Cyclical dependence and timing in market neutral hedge funds*

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Abstract

We explore a new dimension of dependence of hedge fund returns with the market portfolio by examining linear correlation and tail dependence conditional on the financial cycle. Using a large sample of hedge funds that are considered "market neutral", we document that the low correlation of market neutral hedge funds with the market is composed of a negative correlation during bear periods and a positive one during bull periods. In contrast, the remaining styles present a positive correlation throughout the cycle. We also find that while they present tail dependence during bull periods, we cannot reject tail neutrality in times of financial turmoil. Consistent with these results, we show that market neutral hedge funds present state timing ability that cannot be explained by other forms of timing ability. Using individual hedge fund data, we find that funds that implement share restrictions are more likely to time the state.

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

JEL: G11, G23.

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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 market returns (see for example, Agarwal and Naik (2004) and Fung and Hsieh (1999)). This characteristic has propelled growth in an industry whose size was estimated to have swollen from $100 billion in 1997 to $3.018 trillion in 2017.[1]

Knowing the dependence that exists 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 hedge fund managers take. In particular, policymakers have implicated hedge funds as having had a role in several crises, the best known of which is the near-collapse of LTCM in 1998.[2] These findings, hence, underscore the need for a more thorough understanding of the dependence that exists between hedge funds and the stock market, and its implications for their trading behavior.

Hedge funds are usually classified by their investment styles. One such investment style, called market neutral, refers to "funds that actively seek to avoid major risk factors, but take bets on relative price movements utilising strategies such as long-short equity, stock index arbitrage, convertible bond arbitrage, and fixed income arbitrage" (Fung and Hsieh (1999), p. 319). They are not only one of the largest, but are also among the most popular investment styles in the industry.[3] As such, empirical literature has investigated the "neutrality" of these funds to the market index, of which there are numerous definitions. The most prominent one, which is the focus of this paper, is the "neutrality" of these funds 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 asset 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 (see, for example, Agarwal and Naik (2004), Fung and Hsieh (2001), and Patton and Ramadorai

[1]Source: 2017 Credit Suisse Global Survey of Hedge Fund Manager Appetite and Activity.

[2]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.

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

(2013)).

The first departure of this paper from previous literature is to study how dependence between market neutral hedge fund and stock returns changes conditional on the state of the market, both at the aggregate and individual fund level. This provides us with an intuitive manner to link the evolution of hedge fund and stock market price movements to financial cycles. 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)).

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. The result of our estimations indicate that the correlation between market neutral hedge funds and the stock market changes according to the 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 other hedge funds that exhibit similar characteristics in terms of trading strategies appear to have positive correlation in both bull and bear periods.

The fact that the correlation between market neutral hedge fund returns and that of the market flips sign suggests that managers of this fund style pursue trading strategies that arise from varying business conditions. To this end, the second contribution of this paper is to investigate whether market neutral hedge funds display the ability to time financial cycles. We utilise the Pagan and Sossounov (2003) state indicator to measure timing ability and modify the Henriksson and Merton (1981) market timing model. We estimate three state timing models: the single-factor model, the Fama French three-factor model, and the four factor model of Carhart (1997). Compared to the other hedge fund styles in our study, we find that market neutral hedge funds exhibit significant state timing ability that cannot be explained by other types of timing ability, such as return, volatility, and liquidity timing. Our results are also robust to the definition of the economic state, which suggest that hedge fund managers incorporate information about financial and business cycles in their trading decisions. Moreover, our results are robust to alternative explanations. In particular, we recognize that some of the assets that hedge funds hold might be illiquid, or have nonlinear payoffs. To this end, we conduct tests that control for illiquid holdings and options trading, and show that our evidence of state timing ability is robust to these explanations. Finally, using individual hedge fund data, we find that market neutral hedge funds that have lockup periods appear to time better.

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 economic state. 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 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 is also related to 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. Relative to these papers, our results suggest that market neutral hedge fund managers exhibit

[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.

an additional timing skill, that of the ability to adjust their risk exposures using information on financial cycles[5]. 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, which has been widely studied in the context of mutual funds (see Moskowitz (2000), De Souza and Lynch (2012), and Kacperczyk et al. (2014), for recent work).

Finally, our paper contributes to studies that attempt to understand asymmetric 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 whether market neutral hedge funds exhibit state timing. Section 5 shows the implications of our results for risk management. We present the results of dependence and state timing for individual hedge funds in section 6. Finally, section 7 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." As they emphasise, 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. This definition does not preclude the possibility of negative return realisations in bull periods or positive return realisations 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

[5] Bali et al. (2014), using a macroeconomic uncertainty index constructed from available state information, show that market neutral hedge fund managers are unable to time macroeconomic risk. The reason why they are unable to find this result, however, is perhaps because they do not account for financial cycles.

literature. Section 1 of the Supplemental Material provides details on the dating algorithm.

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 (2003) algorithm with that of the NBER. As can be seen, the correspondence is good, with the correlation between the two periods being approximately 58 percent. The dating algorithm we employ, however, identifies two additional bear periods. The first, from March 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.[6]

[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.

[6]The duration of a bull period in Pagan and Sossounov (2003) 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.

[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 the observation by Joenväärä et al. (2016) that empirical analyses using this database yield similar results as that from an aggregate database.

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 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 minimise the influence of "backfill bias", which is related to the fact that hedge funds enter a database with a history of good returns, we consider data starting from January 1999.[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.]

Panel A of 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.

[Table 3 about here.]

2.3 Factors

Panel B of Table 3 presents the summary statistics of the economic factors that we use in the empirical analysis of the market timing models: the S&P 500 index, the Fama-French (FF) size and book-to-market factors, and a momentum portfolio similar to Carhart (1997).

[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.

The unconditional market return is 0.6 percent; however, in bear periods, the market does not perform well, with a mean return of -3.1 percent and a standard deviation of 5 percent. This is in contrast to its performance in bull periods.

Finally, Table 4 presents the correlation matrices of 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. Moreover, market neutral hedge funds are not highly correlated with the other hedge fund styles, with the exception of equity hedge and fund of funds. The other hedge fund styles appear to be highly correlated with each other, though. 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 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 4 about here.]

3 Modeling dependence

The first objective of this paper is to analyse 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)):

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

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 parameterisation:

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

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 characterised 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, $\frac{C_{\theta_c}(u_1,u_2)}{C_{\theta_c}(1-u_1,1-u_2)} = 1$ 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, $\frac{\hat{C}_{\theta_c}(\tau,\tau)}{\hat{C}_{\theta_c}(1-\tau,1-\tau)}$, which suggests that symmetry is not a far-fetched assumption. The slight deviation for lower values of τ might be due to the estimation error that increases as τ decreases. [9]

[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,

[9] An alternative to the Student's-t copula considered by Nelsen (2007) is the Gumbel copula, but it presents too much asymmetry.

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

Table 5 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.[10] 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 summarise 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 5 about here.]

The first panel of Table 5 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

[10]The Gaussian copula is equivalent to the Student's t-copula with $\eta^{-1} = 0$.

creates an overrejection 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, 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. 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). In contrast to market neutral funds, the correlation for the remaining styles is mostly the same in each period which suggests that, due to their investment strategies, the managers of these funds are not able to "time the state", or if they do, time the state inefficiently.

4 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.[11] As our results in the previous section suggest, market neutral hedge funds seem

[11] Admati et al. (1986) formalise the Treynor and Mazuy (1966) model by assuming that managers have ex-

to adjust their exposures with respect to financial conditions. In this regard, we modify the market timing model of Henriksson and Merton (1981):

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \varepsilon_t \tag{2}$$

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: $S_t = \mathbf{1}(s_t = bull)$; 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. $K = 1$ for the single factor market model, $K = 3$ for the Fama-French three-factor model. and $K = 4$ for the Carhart four-factor model.

Before discussing the results of the state timing tests, we present the regressions that study the abnormal performance of the funds we consider in Table 6. Alphas from most of the hedge fund indices are positive and significant, with the exception of fund of funds. Most of the funds in our sample also exhibit a positive loading on the size portfolio, suggesting that most of these funds invest in small-cap stocks. Meanwhile, market neutral hedge funds, equity hedge funds, and fund of funds exhibit a positive loading in the momentum portfolio, which implies that they invest in stocks with good positive performance.

[Table 6 about here.]

Table 7 presents the results from the state timing regressions with index data. The results indicate that market neutral hedge funds exhibit state timing across model specifications. The timing coefficients are statistically significant across all regressions. We also find that after controlling for state timing, the alpha becomes less significant albeit with a smaller magnitude, in comparison with the regressions without state timing in Table 6. This result suggests that a substantial proportion of the aggregate abnormal return can be explained by state timing. Interestingly, the market beta is statistically insignificant, suggesting that market neutral hedge funds indeed are able to "neutralise" the market with their trading strategies. Comparing market neutral hedge funds with other "neutral" types of hedge funds, only the equity hedge style appears to exhibit state timing behavior. This result is not surprising, as this style is closest to market neutral hedge funds in the type of investment objectives it pursues; the main difference is that equity hedge funds do not aim to neutralise the market.

ponential 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 modeled via put or call options.

[Table 7 about here.]

To determine whether our results are robust to the definition of states, we conduct the same regressions as in equation (2), but varying our state indicator to be that of the NBER recession and expansion periods. As the results of Table 12 in section 3 of the Supplemental Material indicate, we find that indeed, market neutral hedge funds and equity hedge funds time the financial state, while the other hedge fund styles do not.

4.1 Controlling for market, volatility and liquidity timing

Our model of state timing (2) focuses on the adjustment of hedge fund beta in response to financial cycles. However, 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 state of the economy, 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:

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \delta r_{m,t} M_t + \lambda r_{m,t}(Vol_t - \overline{Vol}) + \psi r_{m,t}(Liq_t - \overline{Liq}) + \varepsilon_{f,t} \quad (3)$$

where M_t is either $\mathbf{1}(r_{m,t} > 0)$ (as in the Henriksson and Merton (1981) market timing model), or $r_{m,t}$ (as in the Treynor and Mazuy (1966) market timing model), Vol_t is the market volatility in month t as measured by the CBOE S&P 500 index option implied volatility (i.e., VIX), and Liq_t is the market liquidity measure of Pástor and Stambaugh (2003). The coefficients γ, δ, λ, and ψ measure state timing, market timing, volatility timing, and liquidity timing, respectively.

Table 8 presents the results from the estimation with model 3, both with the Treynor and Mazuy (1966) and Henriksson and Merton (1981) market timing models. The results of both specifications indicate that even after controlling for return, volatility and liquidity timing, we still find significant evidence of market neutral hedge funds exhibiting state timing skill. In fact, the magnitudes of the state timing coefficients are not smaller than those in the main regressions. While we find some evidence of perverse volatility timing, as indicated by the negative coefficient on λ, the magnitude is small. Notice as well that in the Treynor and Mazuy (1966) market timing model, alpha is insignificant, while in the Henriksson and Merton (1981) market timing model, alpha is statistically significant. While inconclusive, this result suggests that market neutral hedge funds display stronger timing ability than stock selection ability.

[Table 8 about here.]

With respect to other hedge fund styles, we find similar results as with that of the baseline analysis; that is, with the exception of equity hedge, the other hedge fund styles do not seem to exhibit state timing, even after the addition of controls of other types of timing. The results are robust to the state indicator, as Table 13 of the Supplemental Material shows.[12]

4.2 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:

$$r_{f,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{j,t} + \gamma r_{m,t} S_t + \beta_{m,-1} r_{m,t-1} + \beta_{m,-2} r_{m,t-2} + \gamma_{-1} r_{m,t-1} S_{t-1} + \gamma_{-2} r_{m,t-2} S_{t-2} + \varepsilon_{f,t} \quad (4)$$

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 9 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. While the state timing coefficient has become significant for other hedge fund styles, the abnormal return coefficient has become insignificant as well; this result suggests that for these funds, state timing abilities are able to explain abnormal return performance. Changing the state indicator to the NBER recession indicator does not alter the results, as Table 14 of the Supplementary Appendix indicates.

[12] In Table 15 of the Supplemental Material, we verify whether the hedge fund styles possess the other forms of timing through tests of return, volatility and liquidity timing, separately. The results of the Carhart four-factor model estimations indicate that market neutral hedge funds possess return timing. However, this finding is suspect, as the results of the Fama French three-factor model and the simple timing model (which are not reported here) do not indicate that these funds exhibit return timing skill.

[Table 9 about here.]

4.3 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.

Table 10 presents the results of the estimations for both the single factor model and the Carhart four-factor model. As the results indicate, our results are robust even after controlling for potential option trading. These results suggest that our state timing model is not misspecified.

[Table 10 about here.]

5 Consequences for 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.[13] 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*:

$$Prob\,(F_f(r_f) < \textit{rank-CVaR}_{\alpha,\beta}|F_m(r_m) < 1-\beta) = \frac{C(\textit{rank-CVaR}_{\alpha,\beta},\beta)}{1-\beta} = 1-\alpha.$$

$Rank - CVaR$ 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

[13] Agarwal and Naik (2004) utilise 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, $\Delta CoVaR$

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 characterise 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 bear period. Therefore, we transform the $Rank - CVaR$ to $CVaR$ by inverting the marginal distribution of hedge fund returns which we assume follow a Student's-t.[14]

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%

[14]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.

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.]

6 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.[15] 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 state.

6.1 Dependence

We estimate the model in section 3 for each fund separately and we perform inference based on a different bootstrap per fund. Table 11 gathers the cross-sectional average and 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.[16]

[Table 11 about here.]

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

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

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.[17]

6.2 State timing

Table 12 presents results for state timing at the individual hedge fund level. 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% level. Moreover, according to the Fama French 3 factor model, around 13 percent of funds exhibit superior state timing abilities, while 5 percent of funds exhibit perverse state timing abilities.

[Table 12 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.[18]

We now examine the relationship between state timing and fund characteristics. Specifically, we regress the state timing coefficients of individual market neutral hedge funds estimated from the four-factor state timing model on fund characteristics. We look at nine fund attributes, including 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.

Table 13 presents the regression results. We find that there is a relationship between having a fund lockup period and being a successful state timer. This finding is consistent with the idea that for some market neutral hedge funds, the imposition of share restrictions (such as fund

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

[18]We run separate return, volatility and liquidity timing regressions for each of the individual funds in our sample. The results in Table 40 of the Supplemental Material indicate that market neutral hedge funds are more likely to be return timers than volatility or liquidity timers.

lockup periods) provides the manager with greater discretion in the management of the assets under their investment (Aragon (2007)). Thus, in bull periods, market neutral hedge funds are able to ride the stock market; in bear periods, however, as these funds have share restrictions, they are prevented to use asset fire sales to cut back on their losses. Instead, they resort to their timing skills to manage the portfolio's risk exposures.

[Table 13 about here.]

6.3 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 14 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 14 about here.]

Table 15 presents the results of the state timing regressions for the single-factor model.[19] 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.

[Table 15 about here.]

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

7 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 di-

[19] The complete results for the other timing models are presented in Tables 41 and 42 of the Supplemental Material.

mension 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 business cycles, and find strong evidence that market neutral hedge funds are able to adjust their strategies according to the economic state. 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. In particular, we find that market neutral hedge funds that have lockup periods appear to be better state timers. The evidence that we find underscores the importance of understanding and incorporating business 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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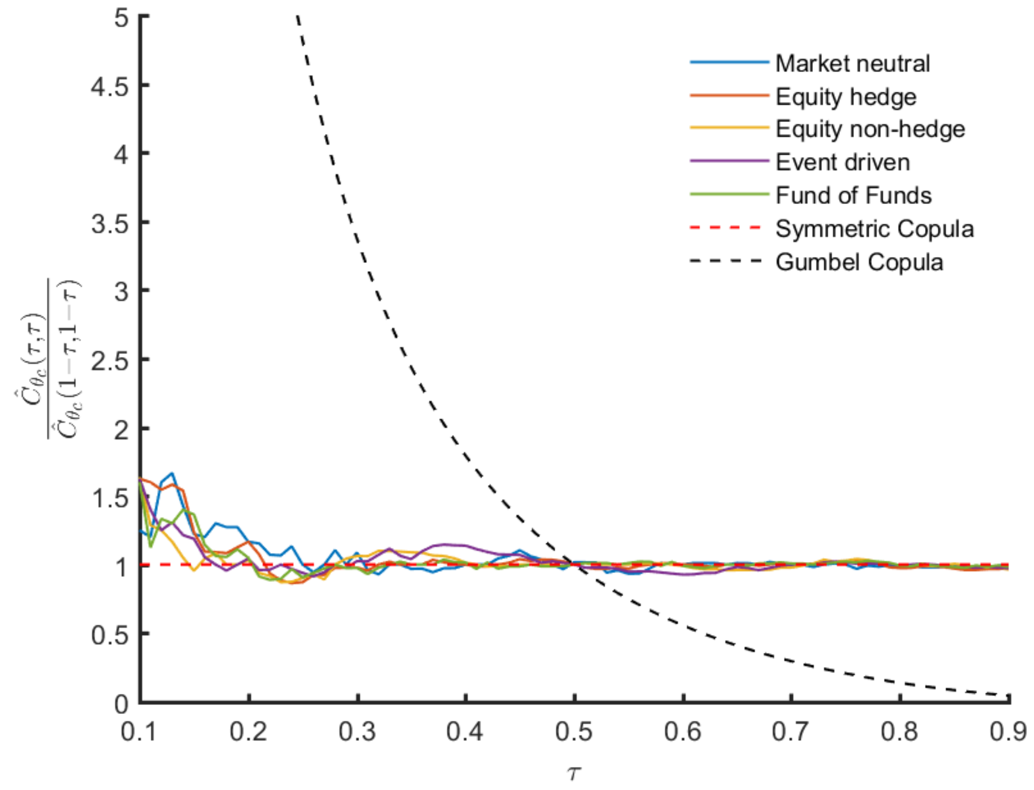
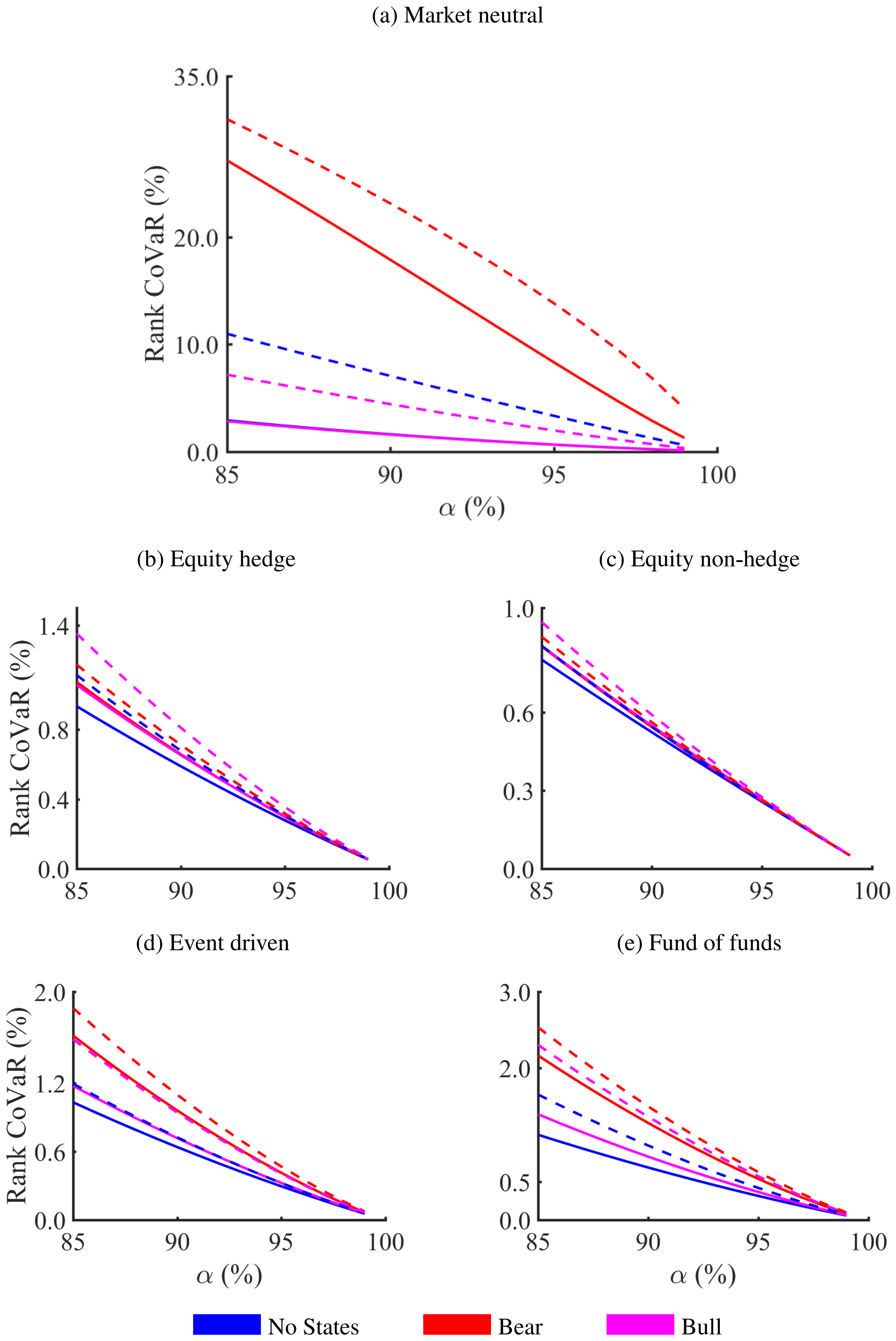
Figures

Figure 1: Asymmetry Ratio.



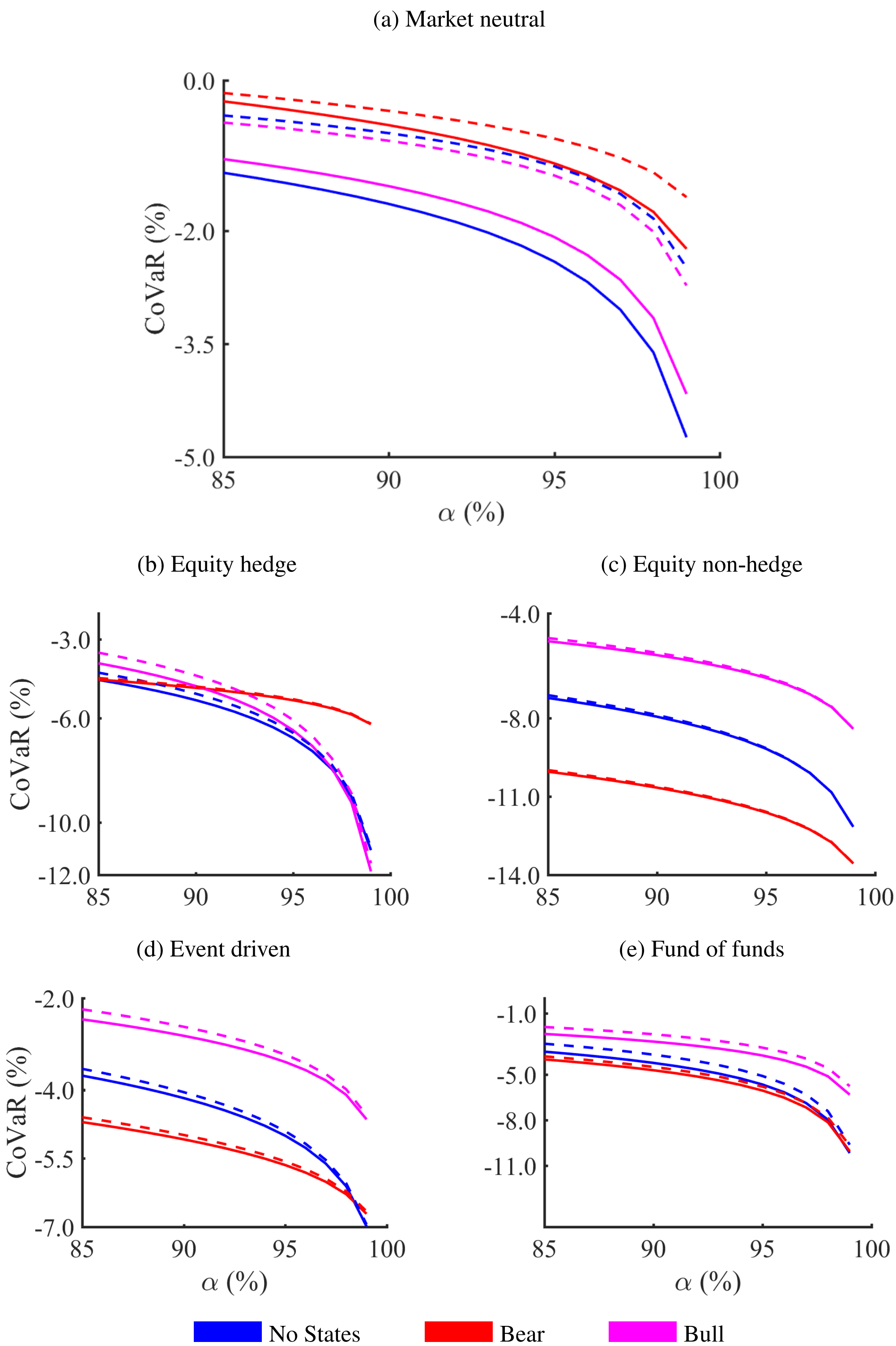
Note: Each solid line of this figure depicts $\frac{\hat{C}_{\theta_c}(\tau,\tau)}{\hat{C}_{\theta_c}(1-\tau,1-\tau)}$ using the empirical copula for the different hedge fund styles. The dashed lines represent the theoretical values of the ratio for the Student's-t copula and the Gumbel copula.

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. 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
No States				
Market neutral	0.004	0.009	0.015	4.538
Equity hedge	0.007	0.021	0.823	7.405
Equity non-hedge	0.008	0.033	-0.609	4.691
Event driven	0.007	0.019	-0.985	6.955
Fund of funds	0.004	0.015	-0.719	7.416
Bear				
Market neutral	0.003	0.011	-0.637	3.459
Equity hedge	-0.005	0.018	-0.133	2.724
Equity non-hedge	-0.015	0.036	-0.299	3.107
Event driven	-0.007	0.019	-0.447	2.686
Fund of funds	-0.007	0.018	-1.586	6.263
Bull				
Market neutral	0.005	0.008	0.516	4.463
Equity hedge	0.011	0.020	1.092	8.517
Equity non-hedge	0.014	0.029	-0.528	5.859
Event driven	0.011	0.017	-1.262	10.978
Fund of funds	0.007	0.013	0.146	6.161

Panel B: Factors	Mean	St. Dev.	Skewness	Kurtosis
No States				
Market	0.006	0.044	-0.614	3.972
SMB	0.002	0.035	0.791	11.515
HML	0.003	0.032	0.104	5.439
UMD	0.004	0.054	-1.419	11.890
Bear				
Market	-0.031	0.050	-0.144	3.022
SMB	0.002	0.032	0.313	2.507
HML	0.007	0.046	0.122	3.686
UMD	0.016	0.066	-1.247	12.928
Bull				
Market	0.015	0.037	-0.528	5.859
SMB	0.002	0.035	0.877	12.928
HML	0.001	0.028	0.122	3.686
UMD	0.000	0.050	-1.662	15.487

Note: Market is the return on the S&P 500 index. SMB and HML are the Fama French size and book-to-market factors, and UMD is the Carhart (1997) momentum factor. Returns are in percentage points.

Table 4: Correlation matrix

	Market	Market neutral	Equity hedge	Equity non-hedge	Event driven	Fund of funds
No States						
Market	1					
Market neutral	0.184	1				
Equity hedge	0.684	0.517	1			
Equity non-hedge	0.852	0.372	0.919	1		
Event driven	0.710	0.348	0.831	0.891	1	
Fund of funds	0.606	0.531	0.886	0.848	0.856	1
Bear						
Market	1					
Market neutral	-0.183	1				
Equity hedge	0.753	0.272	1			
Equity non-hedge	0.860	0.098	0.951	1		
Event driven	0.616	0.278	0.906	0.880	1	
Fund of funds	0.535	0.447	0.823	0.811	0.878	1
Bull						
Market	1					
Market neutral	0.305	1				
Equity-hedge	0.620	0.592	1			
Equity non hedge	0.813	0.467	0.910	1		
Event driven	0.671	0.356	0.791	0.872	1	
Fund of funds	0.538	0.567	0.905	0.831	0.820	1

Note: Market corresponds to the S&P 500 return. Bear and bull states are defined by the periods in the Pagan and Sossounov (2003) procedure. Data is from January 1999 to December 2016.

Table 5: 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 6: Abnormal performance of market neutral hedge funds

	α	β_m	β_{smb}	β_{hml}	β_{umd}
Market neutral hedge funds					
Single factor model	0.002***	0.037**			
	(0.001)	(0.018)			
Fama-French 3 factor model	0.002***	0.033*	0.027*	-0.023	
	(0.001)	(0.018)	(0.014)	(0.030)	
Carhart 4 factor model	0.002***	0.076***	0.017	0.013	0.099***
	(0.000)	(0.013)	(0.015)	(0.021)	(0.013)
Equity hedge					
Single factor model	0.004***	0.320***			
	(0.001)	(0.025)			
Fama-French 3 factor model	0.004***	0.298***	0.225***	-0.085*	
	(0.001)	(0.020)	(0.036)	(0.047)	
Carhart 4 factor model	0.003***	0.326***	0.219***	-0.062	0.064***
	(0.001)	(0.022)	(0.033)	(0.039)	(0.024)
Equity non-hedge					
Single factor model	0.003**	0.634***			
	(0.001)	(0.032)			
Fama-French 3 factor model	0.002**	0.606***	0.331***	-0.042	
	(0.001)	(0.027)	(0.032)	(0.044)	
Carhart 4 factor model	0.002**	0.616***	0.329***	-0.033	0.024
	(0.001)	(0.029)	(0.034)	(0.044)	(0.019)
Event driven					
Single factor model	0.004***	0.306***			
	(0.001)	(0.028)			
Fama-French 3 factor model	0.003***	0.295***	0.187***	0.047	
	(0.001)	(0.026)	(0.025)	(0.042)	
Carhart 4 factor model	0.003***	0.290***	0.188***	0.043	-0.010
	(0.001)	(0.028)	(0.025)	(0.046)	(0.018)
Fund of funds					
Single factor model	0.001	0.213***			
	(0.001)	(0.030)			
Fama-French 3 factor model	0.001	0.200***	0.135***	-0.039	
	(0.001)	(0.029)	(0.026)	(0.038)	
Carhart 4 factor model	0.001	0.230***	0.128***	-0.013	0.069***
	(0.001)	(0.028)	(0.022)	(0.031)	(0.015)

Note: The table shows the abnormal return performance at the index level using the single factor, Fama-French 3-factor, and the Carhart 4-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, β_m is the market return and $\beta_k, k = \{smb, hml, umd\}$ are the other market factors. *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 7: State timing tests – index fund level

	α	γ	β_m	β_{smb}	β_{hml}	β_{umd}
Market neutral hedge funds						
Single factor model	0.002***	0.097***	-0.023			
	(0.001)	(0.033)	(0.028)			
Fama French 3 factor model	0.003***	0.095***	-0.025	0.027*	-0.021	
	(0.001)	(0.037)	(0.030)	(0.015)	(0.028)	
Carhart 4 factor model	0.001**	0.070***	0.031	0.019	0.012	0.095***
	(0.000)	(0.021)	(0.019)	(0.014)	(0.019)	(0.011)
Equity hedge						
Single factor model	0.003***	0.061	0.282***			
	(0.001)	(0.044)	(0.031)			
Fama French 3 factor model	0.005***	0.078**	0.250***	0.225***	-0.083*	
	(0.001)	(0.036)	(0.023)	(0.039)	(0.048)	
Carhart 4 factor model	0.003***	0.063*	0.285***	0.221***	-0.063*	
	(0.001)	(0.034)	(0.027)	(0.034)	(0.036)	
Equity non-hedge						
Single factor model	0.002*	0.026	0.618***			
	(0.001)	(0.067)	(0.053)			
Fama French 3 factor model	0.004***	0.050	0.575***	0.330***	-0.039	
	(0.001)	(0.052)	(0.043)	(0.032)	(0.043)	
Carhart 4 factor model	0.002*	0.049	0.585***	0.330***	-0.034	0.021
	(0.001)	(0.054)	(0.048)	(0.033)	(0.042)	(0.019)
Event driven						
Single factor model	0.003**	0.049	0.276***			
	(0.001)	(0.063)	(0.044)			
Fama French 3 factor model	0.005***	0.058	0.259***	0.185***	0.050	
	(0.001)	(0.056)	(0.044)	(0.026)	(0.040)	
Carhart 4 factor model	0.003**	0.067	0.247***	0.190***	0.041	-0.013
	(0.001)	(0.058)	(0.048)	(0.025)	(0.042)	(0.017)
Fund of funds						
Single factor model	0.001	-0.017	0.223***			
	(0.001)	(0.065)	(0.064)			
Fama French 3 factor model	0.003***	-0.010	0.206***	0.132***	-0.036	
	(0.001)	(0.065)	(0.065)	(0.028)	(0.041)	
Carhart 4 factor model	0.001	-0.027	0.247***	0.127***	-0.013	0.070***
	(0.001)	(0.061)	(0.063)	(0.022)	(0.032)	(0.017)

Note: The table shows the abnormal return and timing abilities at the index level using the single factor, Fama-French 3 factor, and the Carhart 4-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, β_m is the market return and $\beta_k, k = \{smb, hml, umd\}$ are the other market factors. *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 8: Controlling for market, volatility and liquidity timing

	α	γ	β_m	δ	λ	ψ	β_{smb}	β_{hml}	β_{umd}
Henriksson and Merton (1981) model									
Market neutral hedge funds	0.002**	0.085***	0.032	-0.002	0.002	0.227	0.016	-0.001	0.094***
	(0.001)	(0.024)	(0.034)	(0.002)	(0.002)	(0.215)	(0.016)	(0.026)	(0.011)
Equity hedge	0.004**	0.091**	0.265***	-0.001	0.004**	0.386	0.222***	-0.079**	0.057**
	(0.002)	(0.038)	(0.040)	(0.003)	(0.002)	(0.237)	(0.034)	(0.039)	(0.022)
Equity non-hedge	0.001	0.100*	0.489***	0.003	0.007***	0.477	0.319***	-0.066	0.016
	(0.002)	(0.051)	(0.047)	(0.003)	(0.003)	(0.299)	(0.033)	(0.045)	(0.019)
Event driven	0.002	0.103	0.170***	0.003	0.006	0.535	0.181***	0.016	-0.018
	(0.001)	(0.071)	(0.063)	(0.002)	(0.004)	(0.359)	(0.026)	(0.048)	(0.018)
Fund of funds	-0.000	0.030	0.131***	0.003	0.008**	0.351	0.115***	-0.041	0.064***
	(0.001)	(0.038)	(0.042)	(0.002)	(0.003)	(0.247)	(0.025)	(0.037)	(0.016)
Treynor and Mazuy (1966) model									
Market neutral hedge funds	0.001	0.066**	0.017	0.387*	0.004*	0.207	0.016	-0.001	0.096***
	(0.001)	(0.026)	(0.026)	(0.222)	(0.002)	(0.193)	(0.015)	(0.023)	(0.012)
Equity hedge	0.003***	0.082**	0.255***	0.194	0.005*	0.376	0.221***	-0.079**	0.058**
	(0.001)	(0.038)	(0.035)	(0.416)	(0.002)	(0.239)	(0.034)	(0.039)	(0.024)
Equity non-hedge	0.002**	0.109*	0.512***	-0.211	0.006*	0.491	0.321***	-0.064	0.015
	(0.001)	(0.055)	(0.047)	(0.415)	(0.003)	(0.298)	(0.033)	(0.046)	(0.021)
Event driven	0.004***	0.152**	0.173***	-0.955*	0.003	0.579	0.178***	0.015	-0.025
	(0.001)	(0.075)	(0.063)	(0.530)	(0.004)	(0.351)	(0.025)	(0.050)	(0.021)
Fund of funds	0.002**	0.053	0.157***	-0.464	0.005	0.377	0.116***	-0.039	0.061***
	(0.001)	(0.044)	(0.041)	(0.311)	(0.004)	(0.239)	(0.024)	(0.038)	(0.018)

Note: The table shows the abnormal return and timing abilities at the index level using the Carhart 4-factor model controlling for other types of timing abilities 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, β_m is the coefficient corresponding to the market return, δ is the market timing coefficient, λ is the volatility timing coefficient, ψ is the liquidity timing coefficient, and $\beta_k, k = \{smb, hml, umd\}$ are the coefficients of the other pricing factors. *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 9: Controlling for illiquid holdings

	α	γ	β_m	$\beta_{m,lag1}$	$\beta_{m,lag2}$	$\gamma_{m,lag1}$	$\gamma_{m,lag2}$	β_{smb}	β_{hml}	β_{umd}
Market neutral hedge funds										
Single factor model	0.001**	0.113***	-0.032	0.017	0.039***	-0.068	0.065			
	(0.001)	(0.030)	(0.026)	(0.022)	(0.013)	(0.058)	(0.046)			
Carhart 4 factor model	0.001	0.081***	0.024	0.010	0.015	0.004	0.016	0.016	0.008	0.093***
	(0.001)	(0.021)	(0.020)	(0.016)	(0.009)	(0.023)	(0.021)	(0.015)	(0.020)	(0.011)
Equity hedge										
Single factor model	0.002*	0.102**	0.258***	0.051	0.046*	-0.076	0.106**			
	(0.001)	(0.045)	(0.034)	(0.041)	(0.025)	(0.047)	(0.046)			
Carhart 4 factor model	0.002**	0.098***	0.262***	0.028	0.033**	-0.029	0.097**	0.215***	-0.080**	0.056**
	(0.001)	(0.033)	(0.028)	(0.030)	(0.015)	(0.048)	(0.038)	(0.032)	(0.038)	(0.024)
Equity non-hedge										
Single factor model	0.002	0.096	0.572***	0.129***	0.023	-0.179**	0.166**			
	(0.002)	(0.070)	(0.056)	(0.041)	(0.026)	(0.074)	(0.073)			
Carhart 4 factor model	0.001	0.107*	0.547***	0.088***	0.023	-0.161***	0.192***	0.315***	-0.060	0.014
	(0.001)	(0.056)	(0.051)	(0.031)	(0.015)	(0.054)	(0.043)	(0.029)	(0.044)	(0.021)
Event driven										
Single factor model	0.002	0.115*	0.233***	0.102***	0.039**	-0.083	0.107**			
	(0.001)	(0.063)	(0.044)	(0.028)	(0.016)	(0.053)	(0.045)			
Carhart 4 factor model	0.002	0.127**	0.206***	0.072***	0.049***	-0.096*	0.141***	0.179***	0.014	-0.024
	(0.001)	(0.060)	(0.051)	(0.027)	(0.013)	(0.051)	(0.038)	(0.023)	(0.044)	(0.018)
Fund of funds										
Single factor model	0.000	0.037	0.188***	0.085***	0.055***	-0.102**	0.096***			
	(0.001)	(0.062)	(0.060)	(0.025)	(0.018)	(0.043)	(0.034)			
Carhart 4 factor model	-0.000	0.023	0.210***	0.070***	0.039***	-0.052	0.074**	0.118***	-0.037	0.062***
	(0.001)	(0.059)	(0.060)	(0.023)	(0.013)	(0.046)	(0.036)	(0.022)	(0.035)	(0.018)

Note: The table shows the abnormal return and state timing abilities at the index level using the single factor model and the Carhart 4-factor models during the period January 1999 to December 2016, after controlling for illiquid holdings. 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, β_m is the coefficient corresponding to the market return, $\beta'_{m,lag}s$ are the lagged market return coefficients, $\gamma'_{m,lag}s$ are the lagged state timing coefficients, and $\beta_k, k = \{smb, hml, umd\}$ are the coefficients of the other pricing factors. *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 10: Controlling for options trading

	α	γ	β_m	β_{ac}	β_{ap}	γ_{oc}	γ_{op}	β_{smb}	β_{hml}	β_{umd}
Market neutral hedge funds										
Single factor model	0.001*	0.090**	-0.008	0.009***	-0.009***	-0.011				
	(0.001)	(0.036)	(0.029)	(0.002)	(0.002)	(0.010)				
Carhart 4 factor model	0.001	0.067***	0.039	0.006***	-0.005**	-0.001	0.001	0.019	0.007	0.092***
	(0.001)	(0.025)	(0.024)	(0.002)	(0.002)	(0.007)	(0.006)	(0.015)	(0.021)	(0.013)
Equity hedge										
Single factor model	0.003**	0.087	0.246***	0.003	-0.007	-0.037*	0.031*			
	(0.002)	(0.053)	(0.044)	(0.006)	(0.005)	(0.019)	(0.017)			
Carhart 4 factor model	0.003**	0.092**	0.256***	0.004	-0.004	-0.012	0.010	0.236***	-0.047	0.061**
	(0.001)	(0.037)	(0.035)	(0.003)	(0.004)	(0.010)	(0.009)	(0.036)	(0.041)	(0.024)
Equity non-hedge										
Single factor model	0.002	0.049	0.581***	0.004	-0.009*	-0.040***	0.033**			
	(0.002)	(0.084)	(0.070)	(0.007)	(0.005)	(0.015)	(0.013)			
Carhart 4 factor model	0.001	0.078	0.553***	0.007	-0.008**	-0.014	0.011	0.342***	-0.020	0.023
	(0.001)	(0.062)	(0.057)	(0.004)	(0.004)	(0.010)	(0.009)	(0.037)	(0.049)	(0.020)
Event driven										
Single factor model	0.002	0.095	0.222***	-0.001	-0.004	-0.010	0.004			
	(0.002)	(0.077)	(0.062)	(0.004)	(0.004)	(0.009)	(0.008)			
Carhart 4 factor model	0.002	0.125*	0.183***	0.000	-0.004	-0.003	-0.002	0.197***	0.063	-0.007
	(0.002)	(0.065)	(0.058)	(0.003)	(0.002)	(0.007)	(0.006)	(0.026)	(0.048)	(0.017)
Fund of funds										
Single factor model	0.001	0.000	0.196***	0.003	-0.006*	-0.023*	0.019			
	(0.001)	(0.068)	(0.066)	(0.004)	(0.004)	(0.013)	(0.012)			
Carhart 4 factor model	0.001	-0.004	0.217***	0.002	-0.003	-0.007	0.005	0.136***	0.002	0.071***
	(0.001)	(0.063)	(0.067)	(0.002)	(0.002)	(0.008)	(0.007)	(0.023)	(0.037)	(0.019)

Note: The table shows the abnormal return and state timing abilities at the index level using the single factor model and the Carhart 4-factor models during the period January 1999 to December 2016, after controlling for option trading. 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, β_m is the coefficient corresponding to the market return, β_{oc}, β_{ac}, β_{op} and β_{ap} are the Agarwal and Naik (2004) option factors, and $\beta_k, k = \{smb, hml, umd\}$ are the coefficients of the other pricing factors. *** - significance at 1% level, ** - significance at 5% level, * - significance at 10% level.

Table 11: 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 12: State timing for individual funds

	%of (+) and significant α	% of (+) and significant γ	% of (-) and significant γ
Market neutral hedge funds			
Single factor	0.462	0.129	0.043
Fama French 3 factor	0.457	0.133	0.057
Carhart 4 factor	0.433	0.100	0.048
Equity hedge			
Single factor	0.411	0.124	0.074
Fama French 3 factor	0.381	0.127	0.076
Carhart 4 factor	0.373	0.121	0.079
Equity non-hedge			
Single factor	0.307	0.108	0.131
Fama French 3 factor	0.285	0.117	0.149
Carhart 4 factor	0.293	0.112	0.162
Event driven			
Single factor	0.609	0.070	0.191
Fama French 3 factor	0.570	0.063	0.199
Carhart 4 factor	0.566	0.055	0.207
Fund of funds			
Single factor	0.417	0.035	0.208
Fama French 3 factor	0.415	0.050	0.249
Carhart 4 factor	0.385	0.034	0.236

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

Table 13: Timing ability and market neutral hedge fund characteristics

Variable	**Coefficient**	**(Std. Err.)**
High watermark (dummy)	0.024	(0.070)
Fund size (in logs)	0.008	(0.006)
Fund management fee (in percent)	-0.009	(0.028)
Fund incentive fee (in percent)	-0.003	(0.003)
Fund minimum investment (in logs)	-0.001	(0.007)
Offshore fund (dummy)	0.021	(0.029)
Fund age (in logs)	-0.046	(0.033)
Fund leverage (dummy)	-0.068	(0.074)
Fund redemption (dummy)	-0.039	(0.050)
Fund lockup (dummy)	0.070	(0.034)
Intercept	0.243	(0.216)
N	193	
R^2	0.062	

Note: This regression shows the relationship between market neutral hedge funds' state timing abilities and fund characteristics. The dependent variable is the state timing coefficient from the Carhart 4-factor model for individual funds.

Table 14: 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 15: State timing – dead and alive hedge funds

	%of (+) and significant α	% of (+) and significant γ	% of (-) and significant γ
Dead funds			
Market neutral hedge funds	0.386	0.106	0.053
Equity hedge	0.383	0.120	0.090
Equity non-hedge	0.280	0.111	0.123
Event driven	0.569	0.075	0.138
Fund of funds	0.414	0.041	0.199
Alive funds			
Market neutral hedge funds	0.590	0.167	0.026
Equity hedge	0.466	0.134	0.044
Equity non-hedge	0.349	0.103	0.142
Event driven	0.695	0.061	0.305
Fund of funds	0.426	0.018	0.235

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).