CYCLICAL DEPENDENCE IN MARKET NEUTRAL HEDGE FUNDS

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Abstract

We examine linear correlation and tail dependence between market neutral hedge funds and the market portfolio conditional on the financial cycle. We document that the low correlation between these funds and the S&P 500 consists of a negative correlation during bear periods and a positive one during bull periods. In contrast, the remaining styles present a positive correlation across cycles. We also find that these funds present tail dependence only during bull periods. We study their implications for market timing and risk management.

Keywords: hedge funds, market neutrality, market timing, tail dependence, risk management.

JEL classification: G11, G23.

Resumen

En este documento analizamos la correlación lineal y la dependencia de colas entre los fondos de cobertura denominados *market neutral* y la cartera de mercado condicionado en el ciclo económico. Documentamos que la baja correlación entre estos fondos y el índice S&P 500 resulta de la combinación de una correlación negativa en períodos bajistas y una correlación positiva en períodos alcistas. Este resultado es específico de este grupo de fondos, puesto que el resto de los fondos de cobertura presentan una correlación positiva independientemente del ciclo económico. Respecto a la dependencia de colas de estos fondos con el mercado, encontramos que es significativa únicamente en períodos alcistas. Finalmente, presentamos las implicaciones de estos resultados en la gestión de riesgos y evaluamos la habilidad de los gestores para entrar o salir del mercado en el momento adecuado.

Palabras clave: fondos de cobertura, neutralidad de mercado, *market timing,* dependencia de colas, gestión de riesgo

Códigos JEL: G11, G23.

1 Introduction

It is widely thought that some hedge funds offer an advantage over other investment vehicles in that they are immune from market fluctuations that makes them attractive to investors, especially during uncertain times. Indeed, numerous empirical studies have found low correlations between hedge fund returns and aggregate stock market returns (e.g., Agarwal and Naik (2004) and Fung and Hsieh (1999)). Understanding the linkages that exist between hedge funds and asset markets is particularly important, as crashes in this industry might lead to potentially devastating effects in financial markets, given the leveraged positions they take.[1]. In this regard, the purpose of this paper is to analyze the regime-switching dependence between hedge funds and the stock market conditional on the financial cycle, with a particular focus on market neutral hedge funds.

Market neutral hedge funds are those that actively seek to avoid major risk factors, but take bets on relative price movements utilizing strategies such as long-short equity, stock index arbitrage, convertible bond arbitrage, and fixed income arbitrage (Fung and Hsieh (1999)). They are not only one of the largest, but are also among the most popular investment styles in the industry.[2] As such, empirical literature has investigated the "neutrality" of these funds to the market index, the most prominent of which is their dependence to market tail risk (Patton (2009)). While numerous studies have found that there is little to no correlation between these funds and the market index, there is no consensus on whether they are exposed to tail risk or not. Most of these papers assume, however, that the joint distribution of hedge fund and stock market index returns is fairly static over time. This assumption appears to be contradictory, as it is well known that the trading strategies hedge fund managers employ tend to be dynamic in nature (e.g., Agarwal and Naik (2004), Fung and Hsieh (2001a), and Patton and Ramadorai (2013)).

The first departure of this paper from previous literature is to study how dependence

[1]Ben-David et al. (2012) document that hedge funds in the US got rid of their equity holdings during the 2007-2009 financial crisis. Meanwhile, Adams et al. (2014) finds that spillovers from hedge funds to other financial markets increased in periods of financial distress.

[2]In the 2017 Credit Suisse Global Survey of Hedge Fund Manager Appetite and Activity, market neutral hedge funds account for 29 percent of the total net demand of institutional investors, the second largest of all categories.

between market neutral hedge fund and stock returns changes conditional on the financial cycle, both at the aggregate and individual fund level. To quantify this dependence, we estimate a Student's t-copula model with dependence parameters that vary according to the state. We identify financial cycles via a simple algorithm that detects bull and bear periods through stock price movements (Pagan and Sossounov (2003))[3]. The result of our estimations indicate that the correlation between market neutral hedge funds and the stock market changes according to the financial cycle state. In particular, the correlation is negative in bear periods and positive in bull periods. This result is unique to market neutral hedge funds, as others which exhibit similar characteristics in terms of trading strategies have positive correlation in both bull and bear periods.

The regime-changing correlation between market neutral hedge fund returns and that of the market according to the financial cycle might arise from managers' ability to time the market, or at least, to time the state. We explore this hypothesis by adapting the Henriksson and Merton (1981) market timing model to capture state timing ability. In line with the hypothesis, we find that market neutral hedge funds exhibit significant state timing ability compared to other hedge fund styles.

Shifts in dependence between hedge funds and the stock market have important consequences for risk management. In this light, we consider how conditional Value-at-Risk (CVaR) changes according to the financial regime. Counterintuitively, we find that the CVaR for market neutral hedge funds is higher in bear periods than in bull periods. This is a consequence of the negative correlation during these periods, which counteracts the shift in the marginal distributions of market neutral hedge funds and the market. Our analysis suggests that if hedge fund managers do not take into account tail risk, then they would accrue greater losses than what they would have otherwise; meanwhile, hedge fund managers who do not take into account information from states accumulate more equity than they would have otherwise.

Our paper connects with the vast literature that studies the dependence between hedge funds and the stock market. Brown and Spitzer (2006) propose a tail neutrality

[3]We find that the bull and bear periods this algorithm captures coincide not only with NBER recession and expansion periods, but also with other significant events that have had an impact on financial markets, such as the European sovereign debt crisis, and the recent Chinese stock market crash.

measure which uses a simple binomial test for independence, and find that hedge funds exhibit tail dependence. They also confirm the result via logit regressions similar to those employed by Boyson et al. (2010). Patton (2009), meanwhile, proposes a test statistic using results from extreme value theory and concludes that there is no tail dependence between market neutral hedge funds and the market index. The analyses performed in the previous papers, however, are essentially static. Meanwhile, Distaso et al. (2010) use hedge fund index data to model dependence using a time-varying copula, and find that there does not exist tail dependence between hedge fund and market index returns. Finally, Kelly and Jiang (2012) utilise a time-varing tail risk measure and estimate that the average exposure to tail risk of these funds is negative, which they take as evidence of the sensitivity of hedge funds to tail risks.[4] With respect to these papers, we study how dependence varies according to the financial state, which provides an intuitive link to empirical studies that have looked at hedge fund trading behavior during downturns, such as Ben-David et al. (2012). Moreover, our approach allows us to study both tail dependence and correlation jointly.

Our paper complements empirical work that aims to understand hedge fund timing ability (Chen (2007), Chen and Liang (2007) and Cao et al. (2013)). The result of these papers indicate that some hedge funds exhibit return, volatility, and liquidity timing abilities. Meanwhile, Bali et al. (2014), using a macroeconomic risk index constructed from available state information, shows that some hedge funds are able to time macroeconomic risk. Relative to these papers, our results suggest that market neutral hedge fund managers exhibit an additional timing skill, that of the ability to adjust their risk exposures using information on financial cycles. This in turn, allows them to achieve their stated fund objectives. To the best of our knowledge, our paper is the first to study hedge fund performance and its variation over the financial cycle, although this variation has been widely studied in the context of mutual funds (see Moskowitz (2000), Glode (2011), De Souza and Lynch (2012), and Kacperczyk et al. (2014) for recent work)[5]

Finally, our paper contributes to studies that attempt to understand asymmetric

[4]Patton and Ramadorai (2013) use a dynamic framework to analyse risk exposures of hedge funds to different asset classes. However, they do not explicitly study tail dependence.

[5]There is some related work that looks at hedge fund performance over different market conditions.

dependence structures in financial markets using copula methods (see the survey article of Patton (2012) for a review). Most of these papers do not condition on the state of the economy, or infer them using parametric models (e.g., Rodriguez (2007) and Okimoto (2008), among others). In contrast, our approach to identifying states is based on a parsimonious algorithm that is widely used in business cycle dating.

The rest of the paper is organised as follows: Section 2 describes the data employed in this empirical study. We present the copula model for dependence and the results of our estimation in section 3. In section 4, we study the implications of cyclical dependence on market timing and risk management. We present the results of dependence and state timing for individual hedge funds in section 5. Finally, section 6 concludes. Additional results and technical details are gathered in the Supplemental Material.

2 Data

2.1 Defining states

To identify bull and bear periods, we adopt the definition proposed by Pagan and Sossounov (2003); that is, "... bull (bear) markets correspond to periods of generally increasing (decreasing) stock market prices." This definition implies that the stock market has moved from a bull to a bear state when prices have declined for a substantial period since their previous (local) peak. However, it does not preclude the possibility of negative return realizations in bull periods or positive return realizations in bear periods. To determine bull and bear periods in the sample, Pagan and Sossounov (2003) adapt the algorithm in Bry and Boschan (1971), a commonly used algorithm to detect turning points in the business cycle literature.[6]

We employ the S&P 500 as the market index to identify bull and bear periods and for the subsequent analyses in the paper. Table 1 describes the bear and bull periods identified by the algorithm. Panel A compares the results of the Pagan and Sossounov

Akay et al. (2013) extract a common factor across hedge fund style returns using a Markov switching model, and find that there are three regimes: crash, low mean and high mean. This common factor is related to funding liquidity risk. Meanwhile, Sun et al. (2018) study hedge fund performance persistence and show that hedge fund performance persists during hedge fund market downturns and not during upturns. Relative to these papers, we identify the regimes not from hedge fund returns, but from the stock market index, the risk of which is what the hedge funds we are studying is aiming to neutralize.

[6] Section 1 of the Supplemental Material provides details on the dating algorithm.

(2003) algorithm with that of the NBER recession indicator for business cycles. As can be seen, the correlation between the two periods is approximately 58 percent. The dating algorithm we employ, however, identifies two additional bear periods. The first, from May to September 2011, corresponds to events in the European sovereign debt crisis related to concerns over Greek public debt refinancing. Meanwhile, the second, from June to September 2015, coincides with the most turbulent periods of the Chinese stock market crash. Panel B, meanwhile, describes some characteristics about the cycles. The results indicate that the average duration of bull (bear) periods is 47.5 (12.5) months. Moreover, bull (bear) markets rise (fall) by more than 20 percent.

[Table 1 about here.]

2.2 Hedge fund database

The hedge fund database used in this study consists of monthly returns, net of all fees, on funds in the BarclayHedge database that classify themselves as one of the following styles considered to be "neutral": market neutral, equity non-hedge, equity hedge, event driven, or fund of hedge funds.[7] According to BarclayHedge's strategy definitions, market neutral funds are those that focus on making "concentrated bets", which are usually based on mispricings, while limiting general market exposure. These funds achieve their objective through a combination of long and short positions. Equity hedge funds are funds that are exposed to the market, but hedge these exposures through short positions of stocks, or through stock options. Equity non-hedge funds are funds that usually have long exposures to the market. Event-driven funds exploit pricing inefficiencies that may occur before or after corporate events such as bankruptcy, or mergers and acquisitions. Funds of hedge funds invest in multiple hedge funds, which may consist of different strategies.

For an individual hedge fund to be included in the sample, it must have at least 48 months of observations, following Patton (2009). This yields 5,651 active and defunct funds that identify themselves as "market neutral" during the period January 1994 to

[7] The choice of BarclayHedge over other databases commonly used in the hedge fund literature (e.g., TASS or Hedge Fund Research) is mainly motivated by data availability and the observation by Joenväärä et al. (2016) that empirical analyses using this database yield similar results as that from an aggregate database.

December 2016. Because we perform our estimations using both alive and dead funds, our results are less susceptible to survivorship bias, which arises when only returns from alive funds are used to understand hedge fund performance (see Chen and Liang (2007) and references therein). Nevertheless, we perform the analyses in the paper with alive and dead funds, respectively, and our results do not change. To minimize the influence of "backfill bias", which is related to the fact that hedge funds enter a database with a history of good returns, we truncate the first two years of returns and start our estimation on January 1999, as is standard in the hedge fund literature (Fung and Hsieh (2000)).[8] Finally, before subjecting the hedge funds to our analyses, we filter the hedge fund returns via a MA(4) filter, following Getmansky et al. (2004). We also perform our analyses with an MA(0) and MA(2) filter. Table 2 presents the number of observations available on each of the hedge funds in the sample. The median history across hedge fund styles ranges from 76 to 110 months. Moreover, around 60 percent of funds in our sample consist of dead hedge funds, while the rest are alive funds.

[Table 2 about here.]

Table 3 presents the summary statistics of the hedge fund indices. We find that, throughout the sample period, the hedge funds in the sample provide an average return net-of-fees of approximately 0.4 to 0.8 percent per month, with a standard deviation of 0.9 to 3.3 percent, depending on the fund. Conditional on the state, however, market neutral hedge funds perform the same in both periods, while the other hedge fund styles have a negative mean return in bear periods than in bull periods. Moreover, the other hedge fund styles appear to be more volatile in bear periods than in bull periods. Finally, the last column of the table presents the correlation of the hedge fund indexes and the market and the hedge funds we consider. Unconditionally, we find that market neutral hedge funds are the least correlated with respect to the market. Meanwhile, the other hedge fund styles appear to be positively correlated with the market return.The correlation between market neutral hedge funds and the stock market changes conditional on the state, however. In particular, they are negatively correlated with the market

[8] Our index data starts at January 1997, and we estimate our models starting from this period. The results, which are in the Supplemental Material, remain the same.

in bear periods, while they are positively correlated with the market in bull periods. The correlation between other hedge fund styles and the market remain to be similar, regardless of the time period.

[Table 3 about here.]

3 Modelling regime-switching dependence

The first objective of this paper is to analyze the dependence that exists between market neutral hedge funds and the market portfolio. In particular, we aim to differentiate the effect of the financial cycle, which is predictable, from tail dependence that cannot be easily predicted. This is particularly relevant because the type of dependence that exists has different implications for risk management. On the one hand, the existence of tail dependence implies that hedge funds are sensitive to extreme left tail events. The existence of state dependence, on the other hand, implies that there is a persistent, common latent factor that drives the dependence between hedge funds and the market index; therefore, the occurrence of "extreme left" tail events become more predictable.

To focus on the dependence structure, we follow Patton (2009) and we model the marginal distributions and the copula separately. More formally, let $\{(x_{ft}, x_{mt})\}_{t=1}^{T}$, $t = 1, \ldots, T$ be the hedge fund and market returns, respectively. The conditional cumulative joint distribution function satisfies (Patton (2006)):

$$F(x_{ft}, x_{mt}|s_t) = C_{\theta_{ct}}\left(F_f(x_{ft}|s_t), F_m(x_{mt}|s_t)|s_t\right), \tag{1}$$

where $C_{\theta_{ct}}$ is the conditional copula with state-varying parameters θ_{s_t}, s_t is the state, and $F_i(x_{it}|s_t)$ are the marginal c.d.f's of x_{it} conditional on the state.

As the parameters of interest for this paper are θ_{s_t}, it is unnecessary to model the marginal distributions. Instead, we obtain a non-parametric estimator of the conditional quantile function by dividing the sample according to the state and computing the empirical distribution function:

$$\hat{F}_i(a_t|s_t = s) = \frac{1}{T_s}\sum_{t=1}^{T_s} \mathbf{1}_{(x_{it}\leq a)}\mathbf{1}_{(s_t=s)}$$

where $T_s = \sum \mathbf{1}_{(s_t=s)}$.

We model the copula as a Student's t, which has the following parameterization:

$$C_{\theta_{ct}}(u_1, u_2|s_t) = \int_{-\infty}^{\tau_{\delta_{s_t}}^{-1}(u_1)} \int_{-\infty}^{\tau_{\delta_{s_t}}^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\delta_{s_t}^2}} \left(1 + \frac{r^2 - 2\delta_{s_t} rs + s^2}{\eta_{s_t}^{-1}(1-\delta_{s_t}^2)}\right)^{-\frac{\eta_{s_t}^{-1}+1}{2}} drds \quad (2)$$

where the copula parameters δ_{s_t} and $\eta_{s_t}^{-1}$ are the correlation and degrees of freedom parameters respectively, which are allowed to change with the state. This parameterisation provides the following two advantages. First, it allows the series to be negatively or positively correlated. Second, since it is characterized by two parameters, it accommodates different degrees of tail dependence regardless of the correlation between the series. Precisely, the degree of lower tail dependence for a given state equals:

$$\lambda_s := \lim_{u \to 0^+} Prob(X < F_f^{-1}(u)|Y < F_m^{-1}(u)) = 2t_{\eta_s+1}\left(-\sqrt{\eta_s+1}\sqrt{1-\delta_s}/\sqrt{1+\delta_s}\right)$$

where we used t_η to represent the c.d.f of a Student's t-distribution with η degrees of freedom.

Nevertheless, this copula has some limitations. By construction it is symmetric; hence, $\dfrac{C_{\theta_c}(u_1, u_2)}{C_{\theta_c}(1-u_1, 1-u_2)} = 1$ for all u_1 and u_2. To assess the validity of the assumption we depict in Figure 1 the ratio between the copula's empirical c.d.f and its inverse, $\dfrac{\hat{C}_{\theta_c}(\tau, \tau)}{\hat{C}_{\theta_c}(1-\tau, 1-\tau)}$, which suggests that symmetry is not a far-fetched assumption. Although there is a slight deviation for lower values of τ, it is significantly lower than for an alternative copula as the Gumbel. Moreover, every fund type present the same pattern; hence, our findings, mainly concentrated on market neutral hedge funds, are unlikely to come from this model misspecification.

[Figure 1 about here.]

We estimate the model via maximum likelihood with and without state dependence. Inference about the lack of tail dependence, $\eta_s^{-1} = 0$, however, presents several challenges. First, under the null hypothesis, the parameter of interest lies on the boundary of the parameter space; this, in turn, invalidates the usual asymptotic inference (Andrews, 1999). Second, the MA filtering and the non-parametric estimation of the quantile function also influence inference. To tackle these issues, we rely on the parametric bootstrap to test three different hypotheses: (i.) there is no tail dependence unconditionally, or (ii.) during the bear or (iii.) bull period. These hypotheses are equivalent to testing if the series are related through a Gaussian copula in the three different scenarios. Therefore, we use as test statistic the log-likelihood ratio between a Student's-t and Gaussian copula. [9]

Table 4 shows all the estimated dependence measures. In the first column we present the estimated correlation parameter from the Student's t-copula while the third column includes the same parameter in the case of the Gaussian copula. In general, we observe that the latter is smaller than the former. Therefore, if we fail to take into account the tails of the copula, we underestimate the dependence between the two series. The size of the tails are given by the interaction between the degrees of freedom (η) and the correlation parameter (δ), which we summarize into the tail dependence parameter in the second column. The last column tests the presence of tail dependence by comparing the model with a Student's t- and a Gaussian copula as explained in section 3.

[Table 4 about here.]

The first panel of Table 4 presents the estimated dependence coefficients without conditioning on the cycle. Market neutral hedge funds present a low correlation with the market (13%), especially if we compare them with other styles considered neutral as well, whose correlation parameter ranges from 67% to 87%. A similar pattern across styles arises in terms of tail dependence. We find that market neutral hedge funds are those with the smallest tail dependence (19%) and equity non-hedge funds almost triple that probability. Nonetheless, the tail dependence parameter is significant for market neutral funds. This result is consistent with Brown and Spitzer (2006), who hinges on parametric tests, but contradicts Patton (2009)'s findings based on non-parametric tests. The different conclusions might be due to the effects of cyclicality on each of the methodologies. On the one hand, if we do not consider two states in a parametric estimation, the non-linear dependence created through the common state creates an over-rejection of the tail neutrality hypothesis. On the other hand, non-parametric tests overweight the left-tail observations which mostly belong to the bad state. Therefore,

[9]Section 2 of the Supplemental Material contains a brief description of the bootstrap.

the estimated tail dependence parameter is closer to the one of the bear periods than to the unconditional one.

The previous results conceal an important heterogeneity across different financial states. During bear periods, the hypothesis of tail neutrality cannot be rejected for any of the different styles while it is rejected during bull periods which might be the reason underlying the lack of significance in Patton (2009). This result is consistent with recent empirical results (e.g., Ben-David et al., 2012; Patton and Ramadorai, 2013) which assert that hedge funds have cut their exposures to the market during unfavorable periods. This might be due to either one of two prominent hypotheses. The former is related to the hypothesis that due to funding constraints or lender pressure, hedge fund managers resort to asset fire sales (e.g., Brunnermeier and Pedersen (2009), Shleifer and Vishny (2011), Boyson et al. (2014), Ben-Rephael (2017)). The latter reason offered in the literature stems from the fact that in bear periods, hedge funds move their capital away from equities to alternative investment opportunities in attempt to time the market.

The heterogeneity across states becomes more prominent in the case of market neutral funds whose correlation with the market changes sign across states. During bear periods, these hedge funds become a hedging asset; meanwhile, during bull periods, their returns follow those of the market. The change in correlation is consistent with hedge fund mangers changing their positions according to some private signal (Admati et al., 1986).

4 Implications of regime-switching dependence

The evidence of regime-switching dependence by market neutral hedge funds can have potential implications for hedge fund investment strategies or for risk management, which we study in this section of the paper.

4.1 State timing

Market timing models test for the ability of a fund manager to adjust his portfolio's exposures after observing a signal about future market returns. The successful market timer increases the portfolio weights on equities prior to a positive market signal, and decreases the weight on equities prior to a negative market signal.

The typical market timing models (i.e., Treynor and Mazuy (1966) and Henriksson and Merton (1981)) rely on a signal on whether the returns on the market portfolio will increase or decrease.[10] The results in the previous section suggest that the switch in regime dependence is consistent with these funds adjusting their exposures with respect to the financial cycle. In this regard, we modify the market timing model of Henriksson and Merton (1981):

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \varepsilon_t \tag{3}$$

in which β_j is the loading on factor j, to test for state timing. The variable S_t is what we call the "state timing" term, and is defined as: $S_t = \mathbf{1}(s_t = \mathit{bull})$; that is, once a hedge fund manager observes a signal that the market is in a bull state, he would increase fund exposure. The coefficient γ, hence, measures state timing. We study the presence of state timing for four different factor models: the single factor model, the Fama-French three factor model, the four-factor model by Carhart (1997), and the Fung and Hsieh (2001b) seven-factor model.

Table 5 presents the results from the state timing regressions with index data. For brevity, we report only the coefficients of the state timing coefficient, the market factor, and alpha. The results indicate that market neutral hedge funds exhibit state timing across model specifications. Comparing market neutral hedge funds with other "neutral" types of hedge funds, only the equity hedge style appears to exhibit state timing behavior similar to market neutral hedge funds, as it appears to have a significant timing coefficient across three out of the four specifications. This result is not surprising, as this style is closest to market neutral hedge funds in the type of investment objectives it pursues.

[Table 5 about here.]

Robustness. Our model of state timing (3) focuses on the adjustment of hedge fund beta in response to changes in financial cycles. However, hedge fund managers can also pursue different strategies that can vary with financial cycles. These include:

[10] Admati et al. (1986) formalize the Treynor and Mazuy (1966) model by assuming that managers have exponential utility and a Normal distribution for the returns, and show that the market beta is a product of the manager's risk tolerance and the precision of his signal quality. Henriksson and Merton (1981) show that a manager is assumed to time the market by shifting portfolio weights discretely; the corresponding convexity is modelled via put or call options.

1. Return (Henriksson and Merton (1981))[11], volatility (Chen and Liang (2007)), and/or liquidity timing (Cao et al. (2013));
2. Macroeconomic risk timing (Bali et al. (2014));
3. Definition of financial states (Kacperczyk et al. (2014));
4. Controlling for illiquid holdings (Getmansky et al. (2004)), for options trading (Agarwal and Naik (2004)), or for funding liquidity (Frazzini and Pedersen (2014)).

To determine whether our results are robust to these alternative strategies, we re-estimate the models taking into account these factors. We show in section 3 of the Supplemental Material that our results are mainly robust across all specifications. That is, once we control for these alternative strategies, the evidence of the presence of state timing persists.

4.2 Risk management

Aside from the consequences in terms of the information used by investors, shifts in the dependence structure across states have important implications in terms of risk management. To illustrate this, we consider how Conditional Value-at-Risk (CVaR) changes depending on the financial state.[12] CVaR is defined as the threshold such that the probability of a return lower than that threshold equals α given that the return of the market is below the VaR_β:

$$Prob(-r_f < CVaR_{\alpha,\beta} | r_m < F_m^{-1}(1-\beta)) = \alpha$$

One advantage of this measure is that it relies heavily on the dependence of the two time series, instead of focusing on the marginal distributions. To compute the CVaR, we first compute the component that just rely on the copula which we refer to as *rank-CVaR*:

[11] It could be the case that our state indicator is collinear with periods when $r_t > 0$, which is the timing indicator of the Henriksson and Merton (1981) model, which implies that state timing and return timing are the same. We checked for this possibility, and we find that this only occurs 27.86% of the time. Moreover, there is a negative correlation between our timing dummy and the market timing dummy.

[12] Agarwal and Naik (2004) utilize a mean-CVaR framework to study the portfolio allocation decision of hedge funds. Adrian and Brunnermeier (2016) uses CVaR to define their systemic risk measure, $\Delta CoVaR$

$$Prob\left(F_f(r_f) < rank\text{-}CVaR_{\alpha,\beta} | F_m(r_m) < 1-\beta\right) = \frac{C(rank\text{-}CVaR_{\alpha,\beta}, \beta)}{1-\beta} = 1-\alpha.$$

$Rank - CVaR$ measures the dependence between the market and the fund in the left tail of the distribution. If the variables are independent, $Rank - CVaR$ equals $1-\alpha$. However, if they present positive dependence, $Rank - CVaR$ is lower than $1-\alpha$ whereas it is greater than $1-\alpha$ for those variables that are negatively related. At the same time, in the case of the Student's t-copula, if we consider high values of α and β, tail dependence plays a major role; however, as one of the parameters decreases, the importance of linear correlation increases.

Figure 2a shows that during bear periods, market neutral hedge funds present a $Rank - CVaR$ greater than $1-\alpha$, which implies a negative dependence with the market. Intuitively, the probability to obtain a return below the 20% percentile when the market return is lower than its $(1-\alpha)$-percentile is 11%, almost half of the unconditional probability. This result is driven by the negative correlation present during these periods; actually, if we consider tail neutrality, the relationship becomes even more negative. On the other hand, during bull states market neutral funds positively correlate with the market.

[Figure 2 about here.]

Even if the remaining "neutral" styles do not present a strong cyclicality in terms of dependence, Figures 2b-2e provide some insights about the different ingredients of the model. For example, if we estimate the model without taking into account the states, we do not obtain the unconditional risk but an overestimation of the risk. In contrast, the difference between the Gaussian and non-Gaussian measures implies that we underestimate the risk across the left tail if we do not account for tail risk.

Although $Rank - CVaR$ is useful to characterize the dependence between a hedge fund and the market, it does not provide a good measure of risk because it disregards that the α-percentile during a bear period is lower than the same percentile during a bull period. Therefore, we transform the $Rank - CVaR$ to $CVaR$ by inverting the marginal distribution of hedge fund returns which we assume follows a Student's-t.[13]

[13] Inverting the empirical distribution provide similar qualitative results but requires extrapolation. Other distributions such as the Gaussian distribution or the generalized Pareto also lead to the same results.

As a consequence of the negative correlation, Figure 3a shows that the $CVaR$ during financial crisis for market neutral hedge funds is higher than during bull periods. If we consider an investor who needs to hold a $-CVaR_{0.95,0.95}$ percent of its investment as collateral, she would hold a 1.1% during bear times but a 2.1% during bear periods. Moreover, if she does not include the financial state when managing the risk, she would hold 2.4% in every period. Likewise, if she disregards tail risk and just considers linear correlation, she would hold 0.7% during bear periods and 1.2% during bull periods. These level of collateral would not cover the investor against tail risk.

Although the correlation between the other fund styles and the market is almost constant through the cycle, Figure 3b-3e shows significant differences between bull and bear periods, especially in the case of event driven funds and fund of funds. This change in risk might be due to two different reasons: a change in tail dependence or a shift of the marginal distributions. If the former is the main driver, bull periods would present a lower $CVaR$ which is not the case; moreover, the parameters from the Gaussian copula would not present differences across state. Therefore, it is mostly a result of the shift of marginal distributions.

[Figure 3 about here.]

5 Evidence from individual funds

The previous results rely on index data, which provide a view of the market via taking into account the importance of each fund.[14] Additionally, aggregation eliminates part of the idiosyncratic risk of each fund which leads to a precise estimation of the relationship of these funds with the market. However, as our previous analysis cannot identify idiosyncratic tail risk, we might underestimate tail dependence. Individual level data allow us to measure this risk and shed some light on the characteristics of funds that time the financial cycle.

5.1 Dependence

We estimate the model in section 3 for each fund separately and we perform inference based on a different bootstrap per fund. Table 6 gathers the cross-sectional average and

[14] Alternatively, the index results can be interpreted as a portfolio of market neutral hedge funds from the combination of individual hedge funds.

standard deviation of the correlation parameter and the degree of tail dependence, and the proportion of funds for which we reject the null hypothesis of tail neutrality at the 5% significance level. Consistent with the results on the indexes we find that a significant proportion of the funds present tail dependence during bull periods, or if we consider constant parameters; but we cannot reject tail neutrality during bear periods in most of the cases.[15]

[Table 6 about here.]

The estimation also provides evidence that market neutral hedge funds present lower correlation and tail dependence than the remaining hedge fund styles regardless of the financial period. Regarding the state variability of the parameters, although the table indicates changes in correlation across states, the estimates become extremely noisy due to the non-parametric marginal estimation; therefore, we rely on the timing model to provide some insight to manager's decisions.[16]

5.2 State timing

Table 7 presents results for state timing at the individual hedge fund level, for the four factor models that we considered. Across all models, we find that approximately 40 to 46 percent of market neutral hedge funds have a significantly positive abnormal return at the 5 percent level. We also find that across all models, around 10-17 percent of market neutral hedge funds are state timers, while 2-6 percent are perverse state timers.

[Table 7 about here.]

In comparison with other hedge fund styles, equity hedge appear to exhibit similar proportions of superior state timers as market neutral hedge funds. Meanwhile, equity non-hedge, fund of funds and event driven funds appear to have a larger proportion of perverse state timers. The fact that there are more perverse state timers corroborates the finding in the earlier section that only equity hedge and market neutral hedge funds exhibit state timing abilities.

[15] Although the average tail dependence does not change across state significantly, its distribution tilts towards 0 which drives the test's results.

[16] For some funds the marginal estimation is computed using 20 observations which is the minimum number of observations we require for this analysis.

In section 5 of the Supplemental Material, we study the implications of state timing on fund survival. The results that we obtain indicate that funds that are able to time the financial cycle have higher probabilities of survival. This result is particularly true for market neutral hedge funds and equity hedge funds.

5.3 Are dead funds different from alive funds?

To assess how survivorship bias might affect the results, we present the results of the copula model and the state timing regressions for alive and dead hedge funds, respectively.

Table 8 presents the results of the dependence measures for the copula model. We find that, for both types of funds, we tend to reject tail dependence in bull periods and in unconditional periods. We also find that we cannot reject Gaussianity during bear periods. We also find that for both alive and dead funds, the correlation between the fund and the market is lower during bear periods than bull periods.

[Table 8 about here.]

Table 9 presents the results of the state timing regressions for the single-factor model.[17] It appears that there does not seem to be substantial differences between alive and dead hedge funds with respect to the proportion of funds that exhibit state timing. In particular, the result that there are more successful state timers among the market neutral hedge fund and equity hedge fund styles persists for both alive and dead funds. There do appear to be differences across dead and alive funds in terms of the average state timing coefficient, although the significance is at the 10 percent level.

[Table 9 about here.]

In sum, we can conclude that our results are not (overly) influenced by the presence (absence) of "dead" funds in the dataset.

[17] The complete results for the other timing models are presented in Tables 42 and 43 of the Supplemental Material.

6 Conclusion

In this paper, we explore dependence between hedge funds and the market portfolio. As opposed to previous papers, we study this question conditional on financial cycles. This dimension is important, as it has been shown that hedge funds are one of the most dynamic investment vehicles, and thus, their performance is affected by market conditions.

We find evidence that market neutral and other hedge fund styles exhibit tail dependence during bull periods, but not during bear periods. Moreover, we find that as opposed to other hedge fund styles, the correlation between market neutral hedge funds and the stock market changes with the economic state. We link this behavior to the ability of hedge fund managers to time market regimes, and find evidence that market neutral hedge funds are able to adjust their strategies according to the financial cycles. We illustrate how disregarding changes in dependence might lead to inaccurate risk management practices. Finally, we find that our results on dependence and state timing hold in individual fund data. The evidence that we find underscores the importance of understanding and incorporating financial cycle conditions in asset management and investment decision making.

Our results lead to several implications for future research. First, the assumption of constant dependence parameters generate severe biases which supports the use of conditioning variables or more flexible dynamic models such as GAS models (Creal et al., 2013). Second, although we show that hedge fund managers are able to time the economic state with information that cannot be captured by either volatility or liquidity, the precise features of their information sets remain an open question. A fruitful approach for future research would be along the lines of the paper by Kacperczyk et al. (2014), who distinguish which types of information mutual fund managers use to create value.

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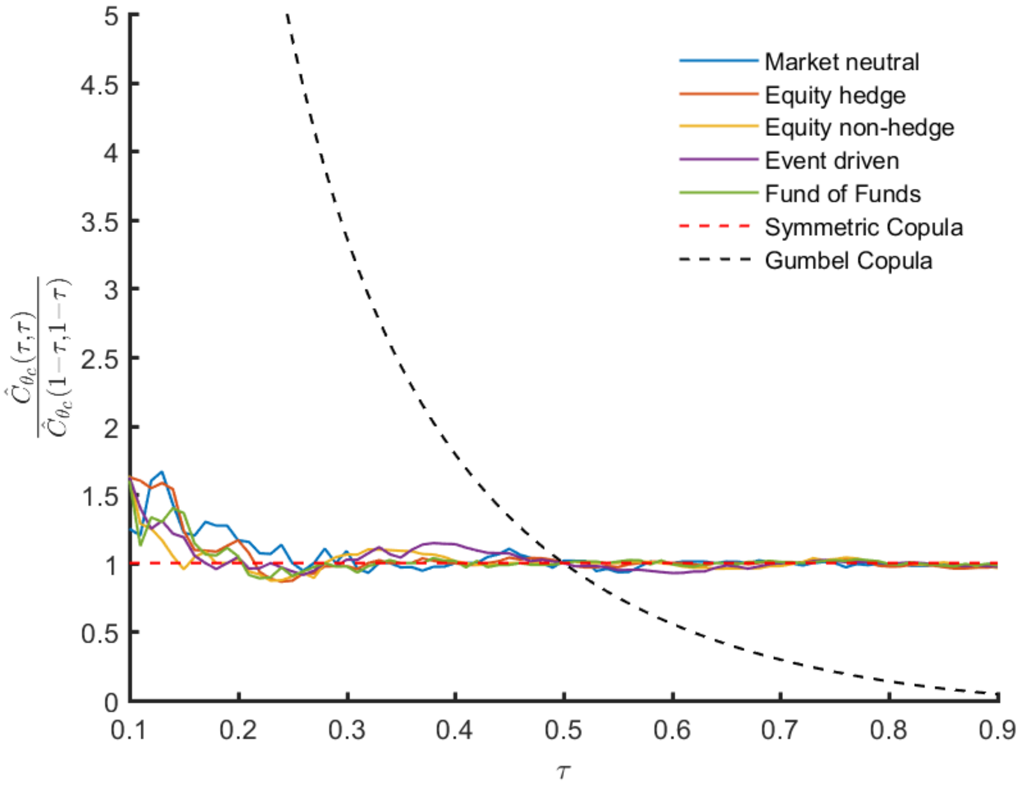
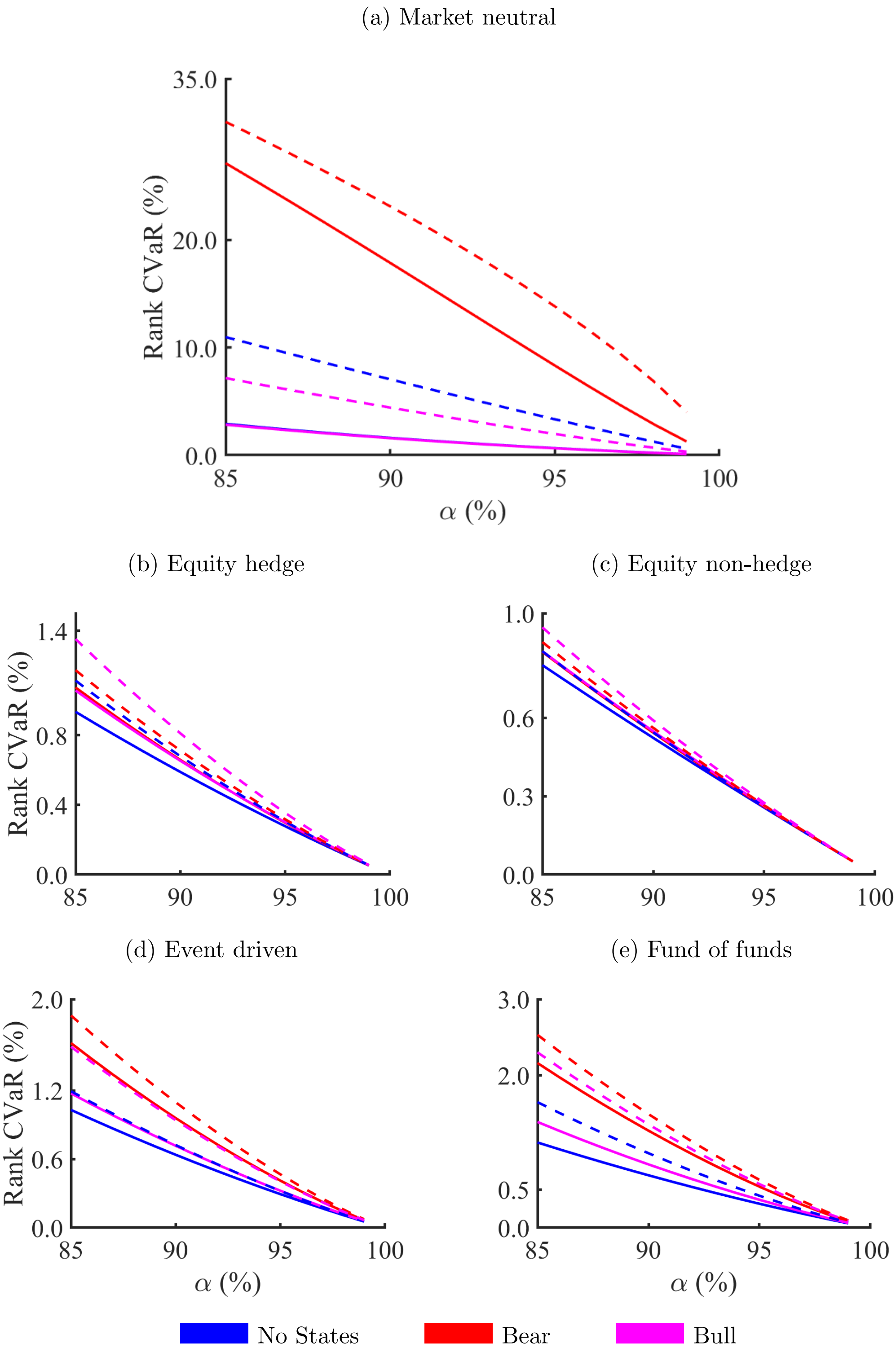
Figures

Figure 1: Asymmetry Ratio.



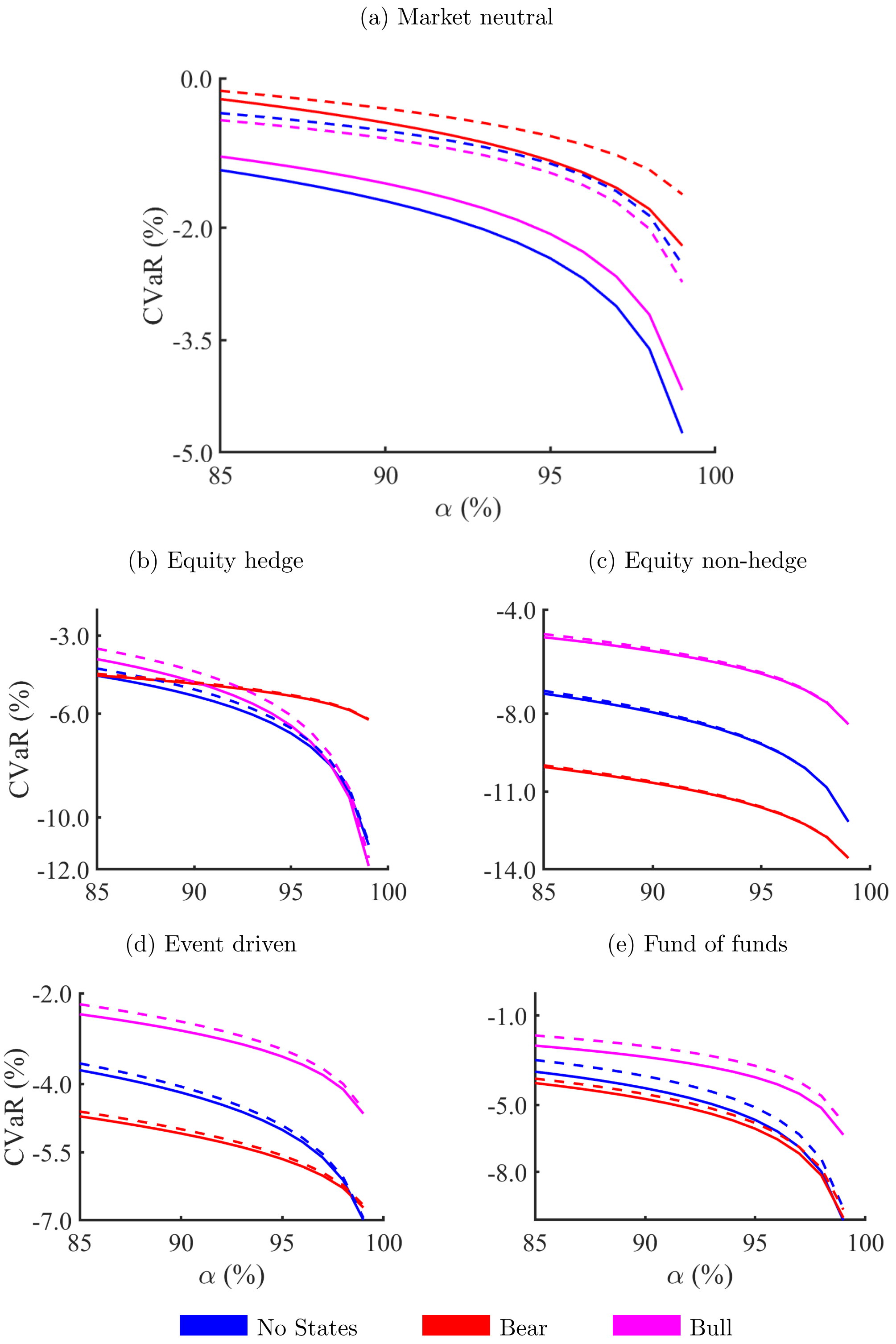
Note: Each solid line of this figure depicts $\frac{\hat{C}_{\theta_c}(\tau,\tau)}{\hat{C}_{\theta_c}(1-\tau,1-\tau)}$ using the empirical copula for the different hedge fund styles. The dashed lines represent the theoretical values of the ratio for the Student's-t copula and the Gumbel copula.

Figure 2: Rank-CVaR



Note: Rank-$CVaR$ is defined as $Prob\left(F_f(r_f) < \textit{rank-CVaR}_{\alpha,\beta} | F_m(r_m) < 1-\beta\right) = 1-\alpha$. Each plot in this figure corresponds to this risk measure for one hedge fund style. The solid lines consider the case of the Student's-t copula while the dashed lines correspond to the Gaussian case. Different colors consider different states (bull, bear or assuming that both states have the same parameters). $\beta = 95\%$.

Figure 3: CVaR



Note: $CVaR$ is defined as $Prob(r_f < CVaR_{\alpha,\beta}|r_m < F_m^{-1}(\beta)) = 1 - \alpha$. Each plot in this figure corresponds to this risk measure for one hedge fund style. The solid lines consider the case of the Student's t-copula while the dashed lines correspond to the Gaussian case. Different colors consider different states (bull, bear or assuming that both states have the same parameters). $\beta = 95\%$.

Tables

Table 1: Bear and bull periods

Panel A: Peaks and Troughs	
Peak	Trough
9/2000 (3/2001)	9/2002 (3/2001)
11/2007 (12/2007)	2/2009 (6/2009)
5/2011	9/2011
6/2015	9/2015
Panel B: Characteristics	
Bull duration	47.5
	(0.000)
Bear duration	12.5
	(0.008)
Bear amplitude	-0.389
	(0.000)
Bull amplitude	0.725
	(0.000)

Note: The first panel compares the bull and bear periods identified by the Pagan and Sossounov (2003) algorithm, and that identified by the NBER (in parentheses). The second panel shows characteristics of bear and bull periods. Duration is in months, while amplitudes are percent changes. The duration of a bull period is defined as $D_t = NTP^{-1} \sum_{t=1}^{T} S_t$, where S_t is a binary variable that takes on 1 when a bull period exists and NTP is the number of peaks. The amplitude of a cycle is defined as $A_t = NTP^{-1} \sum_{t=1}^{T} S_t \Delta \ln P_t$, where P_t is the stock price, or in our case, the stock market index. Asymptotic standard errors are in parentheses. The sample period is January 1997 to December 2016.

Table 2: Summary statistics on the number of observations

	Market neutral	Equity hedge	Equity non-hedge	Event driven	Fund of funds	Total
Minimum	56	48	49	59	48	-
0.25 quantile	73	74	61	79	76	-
Median	89	97	76	110	101	-
Mean	101	110	108	120	113	-
0.75 quantile	114	134	148	148	141	-
Maximum	236	240	240	238	240	-
Number of dead funds	132	736	440	174	2,153	3,635
Number of alive funds	78	367	654	82	746	1,927
Total number of funds	210	1,094	1,103	256	2,899	5,562

Note: The sample period is January 1997 to December 2016. Dead funds are those that have ceased operations during the sample period.

Table 3: Summary statistics

Panel A: Hedge funds	Mean	St. Dev.	Skewness	Kurtosis	Correlation
No States					
Market neutral	0.004	0.009	0.015	4.538	0.184
Equity hedge	0.007	0.021	0.823	7.405	0.684
Equity non-hedge	0.008	0.033	-0.609	4.691	0.852
Event driven	0.007	0.019	-0.985	6.955	0.710
Fund of funds	0.004	0.015	-0.719	7.416	0.606
Bear					
Market neutral	0.003	0.011	-0.637	3.459	-0.183
Equity hedge	-0.005	0.018	-0.133	2.724	0.753
Equity non-hedge	-0.015	0.036	-0.299	3.107	0.860
Event driven	-0.007	0.019	-0.447	2.686	0.616
Fund of funds	-0.007	0.018	-1.586	6.263	0.535
Bull					
Market neutral	0.005	0.008	0.516	4.463	0.305
Equity hedge	0.011	0.020	1.092	8.517	0.620
Equity non-hedge	0.014	0.029	-0.528	5.859	0.813
Event driven	0.011	0.017	-1.262	10.978	0.671
Fund of funds	0.007	0.013	0.146	6.161	0.538

Note: Returns are in percentage points. The sample period is January 1997 to December 2016. *Correlation* refers to the correlation between the hedge fund index and the S&P500

Table 4: Copula Parameters

	Student's-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.130	0.173	0.095	0.000
Equity hedge	0.776	0.334	0.748	0.000
Equity non-hedge	0.873	0.524	0.852	0.000
Event driven	0.741	0.216	0.724	0.060
Fund of funds	0.669	0.293	0.625	0.000
Bear				
Market neutral	-0.281	0.003	-0.248	0.260
Equity hedge	0.760	0.000	0.730	0.690
Equity non-hedge	0.853	0.000	0.834	0.660
Event driven	0.631	0.000	0.590	0.760
Fund of funds	0.547	0.000	0.504	0.670
Bull				
Market neutral	0.226	0.152	0.217	0.000
Equity hedge	0.713	0.276	0.685	0.000
Equity non-hedge	0.830	0.386	0.808	0.000
Event driven	0.663	0.240	0.637	0.060
Fund of funds	0.578	0.219	0.530	0.000

Note: Bear and bull states are defined by the periods in the Pagan and Sossounov (2003) procedure. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 5: State timing at the index level

	α	γ	$r_{m,t}$	R^2
Market neutral hedge funds				
Single factor model	0.00159***	0.0969***	-0.0228	0.085
	(0.000542)	(0.0333)	(0.0284)	
Fama French 3 factor model	0.00158***	0.100***	-0.0285	0.114
	(0.000538)	(0.0348)	(0.0286)	
Carhart 4 factor model	0.00118**	0.0701***	0.0315*	0.414
	(0.000479)	(0.0266)	(0.0191)	
Fung Hsieh factor model	0.00152***	0.0867***	0.680**	0.119
	(0.000553)	(0.0318)	(0.344)	
Equity hedge funds				
Single factor model	0.00339***	0.0607	0.282***	0.486
	(0.00103)	(0.0494)	(0.0309)	
Fama French 3 factor model	0.00303***	0.0827**	0.247***	0.684
	(0.000830)	(0.0350)	(0.0223)	
Carhart 4 factor model	0.00278***	0.0634*	0.285***	0.706
	(0.000670)	(0.0334)	(0.0252)	
Fung Hsieh factor model	0.00297***	0.103**	4.774***	0.635
	(0.000934)	(0.0494)	(1.168)	
Equity non-hedge funds				
Single factor model	0.00244*	0.0264	0.618***	0.703
	(0.00128)	(0.0705)	(0.0503)	
Fama French 3 factor model	0.00172**	0.0554	0.572***	0.863
	(0.000861)	(0.0520)	(0.0425)	
Carhart 4 factor model	0.00163*	0.0486	0.585***	0.864
	(0.000845)	(0.0525)	(0.0437)	
Fung Hsieh factor model	0.00160*	0.117**	6.726***	0.858
	(0.000917)	(0.0560)	(0.750)	
Event driven funds				
Single factor model	0.00333***	0.0494	0.275***	0.513
	(0.00110)	(0.0648)	(0.0416)	
Fama French 3 factor model	0.00276**	0.0631	0.255***	0.623
	(0.00115)	(0.0566)	(0.0438)	
Carhart 4 factor model	0.00282***	0.0673	0.247***	0.627
	(0.000987)	(0.0594)	(0.0440)	
Fung Hsieh factor model	0.00271***	0.111**	3.183***	0.693
	(0.00102)	(0.0467)	(0.507)	
Fund of hedge funds				
Single factor model	0.00143*	-0.0172	0.223***	0.382
	(0.000843)	(0.0622)	(0.0528)	
Fama French 3 factor model	0.00119	-0.00458	0.203***	0.497
	(0.000771)	(0.0646)	(0.0635)	
Carhart 4 factor model	0.000903	-0.0268	0.247***	0.529
	(0.000692)	(0.0554)	(0.0515)	
Fung Hsieh factor model	0.000980	0.0391	2.141**	0.525
	(0.000838)	(0.0417)	(0.828)	

Note: The table shows the abnormal return and timing abilities at the index level using the single factor, Fama-French 3 factor, the Carhart 4-factor model and the Fung Hsieh factor model during the period January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003). α is the abnormal return, γ is the state timing coefficient, and $r_{m,t}$ is the market return. *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 6: Copula parameters for individual funds

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.077	0.203	0.064	0.096	0.167
Equity hedge	0.343	0.274	0.130	0.137	0.267
Equity non-hedge	0.564	0.294	0.228	0.184	0.316
Event driven	0.440	0.194	0.157	0.142	0.313
Fund of funds	0.482	0.200	0.165	0.147	0.294
Total	0.497	0.256	0.168	0.156	0.267
Bear					
Market neutral	0.026	0.306	0.099	0.120	0.062
Equity hedge	0.286	0.377	0.121	0.170	0.055
Equity non-hedge	0.533	0.360	0.202	0.231	0.069
Event driven	0.383	0.291	0.189	0.180	0.121
Fund of funds	0.336	0.273	0.162	0.167	0.069
Total	0.393	0.332	0.162	0.184	0.055
Bull					
Market neutral	0.081	0.206	0.079	0.104	0.143
Equity hedge	0.334	0.260	0.134	0.149	0.212
Equity non-hedge	0.541	0.292	0.212	0.187	0.266
Event driven	0.402	0.206	0.129	0.145	0.207
Fund of funds	0.433	0.193	0.141	0.138	0.227
Total	0.450	0.247	0.152	0.154	0.212

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 7: State timing for individual funds

	%of (+) and significant α	% of (+) and significant γ	% of (-) and significant γ	Mean α	Mean γ
Market neutral hedge funds					
Single factor	0.462	0.129	0.043	0.006	0.051
Fama French 3 factor	0.457	0.133	0.057	0.006	0.046
Carhart 4 factor	0.433	0.100	0.048	0.004	0.045
Fung Hsieh model	0.414	0.167	0.028	0.004	0.040
Equity hedge					
Single factor	0.411	0.124	0.074	0.005	0.021
Fama French 3 factor	0.381	0.127	0.076	0.005	0.027
Carhart 4 factor	0.373	0.121	0.079	0.004	0.017
Fung Hsieh model	0.378	0.127	0.051	0.004	0.052
Equity non-hedge					
Single factor	0.307	0.108	0.131	0.004	-0.043
Fama French 3 factor	0.285	0.117	0.149	0.004	-0.043
Carhart 4 factor	0.293	0.112	0.162	0.004	-0.059
Fung Hsieh model	0.267	0.128	0.121	0.004	0.022
Event driven					
Single factor	0.609	0.070	0.191	0.006	-0.040
Fama French 3 factor	0.570	0.063	0.199	0.005	-0.047
Carhart 4 factor	0.566	0.055	0.207	0.005	-0.061
Fung Hsieh model	0.601	0.113	0.100	0.005	-0.062
Fund of funds					
Single factor	0.417	0.035	0.208	0.003	-0.073
Fama French 3 factor	0.415	0.050	0.249	0.003	-0.077
Carhart 4 factor	0.385	0.034	0.236	0.003	-0.083
Fung Hsieh model	0.362	0.076	0.106	0.003	-0.014

Note: The following table shows abnormal return and return timing abilities at the fund level using the single-factor, Fama French three-factor, the Carhart four-factor model and the Fung Hsieh model during the period of January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003).

Table 8: Copula model results for dependence and correlation – dead and alive hedge funds

	Proportion of rejections Tail dependence = 0			Average correlation		
	Bear	Bull	No states	Bear	Bull	No states
Dead funds						
Market neutral hedge funds	0.091	0.174	0.197	0.030	0.090	0.083
Equity hedge	0.049	0.239	0.255	0.301	0.320	0.331
Equity non-hedge	0.091	0.277	0.318	0.501	0.509	0.529
Event driven	0.132	0.218	0.310	0.374	0.394	0.430
Fund of funds	0.063	0.207	0.261	0.327	0.405	0.456
Alive funds						
Market neutral hedge funds	0.026	0.077	0.090	-0.012	0.071	0.056
Equity hedge	0.019	0.104	0.120	0.443	0.412	0.420
Equity non-hedge	0.018	0.124	0.147	0.706	0.604	0.622
Event driven	0.049	0.098	0.122	0.506	0.445	0.466
Fund of funds	0.005	0.112	0.144	0.462	0.526	0.534

Note: Bear and bull states are defined by the state indicator of Pagan and Sossounov (2003). The first three columns correspond to the test of the Gaussian vs. the Student's-t copula. The subsequent three columns correspond to the average correlation between the individual hedge funds in the dead and alive subsample.

Table 9: State timing – dead and alive hedge funds

	%of (+) and significant α	% of (+) and significant γ	% of (-) and significant γ	mean α	mean γ
Dead funds					
Market neutral hedge funds	0.386	0.106	0.053	0.005	0.036†
Equity hedge	0.383	0.120	0.090	0.005	0.017†
Equity non-hedge	0.280	0.111	0.123	0.004	-0.073
Event driven	0.569	0.075	0.138	0.006	-0.009
Fund of funds	0.414	0.041	0.199	0.003	-0.074
Alive funds					
Market neutral hedge funds	0.590	0.167	0.026	0.005	0.056†
Equity hedge	0.466	0.134	0.044	0.004	0.031†
Equity non-hedge	0.349	0.103	0.142	0.004	-0.047
Event driven	0.695	0.061	0.305	0.005	-0.113
Fund of funds	0.426	0.018	0.235	0.002	-0.072

Note: The following table shows abnormal return and state timing abilities at the fund level using the single-factor model during the period of January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003). † signifies that the null hypothesis that dead and alive funds are similar can be rejected at a 10% significance level using the mean test; †† - significance at 5% level; † † † - significance at 1% level.

Supplemental Material to "Cyclical dependence in market neutral hedge funds"

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The Supplemental Material describes the dating algorithm used in the paper, the bootstrap procedure used in the calculation of the test for tail dependence, and additional results both using index and individual data. The organisation of the Supplemental Material is as follows: Section 1 discusses the financial cycle dating algorithm as described in Pagan and Sossounov (2003). Section 2 briefly explains the bootstrap procedure used in the paper. Section 3 and 4 provide additional results using index and individual hedge fund data, respectively. Section 5 shows the implications of state timing for fund survival.

1 Dating algorithm of Pagan and Sossounov (2003)

The procedure proposed by Pagan and Sossounov (2003) is a pattern-recognition program that seeks to isolate the patterns using a sequence of rules, which can be classified into two main categories. The first deals with the location of peaks and troughs, which involves locating points that are higher or lower than a window of surrounding points. The second involves measuring the durations between the turning points, and censoring rules to restrict the minimal lengths of any phase as well as those of complete cycles.

The procedure for determination of turning points in the data are the following:

1. Determination of initial turning points in the raw data.
   (a) Pagan and Sossounov (2003) determine initial turning points by choosing local peaks (troughs) as occurring when they are the highest (lowest) values in a window eight months on either side of the date.
   (b) If there are multiple peaks/troughs, an enforcement of alternation of turns is done by selecting the highest of multiple peaks (or the lowest of multiple troughs).
2. Censoring operations (ensure alternation after each)
   (a) Eliminate turns within 6 months of the beginning and the end of the time series.
   (b) Eliminate peaks (troughs) at both ends of series which are lower or higher.
   (c) Eliminate cycles whose duration is less than 16 months.
   (d) Eliminate phases (i.e, increasing/decreasing trend) whose duration is less than 4 months (unless fall/rise exceeds 20 percent).
3. Statement of final turning points.

2 Bootstrap

As described in the main text, the challenges inherent in inference about the lack of tail dependence are: (i.) first, that the parameter of interest lies in the boundary of the parameter space, which renders the usual asymptotic inference as invalid (Andrews (1999)); and (ii.) second, that the MA filter and the nonparametric estimation of the quantiles also have influence. To this end, we consider the following bootstrap algorithm.

Consider the null hypothesis in which the bear state does not present tail dependence.

The bootstrap algorithm is as follows:

1. Draw $\{F_F(x_{Mt}^{(b)}|s_t), F_F(x_{Ft}^{(b)}|s_t\})_t^{T_{bear}}$ from a Gaussian copula with parameter δ_{bear} for those periods corresponding to a bear state.

2. Invert the empirical c.d.f. using linear interpolation to obtain $\{x_{Mt}^{(b)}, x_{Ft}^{(b)}\}_{t=1}^{T_{bear}}$.

3. Using the estimated coefficients of the MA, construct a sample of the original returns: $\{r_{Mt}^{(b)}, r_{Ft}^{(b)}\}_{t=1}^{T_{bear}}$.

4. Re-estimate the MA and filter the data to obtain the filtered bootstrap sample: $\{\tilde{x}_{Mt}^{(b)}, \tilde{x}_{Ft}^{(b)}\}_{t=1}$.

5. Obtain the empirical c.d.f. and estimate the Student's-t copula. This step leads to the bootstrap parameter $\theta_{bear}^{(b)}$.

6. Estimate the Gaussian copula using the bootstrap data to obtain $\delta^{*^{(b)}}$.

7. Compute the log-likelihood ratio:

$$LR^{(b)} = \sum_{t=1}^{T_{bear}} f^{Student's-t}\left(\tilde{x}_{Mt}^{(b)}, \tilde{x}_{Ft}^{(b)}; \theta_{bear}^{(b)}\right) - f^{Gaussian}\left(\tilde{x}_{Mt}^{(b)}, \tilde{x}_{Ft}^{(b)}; \delta^{*^{(b)}}\right)$$

   where f^c is the log-p.d.f. of copula c.

8. Repeat 100 times steps 1 to 8.

9. Compare the LR obtained using the original sample with the distribution of $LR^{(b)}$.

We follow the same method for the remaining hypotheses but we use the corresponding data and parameters as inputs.

3 Robustness checks using index data

3.1 Estimation of regime-switching dependence

To obtain the baseline results, we filter the data using an MA(4) filter and drop the first two years of the sample (1997 and 1998) to avoid backfill bias. To verify whether the results are influenced by the filtering procedure, we re-estimate the model with unfiltered data, and with an MA(2) filter. We also re-estimate the model by starting at 1997, the first year of the sample. Table 1 to 5 show the results of the estimation of the copula model. As our tables indicate, the results remain the same.

Likewise, we define the states as proposed by Pagan and Sossounov (2003), instead of using the data from the NBER, because the states are linked to the financial markets. Nonetheless, to tackle the issue that the states are estimated using the same data we use for the dependence parameters, Tables 6 to 11 present the same results as Table 4 using NBER to define our states. We observe that the same conclusions arise; moreover, the correlation between market neutral hedge funds and the asset market becomes more cyclical.

3.2 State timing

In this subsection, we verify whether the state timing tests are robust to the following factors:

1. Return (Henriksson and Merton (1981)), volatility (Chen and Liang (2007)) and/or liquidity timing (Cao et al. (2013));
2. Macroeconomic risk timing (Bali et al. (2014)) or the definition of states (Kacperczyk et al. (2014));
3. Controlling for illiquid holdings (Getmansky et al. (2004)), for options trading (Agarwal and Naik (2004)), or for funding liquidity (Frazzini and Pedersen (2014)).

We discuss each of the robustness tests in turn. For all of the estimations that we will present here, we show the results for the Fama-French model as the baseline model, although we obtain similar results for the other factor models that we present in the paper.[1]

Return, volatility and liquidity timing. Hedge fund managers can also time market returns, volatility (Chen and Liang (2007)) and/or liquidity (Cao et al. (2013)). Because market returns, volatility and liquidity can vary with the financial cycle, our evidence for state timing can be interpreted instead as evidence for return timing, volatility timing, or liquidity timing ability. To this end, we augment the state timing model by estimating the following model specification:

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \beta_{vol} Vol_t + \beta_{liq} Liq_t + \gamma r_{m,t} S_t + \delta r_{m,t} M_t + \lambda r_{m,t}(Vol_t - \overline{Vol}) + \psi r_{m,t}(Liq_t - \overline{Liq}) + \varepsilon_{f,t} \quad (1)$$

where M_t is either $\mathbf{1}(r_{m,t} > 0)$ (as in the traditional return timing model), Vol_t is the market volatility in month t as measured by the VIX, and Liq_t is the aggregate market liquidity measure of Pástor and Stambaugh (2003). The coefficients γ, δ, λ, and ψ measure state timing, return timing, volatility timing, and liquidity timing, respectively.

The results of this estimation are in Table 5. We find that both market neutral and equity hedge funds appear to be state timers. We also find that the liquidity factor is significant for most of these funds.

Macroeconomic risk timing. Recent literature (Bali et al. (2014)) has shown that macroeconomic risk is priced in the cross section of hedge fund returns, and that some hedge funds exhibit timing with respect to uncertainty in the macroeconomy. Although macroeconomic and financial cycles are different, they can potentially coincide in certain periods. We thus test whether state timing survives after controlling for macroeconomic risk. We estimate the following regression:

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \delta r_{m,t} Macro_t + \varepsilon_{f,t} \quad (2)$$

where $Macro_t$ is a variable that is equal to one when the macroeconomic risk factor developed by Bali et al. (2014) is above the mean value.

[1] The results for these estimations are available upon request.

The estimation results are in Table 5. Consistent with the results in Bali et al. (2014), we find that none of our hedge funds are timing the market based on macroeconomic risk. We still find, however, that market neutral and equity hedge funds still exhibit state timing ability.

Cycle indicator. There is research in the mutual funds literature that uses the NBER recession indicator to identify states (Kacperczyk et al. (2014)). Although more widely used as a business cycle indicator, we study whether the main results change if we use the NBER cycle indicator as an alternative indicator for state timing, given the high correlation between the two indicators (57%). To do so, we re-estimate the main model, replacing the indicator for states with the NBER indicator.

The estimation results are in Table 5. The results that we obtained indicate that both market neutral hedge funds and equity hedge funds exhibit state timing, even when we change the indicator of the cycle to the NBER recession and expansion periods.

Controlling for illiquid holdings. Getmansky et al. (2004) show that hedge fund returns exhibit serial correlation. One potential reason for this is because hedge funds typically use illiquid assets that are traded infrequently; hence, this might lead to biased estimates of timing ability if the extent of stale pricing is related to the market factor, as has been shown in the context of bond mutual fund data by Chen et al. (2010). Following Chen and Liang (2007) and Cao et al. (2013), we estimate the following regression:

$$
\begin{aligned}
r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \beta_{m,-1} r_{m,t-1} + \beta_{m,-2} r_{m,t-2} \\
+ \gamma_{-1} r_{m,t-1} S_{t-1} + \gamma_{-2} r_{m,t-2} S_{t-2} + \varepsilon_{f,t} \quad (3)
\end{aligned}
$$

where we introduce two lagged market excess returns, and the interaction between the lagged market returns and the lagged state indicators as additional controls.

As the results in Table 5 indicate, even after controlling for illiquid holdings, the estimates of contemporaneous timing ability are still significantly different from zero, though the market lagged returns and the interaction between the marked lagged return and the state indicator pick up some explanatory power. These results suggest that although there is some thin trading, this does not significantly affect inference about the timing skills of these funds.

Controlling for options trading. Fung and Hsieh (2001) find evidence that some hedge fund strategies can exhibit option-like returns. As Jagannathan and Korajczyk (1986) show, if a fund invests in options, or in stocks with option-like payoffs, then it can be misconstrued as a market timer because of options' nonlinear payoffs. To address the potential non-linearity from options trading, we consider alternative factor models that include the option factors of Agarwal and Naik (2004). The factors are constructed from at-the-money and out-of-the-money European put and call options on the S&P 500 index.[2] The estimation we pursue, hence, is the following:

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \beta_{Put} Put_t + \beta_{Call} Call_t + \varepsilon_{f,t} \tag{4}$$

The results, which are in Table 5, show that among all of the funds that we consider, market neutral and equity hedge funds retain their state timing abilities even after

"Betting-against-beta". Given that market neutral hedge funds usually combine long and short positions to eliminate the correlation with the equity market, we check whether the timing coefficient and the model alpha's are different from zero by estimating the following model:

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \delta r_{m,t} BAB_t + \varepsilon_{f,t} \tag{5}$$

where BAB_t is the "betting-against-beta" factor as suggested by Frazzini and Pedersen (2014). This factor is also related to funding liquidity.

The results of this estimation are in Table 5, which indicate that even after controlling for the "betting-against-beta" factor, the presence of state timing exists. However, the introduction of this factor results in the alpha of market neutral hedge funds being statistically insignificant.

[2]We thank Vikas Agarwal for supplying us the data.

4 Robustness checks using individual data

Tables 18 to 23 present the estimation of the copula model with the MA(0) and MA(2) filter, but for individual hedge fund data. As the results indicate, there does not appear to be much differences between the results that are in the main text, and those that are provided here.

Moreover, to understand if the results are driven by dead or alive hedge funds, we re-estimate the copula model for each subsample. We report the results in Tables 29 to 34 for the case of dead funds, and in Tables 35 to 40 for the case of alive funds. Both groups present similar results. In particular, the correlation between the fund and the market is lower during bear periods than during bull periods, and we tend to reject tail dependence if we do not separate the states or if we consider only bull periods but we cannot reject Gaussianity during bear periods.

Table 41 presents the results of the state timing regressions when the equivalent state indicator is the NBER recession indicator. Our results confirm that market neutral hedge funds and equity hedge funds are superior state timers compared to the other hedge fund styles. Moreover, the proportion of funds that obtain abnormal returns and are superior state timers are quite similar to the those obtained with the Pagan and Sossounov (2003) indicator. Finally, Tables 42 to 43 show that there are no substantial differences between alive and dead hedge funds.

5 Implications of state timing on fund survival

In this section of the Supplemental Material, we study the implications of being a state timer on fund survival. To study fund survival, we estimate the following logit regression:

$$\Pr(d_i = 1|\mathbf{X}, S_i) = \Phi(\mathbf{X}'\beta + \gamma S_i) \tag{6}$$

where d_i is an indicator that is equal to one when the fund is still surviving at the end of the sample, $\mathbf{X}$ is a vector of characteristics, and S_i is an indicator that is equal to one when the fund is a survivor or not. We consider the following hedge fund attributes as characteristics: fund age, fund size, fund management and incentive fees, and dummy variables for high watermark provisions, fund leverage, fund redemption, offshore fund, and fund lockups. For the estimation that we pursue here, we identify state timers from the estimation with the classic Fama-French model.

We present the results of the marginal effects of the logit regressions in Table 44. As the results indicate, the probability of survival increases by two percent for state timers. With respect to fund characteristics, we find a positive, quadratic relationship between fund age and fund survival, and a positive relationship between fund size. Funds that appear to have liquidity restrictions also tend to have a higher probability of survival. We then look at whether there are differences by fund type via introducing interaction terms between the state timer dummy and the fund type. We present the results of the marginal effects of those interactions for brevity, as the other results remain the same. As the results indicate, market neutral and equity hedge funds that are state timers are more likely to survive.

Table 1: Copula Parameters. State: Pagan Filter: MA(0) Initial year: 1999

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.122	0.161	0.084	0.000
Equity hedge	0.758	0.205	0.741	0.020
Equity non-hedge	0.856	0.404	0.840	0.010
Event driven	0.703	0.181	0.686	0.100
Fund of funds	0.616	0.136	0.590	0.050
Bear				
Market neutral	-0.281	0.003	-0.248	0.310
Equity hedge	0.760	0.000	0.730	0.830
Equity non-hedge	0.853	0.000	0.834	0.850
Event driven	0.631	0.000	0.590	0.740
Fund of funds	0.547	0.000	0.504	0.740
Bull				
Market neutral	0.226	0.152	0.217	0.000
Equity hedge	0.713	0.276	0.685	0.000
Equity non-hedge	0.830	0.386	0.808	0.000
Event driven	0.663	0.240	0.637	0.040
Fund of funds	0.578	0.219	0.530	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 2: Copula Parameters. State: Pagan Filter: MA(2) Initial year: 1999

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.130	0.147	0.091	0.000
Equity hedge	0.769	0.294	0.746	0.000
Equity non-hedge	0.869	0.507	0.846	0.000
Event driven	0.745	0.255	0.726	0.010
Fund of funds	0.657	0.229	0.621	0.000
Bear				
Market neutral	-0.281	0.003	-0.248	0.290
Equity hedge	0.760	0.000	0.730	0.740
Equity non-hedge	0.853	0.000	0.834	0.730
Event driven	0.631	0.000	0.590	0.750
Fund of funds	0.547	0.000	0.504	0.740
Bull				
Market neutral	0.226	0.152	0.217	0.000
Equity hedge	0.713	0.276	0.685	0.020
Equity non-hedge	0.830	0.386	0.808	0.000
Event driven	0.663	0.240	0.637	0.050
Fund of funds	0.578	0.219	0.530	0.010

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 3: Copula Parameters. State: Pagan Filter: MA(0) Initial year: 1997

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.217	0.181	0.187	0.000
Equity hedge	0.766	0.309	0.745	0.000
Equity non-hedge	0.855	0.453	0.837	0.000
Event driven	0.704	0.271	0.686	0.030
Fund of funds	0.624	0.226	0.593	0.010
Bear				
Market neutral	-0.281	0.003	-0.248	0.270
Equity hedge	0.760	0.000	0.730	0.810
Equity non-hedge	0.853	0.000	0.834	0.760
Event driven	0.631	0.000	0.590	0.830
Fund of funds	0.547	0.000	0.504	0.750
Bull				
Market neutral	0.325	0.169	0.305	0.000
Equity hedge	0.727	0.371	0.691	0.000
Equity non-hedge	0.829	0.454	0.803	0.000
Event driven	0.663	0.305	0.633	0.000
Fund of funds	0.586	0.277	0.536	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 4: Copula Parameters. State: Pagan Filter: MA(2) Initial year: 1997

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.224	0.183	0.191	0.000
Equity hedge	0.783	0.376	0.754	0.000
Equity non-hedge	0.870	0.519	0.847	0.000
Event driven	0.756	0.280	0.739	0.010
Fund of funds	0.673	0.245	0.640	0.010
Bear				
Market neutral	-0.281	0.003	-0.248	0.250
Equity hedge	0.760	0.000	0.730	0.780
Equity non-hedge	0.853	0.000	0.834	0.840
Event driven	0.631	0.000	0.590	0.790
Fund of funds	0.547	0.000	0.504	0.750
Bull				
Market neutral	0.325	0.169	0.305	0.000
Equity hedge	0.727	0.371	0.691	0.000
Equity non-hedge	0.829	0.454	0.803	0.000
Event driven	0.663	0.305	0.633	0.000
Fund of funds	0.586	0.277	0.536	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 5: Copula Parameters. State: Pagan Filter: MA(4) Initial year: 1997

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.226	0.188	0.195	0.000
Equity hedge	0.786	0.382	0.757	0.000
Equity non-hedge	0.872	0.515	0.852	0.000
Event driven	0.757	0.264	0.741	0.050
Fund of funds	0.681	0.305	0.640	0.000
Bear				
Market neutral	-0.281	0.003	-0.248	0.330
Equity hedge	0.760	0.000	0.730	0.790
Equity non-hedge	0.853	0.000	0.834	0.730
Event driven	0.631	0.000	0.590	0.740
Fund of funds	0.547	0.000	0.504	0.730
Bull				
Market neutral	0.325	0.169	0.305	0.000
Equity hedge	0.727	0.371	0.691	0.000
Equity non-hedge	0.829	0.454	0.803	0.000
Event driven	0.663	0.305	0.633	0.010
Fund of funds	0.586	0.277	0.536	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 6: Copula Parameters. State: NBER Filter: MA(0) Initial year: 1999

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.122	0.161	0.084	0.000
Equity hedge	0.758	0.205	0.741	0.050
Equity non-hedge	0.856	0.404	0.840	0.000
Event driven	0.703	0.181	0.686	0.120
Fund of funds	0.616	0.136	0.590	0.060
Bear				
Market neutral	-0.423	0.009	-0.336	0.130
Equity hedge	0.836	0.000	0.799	0.820
Equity non-hedge	0.914	0.000	0.894	0.780
Event driven	0.737	0.000	0.683	0.720
Fund of funds	0.610	0.000	0.542	0.790
Bull				
Market neutral	0.238	0.144	0.212	0.000
Equity hedge	0.748	0.279	0.724	0.030
Equity non-hedge	0.844	0.401	0.826	0.000
Event driven	0.700	0.226	0.676	0.040
Fund of funds	0.634	0.180	0.602	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 7: Copula Parameters. State: NBER Filter: MA(2) Initial year: 1999

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.130	0.147	0.091	0.000
Equity hedge	0.769	0.294	0.746	0.010
Equity non-hedge	0.869	0.507	0.846	0.000
Event driven	0.745	0.255	0.726	0.040
Fund of funds	0.657	0.229	0.621	0.000
Bear				
Market neutral	-0.423	0.009	-0.336	0.190
Equity hedge	0.836	0.000	0.799	0.840
Equity non-hedge	0.914	0.000	0.894	0.700
Event driven	0.737	0.000	0.683	0.720
Fund of funds	0.610	0.000	0.542	0.750
Bull				
Market neutral	0.238	0.144	0.212	0.000
Equity hedge	0.748	0.279	0.724	0.020
Equity non-hedge	0.844	0.401	0.826	0.000
Event driven	0.700	0.226	0.676	0.040
Fund of funds	0.634	0.180	0.602	0.040

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 8: Copula Parameters. State: NBER Filter: MA(4) Initial year: 1999

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.130	0.173	0.095	0.000
Equity hedge	0.776	0.334	0.748	0.000
Equity non-hedge	0.873	0.524	0.852	0.000
Event driven	0.741	0.216	0.724	0.020
Fund of funds	0.669	0.293	0.625	0.000
Bear				
Market neutral	-0.423	0.009	-0.336	0.180
Equity hedge	0.836	0.000	0.799	0.660
Equity non-hedge	0.914	0.000	0.894	0.650
Event driven	0.737	0.000	0.683	0.750
Fund of funds	0.610	0.000	0.542	0.810
Bull				
Market neutral	0.238	0.144	0.212	0.000
Equity hedge	0.748	0.279	0.724	0.020
Equity non-hedge	0.844	0.401	0.826	0.000
Event driven	0.700	0.226	0.676	0.040
Fund of funds	0.634	0.180	0.602	0.060

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 9: Copula Parameters. State: NBER Filter: MA(0) Initial year: 1997

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.217	0.181	0.187	0.000
Equity hedge	0.766	0.309	0.745	0.010
Equity non-hedge	0.855	0.453	0.837	0.000
Event driven	0.704	0.271	0.686	0.020
Fund of funds	0.624	0.226	0.593	0.000
Bear				
Market neutral	-0.423	0.009	-0.336	0.170
Equity hedge	0.836	0.000	0.799	0.770
Equity non-hedge	0.914	0.000	0.894	0.790
Event driven	0.737	0.000	0.683	0.800
Fund of funds	0.610	0.000	0.542	0.770
Bull				
Market neutral	0.332	0.148	0.313	0.000
Equity hedge	0.763	0.407	0.733	0.000
Equity non-hedge	0.845	0.474	0.824	0.000
Event driven	0.701	0.320	0.674	0.000
Fund of funds	0.641	0.279	0.603	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 10: Copula Parameters. State: NBER Filter: MA(2) Initial year: 1997

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.224	0.183	0.191	0.000
Equity hedge	0.783	0.376	0.754	0.000
Equity non-hedge	0.870	0.519	0.847	0.000
Event driven	0.756	0.280	0.739	0.000
Fund of funds	0.673	0.245	0.640	0.000
Bear				
Market neutral	-0.423	0.009	-0.336	0.170
Equity hedge	0.836	0.000	0.799	0.830
Equity non-hedge	0.914	0.000	0.894	0.690
Event driven	0.737	0.000	0.683	0.760
Fund of funds	0.610	0.000	0.542	0.790
Bull				
Market neutral	0.332	0.148	0.313	0.000
Equity hedge	0.763	0.407	0.733	0.000
Equity non-hedge	0.845	0.474	0.824	0.000
Event driven	0.701	0.320	0.674	0.000
Fund of funds	0.641	0.279	0.603	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 11: Copula Parameters. State: NBER Filter: MA(4) Initial year: 1997

	Students-t Copula		Gaussian Copula	Tail dep.=0
	Correlation	Tail dependence	Correlation	p-value
No States				
Market neutral	0.226	0.188	0.195	0.000
Equity hedge	0.786	0.382	0.757	0.000
Equity non-hedge	0.872	0.515	0.852	0.000
Event driven	0.757	0.264	0.741	0.030
Fund of funds	0.681	0.305	0.640	0.000
Bear				
Market neutral	-0.423	0.009	-0.336	0.170
Equity hedge	0.836	0.000	0.799	0.720
Equity non-hedge	0.914	0.000	0.894	0.670
Event driven	0.737	0.000	0.683	0.740
Fund of funds	0.610	0.000	0.542	0.740
Bull				
Market neutral	0.332	0.148	0.313	0.030
Equity hedge	0.763	0.407	0.733	0.000
Equity non-hedge	0.845	0.474	0.824	0.000
Event driven	0.701	0.320	0.674	0.000
Fund of funds	0.641	0.279	0.603	0.000

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 12: Robustness to return, volatility and liquidity timing

VARIABLES	MNHF	Equity hedge	Equity non-hedge	Event driven	Funds of funds
Market	0.00212	0.266***	0.563***	0.253***	0.178***
	(0.0369)	(0.0325)	(0.0505)	(0.0520)	(0.0525)
SMB	0.0376**	0.244***	0.341***	0.197***	0.146***
	(0.0175)	(0.0364)	(0.0286)	(0.0240)	(0.0235)
HML	-0.0160	-0.0733**	-0.0381	0.0535	-0.0245
	(0.0206)	(0.0325)	(0.0348)	(0.0344)	(0.0297)
Change in the VIX	9.20e-05	0.000232	0.000124	-5.69e-05	0.000276
	(0.000181)	(0.000193)	(0.000194)	(0.000194)	(0.000213)
Levels of aggregate liquidity	0.000428	0.0209*	0.0344**	0.0274**	0.0331**
	(0.0103)	(0.0119)	(0.0138)	(0.0134)	(0.0132)
Return timing	-0.00296*	-0.00373	-0.00174	-0.000990	-0.000859
	(0.00156)	(0.00249)	(0.00286)	(0.00317)	(0.00238)
Volatility timing	0.00888**	0.0109***	0.00789	0.00716	0.0105*
	(0.00406)	(0.00365)	(0.00491)	(0.00526)	(0.00627)
Liquidity timing	0.0629	0.0269	-0.0380	0.103	-0.221
	(0.178)	(0.210)	(0.286)	(0.223)	(0.332)
γ (State timing)	0.106***	0.109***	0.0877	0.0820	0.0284
	(0.0376)	(0.0373)	(0.0556)	(0.0680)	(0.0533)
Constant	0.00291***	0.00528***	0.00342**	0.00354**	0.00235
	(0.000928)	(0.00149)	(0.00163)	(0.00155)	(0.00143)
Observations	227	227	227	227	227
R-squared	0.173	0.713	0.874	0.644	0.554

Note: The table shows the abnormal return and timing abilities at the index level using the classic Fama-French 3 factor model augmented with return, liquidity and volatility factors, and their respective timing factors during the period January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003). *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 13: Robustness to macroeconomic timing

VARIABLES	MNHF	Equity hedge	Equity non hedge	Event driven	Funds of funds
Market	-0.0417	0.237***	0.576***	0.268***	0.196***
	(0.0278)	(0.0242)	(0.0402)	(0.0395)	(0.0629)
SMB	0.0344***	0.231***	0.331***	0.183***	0.138***
	(0.0128)	(0.0384)	(0.0328)	(0.0255)	(0.0267)
HML	-0.0227	-0.0855*	-0.0430	0.0441	-0.0385
	(0.0254)	(0.0444)	(0.0413)	(0.0375)	(0.0382)
Bali et al. (2014) index	-0.000656**	-0.000465	0.000181	0.000789*	-0.000265
	(0.000258)	(0.000416)	(0.000467)	(0.000462)	(0.000382)
Macro timing	-0.000210	-0.000119	0.000165	-0.000455	-0.000477
	(0.00126)	(0.00220)	(0.00226)	(0.00245)	(0.00167)
γ (State timing)	0.119***	0.0957**	0.0499	0.0435	0.00419
	(0.0330)	(0.0387)	(0.0505)	(0.0525)	(0.0646)
Constant	0.00170**	0.00310**	0.00162	0.00299	0.00145
	(0.000785)	(0.00139)	(0.00155)	(0.00191)	(0.00122)
Observations	239	239	239	239	239
R-squared	0.143	0.684	0.863	0.629	0.500

Note: The table shows the abnormal return and timing abilities at the index level using the classic Fama-French 3 factor model augmented with the macroeconomic risk factor of Bali et al. (2014) and the respective timing factor during the period January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003). *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 14: Changing the indicator of state timing

VARIABLES	MNHF	Equity hedge	Equity non-hedge	Event driven	Funds of funds
Market	-0.0399	0.239***	0.583***	0.237***	0.213***
	(0.0371)	(0.0294)	(0.0521)	(0.0517)	(0.0675)
SMB	0.0316*	0.229***	0.333***	0.190***	0.134***
	(0.0178)	(0.0374)	(0.0297)	(0.0235)	(0.0231)
HML	-0.0113	-0.0762**	-0.0384	0.0547	-0.0416
	(0.0231)	(0.0343)	(0.0344)	(0.0335)	(0.0312)
State timing (recession)	0.101**	0.0809**	0.0318	0.0793	-0.0181
	(0.0401)	(0.0375)	(0.0585)	(0.0609)	(0.0711)
Constant	0.00204***	0.00342***	0.00207**	0.00299***	0.00123*
	(0.000511)	(0.000724)	(0.000832)	(0.000859)	(0.000703)
Observations	239	239	239	239	239
R-squared	0.111	0.683	0.862	0.625	0.498

Note: The table shows the abnormal return and timing abilities at the index level using the classic Fama-French 3 factor model with the NBER recession indicator as the relevant timing indicator during the period January 1999 to December 2016. The state indicator is the NBER recession indicator. *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 15: Robustness to illiquid holdings

VARIABLES	MNHF	Equity hedge	Equity non-hedge	Event driven	Funds of funds
Market	-0.0368	0.226***	0.537***	0.220***	0.169***
	(0.0286)	(0.0254)	(0.0416)	(0.0419)	(0.0517)
SMB	0.0289	0.223***	0.317***	0.174***	0.126***
	(0.0177)	(0.0402)	(0.0291)	(0.0226)	(0.0239)
HML	-0.0222	-0.0977***	-0.0651*	0.0181	-0.0585**
	(0.0200)	(0.0332)	(0.0333)	(0.0326)	(0.0294)
Lagged return (t-1)	0.0171	0.0325	0.0895**	0.0692**	0.0745**
	(0.0242)	(0.0382)	(0.0417)	(0.0338)	(0.0357)
Lagged return (t-2)	0.0380***	0.0466***	0.0257	0.0438**	0.0553***
	(0.0132)	(0.0176)	(0.0170)	(0.0171)	(0.0169)
State timing (t-1)	-0.0706	-0.0764*	-0.174***	-0.0721	-0.102**
	(0.0532)	(0.0394)	(0.0547)	(0.0517)	(0.0469)
State timing (t-2)	0.0702	0.129***	0.200***	0.125***	0.108***
	(0.0489)	(0.0274)	(0.0388)	(0.0404)	(0.0311)
State timing	0.117***	0.121***	0.114**	0.117**	0.0482
	(0.0337)	(0.0367)	(0.0508)	(0.0577)	(0.0570)
Constant	0.00134**	0.00194***	0.000870	0.00126	0.000160
	(0.000623)	(0.000743)	(0.000913)	(0.00106)	(0.000772)
Observations	235	235	235	235	235
R-squared	0.172	0.720	0.886	0.688	0.583

Note: The table shows the abnormal return and timing abilities at the index level using the classic Fama-French 3 factor model augmented with variables that control for illiquid holdings, during the period January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003). *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 16: Robustness to option trading

VARIABLES	Market neutral	Equity hedge	Equity non-hedge	Event driven	Funds of funds
Market	-0.00759	0.225***	0.541***	0.187***	0.181***
	(0.0283)	(0.0295)	(0.0476)	(0.0507)	(0.0532)
SMB	0.0285	0.242***	0.344***	0.197***	0.143***
	(0.0200)	(0.0397)	(0.0314)	(0.0237)	(0.0251)
HML	-0.0270	-0.0694*	-0.0288	0.0656*	-0.0242
	(0.0234)	(0.0355)	(0.0390)	(0.0373)	(0.0343)
ATM call options	0.00951***	0.00646	0.00784	0.000101	0.00447
	(0.00290)	(0.00422)	(0.00475)	(0.00277)	(0.00309)
OTM call options	-0.00955***	-0.00740*	-0.00917**	-0.00333	-0.00612**
	(0.00282)	(0.00404)	(0.00433)	(0.00246)	(0.00308)
ATM put options	-0.00694	-0.0165	-0.0155	-0.00233	-0.0118
	(0.00918)	(0.0136)	(0.00952)	(0.00683)	(0.0104)
OTM put options	0.00779	0.0139	0.0123	-0.00298	0.00953
	(0.00867)	(0.0129)	(0.00901)	(0.00663)	(0.00985)
State timing	0.0900**	0.107***	0.0842	0.123*	0.0137
	(0.0348)	(0.0350)	(0.0567)	(0.0668)	(0.0595)
Constant	0.00136*	0.00299***	0.00153	0.00166	0.000831
	(0.000717)	(0.000930)	(0.00106)	(0.00132)	(0.000931)
Observations	199	199	199	199	199
R-squared	0.159	0.705	0.871	0.658	0.507

Note: The table shows the abnormal return and timing abilities at the index level using the classic Fama-French 3 factor model augmented with variables that control for option trading according to Agarwal and Naik (2004), during the period January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003). *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 17: Robustness to "betting-against-beta" factor

VARIABLES	MNHF	Equity hedge	Equity non-hedge	Event driven	Funds of funds
Market	-0.00361	0.261***	0.599***	0.285***	0.240***
	-0.0216	(0.0219)	(0.0302)	(0.0335)	(0.0448)
SMB	0.0445***	0.236***	0.349***	0.206***	0.157***
	-0.0129	(0.0354)	(0.0299)	(0.0252)	(0.0268)
HML	-0.0662***	-0.111***	-0.0883**	-0.00502	-0.102***
	-0.0235	(0.0355)	(0.0402)	(0.0406)	(0.0317)
BAB	0.0872***	0.0511	0.0945***	0.103***	0.129***
	-0.0183	(0.0340)	(0.0321)	(0.0314)	(0.0345)
γ (State timing)	0.0998***	0.0825**	0.0549	0.0625	-0.00530
	-0.0279	(0.0321)	(0.0408)	(0.0489)	(0.0404)
Constant	0.000857	0.00261**	0.000936	0.00191	0.000126
	(0.000602)	(0.00104)	(0.000945)	(0.00119)	(0.000947)
Observations	239	239	239	239	239
R-squared	0.256	0.693	0.874	0.656	0.587

Note: The table shows the abnormal return and timing abilities at the index level using the classic Fama-French 3 factor model augmented with variables that control for funding liquidity according to the "betting against beta" factor of Frazzini and Pedersen (2014), during the period January 1999 to December 2016. The state indicator is the bear-and-bull indicator of Pagan and Sossounov (2003). *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 18: Copula parameters for individual funds. State: NBER Filter: MA(0) Initial year: 1997

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	-0.006	0.192	0.069	0.059	0.081
Equity hedge	0.372	0.280	0.139	0.149	0.101
Equity non-hedge	0.545	0.341	0.258	0.180	0.146
Event driven	0.454	0.193	0.201	0.137	0.152
Fund of funds	0.442	0.188	0.150	0.126	0.123
Total	0.464	0.259	0.171	0.149	0.101
Bear					
Market neutral	-0.065	0.408	0.077	0.116	0.014
Equity hedge	0.429	0.374	0.157	0.208	0.015
Equity non-hedge	0.607	0.415	0.206	0.263	0.016
Event driven	0.500	0.311	0.251	0.239	0.023
Fund of funds	0.429	0.266	0.081	0.140	0.008
Total	0.505	0.344	0.127	0.197	0.015
Bull					
Market neutral	0.012	0.188	0.063	0.050	0.090
Equity hedge	0.360	0.274	0.141	0.145	0.096
Equity non-hedge	0.529	0.334	0.236	0.178	0.133
Event driven	0.440	0.191	0.178	0.135	0.121
Fund of funds	0.446	0.188	0.150	0.135	0.112
Total	0.467	0.255	0.165	0.150	0.096

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 19: Copula parameters for individual funds. State: NBER Filter: MA(2) Initial year: 1997

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	-0.004	0.186	0.047	0.049	0.057
Equity hedge	0.370	0.277	0.132	0.139	0.092
Equity non-hedge	0.542	0.336	0.241	0.175	0.150
Event driven	0.460	0.196	0.192	0.134	0.141
Fund of funds	0.454	0.193	0.162	0.130	0.132
Total	0.483	0.259	0.171	0.147	0.092
Bear					
Market neutral	-0.065	0.408	0.077	0.116	0.014
Equity hedge	0.429	0.374	0.157	0.208	0.018
Equity non-hedge	0.607	0.415	0.206	0.263	0.015
Event driven	0.500	0.311	0.251	0.239	0.023
Fund of funds	0.429	0.266	0.081	0.140	0.011
Total	0.505	0.344	0.127	0.197	0.018
Bull					
Market neutral	0.012	0.188	0.063	0.050	0.090
Equity hedge	0.360	0.274	0.141	0.145	0.095
Equity non-hedge	0.529	0.334	0.236	0.178	0.133
Event driven	0.440	0.191	0.178	0.135	0.125
Fund of funds	0.446	0.188	0.150	0.135	0.112
Total	0.467	0.255	0.165	0.150	0.095

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 20: Copula parameters for individual funds. State: NBER Filter: MA(4) Initial year: 1997

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.008	0.188	0.051	0.047	0.067
Equity hedge	0.371	0.277	0.128	0.142	0.090
Equity non-hedge	0.545	0.336	0.241	0.173	0.144
Event driven	0.459	0.193	0.194	0.137	0.148
Fund of funds	0.460	0.191	0.165	0.130	0.128
Total	0.486	0.258	0.173	0.147	0.090
Bear					
Market neutral	-0.065	0.408	0.077	0.116	0.014
Equity hedge	0.429	0.374	0.157	0.208	0.017
Equity non-hedge	0.607	0.415	0.206	0.263	0.016
Event driven	0.500	0.311	0.251	0.239	0.023
Fund of funds	0.429	0.266	0.081	0.140	0.009
Total	0.505	0.344	0.127	0.197	0.017
Bull					
Market neutral	0.012	0.188	0.063	0.050	0.090
Equity hedge	0.360	0.274	0.141	0.145	0.095
Equity non-hedge	0.529	0.334	0.236	0.178	0.134
Event driven	0.440	0.191	0.178	0.135	0.125
Fund of funds	0.446	0.188	0.150	0.135	0.108
Total	0.467	0.255	0.165	0.150	0.095

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 21: Copula parameters for individual funds. State: State Pagan Filter: MA(0) Initial year: 1997

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.086	0.202	0.081	0.099	0.219
Equity hedge	0.350	0.279	0.141	0.145	0.306
Equity non-hedge	0.575	0.297	0.253	0.193	0.354
Event driven	0.456	0.192	0.178	0.136	0.375
Fund of funds	0.477	0.199	0.165	0.144	0.314
Total	0.497	0.257	0.176	0.159	0.306
Bear					
Market neutral	0.026	0.306	0.099	0.120	0.067
Equity hedge	0.286	0.377	0.121	0.170	0.059
Equity non-hedge	0.533	0.360	0.202	0.231	0.072
Event driven	0.383	0.291	0.189	0.180	0.133
Fund of funds	0.336	0.273	0.162	0.167	0.067
Total	0.393	0.332	0.162	0.184	0.059
Bull					
Market neutral	0.089	0.195	0.071	0.084	0.162
Equity hedge	0.334	0.261	0.137	0.149	0.237
Equity non-hedge	0.541	0.289	0.217	0.187	0.289
Event driven	0.412	0.190	0.136	0.142	0.246
Fund of funds	0.431	0.192	0.151	0.140	0.260
Total	0.450	0.245	0.159	0.155	0.237

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 22: Copula parameters for individual funds. State: State Pagan Filter: MA(2) Initial year: 1997

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.070	0.206	0.065	0.100	0.162
Equity hedge	0.346	0.275	0.135	0.140	0.276
Equity non-hedge	0.566	0.294	0.235	0.188	0.328
Event driven	0.442	0.210	0.171	0.140	0.215
Fund of funds	0.476	0.193	0.165	0.145	0.185
Total	0.495	0.253	0.170	0.157	0.276
Bear					
Market neutral	0.016	0.356	0.094	0.141	0.086
Equity hedge	0.286	0.377	0.121	0.170	0.061
Equity non-hedge	0.533	0.360	0.202	0.231	0.072
Event driven	0.465	0.283	0.122	0.163	0.051
Fund of funds	0.418	0.285	0.075	0.136	0.028
Total	0.464	0.338	0.112	0.174	0.061
Bull					
Market neutral	0.123	0.211	0.041	0.083	0.043
Equity hedge	0.334	0.261	0.137	0.149	0.236
Equity non-hedge	0.541	0.289	0.217	0.187	0.302
Event driven	0.485	0.207	0.127	0.162	0.129
Fund of funds	0.543	0.170	0.108	0.142	0.092
Total	0.537	0.242	0.134	0.159	0.236

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 23: Copula parameters for individual funds. State: State Pagan Filter: MA(4) Initial year: 1997

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.089	0.196	0.064	0.092	0.190
Equity hedge	0.346	0.274	0.131	0.135	0.278
Equity non-hedge	0.564	0.292	0.232	0.182	0.323
Event driven	0.446	0.189	0.166	0.141	0.340
Fund of funds	0.482	0.198	0.171	0.146	0.321
Total	0.498	0.253	0.172	0.155	0.278
Bear					
Market neutral	0.026	0.306	0.099	0.120	0.062
Equity hedge	0.286	0.377	0.121	0.170	0.061
Equity non-hedge	0.533	0.360	0.202	0.231	0.069
Event driven	0.383	0.291	0.189	0.180	0.121
Fund of funds	0.336	0.273	0.162	0.167	0.064
Total	0.393	0.332	0.162	0.184	0.061
Bull					
Market neutral	0.089	0.195	0.071	0.084	0.148
Equity hedge	0.334	0.261	0.137	0.149	0.233
Equity non-hedge	0.541	0.289	0.217	0.187	0.292
Event driven	0.412	0.190	0.136	0.142	0.238
Fund of funds	0.431	0.192	0.151	0.140	0.253
Total	0.450	0.245	0.159	0.155	0.233

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 24: Copula parameters for individual funds. State: NBER Filter: MA(0) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	-0.027	0.209	0.061	0.060	0.081
Equity hedge	0.374	0.281	0.133	0.145	0.099
Equity non-hedge	0.547	0.348	0.250	0.184	0.143
Event driven	0.453	0.200	0.190	0.143	0.129
Fund of funds	0.445	0.190	0.131	0.124	0.099
Total	0.463	0.264	0.157	0.150	0.099
Bear					
Market neutral	-0.065	0.408	0.077	0.116	0.014
Equity hedge	0.429	0.374	0.157	0.208	0.015
Equity non-hedge	0.607	0.415	0.206	0.263	0.015
Event driven	0.500	0.311	0.251	0.239	0.020
Fund of funds	0.429	0.266	0.081	0.140	0.010
Total	0.505	0.344	0.127	0.197	0.015
Bull					
Market neutral	-0.012	0.211	0.054	0.050	0.081
Equity hedge	0.362	0.273	0.131	0.141	0.095
Equity non-hedge	0.532	0.342	0.222	0.182	0.116
Event driven	0.438	0.199	0.158	0.144	0.098
Fund of funds	0.450	0.189	0.122	0.128	0.082
Total	0.471	0.259	0.144	0.148	0.095

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 25: Copula parameters for individual funds. State: NBER Filter: MA(2) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	-0.027	0.204	0.041	0.048	0.062
Equity hedge	0.370	0.275	0.126	0.137	0.092
Equity non-hedge	0.545	0.342	0.235	0.178	0.143
Event driven	0.455	0.202	0.183	0.138	0.133
Fund of funds	0.455	0.194	0.152	0.130	0.125
Total	0.481	0.262	0.163	0.147	0.092
Bear					
Market neutral	-0.065	0.408	0.077	0.116	0.014
Equity hedge	0.429	0.374	0.157	0.208	0.018
Equity non-hedge	0.607	0.415	0.206	0.263	0.016
Event driven	0.500	0.311	0.251	0.239	0.031
Fund of funds	0.429	0.266	0.081	0.140	0.010
Total	0.505	0.344	0.127	0.197	0.018
Bull					
Market neutral	-0.012	0.211	0.054	0.050	0.071
Equity hedge	0.362	0.273	0.131	0.141	0.090
Equity non-hedge	0.532	0.342	0.222	0.182	0.124
Event driven	0.438	0.199	0.158	0.144	0.102
Fund of funds	0.450	0.189	0.122	0.128	0.082
Total	0.471	0.259	0.144	0.148	0.090

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 26: Copula parameters for individual funds. State: NBER Filter: MA(4) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	-0.011	0.205	0.044	0.048	0.062
Equity hedge	0.371	0.275	0.122	0.139	0.083
Equity non-hedge	0.546	0.342	0.234	0.176	0.137
Event driven	0.453	0.197	0.184	0.143	0.129
Fund of funds	0.460	0.191	0.155	0.131	0.121
Total	0.484	0.261	0.164	0.147	0.083
Bear					
Market neutral	-0.065	0.408	0.077	0.116	0.014
Equity hedge	0.429	0.374	0.157	0.208	0.018
Equity non-hedge	0.607	0.415	0.206	0.263	0.016
Event driven	0.500	0.311	0.251	0.239	0.020
Fund of funds	0.429	0.266	0.081	0.140	0.011
Total	0.505	0.344	0.127	0.197	0.018
Bull					
Market neutral	-0.012	0.211	0.054	0.050	0.076
Equity hedge	0.362	0.273	0.131	0.141	0.089
Equity non-hedge	0.532	0.342	0.222	0.182	0.121
Event driven	0.438	0.199	0.158	0.144	0.098
Fund of funds	0.450	0.189	0.122	0.128	0.082
Total	0.471	0.259	0.144	0.148	0.089

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 27: Copula parameters for individual funds. State: State Pagan Filter: MA(0) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.076	0.212	0.080	0.105	0.210
Equity hedge	0.349	0.281	0.137	0.146	0.283
Equity non-hedge	0.575	0.300	0.249	0.195	0.336
Event driven	0.452	0.200	0.173	0.134	0.336
Fund of funds	0.479	0.200	0.155	0.144	0.277
Total	0.497	0.259	0.169	0.161	0.283
Bear					
Market neutral	0.026	0.306	0.099	0.120	0.067
Equity hedge	0.286	0.377	0.121	0.170	0.059
Equity non-hedge	0.533	0.360	0.202	0.231	0.072
Event driven	0.383	0.291	0.189	0.180	0.105
Fund of funds	0.336	0.273	0.162	0.167	0.069
Total	0.393	0.332	0.162	0.184	0.059
Bull					
Market neutral	0.081	0.206	0.079	0.104	0.138
Equity hedge	0.334	0.260	0.134	0.149	0.218
Equity non-hedge	0.541	0.292	0.212	0.187	0.279
Event driven	0.402	0.206	0.129	0.145	0.223
Fund of funds	0.433	0.193	0.141	0.138	0.229
Total	0.450	0.247	0.152	0.154	0.218

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 28: Copula parameters for individual funds. State: State Pagan Filter: MA(2) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.076	0.207	0.067	0.102	0.181
Equity hedge	0.344	0.276	0.133	0.139	0.267
Equity non-hedge	0.566	0.296	0.232	0.190	0.311
Event driven	0.446	0.202	0.170	0.140	0.320
Fund of funds	0.478	0.202	0.167	0.147	0.314
Total	0.496	0.258	0.170	0.158	0.267
Bear					
Market neutral	0.026	0.306	0.099	0.120	0.052
Equity hedge	0.286	0.377	0.121	0.170	0.060
Equity non-hedge	0.533	0.360	0.202	0.231	0.074
Event driven	0.383	0.291	0.189	0.180	0.125
Fund of funds	0.336	0.273	0.162	0.167	0.070
Total	0.393	0.332	0.162	0.184	0.060
Bull					
Market neutral	0.081	0.206	0.079	0.104	0.138
Equity hedge	0.334	0.260	0.134	0.149	0.212
Equity non-hedge	0.541	0.292	0.212	0.187	0.267
Event driven	0.402	0.206	0.129	0.145	0.207
Fund of funds	0.433	0.193	0.141	0.138	0.229
Total	0.450	0.247	0.152	0.154	0.212

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 29: Copula parameters for **dead** funds. State: NBER Filter: MA(0) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	-0.054	0.230	0.049	0.053	0.061
Equity hedge	0.354	0.294	0.123	0.152	0.072
Equity non-hedge	0.501	0.414	0.238	0.187	0.132
Event driven	0.453	0.235	0.210	0.147	0.126
Fund of funds	0.425	0.190	0.121	0.122	0.096
Total	0.446	0.277	0.144	0.148	0.072
Bear					
Market neutral	-0.084	0.436	0.054	0.099	0.008
Equity hedge	0.422	0.372	0.155	0.207	0.016
Equity non-hedge	0.544	0.484	0.195	0.254	0.014
Event driven	0.496	0.314	0.269	0.220	0.006
Fund of funds	0.418	0.265	0.087	0.146	0.012
Total	0.466	0.351	0.124	0.190	0.016
Bull					
Market neutral	-0.044	0.229	0.044	0.050	0.076
Equity hedge	0.337	0.287	0.127	0.146	0.080
Equity non-hedge	0.486	0.406	0.213	0.184	0.120
Event driven	0.434	0.238	0.187	0.153	0.098
Fund of funds	0.427	0.191	0.112	0.127	0.073
Total	0.442	0.273	0.133	0.147	0.080

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 30: Copula parameters for **dead** funds. State: NBER Filter: MA(2) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	-0.052	0.228	0.027	0.036	0.045
Equity hedge	0.348	0.286	0.117	0.140	0.076
Equity non-hedge	0.497	0.407	0.223	0.179	0.140
Event driven	0.446	0.238	0.193	0.136	0.126
Fund of funds	0.432	0.194	0.143	0.129	0.117
Total	0.452	0.276	0.152	0.145	0.076
Bear					
Market neutral	-0.084	0.436	0.054	0.099	0.008
Equity hedge	0.422	0.372	0.155	0.207	0.016
Equity non-hedge	0.544	0.484	0.195	0.254	0.015
Event driven	0.496	0.314	0.269	0.220	0.011
Fund of funds	0.418	0.265	0.087	0.146	0.011
Total	0.466	0.351	0.124	0.190	0.016
Bull					
Market neutral	-0.044	0.229	0.044	0.050	0.061
Equity hedge	0.337	0.287	0.127	0.146	0.080
Equity non-hedge	0.486	0.406	0.213	0.184	0.122
Event driven	0.434	0.238	0.187	0.153	0.098
Fund of funds	0.427	0.191	0.112	0.127	0.069
Total	0.442	0.273	0.133	0.147	0.080

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 31: Copula parameters for **dead** funds. State: NBER Filter: MA(4) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.061	0.142	0.042	0.053	0.141
Equity hedge	0.370	0.258	0.133	0.130	0.281
Equity non-hedge	0.628	0.180	0.247	0.177	0.305
Event driven	0.462	0.160	0.181	0.145	0.305
Fund of funds	0.552	0.170	0.195	0.141	0.399
Total	0.560	0.225	0.190	0.154	0.281
Bear					
Market neutral	0.014	0.221	0.115	0.100	0.077
Equity hedge	0.251	0.370	0.151	0.168	0.082
Equity non-hedge	0.595	0.257	0.215	0.231	0.053
Event driven	0.404	0.204	0.228	0.189	0.134
Fund of funds	0.361	0.225	0.211	0.165	0.088
Total	0.420	0.298	0.198	0.185	0.082
Bull					
Market neutral	0.057	0.140	0.047	0.060	0.090
Equity hedge	0.367	0.238	0.101	0.130	0.161
Equity non-hedge	0.601	0.190	0.216	0.184	0.250
Event driven	0.421	0.173	0.120	0.133	0.195
Fund of funds	0.507	0.160	0.146	0.123	0.263
Total	0.515	0.214	0.150	0.147	0.161

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 32: Copula parameters for **dead** funds. State: State Pagan Filter: MA(0) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.083	0.234	0.088	0.115	0.242
Equity hedge	0.340	0.287	0.139	0.150	0.276
Equity non-hedge	0.542	0.343	0.239	0.196	0.339
Event driven	0.440	0.215	0.166	0.135	0.310
Fund of funds	0.455	0.206	0.142	0.145	0.237
Total	0.466	0.269	0.159	0.161	0.276
Bear					
Market neutral	0.030	0.335	0.092	0.127	0.068
Equity hedge	0.301	0.379	0.108	0.169	0.045
Equity non-hedge	0.501	0.400	0.196	0.231	0.082
Event driven	0.374	0.323	0.171	0.174	0.092
Fund of funds	0.327	0.288	0.144	0.164	0.057
Total	0.384	0.345	0.147	0.181	0.045
Bull					
Market neutral	0.090	0.226	0.091	0.114	0.167
Equity hedge	0.320	0.267	0.148	0.155	0.242
Equity non-hedge	0.509	0.329	0.210	0.188	0.299
Event driven	0.394	0.219	0.133	0.150	0.218
Fund of funds	0.405	0.197	0.139	0.143	0.219
Total	0.418	0.255	0.152	0.157	0.242

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 33: Copula parameters for **dead** funds. State: State Pagan Filter: MA(2) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.087	0.228	0.076	0.113	0.205
Equity hedge	0.335	0.280	0.135	0.142	0.262
Equity non-hedge	0.532	0.337	0.225	0.191	0.343
Event driven	0.434	0.216	0.159	0.136	0.310
Fund of funds	0.453	0.206	0.160	0.150	0.281
Total	0.465	0.265	0.165	0.159	0.262
Bear					
Market neutral	0.030	0.335	0.092	0.127	0.061
Equity hedge	0.301	0.379	0.108	0.169	0.052
Equity non-hedge	0.501	0.400	0.196	0.231	0.073
Event driven	0.374	0.323	0.171	0.174	0.109
Fund of funds	0.327	0.288	0.144	0.164	0.066
Total	0.384	0.345	0.147	0.181	0.052
Bull					
Market neutral	0.090	0.226	0.091	0.114	0.159
Equity hedge	0.320	0.267	0.148	0.155	0.236
Equity non-hedge	0.509	0.329	0.210	0.188	0.284
Event driven	0.394	0.219	0.133	0.150	0.224
Fund of funds	0.405	0.197	0.139	0.143	0.212
Total	0.418	0.255	0.152	0.157	0.236

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 34: Copula parameters for **dead** funds. State: State Pagan Filter: MA(4) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.083	0.222	0.073	0.107	0.197
Equity hedge	0.331	0.280	0.128	0.141	0.255
Equity non-hedge	0.529	0.334	0.217	0.186	0.318
Event driven	0.430	0.207	0.146	0.139	0.310
Fund of funds	0.456	0.204	0.154	0.147	0.261
Total	0.469	0.264	0.158	0.156	0.255
Bear					
Market neutral	0.030	0.335	0.092	0.127	0.091
Equity hedge	0.301	0.379	0.108	0.169	0.049
Equity non-hedge	0.501	0.400	0.196	0.231	0.091
Event driven	0.374	0.323	0.171	0.174	0.132
Fund of funds	0.327	0.288	0.144	0.164	0.063
Total	0.384	0.345	0.147	0.181	0.049
Bull					
Market neutral	0.090	0.226	0.091	0.114	0.174
Equity hedge	0.320	0.267	0.148	0.155	0.239
Equity non-hedge	0.509	0.329	0.210	0.188	0.277
Event driven	0.394	0.219	0.133	0.150	0.218
Fund of funds	0.405	0.197	0.139	0.143	0.207
Total	0.418	0.255	0.152	0.157	0.239

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 35: Copula parameters for **alive** funds. State: NBER Filter: MA(0) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.042	0.127	0.091	0.068	0.077
Equity hedge	0.414	0.250	0.153	0.130	0.125
Equity non-hedge	0.620	0.181	0.270	0.178	0.149
Event driven	0.453	0.137	0.161	0.135	0.146
Fund of funds	0.508	0.173	0.164	0.124	0.129
Total	0.529	0.215	0.189	0.150	0.125
Bear					
Market neutral	-0.012	0.347	0.136	0.142	0.026
Equity hedge	0.443	0.381	0.160	0.211	0.019
Equity non-hedge	0.706	0.241	0.223	0.277	0.016
Event driven	0.506	0.313	0.222	0.269	0.024
Fund of funds	0.462	0.267	0.059	0.118	0.001
Total	0.554	0.321	0.135	0.213	0.019
Bull					
Market neutral	0.071	0.128	0.079	0.046	0.077
Equity hedge	0.412	0.237	0.140	0.133	0.112
Equity non-hedge	0.604	0.182	0.236	0.178	0.122
Event driven	0.445	0.123	0.116	0.122	0.085
Fund of funds	0.526	0.165	0.157	0.126	0.112
Total	0.531	0.206	0.170	0.148	0.112

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 36: Copula parameters for **alive** funds. State: NBER Filter: MA(2) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.038	0.109	0.076	0.058	0.090
Equity hedge	0.415	0.246	0.144	0.130	0.128
Equity non-hedge	0.620	0.176	0.253	0.175	0.138
Event driven	0.467	0.135	0.167	0.142	0.159
Fund of funds	0.528	0.174	0.180	0.132	0.139
Total	0.552	0.214	0.189	0.150	0.128
Bear					
Market neutral	-0.012	0.347	0.136	0.142	0.026
Equity hedge	0.443	0.381	0.160	0.211	0.030
Equity non-hedge	0.706	0.241	0.223	0.277	0.016
Event driven	0.506	0.313	0.222	0.269	0.049
Fund of funds	0.462	0.267	0.059	0.118	0.005
Total	0.554	0.321	0.135	0.213	0.030
Bull					
Market neutral	0.071	0.128	0.079	0.046	0.077
Equity hedge	0.412	0.237	0.140	0.133	0.117
Equity non-hedge	0.604	0.182	0.236	0.178	0.124
Event driven	0.445	0.123	0.116	0.122	0.110
Fund of funds	0.526	0.165	0.157	0.126	0.119
Total	0.531	0.206	0.170	0.148	0.117

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 37: Copula parameters for **alive** funds. State: NBER Filter: MA(4) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.056	0.119	0.071	0.051	0.090
Equity hedge	0.420	0.243	0.149	0.136	0.120
Equity non-hedge	0.622	0.175	0.255	0.169	0.147
Event driven	0.466	0.127	0.161	0.154	0.122
Fund of funds	0.534	0.172	0.191	0.133	0.144
Total	0.551	0.211	0.195	0.149	0.120
Bear					
Market neutral	-0.012	0.347	0.136	0.142	0.026
Equity hedge	0.443	0.381	0.160	0.211	0.019
Equity non-hedge	0.706	0.241	0.223	0.277	0.018
Event driven	0.506	0.313	0.222	0.269	0.049
Fund of funds	0.462	0.267	0.059	0.118	0.005
Total	0.554	0.321	0.135	0.213	0.019
Bull					
Market neutral	0.071	0.128	0.079	0.046	0.077
Equity hedge	0.412	0.237	0.140	0.133	0.104
Equity non-hedge	0.604	0.182	0.236	0.178	0.124
Event driven	0.445	0.123	0.116	0.122	0.098
Fund of funds	0.526	0.165	0.157	0.126	0.112
Total	0.531	0.206	0.170	0.148	0.104

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 38: Copula parameters for **alive** funds. State: State Pagan Filter: MA(0) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.060	0.141	0.060	0.068	0.154
Equity hedge	0.369	0.266	0.133	0.136	0.297
Equity non-hedge	0.637	0.181	0.266	0.194	0.317
Event driven	0.478	0.160	0.188	0.133	0.390
Fund of funds	0.544	0.164	0.192	0.134	0.404
Total	0.560	0.225	0.194	0.158	0.297
Bear					
Market neutral	0.014	0.221	0.115	0.100	0.064
Equity hedge	0.251	0.370	0.151	0.168	0.079
Equity non-hedge	0.595	0.257	0.215	0.231	0.060
Event driven	0.404	0.204	0.228	0.189	0.122
Fund of funds	0.361	0.225	0.211	0.165	0.089
Total	0.420	0.298	0.198	0.185	0.079
Bull					
Market neutral	0.057	0.140	0.047	0.060	0.115
Equity hedge	0.367	0.238	0.101	0.130	0.177
Equity non-hedge	0.601	0.190	0.216	0.184	0.257
Event driven	0.421	0.173	0.120	0.133	0.171
Fund of funds	0.507	0.160	0.146	0.123	0.276
Total	0.515	0.214	0.150	0.147	0.177

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 39: Copula parameters for **alive** funds. State: State Pagan Filter: MA(2) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.049	0.137	0.045	0.057	0.154
Equity hedge	0.365	0.264	0.127	0.132	0.281
Equity non-hedge	0.631	0.181	0.245	0.188	0.307
Event driven	0.473	0.167	0.194	0.147	0.402
Fund of funds	0.545	0.173	0.185	0.137	0.388
Total	0.559	0.228	0.185	0.155	0.281
Bear					
Market neutral	0.014	0.221	0.115	0.100	0.051
Equity hedge	0.251	0.370	0.151	0.168	0.090
Equity non-hedge	0.595	0.257	0.215	0.231	0.062
Event driven	0.404	0.204	0.228	0.189	0.110
Fund of funds	0.361	0.225	0.211	0.165	0.085
Total	0.420	0.298	0.198	0.185	0.090
Bull					
Market neutral	0.057	0.140	0.047	0.060	0.115
Equity hedge	0.367	0.238	0.101	0.130	0.174
Equity non-hedge	0.601	0.190	0.216	0.184	0.243
Event driven	0.421	0.173	0.120	0.133	0.171
Fund of funds	0.507	0.160	0.146	0.123	0.275
Total	0.515	0.214	0.150	0.147	0.174

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 40: Copula parameters for **alive** funds. State: State Pagan Filter: MA(4) Initial year: 1999

	Correlation		Tail dependence		Tail dep.=0
	Mean	St. Dev.	Mean	St. Dev.	# rejections
No States					
Market neutral	0.061	0.142	0.042	0.053	0.141
Equity hedge	0.370	0.258	0.133	0.130	0.281
Equity non-hedge	0.628	0.180	0.247	0.177	0.305
Event driven	0.462	0.160	0.181	0.145	0.305
Fund of funds	0.552	0.170	0.195	0.141	0.399
Total	0.560	0.225	0.190	0.154	0.281
Bear					
Market neutral	0.014	0.221	0.115	0.100	0.077
Equity hedge	0.251	0.370	0.151	0.168	0.082
Equity non-hedge	0.595	0.257	0.215	0.231	0.053
Event driven	0.404	0.204	0.228	0.189	0.134
Fund of funds	0.361	0.225	0.211	0.165	0.088
Total	0.420	0.298	0.198	0.185	0.082
Bull					
Market neutral	0.057	0.140	0.047	0.060	0.090
Equity hedge	0.367	0.238	0.101	0.130	0.161
Equity non-hedge	0.601	0.190	0.216	0.184	0.250
Event driven	0.421	0.173	0.120	0.133	0.195
Fund of funds	0.507	0.160	0.146	0.123	0.263
Total	0.515	0.214	0.150	0.147	0.161

Note: This table presents the estimated dependence statistics for the different hedge fund styles without conditioning on the state, conditioning on the bear state and conditioning on the bull state. The first two columns correspond to the model with a Student's-t copula. The first one refers to the correlation parameter while the second one presents the tail dependence coefficient $\lambda = 2t_{\eta+1}\left(-\sqrt{\eta+1}\sqrt{1-\delta}/\sqrt{1+\delta}\right)$. The third column corresponds to the correlation coefficient if we consider a Gaussian copula. The fourth column tests the Gaussian vs the Student's-t copula.

Table 41: State timing for individual funds - NBER recession periods

	%of (+) and significant α	% of (+) and significant γ	% of (-) and significant γ
Market neutral hedge funds			
Single factor	0.500	0.100	0.048
FF 3 factor	0.500	0.100	0.048
Carhart 4 factor	0.481	0.081	0.038
Equity hedge			
Single factor	0.461	0.150	0.088
FF 3 factor	0.414	0.148	0.092
Carhart 4 factor	0.410	0.119	0.090
Equity non-hedge			
Single factor	0.421	0.150	0.196
FF 3 factor	0.384	0.150	0.211
Carhart 4 factor	0.388	0.110	0.186
Event driven			
Single factor	0.629	0.102	0.188
FF 3 factor	0.578	0.141	0.188
Carhart 4 factor	0.574	0.137	0.156
Fund of funds			
Single factor	0.393	0.102	0.139
FF 3 factor	0.379	0.086	0.167
Carhart 4 factor	0.376	0.053	0.209

Note: The following table shows abnormal return and return timing abilities at the fund level using the single-factor, Fama French (FF) three-factor, and the Carhart four-factor models during the period of January 1999 to December 2016. The state indicator used is the business cycle dating indicator published by the NBER.

Table 42: State timing for individual funds – alive hedge funds

	%of (+) and significant α	% of (+) and significant γ	% of (-) and significant γ
Market neutral hedge funds			
Single factor	0.590	0.167	0.026
FF 3 factor	0.564	0.154	0.026
Carhart 4 factor	0.538	0.154	0.026
Equity hedge			
Single factor	0.466	0.134	0.044
FF 3 factor	0.471	0.123	0.052
Carhart 4 factor	0.455	0.125	0.060
Equity non-hedge			
Single factor	0.349	0.103	0.142
FF 3 factor	0.342	0.106	0.151
Carhart 4 factor	0.367	0.101	0.172
Event driven			
Single factor	0.695	0.061	0.305
FF 3 factor	0.695	0.061	0.317
Carhart 4 factor	0.683	0.037	0.341
Fund of funds			
Single factor	0.426	0.018	0.235
FF 3 factor	0.445	0.032	0.265
Carhart 4 factor	0.416	0.020	0.267

Note: The following table shows abnormal return and state timing abilities at the fund level of alive funds using the single-factor, Fama French (FF) three-factor, Carhart four-factor, and the conditional return timing models during the period of January 1999 to December 2016. The state indicator used is the Pagan and Sossounov (2003) state indicator.

Table 43: State timing for individual funds – dead hedge funds

	%of (+) and significant α	% of (+) and significant γ	% of (-) and significant γ
Market neutral hedge funds			
Single factor	0.386	0.106	0.053
FF 3 factor	0.386	0.121	0.076
Carhart 4 factor	0.371	0.068	0.061
Equity hedge			
Single factor	0.383	0.120	0.090
FF 3 factor	0.336	0.129	0.088
Carhart 4 factor	0.332	0.120	0.088
Equity non-hedge			
Single factor	0.280	0.111	0.123
FF 3 factor	0.248	0.125	0.147
Carhart 4 factor	0.243	0.120	0.155
Event driven			
Single factor	0.569	0.075	0.138
FF 3 factor	0.506	0.063	0.138
Carhart 4 factor	0.511	0.063	0.144
Fund of funds			
Single factor	0.414	0.041	0.199
FF 3 factor	0.403	0.057	0.243
Carhart 4 factor	0.374	0.039	0.225

Note: The following table shows abnormal return and state timing abilities at the fund level of dead funds using the single-factor, Fama French (FF) three-factor, Carhart four-factor, and the conditional return timing models during the period of January 1999 to December 2016. The state indicator used is the Pagan and Sossounov (2003) state indicator.

Table 44: Fund survival estimations, marginal effects

VARIABLES	Baseline	Interactions
Fund has a lockup period	0.171**	
	(0.0773)	
Fund has watermark	0.719***	
	(0.166)	
Fund performance fees	-0.971***	
	(0.168)	
Fund has a minimum investment	8.601	
	(35.96)	
Fund has a hurdle rate	0.170**	
	(0.0812)	
Offshore funds	-0.0694	
	(0.0778)	
Fund size	0.327***	
	(0.0198)	
Age of fund	-0.560***	
	(0.0304)	
Age of fund (squared)	0.0130***	
	(0.000918)	
State timer	0.119*	
	(0.072)	
State timer x MNHF		0.0404***
		(0.00547)
State timer x Equity hedge		0.0609***
		(0.00161)
State timer x Equity non hedge		0.00178
		(0.00376)
State timer x Event driven		-0.0973
		(0.0603)
State timer x Fund of funds		-0.00337
		(0.00678)
Observations	5,020	5,020
Pseudo-R^2	0.1856	0.1956

Note: This table shows marginal effects of the following variables on the probability of hedge fund survival. These were estimated from a logit model. Standard errors were computed via clustering by hedge fund type.

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