factors. The included lagged factors are: the three-month T-bill yield, the term premium, quality spread and the dividend yield of the S&P 500 index as lagged instruments.

The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors. The number in the table shows the percentage of funds with *t*-statistics of the factor timing coefficients exceeding the indicated values. The percentages are presented per timing factor and for the average of the timing factors.

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≤-1,282	t≥1,282	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	2	4	6	11	18	11	7	4	42	58
SMB	1	2	4	7	29	21	15	10	31	69
YLDCHG	15	20	26	33	10	6	4	2	66	34
BAAMTSY	3	5	8	13	19	12	8	5	43	57
PTFSBD	4	7	10	17	9	5	2	1	58	42
PTFSFX	6	10	16	24	7	4	2	1	67	33
PTFSCOM	2	5	9	15	8	4	3	1	59	41
EM	7	11	15	24	9	5	3	2	63	37
Average	0	0	0	0	0	0	0	0	62	38

Table 12: Controlling for the use of derivatives.

This table presents the distribution of *t*-statistics for the timing coefficients per factor per individual fund using derivatives and without using derivatives. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 \ \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors. The number in the table shows the percentage of funds with *t*-statistics of the factor timing coefficients exceeding the indicated values. The percentages are presented per timing factor and for the average of the timing factors. Panel A presents the distribution of *t*-statistics for the timing coefficients per factor for the funds using derivatives. Panel B shows the distribution of *t*-statistics for the timing coefficients per factor for the funds without using derivatives.

Panel A: Funds using derivatives

Variables	**t≤-2,326**	**t≤-1,960**	**t≤-1,645**	**t≤-1,282**	**t≥1,282**	**t≥1,645**	**t≥1,960**	**t≥2,326**	**Total negative**	**Total positive**
MKT	1	3	5	7	26	18	13	6	32	68
SMB	1	3	4	7	33	24	17	13	33	67
YLDCHG	16	21	27	34	8	4	3	1	64	36
BAAMTSY	5	9	12	19	19	13	9	5	51	49
PTFSBD	5	8	12	16	11	7	4	2	56	44
PTFSFX	10	16	24	31	9	5	3	1	68	32
PTFSCOM	2	4	8	15	10	6	5	3	56	44
EM	9	14	19	29	9	5	3	2	65	35
Average	0	0	0	1	0	0	0	0	64	36

Panel B: Funds not using derivatives

Variables	**t≤-2,326**	**t≤-1,960**	**t≤-1,645**	**t≤-1,282**	**t≥1,282**	**t≥1,645**	**t≥1,960**	**t≥2,326**	**Total negative**	**Total positive**
MKT	2	3	5	8	25	17	11	7	34	66
SMB	2	3	5	7	29	21	16	11	34	66
YLDCHG	16	22	27	33	10	6	3	2	65	35
BAAMTSY	5	7	10	15	19	12	8	5	46	54
PTFSBD	4	8	12	18	11	6	4	2	56	44
PTFSFX	7	12	18	27	7	4	2	1	68	32
PTFSCOM	3	5	8	15	7	4	2	1	58	42
EM	12	16	22	31	9	6	4	2	65	35
Average	0	0	0	1	0	0	0	0	63	37

Table 13: Controlling for fund size.

This table presents the distribution of *t*-statistics for the timing coefficients per factor per individual fund controlling for fund size. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 \;\; \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors. The number in the table shows the percentage of funds with *t*-statistics of the factor timing coefficients exceeding the indicated values. The percentages are presented per timing factor and for the average of the timing factors. Panel A presents the distribution of *t*-statistics for the timing coefficients per factor for the funds with AUM smaller than 50 million dollars. Panel B shows the distribution of *t*-statistics for the timing coefficients per factor for the funds with AUM larger than 50 million dollars and smaller than 150 million dollars. Panel C demonstrates the distribution of *t*-statistics for the timing coefficients per factor for the funds with AUM larger than 150 million dollars.

Panel A: Funds with AUM<50.000.000 dollars

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	2	4	6	16	12	7	12	45
SMB	2	3	4	19	15	10	9	44
YLDCHG	12	17	23	6	4	2	52	12
BAAMTSY	5	7	9	13	8	5	21	26
PTFSBD	4	6	11	8	4	2	21	14
PTFSFX	7	11	16	4	2	1	34	7
PTFSCOM	3	5	9	5	4	2	17	11
EM	11	15	21	6	4	2	47	12
Average	5.75	8.5	12.375	9.625	6.625	3.875	26.625	20.125

Panel B: Funds with AUM >50,000,000 dollars and <150,000,000 dollars

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	2	3	4	17	10	7	9	34
SMB	2	4	6	20	14	10	12	44
YLDCHG	15	22	26	7	4	3	63	14
BAAMTSY	4	6	8	13	9	4	18	26
PTFSBD	4	8	12	7	5	2	24	14
PTFSFX	6	11	18	4	3	1	35	8
PTFSCOM	2	4	8	4	2	1	14	7
EM	13	18	24	5	2	2	55	9
Average	6	9.5	13.25	9.625	6.125	3.75	28.75	19.5

Panel C: Funds with AUM>150.000.000 dollars

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	1	2	4	19	12	6	7	37
SMB	1	2	3	22	17	12	6	51
YLDCHG	23	28	34	4	2	1	85	7
BAAMTSY	4	6	10	13	8	5	20	26
PTFSBD	5	7	10	5	2	1	22	8
PTFSFX	9	15	23	3	2	1	47	6
PTFSCOM	3	5	8	3	2	1	16	6
EM	13	18	25	5	3	2	56	10
Average	7.375	10.375	14.625	9.25	6	3.625	32.375	18.875

Table 14: Controlling for volatility and liquidity timing.

This table presents the distribution of *t*-statistics for the timing coefficients per factor per individual fund controlling for market volatility and market liquidity timing. For each fund we estimate the following Treynor-Mazuy based model:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{k=1}^{K} \gamma_{i,k} {f_{j,t+1}}^2 + \delta_1 MKT_{t+1}(\sigma_{m,t+1} - \overline{\sigma_m}) + \delta_1 MKT_{t+1}(L_{m,t+1} - \overline{L_m}) + \varepsilon_{it}$$

The included independent variables are an equity market factor, (MKT) a size factor (SMB), a bond market factor (YLDCHG), a credit-spread factor (BAAMTSY), three trend-following factors for bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM) and an emerging market factor (EM). The model also includes the quadratic forms of the risk factors and $\gamma_{i,k}$ denotes the exposure to the quadratic form and resembles the factor timing skill per factor. To control for market volatility and market liquidity timing, we include two additional factor where $\sigma_{m,t+1}$ represents the market volatility, which is demeaned with the average market volatility of the total time series ($\overline{\sigma_m}$). $L_{m,t+1}$ denotes the market liquidity factor, which is demeaned with the average market liquidity of the total time series ($\overline{L_m}$). These factors are demeaned with the time series average of the specific factors for ease of use.

The Newey-west *t*-statistics are calculated with heteroskedasticity and autocorrelation consistent standard errors. The number in the table shows the percentage of funds with *t*-statistics of the factor timing coefficients exceeding the indicated values. The percentages are presented per timing factor and for the average of the timing factors.

Variables	t≤-2,326	t≤-1,960	t≤-1,645	t≥1,645	t≥1,960	t≥2,326	Total negative	Total positive
MKT	2	4	5	14	9	5	11	28
SMB	2	3	5	20	15	10	10	45
YLDCHG	14	18	24	6	4	2	56	12
BAAMTSY	4	8	11	8	5	3	23	16
PTFSBD	4	7	12	5	2	1	23	8
PTFSFX	6	10	16	4	2	1	32	7
PTFSCOM	2	5	8	5	3	2	15	10
EM	6	10	14	6	4	2	30	12
Liquidity	4	6	10	9	5	3	20	17
Volatility	2	4	5	37	31	25	11	93
Average	4.6	7.5	11	11.4	8	5.4	23.1	24.8