‘When There Is No Place to Hide’: Correlation Risk and the Cross-Section of Hedge Fund Returns

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ABSTRACT

This paper analyzes the relation between correlation risk and the cross-section of hedge fund returns. Legal framework and investment mandate affect the nature of risks that hedge funds are exposed to: Hedge funds’ ability to enter long-short positions can be useful to reduce market beta, but it can severely expose the funds to unexpected changes in correlations. We use a novel dataset on correlation swaps and investigate this link. We find a number of interesting results. First, the dynamics of hedge funds’ absolute returns are explained to a statistically and economically significant percentage by exposure to correlation risk. Second, different exposures to correlation risk explain cross-sectional differences in hedge fund excess returns. Third, Fama-Macbeth regressions highlight that correlation risk carries the largest and most significant risk premium in the cross-section of hedge fund returns. Fourth, exposure to correlation risk is linked to an asymmetric risk profile: Funds selling protection against correlation increases have maximum drawdowns much higher than funds buying protection against correlation risk. Fifth, failure to account for correlation risk exposures leads to a strongly biased estimation of funds’ risk-adjusted performance. These findings have implications for hedge fund risk management, the categorization of hedge funds according to their risk profile and recent legislation that allows mutual funds to follow so-called 130/30 long-short strategies.

JEL classification: D9, E3, E4, G11, G14, G23

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THIS PAPER ANALYZES THE RELATION BETWEEN CORRELATION RISK AND THE CROSS-SECTION OF hedge fund returns. Correlation risk is the risk deriving from unexpected changes in the correlation between the returns of different assets or asset classes. A large exposure to correlation risk of a managed portfolio can imply a number of potential undesired features, including a low ex-post hedging effectiveness against the risk of some portfolio components and/or a suboptimal degree of ex-post diversification. While correlation risk is an important concern for the development of investment strategies in general, it is of special concern for hedge funds. This arises for at least two reasons. First, the typical capital structure of hedge funds and their contractual arrangements with prime brokers. Second, their investment mandate and the specific risk profile of absolute return, which intrinsically rely more on dynamic hedging strategies thus creating more exposure to unexpected shocks in correlations. These features motivate a rigorous study of the relation between the risk-return profile of hedge fund strategies and the degree of their exposure to correlation risk. In order to study this link, we construct a time series of returns of a factor mimicking portfolio for correlation risk, computed from a unique dataset of actual correlation swaps. The returns of this factor mimicking portfolio allow us to compute model-free measures of market correlation risk premium (from the difference between implied and realized correlation) and to quantify the fraction of expected excess fund return components generated by correlation risk exposure, i.e. the implicit correlation premium in hedge fund returns.[1]

Hedge funds are potentially susceptible to correlation risk for several reasons. The first one is institutional. The private nature of their legal structure grants them contractual flexibility such as lock-ups for investors, whose legal rights are those of a (limited) partner, as opposed to a retail client. These features allow the prime-broker to set special funding conditions, under which hedge funds can implement strategies that would otherwise not be feasible for mutual funds.[2] The funding role played by the prime-broker, however, makes the capital structure of hedge funds potentially fragile: As the 2007-2008 experience shows, when counterparty risk becomes acute during systemic events, prime brokers tend to increase hedge funds' collateral requirements and mandate haircuts in response to higher perceived counterparty risk, thus inducing forced deleveraging of risky positions.[3] Given

[1] See Ramadorai et al. (2008) for a comprehensive study of performance, risk, and capital formation in the hedge fund industry from 1995 to 2004.

[2] The prime broker plays an essential role in the capital structure of a hedge fund. By contrast, most mutual funds, as Almazan, Brown, Carlson, and Chapman (2004) document, are restricted (by government regulations or investor contracts) with respect to using leverage, holding private assets, trading OTC contracts or derivatives, and short-selling. Those that are permitted to do it, do so to a limited extent, due to prime broker restrictions imposed on funds that offer daily liquidity; see also Koski and Pontiff (1999), Deli and Varma (2002) and Agarwal, Boyson and Naik (2009).

[3] Sundaresan (2009), Liu and Mello (2009) and Brunnermeier and Pedersen (2009) shed light on the fragility of the

the small number of prime brokers, it has been argued that this has implications for the systematic nature of changes in correlations.[4]

The second reason is related to their investment mandate. Hedge funds have an absolute return objective, that is returns uncorrelated with the market (Ineichen, 2002). They try to achieve this objective by reducing market beta by means of long-short and arbitrage strategies. These strategies require assumptions about hedge ratios and market betas to implement risk immunization. This different business model generally implies portfolios with low net exposure and high gross exposure which has the potential to affect the risk composition of the portfolio with respect to traditional strategies. The larger the reliance of a strategy on assumptions related to the optimal hedge ratios, the larger the potential exposure to the changes in the parameters underlying these assumptions. An example, above all, are correlations, which enter directly in these calculations. Recent examples of hedge fund correlation crises further illustrate the intuition for the link between correlation risk and hedge fund returns. Khandani and Lo (2007) report that during the week of August 6, 2007, many Long/Short Equity funds experienced unprecedented losses, ranging from -5% to -30% per month, according to press reports. However, stock market losses over the same month were not particularly high by historical standards.[5] What happened? Changes in market expectations following the Bear Stearns debacle induced a substantial risk reallocation and asset rotation that affected correlations of asset prices precipitating large losses for long/short and quantitative managers that found themselves suboptimally hedged.

The third reason is related to the empirical evidence on the spread between implied and realized correlations. A growing literature has documented a large difference between implied and realized correlation, compared to a relatively small variance risk premium in individual stock options (see Driessen, Maenhout and Vilkov (DMV, 2009), Bakshi and Kapadia (2003), Bollen and Whaley (2004) and Carr and Wu (2004), Buraschi, Trojani, and Vedolin (2009)). This literature argues that exposure to correlation risk is priced in equilibrium. In our sample, we find supporting evidence for this argument: the average implied (realized) volatility of the 30 largest individual stock options

capital structure of leveraged investors, such as hedge funds.

[4] A large literature documents that correlations vary over time and tend to increase in times of crisis; See Bollerslev, Engle and Woolridge (1988), Jorion (2000), Moskowitz (2003) and Engle and Sheppard (2006), among others. Pollet and Wilson (2010) find that changes in the sample variance of US stock market returns are almost completely captured by changes in the average variance and the average correlation of the largest 500 US stocks. The average correlation, but not the average variance, strongly predicts future excess stock market returns.

[5] Khandani and Lo (2007) hypothesize that the losses were initiated by the rapid unwinding of sizeable quantitative Long/Short Equity portfolios. Sudden break-downs in correlations can trigger unexpected losses in such portfolios.

from January 1996 to August 2008 is 28.11 (28.08) percent, which yields a statistically insignificant average volatility risk premium of -0.035 percent per year for an individual stock. At the same time, the index implied volatility is systematically above the index realized volatility, as is illustrated in Figure 1, which indicates the existence of a large negative correlation risk premium.

[Insert Figure 1 here]

A large correlation risk premium may not be surprising after all. During bad states, correlation shocks appear to occur systematically across markets and asset classes, typically in connection to large market crashes or periods of economic crises. As a result, investors are likely to find it more difficult to diversify these shocks and, since sudden increases in correlations tend to coincide with periods of high marginal utility, the risk of such an important change of investment opportunities must be compensated ex ante by a risk premium. Figure 2 illustrates this feature in the context of the recent credit crisis. It shows that between November 2007 and March 2008 correlations across equity and fixed income markets increased substantially: The realized S&P500/Nikkei index correlation increased to 0.6, while the S&P500/FTSE 100 correlation rose above 0.7. During the same period, the base correlations in credit markets, implied by the North American CDX index and the iTraxx Europe index, all rose even above 0.9, which indicates a large increase in the price of correlation risk.[6] Surprisingly, however, there is no study available that investigate the link between correlation risk premia and the cross-section of hedge fund returns.

[Insert Figure 2 here]

In standard performance attribution specifications, hedge fund returns are usually regressed on two types of factors: (a) priced risk factors, e.g., a market return, and (b) relative benchmarks, such as, for instance, the return of a synthetic trend-following strategy. Priced risk factors are correlated with the stochastic discount factor. Relative benchmarks, on the other hand, are not interpretable as priced risk factors: they are used to capture managerial skills relative a passive (replicating) strategy. In the context of this classification, our study aims to document the extent to which correlation is a priced risk factor that helps to explain expected excess hedge fund returns. For this reason, we make use of both time-series and cross-sectional information using a Fama-McBeth approach that

[6] Buraschi, Trojani, and Vedolin (2009) develop a structural general equilibrium explanation for the existence of a non zero correlation risk premium and investigate the link between correlation risk premia, economic uncertainty and differences in beliefs across investors.

uses different cross-sectional hedge-fund characteristics, among which net exposure, to control for potential ex-ante correlation exposure.

Our empirical study is based on a time-series of returns of a factor mimicking portfolio for correlation risk from January 1996 until December 2008. We use a unique data set of actual correlation swaps to obtain a factor mimicking portfolio with pure exposure to correlation risk. This approach has at least three advantages, compared to, for example, approaches based on more traditional synthetic strategies, such as dispersion portfolios. First, correlation swaps provide delta and gamma neutral real-world prices, at which hedge funds may have transacted. Second, the correlation risk proxy obtained from correlation swaps is model-free. In contrast, dispersion portfolios require modeling assumptions on delta and vega hedging in order to isolate their correlation risk component. Third, correlation swaps allow us to use a balanced panel of observations, in which the hedge fund holding period exactly matches the horizon of the correlation swap from the first to the last day of each month, thus avoiding any lead-lag bias. The size of the estimated correlation risk premium in our sample is comparable with the results in the literature. DMV (2006) estimate a correlation risk premium of -18 percent per month for their sample (1996-2003), an average monthly realized correlation of 28.6% and an average monthly implied correlation of 46.7%. Figure 3 illustrates this premium by plotting the difference of realized and correlation-swap implied correlations over time.

[Insert Figure 3 here]

We contribute to the extant literature by documenting five sets of new results. First, hedge funds as an industry are exposed to correlation risk: A value-weighted index of hedge fund returns has statistically significant exposure to our correlation risk factor. This finding has important implications also for performance attribution metrics: The alpha of the value-weighted index falls from 5.36 percent to 3.47 percent per year, when a correlation risk factor is added to the benchmark Fung-Hsieh (FH, 2004) seven-factor model.

Second, we study correlation risk exposures conditional on funds' investment objective and net exposure. This gives insight into the categorization of investment styles with respect to their implied correlation risk exposure. In particular, we construct different value-weighted indices classified by investment objective and create a special index of funds with low net exposure. We show that correlation risk exposures are economically particularly high and statistically significant for hedge fund strategies with low net exposure: Long/Short Equity, Option Trader Funds, Merger Arbitrage and

Multi-Strategy funds. This feature implies an even larger bias of standard performance attribution metrics for this class of funds: The alpha of a value-weighted index of all hedge funds with low net exposure falls from 13.71 percent, when using the benchmark FH seven factor model, to 4.25 percent, when using the BKT model, which is an eight factor model that augments the standard FH factors with our correlation risk proxy. The explanatory power of the models for the low net exposure category almost doubles: The R^2 in the BKT model is 17.7 percent and the one in the FH model is 10.5 percent.

Third, we ask whether at the individual fund level correlation risk exposures help explain cross-sectional differences in fund performance. We implement cross-sectional sorts of hedge funds based on their correlation risk exposure and find that funds with large short correlation risk exposures produce excess returns with a large correlation risk component: An economically significant portion of these returns is generated by trading strategies that implicitly sell insurance against unexpected increases in correlations. For instance, funds in the decile with the most negative correlation risk beta t-statistic have an average annualized return of 13.45 percent and a seven-factor FH model alpha of 8.9 percent. When we control for correlation risk in the eight factor BKT model, the alpha falls to -1.78 percent and more than 10 percent of the return of these funds is explained by exposure to correlation risk. This important finding provides new insights into the determinants of hedge funds' risk and performance. It also suggests that ignoring funds' correlation risk exposure can lead to strongly biased performance attribution metrics in the cross-section of hedge funds.

Fourth, we test which risk factor exposures have significant explanatory power and whether correlation risk is priced in the cross-section of hedge fund returns. We find a negative correlation risk premium that is large (-8.49 percent) and strongly statistically significant (t-statistic of -3.24). In addition, when accounting for error in variables (EIV) biases using Shanken (1992) correction, we find that exposure to correlation risk is the only one having explanatory power for the cross-section of hedge fund returns: Funds with large negative correlation risk exposure have higher returns on average. These result holds both for a two-factor augmented CAPM model and the eight-factor BKT model. This finding suggests an important correlation risk premium component in hedge fund returns, stemming from exposure to a systematic (correlation) risk factor.

Fifth, we produce direct insight into the asymmetric risk profile of hedge fund returns in relation to their correlation risk exposure, which is an issue of special interest for risk management purposes. We find that correlation risk exposure strongly affect funds' maximum drawdowns and tail behavior, implying that funds in the decile with the largest negative correlation risk exposure have maximum drawdowns almost three times as large as those in the decile with the largest positive correlation risk exposure. Finally, we implement several robustness checks and find that the results are robust to the use of alternative data bases, equal-weighted indices instead of value-weighted indices and alternative benchmarks that include liquidity factors. While we do not find that correlation risk subsumes liquidity risk, our results suggest that they are distinct economic phenomena in that times when correlations unexpected rise and liquidity severely falls affect hedge fund returns in distinct ways. In our Fama-MacBeth regressions, we also use different estimators (OLS, WLS, GLS) to assess the robustness of our results in small samples (Shanken and Zhou, 2007).

Our findings are relevant for both hedge fund investors and hedge fund managers. First, they show that ignoring correlation risk exposures leads to biased estimates of hedge fund alpha and overestimation of funds' risk-adjusted performance. Moreover, they highlight the importance for hedge fund investors and hedge fund managers to monitor the correlation risk exposure of different hedge fund categories in order to better diversify the risk across funds. Similarly, our results have implications for optimal hedge fund selection, as maximum drawdowns in hedge fund returns are found linked to their exposure to correlation risk.[7] Correlation risk exposures are also important for regulatory reasons. According to standard classification schemes, as for instance the one illustrated by Figure 4, Relative Value and Long/Short Equity strategies are considered conservative, i.e., less risky, given their lack of directional exposure. Similarly, Distressed Securities and Emerging Market funds are often labeled aggressive, due to their directional exposure.[8] Different conclusions emerge when we control for correlation risk exposure.

[Insert Figure 4 here]

Finally, recent European investment fund regulation in the UCITS III directive relaxes some of the investment restrictions of mutual funds.[9] For example, it allows funds to follow so-called 130/30 strategies, which may be 130% long and 30% short. Therefore, our conclusions regarding correlation risk in hedge funds have important potential implications also for risk measurement and disclosure in the context of the recent developments of hybrid asset management products.

[7] See Grossman and Zhao (1993) for drawdown minimization.

[8] These classifications are not based on precise quantitative indicators, but they typically suggest that strategies labeled 'conservative' are less risky than aggressive strategies.

[9] A UCITS compliant fund can be freely marketed to the public in all 30 countries of the European Economic Area, as well as in countries such as Switzerland, Singapore and Hong Kong.

I. Related Literature

Our work borrows from different streams of the literature, related to hedge fund performance, portfolio choice and derivatives pricing. First, our results have implications for the literature on hedge fund performance, which documents the importance of extending traditional performance attribution methods by relative benchmarks, such as synthetic trend-following and option-based replicating portfolios, to calculate performance; see Fung and Hsieh (1997, 2001, 2004) and Agarwal and Naik (2004), among others. In related work, Agarwal, Bakshi and Huij (2008) examine higher-moment risks in hedge fund returns and quantify their importance while Aragon (2007), Sadka (2010) and Teo (2011) have shown that liquidity helps explain cross-sectional differences in hedge fund returns. A large part of this literature focuses on improving the time-series explanatory power of realized hedge fund returns with more accurate fund-specific attributes. In this context, capturing time-variation in hedge funds' risk exposures has recently been shown to improve the fit of factor models (Patton and Ramadorai (2010)) and to affect fund performance appraisals (Bollen and Whaley (2009)). We extend the literature on hedge fund performance and risk evaluation by showing the key role of priced correlation risk in generating the risk-return profile of hedge fund returns, the cross-section of hedge fund risk premia and the asymmetric maximal drawdown features in hedge funds tail risk. These findings are relevant for hedge fund investors whose flows are sensitive to performance. In interesting recent results, Ding, Getmansky, Liang and Wermers (2010) show that hedge funds exhibit a convex flow-performance relation in the absence of share restrictions (similar to mutual funds), but exhibit a concave relation in the presence of restrictions. In particular, our main Fama-MacBeth results show that (i) correlation risk is the most significant risk factor in the context of hedge funds and (ii) correlation risk is priced, while other benchmark factors, like many of the FH model factors, are not priced in the cross-section of hedge fund returns. Our contribution is also related to, but distinct from, Bondarenko (2004), who examines whether hedge fund index returns are exposed to index variance risk and finds supporting evidence for this hypothesis. Our approach is different, as we use a unique data set of correlation swaps to isolate correlation risk from volatility risk components and show that correlation risk is the key risk factor in hedge fund returns. Then, using a large panel of individual hedge fund returns, we find that it is key to capture cross sectional differences in correlation risk exposures in order to understand the risk return profile of hedge fund returns. Finally, we show how the distinct specific features of different hedge fund strategies, such as net exposure, are directly linked to different degrees of correlation risk exposure: As we conjectured, our results are stronger for low net-exposure funds and weaker for more directional strategies. All these questions cannot be addressed using aggregate hedge fund index data.

Second, our findings are related to many relevant questions in the literature on optimal portfolio choice. Buraschi, Porchia and Trojani (2010) propose a portfolio choice framework in which both volatility and correlation risk are jointly modeled. They show that the optimal hedging demand against unexpected changes in correlations can be a non-negligible fraction of the myopic portfolio, often dominating the pure volatility hedging demand, even in very simple portfolio allocation settings. In related work, Leippold, Egloff and Wu (2009) consider a portfolio problem with variance swap contracts on the S&P500 index and study how investors can use these contracts to account for the large index variance risk premium in optimal dynamic asset allocation. They find that the optimal portfolio with index variance swaps is very different from the one of an investor that can invest only in the index and the risk less asset. Detemple, Garcia and Rindisbacher (2010) study optimal portfolios with non redundant hedge funds. They first use factor regression models with option like risk factors and no-arbitrage principles to identify the market price of hedge fund risk, the volatility of hedge fund returns and the correlation between hedge fund and market returns. They then show that incorporating carefully selected hedge fund classes in asset allocation can be a source of economic gains. Our paper shows that hedge fund returns are significantly exposed to correlation risk and that hedge fund excess returns contain a substantial correlation risk premium component. These features imply that correlation risk is likely an important factor for correctly identifying the conditional risk-return trade-off of hedge fund returns, with potential large implications for the structure of optimal portfolios including hedge funds.

Finally, our work also borrows from several studies investigating the variance and correlation risk premia embedded in options. Buraschi and Jackwerth (2001) show that S&P500 option returns cannot be spanned by a dynamic portfolio in the underlying asset, which suggests that the index volatility is a priced risk factor. The literature examining index options confirms the existence of a large index variance risk premium, but Bakshi and Kapadia (2003) point out that the evidence is very different for individual stock options: Although the Black-Scholes implied volatilities on their 25 individual equity options are higher than historical return volatilities, the difference is much smaller than for index options. They document a small negative volatility risk premium and find no evidence that firm specific volatility is priced. Duarte and Jones (2007) consider an extended sample with more firms and apply a modified two-pass Fama-MacBeth procedure to a large cross section of returns of options on individual equities. They show evidence that the individual volatility risk premium may be state dependent and increasing in the overall market volatility. Buraschi, Trojani and Vedolin (2009) develop a structural economy with uncertainty and heterogeneity in beliefs, in which correlation and volatility risk are priced, and discuss the link between economic uncertainty and asset prices co-movement. In their empirical study, they show that the correlation risk premium is linked in the time series to periods of increased uncertainty and highest dispersion in beliefs. We draw from these insights in our analysis, and construct appropriate correlation risk proxies that can be used to study the correlation risk premia embedded in hedge fund returns. We address this issue using variance and correlation swaps, instead of options, because they are by construction less sensitive to error propagation when deriving risk premia estimates. To construct our factor-mimicking portfolio for correlation risk in the early period where variance and correlation swaps were relatively illiquid, we draw from Carr and Wu (2009), who propose an indirect method for quantifying variance risk premia, based on the difference between realized volatility and a synthetic variance swap rate derived from a particular portfolio of options.

The paper is structured as follows. In Section II we describe the data used in the study. In Section III we review the hedge fund return decomposition methodology as well as the construction of the variance and correlation risk factors. Section IV presents empirical results for hedge fund index returns and individual hedge fund returns. Section V concludes.

II. Data

Our survivorship bias-free hedge fund return data is from the BarclayHedge data base, which contains net-of-fee hedge fund returns from 1990 until December 2008. A key distinguishing feature of this database is its detailed cross-sectional information on hedge fund characteristics. One of these cross-sectional variables is information about funds' aggregate net long and short exposures based on market value, which is not available in the TASS/Lipper database, another high quality and frequently used hedge fund database.[10] This high quality database contains 11882 hedge funds and funds of funds in December 2008. Table I reports diagnostics for all funds and for the investment objectives we focus on. After applying a range of data filters and excluding funds of funds, our sample includes 8710 individual hedge funds. We use information about funds' net long/short exposure to

[10]In unreported results, available from the authors, we examine value-weighted TASS hedge fund returns and find qualitatively similar results for broad hedge fund categories in the absence of net exposure information.

construct two subgroups of funds with a net long/short exposure below 30%. The first subgroup, which we label All Low Net Exposure (ALNE), consists of all funds that fulfill this requirement. The second subgroup consists of Long-Short Equity (LSE) funds with Low Net Exposure and we label these funds LLNE. Overall, our data base contains 1190 Long/Short Equity funds, 335 funds in class ALNE, 195 LLNE funds, 483 Option Trader funds, 285 Equity Market Neutral funds, 60 Merger Arbitrage funds and 386 Fixed Income Relative Value funds.

As discussed in the introduction, we expect funds applying long/short spread strategies to reduce equity market beta, at the expense of a potential increase in correlation risk exposure. Our empirical analysis supports this expectation. We find in Table I that funds with low net exposure (ALNE) have a stock market beta of 0.19, which is slightly above half the stock market beta of 0.30 for LSE funds. At the same time, ALNE funds produce a FH seven factor model alpha of 14.2 percent per year, which is more than double the alpha of 6.2 percent per year for LSE funds. Is this striking difference in alpha due to pure fund skills or the consequence of an inappropriate measurement of the risks inherent in low net exposure strategies? A simple analysis shows that ALNE funds exhibit a clearly higher tail risk than LSE funds, as captured by kurtosis (5.21 for ALNE funds versus 3.66 for all funds) and Value-at-Risk (3.15 for ALNE versus 1.74 for all funds).[11] Therefore, an important question that begs to be answered is whether the larger tail risk of ALNE funds is the consequence of a systematically larger correlation risk exposure, which is not captured by the FH seven factor model.

Which investment objectives do funds with low net exposure tend to have? Most of the 335 low net exposure funds belong to the Long-Short Equity category (195 funds), which provides some support to the self-declared investment objective. The two next most important categories of low net exposure funds include the Equity Market Neutral (17) and the Multi-strategy (15) groups.

[Insert Table I here]

In order to compute our empirical proxies for correlation risk, we obtain estimates of the market prices of correlation from a unique dataset of actual correlation swaps in the sample period from April 2000 to December 2008, which is obtained from the leader market maker for these contracts (a major international bank). A correlation swap is a contract that pays the difference between a standard estimate of the realized correlation and the fixed correlation swap rate. Since these contracts cost

[11] We use parametric 95% Value-at Risk estimates for a hypothetical $100 million portfolio invested in the value-weighted indices.

zero to enter, the correlation swap rate is the arbitrage free price, i.e., the risk-adjusted expected value, of the realized correlation. The data consists of daily implied and realized correlation quotes of one month maturity correlation swaps for the S&P500. A positive (long) position in a correlation swap is a claim to a payoff proportional to the difference between the realized correlation during the tenor of the contract and the correlation swap rate fixed at the begin of the month.[12]

Since correlation swap quotes are only available after March 2000, we also create a synthetic correlation swap time series for the time period from January 1996 to March 2000, using the model-free approaches discussed in Carr and Madan (1998), Britten-Jones and Neuberger (2000), DMV (2006). For the period from April 2000 to December 2008, we find that the correlation between the synthetic correlation proxy and the correlation quotes time series is 92 percent, which supports the use of the synthetic time series in the 1996-2000 period. In order to synthesize correlation swap prices before April 2000, we use options data from Optionmetrics, for S&P500 index options and all individual stock options in the S&P500 list, as well as index and individual stock data. Since this database covers option prices backwards only until January 1996, we focus in our study on hedge fund returns in the sample period from January 1996 to December 2008.

From the OptionMetrics database, we select all put and call options on the index and on the index components. We work with best bid and ask closing quotes rather than the interpolated volatility surfaces provided by OptionMetrics. We use the midquotes for these option data (average of bid and ask). We retain options that have time-to-maturities up to one year and have at least three strike prices at each of the two nearest maturities. We discard options with zero open interest, with zero bid prices, with negative bid-ask spread, and with missing implied volatility or delta. Finally, we use the T-bill rate with 1-month constant maturity to approximate the 30-days risk-free rate. The T-bill rate is obtained from Federal Reserve database.

III. Methodology

In this section, we present our methodology to investigate the relationship between hedge fund returns and correlation risk exposures. First, we introduce our performance measurement framework, which extends the FH seven factor model by two factor mimicking portfolios for variance and correlation risk. Second, we show how we construct the factor mimicking portfolio for correlation risk, using

[12] The series is constructed to correspond to the mid point of the bid and the ask price of a correlation swap.

correlation swap quotes for the period April 2000 to December 2008, and the cross-sections of option prices of S&P500 index and individual options in the period from January 1996 to April 2000.

A. Hedge Fund Return Decomposition

The previous literature on performance attribution takes into account the unique nature of hedge fund strategies, by extending traditional performance attribution regressions to include variables capturing either (a) priced risk factors that help explaining risk premia or (b) fund attributes that are correlated with realized hedge fund returns, even though the latter might not give rise to a priced source of risk in the traditional sense.

Our starting reference point is the FH seven-factor model, in which hedge fund's return $r_{i,t}$ is decomposed into the risk-adjusted performance (α_i) and seven factor exposures (β_i^k):

$$\begin{aligned} r_{i,t} &= \alpha_i + \beta_i^1 SNPMRF_t + \beta_i^2 SCMLC_t + \beta_i^3 BD10RET_t + \beta_i^4 BAAMTSY_t \\ &\quad + \beta_i^5 PTFSBD_t + \beta_i^6 PTFSFX_t + \beta_i^7 PTFSCOM_t + \varepsilon_t^i, \end{aligned} \tag{1}$$

where $r_{i,t}$ is the monthly return on portfolio i in excess of the one-month T-bill return, $SNPMRF$ is the S&P500 excess return, $SCMLC$ is the Wilshire small cap minus large cap return, $BD10RET$ is the change in the constant maturity yield of the 10 year treasury, $BAAMTSY$ is the change in the spread of Moody's Baa - 10 year treasury and PTFS is a trend following strategy (see FH, 2004): $PTFSBD$ is the bond PTFS, $PTFSFX$ is the currency PTFS and $PTFSCOM$ is the commodities PTFS. The first four variables on the RHS of model (1) represent priced risk factors, which are found to be important in explaining expected stock returns, both in the time-series and the cross-section; see, e.g., Fama and French (1993). Therefore, the part of hedge fund excess returns linked to exposure to these factors has the natural interpretation of a risk premium for exposure to these particular sources of systematic risk. The last three variables on the RHS of model (1) are relative benchmarks capturing particular hedge fund "attributes". Relative benchmarks are not in general priced risk factors: They are typically used to capture potential excess return components not related to an exposure to a priced source of risk. They are important to understand the dynamics of hedge fund returns, by providing benchmark returns for synthetic trend-following strategies, and to quantify the added value, in terms of average excess performance, of an (active) hedge fund strategy over and above a simple passive (thus inexpensive) replication strategy.[13]

In order to understand the relation between hedge fund returns, hedge fund business styles, and correlation risk, we extend the benchmark FH model by the returns of two factor mimicking portfolios for correlation risk and variance risk, denoted by CR_t and VR_t, respectively. We label the resulting 9-factor model, the BKT benchmark model:

$$\begin{aligned} r_{i,t} &= \alpha_i + \beta_i^1 SNPMRF_t + \beta_i^2 SCMLC_t + \beta_i^3 BD10RET_t + \beta_i^4 BAAMTSY_t \\ &\quad +\beta_i^5 PTFSBD_t + \beta_i^6 PTFSFX_t + \beta_i^7 PTFSCOM_t + \\ &\quad +\beta_i^8 CR_t + \beta_i^9 VR_t + \varepsilon_t^i. \end{aligned} \tag{2}$$

The construction of the factor mimicking portfolios for correlation and variance risk is detailed in the next sections.

B. Construction of Risk Factors

Ideally, factor mimicking portfolios for correlation or variance risk should generate returns that are proportional to the realized average stock market correlation and the realized average stock market variance, respectively, over a given investment horizon. The price of such contingent claims then directly provides measures of the price of correlation and variance risk. Examples of such contracts are correlation and variance swaps. When correlation or variance swap contracts are either not available or not sufficiently liquid, a natural idea is to construct synthetic correlation and variance swap contracts, using a cross-section of liquid equity index and single stock options, where available. Another possibility is to construct option trading strategies that generate an exposure to correlation, variance and market risk, and to hedge away dynamically in the second step the variance and market risk exposure, in order to isolate the correlation risk exposure. We discuss in more detail these approaches in the next sections.

[13] The Fung and Hsieh (2001) model has been extended to consider other potential attributes. Fung and Hsieh (1997, 2000, 2001), Mitchell and Pulvino (2001) and Agarwal and Naik (2004) discuss the non-linearity of hedge fund strategies and show that a passive rolling strategy based on options helps to explain hedge fund returns. Other papers that investigate hedge fund performance relative to the Fung and Hsieh (2001) model include Bondarenko (2004), Kosowski, Naik, and Teo (2007) and Fung, Hsieh, Ramadorai, and Naik (2008). Results available from the authors upon request show that our findings are robust to the eight factor specification of the Fung-Hsieh model, which includes the return of a stock index lookback straddle (PTFSSTK).

B.1. **Correlation Risk Factor**

The most direct way to measure the price of correlation risk is by using correlation swap contracts, which provide a direct and pure measure of exposure to changes in correlations. Correlation swaps are becoming increasingly popular and are used to hedge against unexpected changes in average pairwise correlation of a pre-determined basket of stocks. A swap buyer pays implied correlation at the maturity T of the contract, i.e., the correlation swap rate $SC_{t,T}$, and receives the correlation $RC_{t,T}$, realized from the initiation to the maturity of the contract.[14] Since the initial price of the correlation swap is zero, the correlation swap rate equals the arbitrage free price of the realized correlation, i.e., its risk neutral expected value:

$$SC_{t,T} = \mathbb{E}_t^{\mathbb{Q}}[RC_{t,T}] \ , \tag{3}$$

where $\mathbb{E}_t^{\mathbb{Q}}[\cdot]$ denotes conditional expectations under risk-neutral measure $\mathbb{Q}$. A long position in a correlation swap entitles to a payout equal to the notional amount multiplied by the difference between the subsequent realized average pairwise correlation on the basket of underlyings and the implied correlation, given by:

$$CR_t := L \cdot (RC_{t,T} - SC_{t,T}) \quad , \tag{4}$$

where L is the notional amount invested. Empirically, this spread is typically negative on average, which is strong support for the hypothesis of a negative correlation risk premium:

$$CRP_{t,T} = \mathbb{E}^{\mathbb{P}}\left[RC_{t,T}\right] - \mathbb{E}^{\mathbb{Q}}\left[RC_{t,T}\right] = \mathbb{E}^{\mathbb{P}}\left[RC_{t,T}\right] - SC_{t,T} < 0 \ , \tag{5}$$

where $\mathbb{P}$ is the physical (statistical) probability measure. Intuitively, a negative correlation risk premium can arise because as realized correlation increases diversification opportunities decrease, making agents more exposed to the larger systematic risk in the economy: Economic agents are willing to pay a premium ex-ante, in order to hedge against states of large average correlations ex-post. Therefore, a positive exposure to correlation risk proxies is in fact an insurance against unexpected increases in average correlations. Similarly, a negative exposure to correlation risk proxies implies an exposure to unexpected increases in correlations, which is typically compensated ex-ante by a positive correlation risk premium.

[14] The correlation swap payoff is typically scaled by the notional amount L invested in the contract.

In our empirical performance attribution regression (2), we can build a replicating portfolio for correlation risk, simply by using directly correlation swaps in the time period from April 2000 to December 2008: Equation (4) reproduces the payoff of this replicating portfolios, which is by construction a zero cost portfolio that gives rise to a natural tradable market-based risk factor in model (2). The fact that all right hand side variables in model (2) are tradable allows to interpret the regression intercept as a risk-adjusted measure of abnormal return.

B.2. **Synthesizing Correlation Risk and Variance Risk Proxies**

In the period from January 1996 to March 2000, correlation swap quotes are not available, so that we have to rely on a different approach to compute our correlation risk proxies. Ideally, we would like these proxies to replicate synthetically the payoff of a fictitious correlation swap in the time period before March 2000.

Implied Correlation and Correlation Risk Proxy. Correlation swap rates can be approximated using a cross-section of market index and individual stock variance swaps, which in turn can be synthesized from the cross-section of market index and individual stock options using well-known techniques. As an approximation to the correlation swap rate, we make use of the concept of an implied correlation (see, for instance, DMV, 2006), defined by:

$$IC_{t,T} := \frac{\mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}^I] - \sum_{i=1}^n w_i^2 \mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}^i]}{\sum_{i \neq j} w_i w_j \sqrt{\mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}^i]\mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}^i]}} = \frac{SV_{t,T}^I - \sum_{i=1}^n w_i^2 SV_{t,T}^i}{\sum_{i \neq j} w_i w_j \sqrt{SV_{t,T}^i SV_{t,T}^j}} \ , \tag{6}$$

where $RV_{t,T}^I$ ($SV_{t,T}^I$) and $RV_{t,T}^i$ ($SV_{t,T}^i$) are the S&P500 index and single stock realized variances (variance swap rates) over time span $[t, T]$, and w_i is the market capitalization weight of stock i. Therefore, consistently with equation (4), our correlation risk proxy for the time period from January 1996 to March 2000 is given by:

$$CR_t = L \cdot (RC_{t,T} - IC_{t,T}) \ . \tag{7}$$

Note that this proxy can be computed using only information about index and single stock variance swap rates. The intuition underlying equation (6) is as follows. The numerator is the risk neutral expectation of a payoff given by:

$$RV^I_{t,T} - \sum_{i=1}^{n} w_i^2 RV^i_{t,T} = \sum_{i\neq j} w_i w_j \int_t^T v_s^i v_s^j \rho_s^{ij} ds \tag{8}$$

where v_s^i is the individual instantaneous volatility of stock i and ρ_s^{ij} is the instantaneous pairwise correlation between stock i and j, assuming a pure-diffusion return process. Therefore, the implied correlation can be interpreted as the risk-neutral expected average correlation, i.e., $IC_{t,T} = \mathbb{E}_t^{\mathbb{Q}}[\int_t^T \overline{\rho}_s ds]$ for some appropriate average correlation process $\overline{\rho}_t$, say, such that:

$$\begin{aligned} \sum_{i\neq j} w_i w_j IC_{t,T} \sqrt{SV^i_{t,T} SV^j_{t,T}} &= \sum_{i\neq j} w_i w_j IC_{t,T} \sqrt{\mathbb{E}_t^{\mathbb{Q}}[RV^i_{t,T}] \mathbb{E}_t^{\mathbb{Q}}[RV^i_{t,T}]} \\ &= \mathbb{E}_t^{Q} \left[\sum_{i\neq j} w_i w_j \int_t^T v_s^i v_s^j \rho_s^{ij} ds \right] . \end{aligned} \tag{9}$$

A concrete verification of the quality of proxy (7) as a correlation risk proxy can be gauged by comparing the statistical behaviour of definitions (4) and (7) for the sample period after April 2000, where both correlation risk proxies can be computed. For that period, we find a remarkable coincidence of these two time series, with a correlation between proxies of 0.92, which supports the use of (7) as a factor mimicking portfolio return for correlation risk before April 2000. For comparison, the correlation between the proxy (4) and a proxy for index variance risk is only about 0.25 in the same time period.

Variance Swap Rates and Proxies of Variance Risk. In order to compute the implied correlation (6), it is necessary to compute the index and single stock variance swap rates $SV^I_{t,T}$ and $SV^i_{t,T}$, $i = 1, \ldots, N$. Variance swap rates are also necessary to compute direct proxies of variance risk. Similar to correlation swaps, a variance swap is a contract that pays at the contract's maturity a payoff given by the difference between realized variance $RV_{t,T}$ and variance swap rate $SV_{t,T}$, multiplied by the notional amount invested:

$$(RV_{t,T} - SV_{t,T})\, L\ . \tag{10}$$

By construction, since the initial price of a variance swap is zero, the variance swap rate is the arbitrage-free price of the future realized variance:

$$SV_{t,T} = \mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}] \ . \tag{11}$$

In particular, the variance risk premium of an asset with realized variance $RV_{t,T}$ is given by:

$$VRP_{t,T} = \mathbb{E}_t^{\mathbb{P}}[RV_{t,T}] - \mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}] = \mathbb{E}_t^{\mathbb{P}}[RV_{t,T}] - SV_{t,T} \ . \tag{12}$$

Empirically, the average variance swap payoff for the index variance is negative, which indicates the existence of a negative risk premium for market variance risk. However, the market variance risk premium is not a pure indicator of ex-ante excess returns deriving from exposure to pure variance risk, because the index variance is a weighted sum of single stock variances and covariances. Therefore, in order to proxy for aggregate variance risk, we use the market weighted sum of the payoffs of individual stock variance swaps, defined by:

$$VR_t = \sum_{i=1}^{n} w_i (RV_{t,T}^i - SV_{t,T}^i) L_i \ . \tag{13}$$

Synthetic Variance Swap Rates. In order to compute index and single stock variance swap rates, we use the standard industry approach and synthesize them from plain (listed) vanilla option prices. This approach also avoids to a good extent the liquidity problems related to the variance swap quotes of individual stocks. In an arbitrage-free market and under the assumption of a continuous swap rate process, the following relation holds (see, e.g., Carr and Madan, 1998, Britten-Jones and Neuberger, 2000 and Carr and Wu, 2009):

$$SV_{t,T} = E_t^{\mathbb{Q}}\left[RV_{t,T}\right] = \frac{2}{(T-t)\, B(t,T)} \int_0^{\infty} \frac{P(K,T)}{K^2} dK, \tag{14}$$

where $B(t,T)$ is the price of a zero coupon bond with maturity T and $P(K,T)$ is the price of a put option with strike K and maturity T on an underlying asset with realized variance $RV_{t,T}$.[15] We use this relation to compute index and single stock variance swap rates. Using equation (13), we then obtain our factor mimicking portfolio for pure variance risk. Using equations (6) and (7), we

[15] For a variance swap such that $T - t = 30$ days, we compute the realized (annualized) variance as:

$$RV_{t,t+30} = \frac{365}{30} \sum_{i=1}^{30} R_{t+i}^2,$$

where R_{t+i} is the daily return of the underlying asset at the end of day $i = 1, \dots, 30$.

then compute our synthetic factor mimicking portfolio for correlation risk in the time period before April 2000, since our actual correlation swap quotes extend back to April 2000. The return of the correlation risk factor can be interpreted as the return on a correlation swap with a \$1 notional amount, abstracting from margin payments.

B.3. **Differences between Correlation Swaps and Option Strategy Benchmarks**

A key advantage of actual correlation swaps, whenever available, is that they allow monthly hedge fund returns to be correctly benchmarked, from the begin until the end of each month, using a balanced panel of holding period horizons for hedge funds, who report their performance from the first to the last day of each month. Holding period returns of factor mimicking portfolios for correlation risk obtained from rolling over time option positions, like for instance dispersion portfolios, feature several potential differences. First, their holding period horizon is unbalanced with respect to the reporting period of hedge fund returns: Index options expire on the Saturday after the third Friday of each month, thus limiting the possibility to obtain volatility and correlation risk factor mimicking portfolios that exactly span hedge funds holding period return horizons, even when using the option-based approach proposed in DMV (2006). Second, even if one were to include an option strategy benchmark by including the strategy return from the third Friday of a given month until the end of the month, the procedure would fail to provide an accurate proxy for variance or correlation risk: Buying an option and selling it before expiration captures changes in implied volatility and it does not isolate the effect of the volatility or correlation risk premia: The latter can only be measured by comparing the purchase price of the option position to its payoff, which is proportional to the difference between implied and realized volatility of the option's underlying. Third, dispersion portfolios require dynamic delta and vega hedging in order to isolate correlation risk exposures. These hedging strategies are model dependent and the hedging errors that may arise in the development of the dispersion strategy could generate undesired exposure to market and volatility risk.

These arguments highlight the usefulness of traded or synthetic variance and correlation swaps to proxy for correlation and variance risk. Some caveats associated with swaps, in comparison, e.g., to options, have also to be considered. In particular, correlation swaps are, unlike options, over-the counter-derivatives that can embed a rent for the intermediary and a potential illiquidity premium. Thus, the correlation risk premium implied by correlation swaps can potentially underestimate the actual correlation risk premium.

B.4. **Similarities and Differences Between Volatility and Correlation Risk**

The variance risk premium of the S&P500 index contains a correlation risk premium and a pure variance risk premium component. What are empirical differences of correlation and index variance risk premia? Table II reports summary statistics of our monthly risk factors for index variance risk and for correlation risk, which correspond to the returns of long positions in index variance and correlation swaps, respectively. The average excess return on the S&P500 index in our sample is 0.20 percent per month. The average index variance risk and correlation risk proxies are -16.73 (in percent squared per month) and -14.33 percent per month, respectively.[16] As expected, these findings show that the estimated correlation risk premium is a large fraction (85 percent) of the index variance risk premium.[17]

[Insert Table II here]

Figure 3 shows that the six-month moving average of the absolute size of our correlation risk proxy features a declining trend over time. An explanation for this phenomenon might be that similar to other markets, such as credit markets, risk capital has flowed into strategies attempting to exploit the negative correlation risk premium, thus reducing the spread between implied and realized correlation over time.

Interestingly, the proxies for correlation and index variance risk feature quite different time series properties, with a correlation risk proxy that is clearly more persistent than the proxy for index variance risk: At lags of 1-12 months, the autocorrelations of the correlation risk proxy are much higher than those for the index variance risk proxy. For instance, the one, two and three months lag autocorrelations for the correlation (variance) risk proxy are 0.45, 0.37 and 0.35 (0.12, 0.03 and 0.02). This evidence highlights the importance of separating these two risk components for

[16] The size of the estimated correlation risk premium in our sample is comparable with the results in the literature. DMV (2006) estimate a correlation risk premium of -18 percent per month for the sample (1996-2003), an average monthly realized correlation of 28.6% and an average monthly implied correlation of 46.7%. For the same subsample (1996-2003), we estimate a monthly correlation risk premium of -16.6 percent, an average monthly realized correlation of 27.3 percent and an average monthly implied correlation of 46.3 percent. Drechsler and Yaron (20110) estimate an index variance risk premium for the period 1990-2007 between -12 and -18 percent, depending on the choice of the implied and realized variance proxies used.

[17] The dominanting role of the correlation risk premium is confirmed by the fact that the estimated average volatility risk premium of individual stocks is small and statistically insignificant, a finding that is also consistent with the previous literature; see, e.g., Bakshi and Kapadia (2003). When we consider the 30 most liquid constituents of the S&P 500 index, we find that their average implied volatility is 32.7 percent, while their average realized volatility is 31.8 percent, which yields a statistically insignificant estimated average volatility risk premium on individual stocks of -0.9 percent.

empirical analysis, especially for performance attribution purposes based on models like model (2). This finding might also provide a possible explanation, the persistence of correlation shocks, for the large average correlation risk premium.

Another important feature of correlation risk is an apparent nonlinearity with respect to aggregate stock market movements, which supports the intuition that correlation risk might be a systematic source of risk, directly impacting the stochastic discount factor. For instance, the index variance risk proxy has been particularly large in a few months at the end of 2008, which have significantly affected the estimated index variance risk premium: The index variance risk proxy in September, October and November of 2008 was 2.1, 4.6, and 2.0 percent per month, respectively, as a consequence of extraordinarily high levels of realized correlations, thus possibly reminding investors and proprietary trading desks shorting correlation of the difference between a risky investment and an arbitrage opportunity! Empirical evidence shows that such market-wide increases in realized correlations, which are a key driver of changes in investment opportunities as they affect diversification, often occur at times of low market returns (see Figure 5). This evidence supports the potential non-linear dependence of correlation risk on economy-wide stock market movements.

[Insert Figure 5 here]

The nonlinear dependence of correlation risk on economy-wide stock market conditions has important implications for assessing the risk-return profile of trading strategies exposed to this source of risk. Note that the annualized Sharpe Ratio in the 1996-2008 period is 0.15 for an investment in the S&P500 index and 3.3 for a short position in the factor-mimicking portfolio for correlation risk.[18] Although these numbers suggest that selling correlation risk might be very attractive from the perspective of a mean-variance investor, it is important to bear in mind that the distribution of the correlation risk proxy features pronounced non normalities, which can cause trading strategies shorting correlation to experience occasional very large losses. For instance, the return of a portfolio shorting our correlation risk proxy in the months September, October and November of 2008, was -24.4, -12.4 and -7.5 percent per month, respectively: While shorting correlation swaps can be unconditionally very profitable, it can be also conditionally very risky. An early indication of the implications of correlation risk exposure for hedge fund returns is offered by the events in August

[18] As Carr and Wu (2009) point out, Sharpe Ratio's from synthetic contracts may be misleading, to the extent that they differ from market prices. The actual profitability of a swap depends also on several practical issues, such as the actual availability of variance swap quotes, their bid-ask spreads and their similarity to their synthetic proxies.

2007. During this month, the correlation risk proxy return was +5.3 percent, while a value-weighted index of All Low Net Exposure Funds (Long-Short Equity funds) produced a return of -1.1 percent (-1.3 percent). Even more dramatically, in September 2008 the correlation risk factor return was +29 percent, while the indices of All Low Net Exposure Funds and Long-Short Equity funds lost 1 percent and 2.5 percent, respectively.

Is the broad empirical evidence provided by our correlation risk proxy consistent with predictions suggested by economic theory? In Merton's (1973) ICAPM model, investors optimally hedge sources of risk that are linked to the marginal utilities of their optimal consumption-investment plans. Buraschi, Porchia and Trojani (2010) study this prediction in an extended portfolio choice framework, which allows for a distinct role of volatility and correlation risk. They show that optimal hedging demands against correlation risk are substantial and typically dominate hedging motives against volatility risk. Such hedging demands are larger for sources of risk that are very persistent and related to changes in the investment opportunity set. These features are consistent with our empirical evidence that correlation risk is more persistent than volatility risk.

The fact that correlation risk is related to market-wide stock market movements (see again Figure 5) also suggests that it is a systematic priced risk factor. Drechsler and Yaron (2008) investigate an economy with time-varying macro-economic uncertainty and provide theoretical arguments for the emergence of a market volatility risk premium. In a structural multiple-trees economy with uncertainty and heterogenous beliefs, Buraschi, Trojani and Vedolin (2009) show that economic uncertainty can produce an endogenous co-movement between asset returns and a time-varying correlation risk premium. In their empirical study, they find that the correlation risk premium is highest when market-wide disagreement about firms future earnings is large, which they show typically happens during crisis periods and down markets. These predictions are broadly consistent with our empirical evidence, as the market wide deleveraging after widespread economic turmoil and uncertainty, such as in August 1998, March 2008 or September-October 2008, is typically linked to systematic correlation shocks. We find that precisely during such phases many hedge funds have suffered large losses, as a consequence of sudden widespread changes in correlations and coinciding collapses in stock prices. As we conjectured in the Introduction, Table III presents early evidence that across the different hedge fund categories Low Net Exposure funds, Long/Short Equity funds and Fixed Income Relative Value funds have the most negative association with our proxy of correlation risk, highlighting their substantial exposure to unexpected increases in correlations.

[Insert Table III here]

IV. Empirical Findings

In this section, we study the empirical relation between correlation risk and the risk-return profile of hedge fund strategies. Hedge fund strategies and trading styles are very heterogeneous. A careful examination of value-weighted hedge fund indices and individual hedge fund returns by investment objective indicates that both correlation and variance risk proxies are often significant in explaining hedge fund returns. However, the degree of exposure to variance or correlation risk, and whether these risks explain hedge fund returns, strongly depends on the characteristics of hedge fund strategies.

First, we study correlation risk exposures of hedge fund absolute returns at the aggregate (index) level, together with their dependence on hedge fund trading styles, and the arising implications for performance evaluation metrics. Second, we investigate the cross-section of correlation risk exposures and their link to the cross-section of hedge fund risk-adjusted returns. Third, we consider portfolio sorted according to correlation risk beta and trading style and study whether the cross-sectional link between correlation risk and hedge fund returns depends on hedge fund styles. Fourth, given the evidence of a priced correlation risk in the literature, we take the analysis a step further and run two-pass Fama-Macbeth regressions, combining time series and cross-sectional information, in order to investigate whether correlation risk is priced in the cross-section of hedge fund returns. Fifth, given the non-linear dynamic structure of correlation risk in good and bad times, we study in more detail large negative market events and document the extent to which realized hedge fund drawdowns are linked to correlation risk exposures.

A. Hedge Fund Index Returns and Correlation Risk Exposures

Table IV reports estimated alpha and beta coefficients of hedge fund index returns for different investment objectives, with respect to performance attribution models (1) and (2), presented in Panel A and C, respectively. Panel B presents the same results with respect to a performance attribution model including the correlation risk proxy, but excluding a measurement for variance risk.

The second row of Table IV, Panel A, highlights an interesting and intriguing result: The alpha of long-short equity hedge funds with low net exposure is a staggering 14.95 percent, but the alpha of all funds (independently of their investment strategy) with low net exposure is 13.71 percent. Even though it is well-known that average hedge funds' alpha is higher than for mutual funds, these results are surprising: According to the traditional performance attribution model (1), a low net exposure is a sure way to generate a large positive performance, independent of the investment strategy! Obviously, this cannot be true and it must be suggestive of an important misspecification of performance attribution model (1). In the sequel, we document the extent to which correlation risk and correlation risk exposure can help explain this apparent puzzle.

[Insert Table IV here]

The first two columns of Table IV, Panel B, indicate that a value-weighted index of all hedge funds has no statistically significant correlation risk beta. At the same time, a value weighted index of all low net exposure hedge funds has a strongly significant negative correlation risk beta. When we stratify with respect to investment style, we find that some hedge fund strategies are particularly exposed to correlation risk: For instance, Long/Short Equity (LSE), Merger Arbitrage (MA), Multi-strategy (MULTI) and Options Trader (OPTS) funds have negative correlation risk beta $t-$statistics equal to -1.77, -1.62, -2.47, -2.13, respectively. These findings highlight the importance of carefully interpreting each fund's risk exposure in the context of the specific economic drivers behind each hedge fund strategy.

When comparing Panels A and B of Table IV, the most striking and key result is that after controlling for hedge fund net exposure, funds ranked in the first tercile of low net exposure funds have both the largest correlation risk exposure and the largest reductions in alpha: The correlation risk $t-$statistic for all funds with low net exposure is -3.73 (column ALNE in Table IV, Panel B) and the reduction in alpha because of correlation risk exposure is about 9.5 percent per year. Similarly, the correlation risk $t-$statistic for long-short equity funds with low net exposure is -3.44 (column LLNE in Table IV, Panel B) and the reduction in alpha because of correlation risk exposure is about 11.6 percent per year. The main implications of these findings are immediate. First, ignoring correlation risk exposure of funds with negative correlation risk beta strongly overestimates funds' risk-adjusted performance and underestimates their actual risk.The abscence of a correlation risk factor in standard benchmark models may be one reason for the finding of Titman and Tiu (2011) that hedge funds that exhibit lower R-squareds with respect to systematic factors have higher alphas.

Second, benchmark performance attribution model (1), which can capture with a good degree of accuracy the risk-return trade-off of long-only hedge fund strategies, implies an important degree of misspecification in capturing relevant characteristics in the dynamics of long-short hedge fund returns.

In Table IV, Panel C, we control for both correlation risk and variance risk exposure, according to BKT model (2). Overall, we find that exposure to both risks is important to explain the risk-return trade-off of hedge funds, but in a very different way for different investment styles. The (positive or negative) exposure to correlation risk is significant for Long/Short Equity (LSE), Multi-strategy (MULTI), Distress (DS), and Options Trader (OPTS) funds, which have a correlation risk beta $t-$statistic of -1.82, -2.39, 2.25 and -2.10, respectively. On the more aggregate level, the correlation risk beta t-statistic of low net exposure funds is -3.81 (ALNE) and -3.61 (LLNE), similarly to the findings in Panel B, thus supporting the previous interpretations. In contrast, exposure to variance risk is not significant for low net exposure funds. Since the Low Net Exposure (ALNE) class includes funds from all investment objectives, these results provide an independent assessment of the key overall importance of correlation risk for the risk-return profile of low net exposure funds: Compared to long-only strategies, these portfolios imply a lower volatility and a lower market beta, but a large exposure to unexpected increases in correlations. Given the potential size of correlation risk premia, the expected excess return and the alpha of these strategies is affected to a considerable amount by exposure to correlation risk. The variance risk beta $t-$statistic is significant for a number of investment objectives and funds with exposure to variance risk have often high net exposures, including Equity Long (t-statistic of -4.29) and Emerging Markets (t-statistic of -2.00). Additional strategies with significant variance risk exposure are Distressed Securities (t-statistic of -5.51), which is often directional in nature, and Convertible Arbitrage (t-statistic of -2.45), which is a strategy trying to profit from the characteristics of implied equity volatilities. To the extent that these strategies are less dependent on leverage and securities lending, we expect them to be not only less exposed to correlation risk, but also more exposed to volatility risk.

Some of the above results are against the common wisdom that volatility, more than correlation, is the important risk to control for, and that it should be so independently of the investment strategy. The usual argument goes as follows. Hedge fund managers receive convex incentives (2 percent fees plus 20 percent of performance). Since the payoff profile of the manager is similar to a call option, in equilibrium the optimal trading strategy of a manager is to be long volatility. Although it might appear at first convincing, this argument is incomplete. Panageas and Westerfield (2009) show that a hedge fund manager engages in risk shifting only in the context of a simple two-period model without capital market frictions. In a dynamic setting with an infinite horizon, a risk-neutral manager would choose a bounded portfolio, despite the option-like character of her compensation. When the horizon is not finite, the fund manager doesn't only care about her near future payoff, but also about the continuation value of her call option, which is in fact a perpetually renewed call option. This continuation value is a key discipline, which prevents the manager to take unbounded risk, and creates incentive to reduce volatility exposure and mitigate risk. A second reason why in practice hedge fund managers often have to reduce excessive exposures to volatility is due to their reliance on prime brokers for leverage and securities lending. In an intertemporal equilibrium context, fund managers naturally fear the removal of leverage and other services after a series of excessive drawdowns. Hedge funds receive capital from not just one, but two counterparties: The investor and the prime broker. The incentive structure for the hedge fund manager is convex with respect to the investor perspective, but it is concave with respect to the prime broker. Even if a fund manager could impose a 'gate' to prevent the investor to redeem, a fund cannot 'gate' the prime broker decision to force liquidation of funds' positions and seize collateral.[19] Therefore, the hedge fund manager is averse to volatility and may seek risk mitigation through hedging, that is, long and short positions, thus exposing the fund to correlation risk. These effects are progressively more severe for more levered strategies. Thus, our empirical findings are consistent with the theoretical insight of Panageas and Westerfield (2009) and Sundaresan (2010).

In order to shed further light on the relation between correlation risk and hedge fund returns, it is useful to study in more detail months corresponding to periods of financial crises or market distress. Interestingly, we find that in August 1998 and September-October 2008 Long/Short Equity funds have experienced large losses, which coincide with the large positive return of a long correlation swap position: In September 2008 the (average pairwise) realized correlation of stocks in the S&P 500 dramatically increased to a level of 65.14 percent, from a level of 35.83 percent in August 2008, and funds with high negative exposure to the correlation risk factor, i.e. funds short correlation, suffered large losses. For instance, in September 2008 the decile of funds with the highest positive beta with respect to the correlation risk proxy generated a positive return of 1.7 percent per month, while the funds with the highest negative beta suffered a loss of -11.3 percent. These examples help to understand more generally also the risk imbedded in other hedge fund investment objectives,

[19] See Healy and Lo (2009) on gates and hedge fund illiquidity.

such as fixed income and relative value funds, as the LTCM collapse suggests, because convergence trades are intrinsically based on assumptions about the dynamics of correlations between asset returns.[20] Overall, the evidence during the 2008 financial crisis highlights even more the importance of monitoring the correlation risk of hedge fund returns.

The above evidence suggests that the correlation risk factor is a statistically significant explanatory variable of hedge fund index returns. For All Long Net Exposure Funds (Long/Short Equity Low Net Exposure funds), for example, the loading on correlation risk explains 9.6 percent (11.76 percent) of the annual return of 14.2 percent (5.3 percent) at the index level. However, the main focus of our study is the ability of correlation risk exposures to explain cross-sectional differences in hedge funds' performance and risk. Therefore, in the next section we turn to correlation risk exposures at the individual hedge fund level.

B. The Cross-Section of Hedge Fund Correlation Risk Exposures

In this section, we take the previous analysis one step deeper and investigate whether, even within each hedge fund style, exposure to correlation risk helps to explain returns, i.e., we study the cross-sectional link between correlation risk exposures and hedge fund excess returns. We follow a simple approach and sort individual hedge funds returns into decile portfolios, based on their BKT-model correlation risk beta t-statistic. In this way, we can distinguish funds with the most significant positive or negative exposure to our correlation risk factor.[21] In a second step, we investigate whether there exists a systematic link between the cross-sectional distribution of correlation risk betas of these portfolios and their excess returns.

Table V, Panel A, reports the results when we sort all funds into decile portfolios. The correlation risk beta β_{CR}^{BKT} ranges from an average of -0.06 for decile 1 to an average of 0.04 for decile 10. From Table V, Panel A, a first striking and key feature emerges: The average absolute return of funds in the top decile (8.46 percent per year) is only about half the average absolute return of funds in the

[20] See, e,g., the HBS case 'Long-Term Capital Management' (Perold, 1999) and the May 1, 2008, Financial Times article 'Fixed income traders pulled into deleveraging vortex': '*Traders making some of the safest bets on the planet – on tiny price moves in ultra-secure US government debt – were hammered in March as hedge funds scrambled to sell assets to cover losses in other markets. [...]The falls are a repeat in miniature of the near-collapse of LTCM in 1998 following big losses on US Treasuries arbitrage trades [...]. But this time round the crisis spread even more rapidly from market to market, taking down arbitrageurs in US Treasuries and convertible bonds among several exposed strategies, because the amount of money hedge funds now run is so much higher. Trades prepared by some highly leveraged funds to protect them from a repeat of LTCM didn't work, either.*'

[21] Results are qualitatively identical if we sort hedge fund returns according to their correlation risk beta, without adjusting for its statistical significance. These results are available upon request.

bottom decile (13.45 percent per year).

[Insert Table V here]

It follows that, after the sorting, the BKT model decomposition of hedge fund risk confirms substantial differences in risk exposures and risk-adjusted performance across decile portfolios. For instance, according to the BKT model decomposition, the bottom decile of funds short in correlation derives about 10.84 percent of the yearly performance from their largest negative exposure to correlation risk, implying a BKT model alpha of -1.78 percent per year. In contrast, the top decile of funds buying correlation risk insurance loses on average 7.30 percent per year because of the negative exposure to correlation risk, implying a BKT model alpha of 11.92 percent per year: The differences in BKT model alphas across deciles can be as large as -13 percent per year. When neglecting correlation risk exposures using FH performance attribution model (1), the difference in alphas between the lowest and highest decile portfolios is only 4 percent per year, which leads to a large underestimation of the risk and a large overestimation of the risk-adjusted performance of fund portfolios in the first decile. The results are quantitatively so important that they reverses the performance ranking based on BKT model's alphas: While the negative correlation beta decile portfolios have the highest FH alpha, they imply the lowest alphas after controlling for correlation risk in BKT model.

Panel B of Table V presents results for sorted portfolios of Low Net Exposure (ALNE) funds. This is the hedge fund class implying the statistically and economically most significant negative exposure to correlation risk at the index level, as a consequence of the tendency of many long/short spread trades to simultaneously reduce market beta and increase correlation risk exposure. The results confirm the evidence that funds with the statistically most significant negative correlation risk beta have abnormally large (uncorrected) alphas, relative to FH performance attribution model (1): Low Net Exposure funds with the most negative correlation risk beta (decile 1) have almost one and a half times as high returns (12.8 percent per year) as the return (9.6 percent per year) of funds with the highest correlation risk beta. For Low Net Exposure funds in decile 1, 7.40 percent of their return is generated by correlation risk exposure. Moreover, their BKT model alpha of 1.2 percent per year is 7.4 percent lower than their FH model alpha of 8.48 percent per year. As a consequence, ignoring correlation risk exposures in Panel B of Table V severely overestimates the performance and underestimates the risk of many ALNE funds.

Since the groups of hedge funds studied in Panels A and B include quite heterogeneous hedge fund strategies and styles, it is useful to investigate in more detail also the specific class of Long/Short Equity (LSE) funds, which is among the most populated groups of hedge funds. Table V, Panel C, summarizes the results. After sorting LSE funds into portfolios according to their correlation risk beta, we find that the lowest decile portfolio has a negative BKT model alpha of 2.3 percent per year, which is 10.3 percentage points lower than its FH model alpha of 12.6 percent per year: Correlation risk exposure accounts on average for 10.5 percent per year of the annual return of Long/Short Equity funds in decile 1, even after controlling for all FH factors. Long/Short Equity funds with the largest positive correlation risk exposure lose about 6.96 percent per year on average, in order to hedge unexpected increases in overall market correlations. Their risk adjusted performance is significantly higher, after adjusting for this effect: Their alpha of 8.52 percent per year with respect to the FH model almost doubles to a level of 15.37 percent per year, according to the BKT model.

Finally, we study in more detail, within the Long/Short Equity group, funds with low net exposure (LLNE): Long/Short Equity funds differ quite significantly in their actual use of long and short positions, and only a strict subgroup has net long positions below 30 percent. Results are presented in Panel D of Table V. We find that for this subgroup results are even stronger, in the sense that funds in the bottom decile have positive average returns of around 14 percent, but funds in the top decile have average returns close to zero. Correlation risk exposure accounts for 9.32 of the return of funds in decile 1 while funds in decile 10 lose 4.11 percent due to their positive correlation risk exposure. Once we account for correlation risk using the BKT model, the alpha of the funds in Decile 1 falls to 0.34 percent from 9.52 percent (based on the FH model) while the alpha of funds in decile 10 rises to 4.23 percent from 0.11.

B.1. **Two Hedge Fund Strategies Under the Magnifying Glass**

Merger Arbitrage Funds. Merger Arbitrage funds have been at the center stage of an important discussion in the hedge fund literature, related to the fact that their returns might be linked to equity index variance risk (Mitchell and Pulvino, 2001). We make use of our performance attribution approach based on BKT model (2) to split the impact of index variance risk on hedge fund returns into its two main components: Correlation risk and average variance risk of the index constituents. Results are presented in Table VI, Panel A.

[Insert Table VI here]

We find that correlation risk exposure, rather than variance risk exposure, is the main driver of the risk return profile of Merger Arbitrage Funds. Merger Arbitrage funds in the decile with the most negative correlation risk exposure have the highest return (13.7 percent per year) and the highest FH model alpha (9.2 percent per year). In contrast, the portfolio of funds in decile 10 produces an average return of 6 percent per year. However, 6.2 percent per year of the apparently superior performance of the portfolio in decile 1 is explained by a significant negative correlation risk exposure. These results are intuitive, given the character of typical strategies played by Merger Arbitrage Funds, which are designed to achieve a low beta by taking simultaneously long positions on potential target companies and short positions on potential acquirers. A distinguishing feature of these strategies is that they focus on pairs of companies involved in merger events: While quantitative equity funds may invest in hundreds of stocks, based on historical covariance matrices, Merger Arbitrage funds are mainly exposed to unexpected changes in the prices of target and acquiring companies.

Option Trader. In recent years, equity and credit derivative hedge funds have sprung up, which explicitly trade alternative asset classes, such as variance and correlation. Some of these funds directly use options, variance swaps or correlation swaps.[22] Other funds use structured credit products and take long-short positions in different tranches of asset-backed securities, such as CDOs and CLOs, thus taking explicit bets on changes in the default correlations of the underlying reference entities.[23] Panel B of Table VI presents our findings for Option Trader strategies. We find that this group of funds differs from Long/Short Equity and Low Net Exposure funds, to the extent that the average return of funds with largest positive correlation risk exposure in the Option Trader group is similar to the average return of funds with the most negative correlation risk exposure in the LNE and LSE classes. The portfolio of Option Trader funds in the bottom decile has a return of 20.74 percent per year, which is about double the average return of 11.83 percent per year of the portfolio in the highest correlation risk beta decile: Correlation risk exposure explains about 41 percent of the difference of average returns between the highest and lowest decile groups. BKT model alphas are −8.38 and 24.45 percent per year for the highest and lowest correlation risk beta deciles, respectively, which shows that Options Trader funds performance is tremendously dependent on the latent correlation risk exposure, which generates economically significant differences in excess returns as a result. In

[22] See, e.g., Granger and Allen (2005) JPMorgan report 'Correlation Vehicles'.

[23] '*We have hedge fund clients who are very active traders of volatility, correlation and dispersion. Trading correlation and dispersion as an asset class can have a diversification effect,...*' (Denis Frances, Global Head of Equity Derivatives Flow Sales at BNP Paribas, FTfm, 28/1/2008).

particular, after correcting for exposure to correlation risk, the risk adjusted performance of Option Trader strategies can change dramatically: The alpha of the lowest (highest) correlation risk beta quintile according to FH model (1) is about 16.2 (8.2) percent per year, but the alpha according to BKT model (2) is about minus 8.4 (plus 24.4) percent per year! These features might derive from the fact that Option Trader Funds explicitly try to model their risk exposures to correlation risk: While Long/Short Equity funds might inadvertently expose themselves to correlation risk, Options Trader funds are likely to be more aware of the importance of measuring and managing this particular source of risk; see, e.g., Granger and Allen (2005). They might even want to bet on it!

C. Is Correlation Risk Priced in the Cross-section of Hedge Fund Returns? Evidence from Fama-Macbeth Regressions

The above results document that correlation risk exposure is important in explaining (i) realized time series of hedge fund index returns and (ii) cross-sectional differences in excess returns of hedge fund portfolios across different investment styles.

While this is a key finding, the deep economic question left to be answered in our analysis is whether correlation risk is a priced tradable risk factor explaining the cross-section of expected excess hedge fund returns: Since correlation risk is linked to market-wide economic conditions, we would expect that some hedge funds are ready to pay a premium, in order to hedge this risk away. In contrast, other fund attributes can be important in explaining realized returns over time, but there is obviously no claim in the literature that they can explain the cross-section of expected excess returns.

If correlation risk is priced, the excess return due to correlation risk exposure is interpretable as a risk premium compensation, deriving for the exposure of a hedge fund strategy to that particular source of systematic risk. If correlation risk is not priced, then our correlation risk proxy has to be interpreted as a relative benchmark, generating excess return compensation without exposure to systematic risks, which hedge fund strategies are able to replicate.

The rigorous way to answer this question is to employ a Fama-Macbeth (1973) approach. We proceed sequentially by first using time series information to identify hedge fund betas and then investigating their ability to explain cross-sectional differences in expected hedge fund returns in our large panel. Since sequential estimation procedures can give rise to errors-in-variables (EIV) issues, we consider four approaches. Each method applied has different small-sample properties.

Let $Y_t = [f_t', R_t']'$, where f_t is the vector of K factors at time t and R_t is a vector of returns on N fund portfolios at time t. We denote the sample moments of Y_t by

$$\widehat{\mu} := \begin{bmatrix} \widehat{\mu}_1 \\ \widehat{\mu}_2 \end{bmatrix} := \frac{1}{T}\sum_{t=1}^{T} Y_t \ ,$$

and

$$\widehat{V} := \begin{bmatrix} \widehat{V}_{11} & \widehat{V}_{12} \\ \widehat{V}_{21} & \widehat{V}_{22} \end{bmatrix} := \frac{1}{T}\sum_{t=1}^{T} \left(Y_t - \widehat{\mu}\right)\left(Y_t - \widehat{\mu}\right)' \ .$$

We follow Kan, Robotti and Shanken (2009), and instead of estimating rolling betas, we estimate betas based on the full sample returns. The estimated betas from the first-pass time-series regression are given by the matrix $\widehat{\beta} = \widehat{V}_{21}\widehat{V}_{11}^{-1}$. We denote the covariance matrix of residuals of the N fund portfolios as $\widehat{\Sigma} = \widehat{V}_{22} - \widehat{V}_{21}\widehat{V}_{11}^{-1}\widehat{V}_{12}$. In the second pass, we run a cross-sectional regression of $\widehat{\mu}_2$ on $\widehat{X} = \left[1_N, \widehat{\beta}\right]$ to estimate γ_W, the vector of risk premia. In this second step, we follow a number of different approaches, related to different choices of weighting matrix W. Given weighting matrix W, γ_W is estimated as:

$$\widehat{\gamma}_W = \left(\widehat{X}'W\widehat{X}\right)^{-1}\widehat{X}'W\widehat{\mu}_2 \tag{15}$$

Table VII reports Fama-Macbeth estimates $\widehat{\gamma}_W$ for different choices of weighting matrix W, in order to assess the robustness of results with respect to different choices of the asymptotic standard errors. We consider both an augmented CAPM model with $K = 2$ factors, given by the index return and our correlation risk proxy (Model 1), and BKT 8-factor model, which augments the FH seven factor model by our proxy for correlation risk (Model 2).

[Insert Table VII here]

We first report results based on a traditional OLS estimator ($W = I$). According to traditional OLS estimators, we find that correlation risk is priced, with respect to both Model 1 and Model 2: The point estimate $\hat{\gamma}_W$ for the correlation risk premium is negative and highly statistically significant, with $t-$statistics of -3.16 and -3.04 respectively. At the same time, the point estimates for the market risk premium and the risk premia of all FH factors, with the exception of the default spread factor (BD10RET), are not statistically significant, indicating that these sources of risk are not priced in the cross-section of hedge fund returns. In contrast, this evidence suggests that correlation risk is indeed a priced risk factor and not simply a fund attribute. The estimated correlation risk premium is large: It is -8.16 percent per year with respect to the augmented CAPM model and -7.48 percent per year with respect to the BKT model. These findings are consistent with the economically large average negative correlation risk premium estimated in Table II. The fact that the market risk premium is not statistically significant might be due to the relatively small number of 156 monthly observations in our sample, or more likely to the fact that many hedge funds are successful in implementing market neutral strategies. The insignificant coefficients of the trend-following FH factors suggest that these variables have indeed to be interpreted as benchmarks for cross-sectional relative value analysis, which however do not generate priced sources of risk.

It is well-known that in Fama-MacBeth regressions the second-pass estimator is subject to a potential error-in-variables (EIV) problem, because the explanatory variables in the cross-sectional regression are measured with error. This feature has four important implications. First, if standard errors fail to include the information that beta coefficients contain measurement error, the implied t-statistics might overstate the precision of the risk premia estimates. Second, OLS estimators may be asymptotically inefficient if errors in the second step regression are correlated or heteroskedastic. Third, the properties of different estimators can be substantially different under the alternative hypothesis that the linear factor model is misspecified, either because of a missing factor or because of a latent non-linearity. Fourth, the OLS estimator of the risk premia might be biased in finite samples.

With regards to the EIV issue, we correct t-statistics using Shanken (1992)'s asymptotically valid EIV adjustment (see Table VII, right panel) and find that, while t-statistics are lower, our conclusions are unchanged: The OLS estimate for the correlation risk premium is statistically significant, with t-statistics of -2.83 (Model 1) and -2.57 (Model 2). To account for potential error correlation or heteroskedasticity, we apply a GLS and a WLS procedure, in order to improve the power of our tests for statistical significance. Table VII, columns two and three, reports GLS and WLS risk premia t-statistics.[24] WLS and GLS results strengthen our previous conclusions using OLS estimators: (i) the statistical significance of the correlation risk premium estimate using GLS standard errors and EIV correction is stronger, with GLS t-statistics of -3.95 and -3.24 in Model (1) and (2), respectively, and (ii) none of the FH risk factors is statistically significant.

[24] In these two cases, we obtain consistent estimators of optimal weighting matrix W in equation (15) using consistent covariance matrix estimator $\widehat{V}$. In our context, we can set $\widehat{W} = \widehat{\Sigma}^{-1}$ for the GLS case and $\widehat{W} = \widehat{\Sigma}_d^{-1}$ for the WLS case, where $\widehat{\Sigma}_d$ is a diagonal matrix containing the diagonal elements of $\widehat{\Sigma}$.

An important potential issue related to the interpretation of our results is linked to the asymptotic distributions of OLS, WLS and GLS Fama-MacBeth estimators, which can be substantially different under a model misspecification[25] or in presence of an interaction between the pricing errors and the errors in the $\widehat{\beta}$ estimates. A Monte Carlo comparison of the relative small sample properties of different estimators is produced in Shanken and Zhou (2007), who also consider GMM and Maximum Likelihood (ML) estimators.[26] Their simulation results show that GLS estimators have desirable properties in small samples and are preferable to OLS, WLS, and GMM estimators, at least in the context of their CAPM specifications. ML estimators, while asymptotically efficient when the model is correctly specified and the normality assumption is satisfied, are slightly less precise than GLS estimators in small samples or when the normality assumption is violated. Given their findings, in our specific context we decided to rely mostly on GLS estimators to interpret our results. However, given Chen and Kan (2004) evidence that the EIV problem may also affect the second stage of GLS t-statistics, we have reported in the right panel of Table VII GLS and WLS statistics based on the EIV correction.

A final concern for the interpretation of our findings is related to the choice of portfolios to include in our Fama-Mac Beth regressions. Given our large cross-section of funds, we explored different portfolio grouping and sorting procedures, in order to construct a set of well-diversified portfolios that minimize measurement error, while maintaining sufficient cross-sectional variation in portfolio betas. Black, Jensen, and Scholes (1972) show that this approach generates N–consistent estimators (as the number of assets goes to infinity) even for a fixed time-series sample size.[27] Our cross-sectional regressions above are based on 27 portfolios, obtained using a triple sort with respect to the market, correlation risk and size factor betas. Given the number of funds and the large number of factors, we have chosen a parsimonious sort starting from all eight factors. We have examined whether our results are robust to forming portfolios based on single sorts (25, 30 and 48 portfolios based on the market or correlation risk betas) or double sorts (25 and 36 portfolios based on the market and correlation risk betas). We have found that our conclusions remain qualitatively unchanged: The correlation risk premium is statistically significant in all specifications, but the

[25] See Proposition 1 in Shanken and Zhou (2007).

[26] GMM relaxes the distributional assumptions of the ML approach, allows for a simple serial correlation and conditional heteroskedasticity correction, and is asymptotically efficient under the null hypothesis. These desirable asymptotic properties, however, do not necessarily hold in small samples or under a model misspecification.

[27] Estimating time-series betas based on portfolios of hedge funds leads to more precise beta estimates, compared to estimating betas using individual hedge fund returns, which tend to have relatively short sample periods.

market risk premium and the risk premia of other hedge fund factors are not.[28]

D. Maximum Drawdowns and Correlation Risk Exposure

An important aspect of Fama and French (1993, 1996) tests for the existence of a value premium, is that book-to-market portfolio returns co-move systematically over time, indicating that value is a systematic risk factor: If you buy value stocks, no matter how diversified you are, you will still keep a risky portfolio, since all value stocks strongly co-move. We study a similar aspect related to correlation risk exposure in the context of hedge funds and investigate the extent to which portfolios of funds sorted with respect to their correlation risk exposure can diversify away downside risk, as measured by maximum drawdowns, i.e., the longest consecutive sequence of losses.[29] Maximum drawdown is sometimes referred to as the peak-to-valley return and is a measure of tail risk closely followed by hedge fund investors.

We sort hedge funds into decile portfolios based on their correlation risk betas. Figure 6 plots the maximum drawdown of hedge funds portfolios across the different deciles.

[Insert Figure 6 here]

A negative correlation risk beta means that a fund is short correlation, implying that hedge fund losses tend to increase when correlations rise. Figure 8 shows that portfolio diversification does not help to diversify away correlation risk: Funds with the most negative exposure to correlation risk, but not funds with large positive correlation risk exposure, tend to suffer drawdowns at the same time. This feature is reflected by the plots in Figure 6: The equally weighted portfolio of funds with the most negative exposure to correlation risk has maximum drawdown of 75 percent, but the equally weighted portfolio of funds with the most positive correlation risk exposure has maximum drawdown of only 5 percent.

These findings give additional insight into the systematic nature of correlation risk and its link to the cross-section of hedge fund returns. Three additional aspects of this link emerge. First, correlation risk strongly affects the tail-risk characteristics of hedge fund returns. From a risk management perspective, this feature shows the added value of monitoring correlation risk exposure, in order to monitor hedge funds maximum drawdowns. Second, maximum drawdowns of funds with the

[28] These results are available upon request from the authors.

[29] See Browne and Kosowski (2010) for details about drawdown minimization in portfolio management.

most negative correlation risk exposure are disproportionately large, indicating a nonlinear relation between correlation risk exposure and hedge fund tail risk. Third, and perhaps most importantly, funds with large negative correlation risk exposure generate large average returns, as we documented in the previous section, but they also more strongly co-move and jointly generate large losses at certain times. In other words, correlation risk cannot be diversified away at the portfolio level: When correlation risk manifests itself, some strategies in the hedge fund and fund of hedge funds universe cannot find a safe place to hide.

E. Robustness Checks

In this section, we document the extent to which our results are robust to (i) the use of equal-weighted, instead of value-weighted, indices and (ii) extended performance attribution factor models that include proxies for liquidity risk.

E.1. Equal-Weighted Versus Value-Weighted Indices

Our findings that value-weighted indices of Low Net Exposure and Long Short Equity funds have statistically significant correlation risk exposures is corroborated by the evidence for equal-weighted indices presented in Table VIII, which is based on the BarclayHedge data.

[Insert Table VIII here]

An equal-weighted average of all individual hedge funds has as correlation risk beta of -0.01, with a t-statistic of -1.69 ($p-$value=0.09). Using equal-weighted indices of All Low Net Exposure funds, leads to a statistically significant negative correlation risk beta ($t_{\beta_{CR}} = -1.64$, p-value=0.10). An equally-weighted index of Long-Short Equity funds also has a statistically significant exposure to correlation risk ($t_{\beta_{CR}} = -2.1$, p-value=0.04). Similar results hold for equally-weighted indices of Merger Arbitrage and Multi-Strategy Funds. The same is not true for Option Trader funds, suggesting that the previous results might partly be driven by Option Trader funds that are larger, in terms of assets under management, than the average fund.

E.2. **Robustness to Liquidity Risk Factor**

Recent work by Aragon (2007) documents that hedge funds alpha are linked to hedge fund lock-up periods, which suggests a potential relation between hedge funds alpha and asset liquidity. Sadka (2010) shows that a (non-tradable) equity market liquidity factor explains cross-sectional differences in hedge fund returns. Although liquidity and correlation are sometimes interpreted as related economic phenomena, we find that they capture different characteristics of hedge fund returns. We build on their works and consider liquidity proxies that have tradable factor interpretations, as the other factors in the BKT model. Then, we augment the BKT model with two liquidity proxies: (a) the Fontaine and Garcia (2008) liquidity factor, for the fixed income market, and (b) the Pastor and Stambaugh (2003) liquidity factor, for the equity market.[30] The advantage of this approach, with respect to a projection on non-tradable factors, is that the intercept of a performance attribution regression can be interpreted as risk-adjusted performance or "alpha". Table IX shows that a significant component of correlation risk is not related to liquidity risk. Even after controlling for this two factors, correlation risk is not subsumed by liquidity risk and it remains a significant explanatory factor in hedge fund returns.

[Insert Table IX here]

We find that value-weighted indices of all funds and Low Net Exposure funds, for example, continue to have a statistically and economically significant negative beta with respect to correlation risk, even after augmenting the BKT model by the two liquidity proxies.

V. Conclusion

In this paper, we have studied the relation between correlation risk exposure and cross-sectional differences in hedge fund performance and risk. We have illustrated how differences in legal framework and investment mandate can imply that hedge funds are severely exposed to correlation risk: Hedge funds ability to enter long-short positions can be useful to reduce market beta, but it is also responsible for a potentially large exposure to unexpected changes in correlations. Our empirical study produces a number of novel findings to the literature. First, we find that high negative correlation risk exposures explain a statistically and economically significant percentage of hedge fund

[30] We thank Jean-Sebastien Fontaine and Rene Garcia for kindly providing us with their data.

returns at the index level. Second, building on empirical and theoretical work, which shows that assets exposed to market-wide increases in correlations command a risk premium, we examine the cross-section of hedge funds' betas with respect to a factor-mimicking portfolio for correlation risk, We find that cross-sectional differences in hedge fund excess returns are explained by differences in correlation risk exposures. Therefore, failure to account for differences in correlation risk exposure leads to a strongly biased estimates of funds' risk-adjusted performance. Third, funds with negative loadings on the correlation risk factor, i.e., sellers of insurance against unexpected increases in correlation, have maximum drawdowns that are significantly higher than funds with positive correlation risk betas. Moreover, the tail behaviour of diversified hedge fund portfolio returns with respect to the correlation risk exposure is strongly asymmetric, which indicates that funds with large negative correlation betas tend to suffer large losses at the same times. Fourth, correlation risk is priced and generates a substantial correlation risk premium component in the cross-section of hedge fund returns. Our results are of great relevance for hedge fund investors, as risk-adjusted (alpha) performance measures ignoring correlation risk exposures overestimate fund performance and underestimate fund risk, as measured, e.g., by maximum drawdown measures, which are key metrics used by hedge fund investors for fund selection. Since hedge funds with low net exposures that hold baskets of long and short positions are exposed to correlation risk and suffer sudden large losses when correlations unexpectedly increase, monitoring and hedging correlation risk exposure is key also for hedge fund portfolio risk management. More broadly, our findings have important implications for the categorization of hedge funds according to risk measures and for recent (UCITS III) legislation that allows mutual funds to follow so-called 130/30 long-short strategies.

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Table I: Statistics of Hedge Funds Returns

This table reports summary statistics for monthly value-weighted hedge fund index excess returns of 17 hedge funds categories. The first row reports results for a value-weighted average of all hedge funds excluding funds of funds. All Low Net Exposure (ALNE) funds are all hedge funds that are reported to have a net long/short exposure below 30 percent. LSE Low Net Exposure (LLNE) funds are Long/Short Equity (LSE) funds that are reported to have a net long/short exposure below 30 percent. The value-weights are rebalanced every month based on a fund's assets under management. Returns are expressed in percent per month. The sample period is January 1996 to December 2008. Columns 2 to 9 report the mean, standard deviation, skewness, kurtosis, minimum, median, maximum of monthly index returns. Columns 10 to 14 report alpha and beta coefficients (with respect to the S&P500), the Sharpe Ratio (SR), the Treynor's measure (TM), and the M-squared measure.

Investment Objective	# Funds	mean	std	skew	kurt	min	med	max	alpha	beta	SR	TM	Msq
ALL (except FoF)	8710	0.52	1.53	-0.17	3.53	-4.28	0.53	4.88	0.48	0.19	0.34	2.53	1.83
All LNE (ALNE)	335	1.18	2.77	1.12	5.30	-5.94	0.67	11.11	1.14	0.19	0.43	5.87	2.22
Long/Short Equity (LSE)	1190	0.73	2.42	0.50	6.21	-8.45	0.59	10.52	0.67	0.30	0.30	2.23	1.66
Low Net Exposure (LLNE)	195	1.28	3.58	1.12	5.24	-6.59	0.76	14.74	1.24	0.19	0.36	6.64	1.90
Equity Long (EL)	615	0.45	3.26	-0.94	4.80	-12.63	1.01	8.18	0.32	0.61	0.14	0.53	0.91
Equity Market Neutral (EMN)	285	0.16	1.01	-0.31	5.17	-3.43	0.24	3.86	0.16	0.03	0.16	6.21	1.03
Options Trader (OPT)	483	0.41	1.46	-0.71	6.80	-6.41	0.48	4.62	0.39	0.08	0.28	5.11	1.57
Event Driven (ED)	218	0.59	2.61	-2.76	18.17	-17.75	0.93	4.95	0.53	0.32	0.23	1.64	1.32
Distressed Securities (DS)	100	0.62	2.69	-0.78	11.40	-12.43	0.81	12.81	0.58	0.20	0.23	2.87	1.34
Merger Arbitrage (MA)	60	0.32	1.26	-1.69	9.86	-6.80	0.44	2.93	0.29	0.16	0.25	1.84	1.45
Fixed Income (FI) Relative Value	386	0.15	1.28	-1.48	7.59	-5.72	0.28	3.54	0.12	0.13	0.12	0.93	0.83
Convertible Arbitrage (CA)	175	0.17	2.44	-1.75	12.05	-13.43	0.25	7.56	0.10	0.35	0.07	0.28	0.60
Macro (MAC)	264	0.53	1.81	0.12	3.53	-4.88	0.58	6.25	0.50	0.18	0.29	2.79	1.63
Emerging Markets (EMG)	575	0.57	3.90	-1.05	6.55	-17.56	1.25	11.49	0.47	0.54	0.15	0.86	0.96
Funds of Funds (FOF)	3172	0.24	1.80	-0.52	6.00	-7.45	0.36	6.36	0.20	0.22	0.13	0.89	0.90
Multi-strategy (MUL)	1551	0.67	2.28	0.09	3.33	-6.50	0.77	7.25	0.68	-0.02	0.29	-41.33	1.63
Managed Futures	555	0.27	1.51	-0.21	3.73	-4.96	0.25	4.10	0.27	0.02	0.18	11.16	1.10

Table II: Summary Statistics for Benchmark Factors

This table reports the summary statistics for different benchmark factors. The sample period is from January 1996 to December 2008. We report the statistical properties for non-overlapping monthly returns of the variance risk and correlation risk factors as well as the Fung and Hsieh model risk factors. Columns 2 to 8 report the mean, standard deviation, skewness, kurtosis, minimum, median and maximum of monthly returns. Columns 9 to 13 report alpha and beta coefficients (with respect to S&P500), the annualized Sharpe Ratio (SR), Treynor's measure (TM), and the M-squared measure. Alpha and Sharpe Ratio are expressed in percent per month. The variance risk factor is constructed from realized and implied volatility estimates. VR and CR correspond to short variance and short correlation swap strategies. VR is reported in percentages squared per month. From January 1996 until March 2000 CR is based on synthetic correlation swaps, followed by market quotes from April 2000 until December 2008.

	mean	**std**	**skew**	**kurt**	**min**	**med**	**max**	**alpha**	**beta**	**SR**	**TM**	**Msq**
VRP500	-16.73	37.09	6.14	63.73	-124.45	-17.26	350.28	-15.96	-3.92	-1.56	4.07	-1.74
CR	-14.33	15.09	-0.47	3.28	-63.39	-12.45	24.41	-14.05	-1.42	-3.29	9.88	-4.00
S&PmRf	0.20	4.50	-0.74	4.11	-16.82	0.77	9.31	0.00	1.00	0.15	0.00	0.49
SCMLC	-0.14	3.94	0.24	6.42	-16.38	-0.17	18.41	-0.13	-0.01	-0.12	9.01	0.14
BD10RET	0.29	2.20	0.16	4.97	-7.57	0.20	9.45	0.31	-0.10	0.46	-3.03	0.89
BAAMTSY	0.02	1.75	-2.42	17.34	-12.10	0.13	4.14	-0.02	0.19	0.04	-0.10	0.34
PTFSBD	-1.26	14.40	1.42	6.26	-25.60	-4.16	68.43	-1.17	-0.48	-0.30	2.43	-0.10
PTFSFX	1.15	18.59	1.08	4.42	-30.15	-1.92	69.22	1.32	-0.89	0.21	-1.49	0.58
PTFSCOM	0.78	14.40	1.22	5.27	-24.20	-2.20	64.36	0.88	-0.50	0.19	-1.76	0.54

Table III: Correlation Matrix of Risk Factors and Hedge Funds Indices

This table reports the correlation matrix of the BKT model risk factors and the hedge fund index returns. The sample period is from January 1996 to December 2008. Panel A shows the unconditional correlation matrix. See Column 1 of Table 1 for investment objective

Panel A: Unconditional Correlation Matrix

	CR	ALL (except FoF)	Long/Short Equity (LSE)	Low Net Exposure (LNE)	Equity Long (EL)	Equity Market Neutral (EMN)	Options Trader (OPTS)	Event Driven (ED)	Distressed Securities (DS)	Merger Arbitrage (MA)	Fixed Income Relative Value (FI)	Convertible Arbitrage (CA)	Macro (MAC)	Emerging Markets (EMG)	Funds of Funds (FOF)	Multi-strategy (MUL)	Managed Futures (MF)
CR	1.00	-0.37	-0.35	-0.35	-0.38	-0.11	-0.29	-0.33	-0.10	-0.35	-0.31	-0.35	-0.33	-0.20	-0.33	-0.20	-0.15
All	-0.37	1.00	0.81	0.53	0.79	0.28	0.33	0.67	0.52	0.60	0.61	0.72	0.90	0.75	0.88	0.57	0.30
LSE	-0.35	0.81	1.00	0.66	0.80	0.23	0.35	0.60	0.33	0.61	0.56	0.71	0.69	0.65	0.88	0.15	0.08
LLNE	-0.35	0.53	0.66	1.00	0.40	0.14	0.23	0.38	0.08	0.34	0.39	0.32	0.51	0.37	0.60	0.26	0.16
EL	-0.38	0.79	0.80	0.40	1.00	0.15	0.29	0.71	0.50	0.68	0.59	0.79	0.65	0.78	0.79	0.10	0.07
EMN	-0.11	0.28	0.23	0.14	0.15	1.00	-0.02	0.27	0.19	0.35	0.27	0.11	0.21	0.10	0.30	0.15	0.10
OPT	-0.29	0.33	0.35	0.23	0.29	-0.02	1.00	0.18	0.06	0.18	0.11	0.19	0.33	0.16	0.31	0.23	0.09
ED	-0.33	0.67	0.60	0.38	0.71	0.27	0.18	1.00	0.58	0.74	0.70	0.67	0.54	0.70	0.74	0.07	0.13
DS	-0.10	0.52	0.33	0.08	0.50	0.19	0.06	0.58	1.00	0.44	0.43	0.55	0.38	0.57	0.54	0.07	0.07
MA	-0.35	0.60	0.61	0.34	0.68	0.35	0.18	0.74	0.44	1.00	0.60	0.63	0.45	0.59	0.64	0.01	0.07
FI	-0.31	0.61	0.56	0.39	0.59	0.27	0.11	0.70	0.43	0.60	1.00	0.71	0.47	0.58	0.70	0.05	0.16
CA	-0.35	0.72	0.71	0.32	0.79	0.11	0.19	0.67	0.55	0.63	0.71	1.00	0.57	0.71	0.78	0.09	-0.04
MAC	-0.33	0.90	0.69	0.51	0.65	0.21	0.33	0.54	0.38	0.45	0.47	0.57	1.00	0.68	0.78	0.62	0.33
EMG	-0.20	0.75	0.65	0.37	0.78	0.10	0.16	0.70	0.57	0.59	0.58	0.71	0.68	1.00	0.78	0.13	0.08
FOF	-0.33	0.88	0.88	0.60	0.79	0.30	0.31	0.74	0.54	0.64	0.70	0.78	0.78	0.78	1.00	0.27	0.17
MUL	-0.20	0.57	0.15	0.26	0.10	0.15	0.23	0.07	0.07	0.01	0.05	0.09	0.62	0.13	0.27	1.00	0.33
MF	-0.15	0.30	0.08	0.16	0.07	0.10	0.09	0.13	0.07	0.07	0.16	-0.04	0.33	0.08	0.17	0.33	1.00

Panel B: Monthly Excess Returns in Crisis Months (in percent per month)

	CR	All	LSE	LLNE	EL	EMN	OPT	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL	MF
2008/Sep.	24.41	-4.21	-2.51	1.31	-9.49	-2.17	2.12	-8.40	-12.36	-4.13	-3.24	-11.32	-2.93	-9.33	-4.93	-1.37	-0.33
2007/July	8.51	-0.13	-0.79	-0.78	-1.13	0.05	-0.94	-0.48	8.88	-0.22	-0.89	-0.85	0.09	2.92	-0.65	-1.01	-0.61
2007/Feb.	19	0	0.4	0.1	0.3	0.7	-1.1	0.3	4.1	0.4	0.6	0.8	-0.6	1.0	0.6	-0.9	-0.6
2006/May	4	-3	-4.8	-6.2	-4.0	-1.5	-2.9	-2.7	2.2	-0.3	-0.9	-0.9	-4.4	-5.3	-3.3	-1.7	-2.4
2005/Oct.	7.6	-0.8	-0.9	1.0	-2.3	0.7	0.9	-2.4	-0.3	-0.9	0.6	0.3	-0.6	-2	-1	-1	1

Table IV: Return Decomposition of Hedge Fund Index Returns

This table reports alpha and beta coefficiencts of hedge fund index returns for different investment objectives. All Low Net Exposure (ALNE) funds are all hedge funds that are reported to have a net long/short exposure below 30 percent. LSE Low Net Exposure (LLNE) funds are Long/Short Equity (LSE) funds that are reported to have a net long/short exposure below 30 percent. The other investment objectives are Equity Long (EL), Equity Market Neutral (EMN), Option Trader (OPT), Event Driven (ED), Distressed Securities (DS), Merger Arbitrage (MA), Fixed Income (FI), Convertible Arbitrage (CA), Macro (MAC), Emerging Markets (EMG), Funds of Funds (FoF), Multi-Strategy (MUL) and Managed Futures (MF). Panel A reports results based on the seven-factor Fung-Hsieh model. The columns show the annualized hedge fund index return, the annualized alpha, the FH betas and the t-statistics of the alpha and FH betas. Panel B reports the alphas for the BKT 8-factor model. Panel C is based on a 9-factor model that includes the BKT model factors and a value-weighted index of invididual option variance risk factor (VW Indiv. VR). The sample period is January 1996 to December 2008.

Panel A: FH -7 Model Alpha and Betas

	All	ALNE	LSE	LLNE	EL	EMN	OPT	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL	MF
HF ret (% p.a.)	6.23	14.16	8.77	15.30	5.34	1.97	4.91	7.07	7.45	3.84	1.80	1.99	6.37	6.86	2.89	8.07	3.25
Alpha (% p.a.)	5.36	13.71	8.32	14.95	3.96	1.55	4.48	6.00	6.34	3.57	1.05	1.11	5.05	5.16	2.16	7.09	2.67
Beta S&P	0.20	0.22	0.36	0.24	0.61	0.03	0.10	0.25	0.08	0.13	0.08	0.28	0.21	0.45	0.21	0.04	0.01
Beta SCM	0.12	0.09	0.26	0.09	0.26	-0.02	0.04	0.12	0.01	0.08	0.05	0.18	0.10	0.15	0.13	0.04	0.01
Beta BD10RET	0.10	-0.06	-0.01	-0.11	0.09	0.03	0.03	-0.05	-0.02	-0.02	0.10	0.16	0.18	0.07	0.02	0.20	0.03
Beta BAAmTSY	0.08	-0.10	-0.28	-0.23	0.09	0.02	-0.07	0.29	0.57	0.10	0.29	0.38	0.05	0.43	0.08	0.09	0.15
Beta PTFSBD	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.04	-0.05	-0.01	-0.01	0.00	0.00	-0.04	-0.02	0.03	-0.01
Beta PTFSFX	0.01	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.00	0.02	0.02
Beta PTFSCOM	0.02	0.03	0.02	0.05	0.02	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.04	-0.01
t-stat Alpha	4.77	5.32	4.80	4.39	2.91	1.55	3.24	3.10	2.78	3.76	1.06	0.70	3.41	1.80	1.58	3.59	1.84
t-stat S&P	8.47	3.99	9.72	3.32	21.06	1.23	3.38	6.08	1.63	6.50	3.91	8.46	6.60	7.37	7.19	1.06	0.46
t-stat SCM	4.80	1.63	6.83	1.26	8.88	-1.14	1.29	2.94	0.13	3.81	2.09	5.22	3.01	2.34	4.24	0.86	0.29
t-stat BD10RET	2.17	-0.63	-0.17	-0.83	1.59	0.71	0.58	-0.60	-0.26	-0.47	2.43	2.51	3.07	0.58	0.33	2.58	0.57
t-stat BAAmTSY	1.29	-0.65	-2.73	-1.18	1.15	0.27	-0.88	2.60	4.31	1.80	4.96	4.13	0.63	2.58	1.05	0.80	1.75
t-stat PTFSBD	0.31	-0.33	-0.29	-0.01	-0.06	-1.43	-0.30	-3.64	-3.45	-1.88	-2.44	-0.15	0.01	-2.12	-1.87	2.76	-1.01
t-stat PTFSFX	1.18	-0.33	-0.60	-0.20	-1.44	0.43	-0.82	0.36	0.41	-0.21	-0.37	-1.13	1.39	-0.24	-0.06	2.42	3.43
t-stat PTFSCOM	2.58	2.07	1.52	2.15	2.16	1.01	2.60	0.88	0.83	-0.31	0.65	-0.35	2.38	0.31	1.72	3.29	-0.66
adj R^2	44.20	10.49	46.65	6.42	81.94	-0.21	7.15	42.86	25.55	41.15	37.71	56.95	30.33	44.27	39.62	22.47	4.94

Panel B: BKT

	All	ALNE	LSE	LLNE	EL	EMN	OPT	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL	MF
HF ret (% p.a.)	6.23	14.16	8.77	15.30	5.34	1.97	4.91	7.07	7.45	3.84	1.80	1.99	6.37	6.86	2.89	8.07	3.25
Alpha (% p.a.)	3.47	4.25	5.20	3.36	3.96	1.18	1.49	3.25	8.90	2.00	-0.25	-0.68	2.37	9.64	0.56	2.19	0.67
Beta CR	-0.01	-0.06	-0.02	-0.07	0.00	0.00	-0.02	-0.02	0.02	-0.01	-0.01	-0.01	-0.02	0.03	-0.01	-0.03	-0.01
Beta S&P	0.19	0.14	0.33	0.15	0.61	0.02	0.08	0.23	0.10	0.12	0.07	0.27	0.19	0.48	0.20	0.01	0.00
Beta SCM	0.12	0.09	0.26	0.09	0.26	-0.02	0.04	0.12	0.01	0.08	0.05	0.18	0.10	0.15	0.13	0.04	0.01
Beta BD10RET	0.10	-0.06	-0.01	-0.10	0.09	0.03	0.03	-0.04	-0.03	-0.02	0.10	0.16	0.18	0.06	0.02	0.21	0.03
Beta BAAmTSY	0.08	-0.13	-0.29	-0.28	0.09	0.01	-0.08	0.28	0.58	0.09	0.28	0.37	0.04	0.45	0.08	0.07	0.14
Beta PTFSBD	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.04	-0.05	-0.01	-0.02	0.00	0.00	-0.03	-0.02	0.03	-0.01
Beta PTFSFX	0.01	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.00	0.02	0.02
Beta PTFSCOM	0.02	0.03	0.01	0.04	0.02	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.04	-0.01
t-stat Alpha	2.17	1.20	2.11	0.71	2.03	0.82	0.76	1.18	2.73	1.48	-0.18	-0.30	1.12	2.36	0.28	0.79	0.32
t-stat CR	-1.65	-3.73	-1.77	-3.44	0.00	-0.36	-2.13	-1.39	1.10	-1.62	-1.28	-1.11	-1.78	1.53	-1.14	-2.47	-1.34
t-stat S&P	7.35	2.54	8.50	1.98	19.59	1.02	2.43	5.19	1.92	5.52	3.19	7.50	5.56	7.46	6.31	0.12	-0.05
t-stat SCM	4.82	1.70	6.88	1.31	8.85	-1.13	1.31	2.95	0.13	3.84	2.10	5.22	3.04	2.35	4.25	0.88	0.30
t-stat BD10RET	2.21	-0.57	-0.13	-0.78	1.59	0.71	0.63	-0.57	-0.28	-0.44	2.46	2.53	3.13	0.55	0.35	2.68	0.60
t-stat BAAmTSY	1.18	-0.93	-2.87	-1.46	1.15	0.24	-1.04	2.51	4.38	1.69	4.86	4.04	0.51	2.69	0.97	0.63	1.66
t-stat PTFSBD	0.20	-0.59	-0.41	-0.24	-0.05	-1.45	-0.44	-3.73	-3.37	-1.99	-2.53	-0.22	-0.11	-2.02	-1.94	2.64	-1.10
t-stat PTFSFX	1.23	-0.25	-0.56	-0.12	-1.43	0.44	-0.78	0.40	0.38	-0.17	-0.34	-1.10	1.45	-0.28	-0.03	2.53	3.47
t-stat PTFSCOM	2.39	1.72	1.32	1.82	2.14	0.96	2.37	0.71	0.95	-0.49	0.50	-0.47	2.17	0.48	1.58	3.04	-0.81
adj R^2	44.84	17.68	47.40	12.79	81.81	-0.80	9.33	43.21	25.66	41.79	37.98	57.02	31.34	44.77	39.74	25.04	5.46

Panel C: BKT + VW Indiv. VR

	All	ALNE	LSE	LLNE	EL	EMN	OPT	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL	MF
HF ret (% p.a.)	6.42	14.13	8.83	14.84	6.34	1.97	4.80	7.96	9.14	4.04	2.15	3.13	6.34	8.27	3.55	7.80	2.90
Alpha (% p.a.)	4.44	2.94	4.77	0.75	6.61	2.18	1.26	6.56	16.31	2.90	0.73	1.68	2.72	12.60	1.90	2.09	-0.27
Beta CR	-0.01	-0.06	-0.02	-0.07	0.00	0.00	-0.02	-0.01	0.03	-0.01	-0.01	-0.01	-0.01	0.03	-0.01	-0.03	-0.01
Beta VW IVR	-0.41	0.10	-0.18	0.32	-0.97	-0.34	-0.06	-1.17	-1.98	-0.41	-0.42	-0.66	-0.24	-1.01	-0.46	0.07	0.04
Beta S&P	0.18	0.15	0.34	0.16	0.60	0.02	0.08	0.22	0.07	0.11	0.07	0.25	0.19	0.47	0.19	0.01	0.00
Beta SCM	0.11	0.10	0.26	0.10	0.24	-0.03	0.04	0.10	-0.03	0.07	0.04	0.17	0.09	0.13	0.13	0.05	0.01
Beta BD10RET	0.13	-0.03	0.01	-0.09	0.06	0.04	0.05	-0.03	0.01	-0.07	0.10	0.12	0.21	0.04	0.08	0.28	0.07
Beta BAAmTSY	0.17	0.10	-0.08	0.04	0.05	0.02	0.01	0.30	0.35	0.03	0.35	0.25	0.15	0.40	0.22	0.22	0.33
Beta PTFSBD	0.00	-0.01	-0.01	-0.01	0.00	-0.01	0.00	-0.04	-0.03	-0.01	-0.01	0.00	0.00	-0.03	-0.01	0.04	-0.01
Beta PTFSFX	0.01	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02
Beta PTFSCOM	0.02	0.03	0.02	0.04	0.02	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.02	0.04	-0.01
t-stat Alpha	2.70	0.77	1.87	0.15	3.34	1.41	0.59	2.31	5.17	2.04	0.51	0.72	1.20	2.87	0.97	0.70	-0.13
t-stat CR	-1.36	-3.81	-1.82	-3.61	0.60	-0.01	-2.10	-0.86	2.25	-1.42	-1.02	-0.81	-1.63	1.81	-0.83	-2.39	-1.44
t-stat VW IVR	-2.20	0.23	-0.60	0.56	-4.29	-1.94	-0.24	-3.61	-5.51	-2.53	-2.57	-2.45	-0.94	-2.00	-2.07	0.21	0.17
t-stat S&P	7.62	2.66	8.92	2.14	20.50	0.89	2.47	5.17	1.50	5.42	3.21	7.37	5.60	7.26	6.69	0.19	0.15
t-stat SCM	4.83	1.80	7.12	1.45	8.66	-1.42	1.30	2.56	-0.59	3.32	2.01	5.10	2.93	2.08	4.54	1.06	0.38
t-stat BD10RET	2.71	-0.31	0.12	-0.63	1.00	0.92	0.78	-0.33	0.08	-1.61	2.50	1.72	3.26	0.30	1.36	3.28	1.08
t-stat BAAmTSY	2.19	0.54	-0.64	0.17	0.48	0.29	0.11	2.22	2.33	0.38	5.00	2.21	1.39	1.90	2.29	1.54	3.16
t-stat PTFSBD	0.59	-0.68	-0.50	-0.48	0.00	-1.12	-0.45	-3.44	-2.68	-2.48	-2.47	-0.18	0.06	-1.89	-1.40	2.97	-1.12
t-stat PTFSFX	1.20	-0.25	-0.54	-0.12	-1.36	0.25	-0.82	0.31	0.51	-0.02	-0.15	-0.53	1.28	-0.11	0.02	2.38	3.24
t-stat PTFSCOM	2.67	1.92	1.66	2.03	2.29	0.86	2.46	0.72	0.89	-0.59	0.81	-0.30	2.24	0.56	2.00	3.14	-0.70
adj R^2	51.15	20.60	52.88	15.48	83.06	1.93	10.95	47.88	32.64	42.71	43.41	51.54	33.90	42.03	47.29	26.77	10.48

Table V: FH and BKT Model Regression Coefficients for Individual Hedge Funds

In this table, we report regression coefficients for individual hedge funds that are sorted by their BKT correlation risk beta t-statistic into deciles. Column 3 reports results for decile 1, which contains individual hedge funds with the most extreme negative correlation risk beta. Given the construction of the CR time-series, funds in this decile can be interpreted as selling insurance against unexpected increases in correlation. Column 12 reports results for decile 10, which contains funds with the highest correlation risk beta. These funds can be interpreted as buying insurance against unexpected increases in correlation. The last column reports the difference between the high and the low portfolio. Rows 1 and 6 report the BKT model correlation risk beta. Row 2 reports the average absolute return per year. Rows 3 to 4 report FH model results. Rows 5 to 16 report BKT model results. Rows 14 to 16 report t-statistics for several BKT model betas. Rows 17 to 19 report the contribution of alpha and several BKT model betas to the total absolute return. Alpha and hedge funds returns are annualized and expressed in a percentage format. The sample period is from January 1996 to December 2008. Panel A-D report results for investment objectives ALL (All Funds), ALNE (All funds with Low Net Exposure), Long/Short Equity and LLNE (Long/Short Equity Funds with Low Net Exposure).

Panel A: All Funds

		low	2	3	4	5	6	7	8	9	high	H-L
	beta_CR	-0.06	-0.05	-0.03	-0.02	-0.01	-0.01	0.00	0.01	0.02	0.04	0.11
	Return (% p.a.)	13.45	11.36	10.36	10.06	8.84	8.85	8.33	7.31	7.41	8.46	-4.99
FH7 Model Coefficients	FH7 Alpha (% p.a.)	8.90	6.92	5.91	5.48	4.40	4.53	4.30	3.30	3.41	4.73	-4.17
	t_alpha	5.15	4.62	4.22	4.27	3.39	3.95	3.93	2.67	2.54	3.36	-1.79
BKT Model Coefficients	BKT Alpha (% p.a.)	-1.78	-0.77	0.13	1.67	2.01	2.99	4.51	4.68	6.49	11.92	13.69
	beta_CR	-0.06	-0.05	-0.03	-0.02	-0.01	-0.01	0.00	0.01	0.02	0.04	0.11
	beta_S&P500	0.12	0.15	0.18	0.22	0.22	0.23	0.23	0.23	0.30	0.30	0.18
	beta_SCMLC	0.12	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.16	0.11	-0.01
	beta_BD10RET	0.10	0.10	0.10	0.10	0.06	0.03	0.01	-0.01	-0.02	-0.07	-0.18
	beta_BAAMTSY	0.00	0.17	0.18	0.19	0.16	0.15	0.12	0.07	-0.02	-0.01	-0.02
	beta_PTFSBD	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
	beta_PTFSFX	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	-0.02
	beta_PTFSCOM	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	-0.02
	t_alpha	-0.82	-0.39	0.07	0.94	1.09	1.83	2.87	2.64	3.43	6.46	5.52
	t_beta_CR	-6.91	-5.48	-4.26	-2.97	-1.81	-1.31	0.18	1.09	2.28	5.45	10.05
	t_beta_S&P	3.46	4.66	6.02	7.76	7.63	8.99	9.31	8.12	9.96	10.14	4.49
	contrib_alpha	-1.78	-0.77	0.13	1.67	2.01	2.99	4.51	4.68	6.49	11.92	13.69
	contrib_CR	10.84	7.81	5.87	3.86	2.43	1.56	-0.21	-1.41	-3.14	-7.30	-18.15
	contrib_S&P500	0.28	0.34	0.43	0.52	0.53	0.55	0.55	0.54	0.71	0.70	0.42

Panel B: All Funds with Low Net Exposure (ALNE)

		low	2	3	4	5	6	7	8	9	high	H-L
	beta_CR	-0.043	-0.069	-0.064	-0.012	-0.020	-0.011	0.028	0.022	0.031	0.086	0.13
	Return (% p.a.)	12.83	12.11	21.27	5.06	9.58	8.49	3.20	9.99	3.56	9.69	-3.14
FH7 Model Coefficients	FH7 Alpha (% p.a.)	8.48	9.10	17.33	1.92	5.91	7.00	-0.92	7.45	0.27	7.60	-0.88
	t_alpha	5.85	3.29	4.53	1.00	2.75	1.17	-0.32	1.63	0.07	2.56	-3.30
BKT Model Coefficients	BKT Alpha (% p.a.)	1.20	-0.86	10.17	0.05	2.88	5.49	3.79	11.14	5.56	16.28	15.08
	beta_CR	-0.043	-0.069	-0.064	-0.012	-0.020	-0.011	0.028	0.022	0.031	0.086	0.13
	beta_S&P500	0.211	0.046	0.099	-0.023	0.186	0.357	0.227	-0.157	-0.247	-0.005	-0.22
	beta_SCMLC	0.147	0.047	0.269	0.092	0.028	-0.040	0.247	0.316	-0.184	0.051	-0.10
	beta_BD10RET	0.014	-0.037	0.085	-0.027	0.030	-0.097	-0.067	0.045	-0.160	-0.201	-0.22
	beta_BAAMTSY	0.011	-0.011	-0.433	-0.110	0.297	-0.641	-0.107	0.162	0.341	-0.170	-0.18
	beta_PTFSBD	-0.013	-0.013	-0.032	-0.010	0.001	0.051	-0.040	-0.005	-0.017	0.001	0.01
	beta_PTFSFX	0.005	-0.009	-0.008	-0.014	-0.004	-0.037	-0.010	-0.043	-0.007	-0.027	-0.03
	beta_PTFSCOM	0.011	0.002	-0.002	0.005	0.011	0.000	0.032	0.027	0.044	0.033	0.02
	t_alpha	0.63	-0.24	1.94	0.02	0.97	0.67	0.93	1.70	0.97	4.26	3.70
	t_beta_CR	-5.34	-4.00	-1.98	-1.00	-1.45	-0.27	1.62	0.79	1.28	3.39	4.88
	t_beta_S&P	6.96	0.76	1.07	-0.54	3.87	2.58	3.51	-1.51	-2.71	-0.08	-2.44
	contrib_alpha	1.20	-0.86	10.17	0.05	2.88	5.49	3.79	11.14	5.56	16.28	15.08
	contrib_CR	7.40	9.77	7.00	1.86	3.01	1.48	-4.78	-3.76	-5.37	-8.46	-15.86
	contrib_S&P500	0.50	-0.02	-0.22	-0.03	0.20	-0.17	0.54	-0.37	-0.59	0.02	-0.48

Panel C: Long/Short Equity

		low	2	3	4	5	6	7	8	9	high	H-L
	beta_CR	-0.061	-0.048	-0.033	-0.029	-0.022	-0.011	-0.006	0.010	0.013	0.040	0.10
	Return (% p.a.)	16.62	13.75	13.76	13.64	11.35	12.06	12.37	9.06	10.38	11.80	-4.82
FH7 Model Coefficients	FH7 Alpha (% p.a.)	12.63	9.87	9.67	9.41	6.82	7.70	9.04	4.76	6.56	8.52	-4.10
	t_alpha	6.86	5.33	4.23	4.81	4.54	5.03	5.57	2.50	3.71	4.28	-2.57
BKT Model Coefficients	BKT Alpha (% p.a.)	2.26	1.67	4.01	4.46	3.15	5.91	7.96	6.49	8.84	15.37	13.11
	beta_CR	-0.061	-0.048	-0.033	-0.029	-0.022	-0.011	-0.006	0.010	0.013	0.040	0.10
	beta_S&P500	0.303	0.349	0.443	0.371	0.425	0.392	0.344	0.497	0.461	0.290	-0.01
	beta_SCMLC	0.285	0.332	0.401	0.317	0.229	0.261	0.229	0.249	0.262	0.130	-0.16
	beta_BD10RET	-0.046	-0.057	0.001	-0.013	0.039	0.051	-0.141	0.037	-0.059	-0.137	-0.09
	beta_BAAMTSY	-0.130	-0.105	-0.271	-0.087	-0.102	-0.153	-0.042	-0.473	-0.278	-0.145	-0.02
	beta_PTFSBD	-0.008	-0.006	-0.005	-0.009	-0.007	-0.010	0.013	-0.009	0.005	0.007	0.01
	beta_PTFSFX	-0.001	-0.001	-0.003	0.002	-0.003	-0.009	-0.001	-0.008	-0.006	0.000	0.00
	beta_PTFSCOM	0.012	0.005	0.007	0.016	0.010	0.009	0.002	-0.007	0.005	-0.003	-0.02
	t_alpha	0.96	0.67	1.25	1.62	1.48	2.70	3.42	2.38	3.50	5.60	3.88
	t_beta_CR	-6.13	-4.60	-2.46	-2.51	-2.42	-1.15	-0.65	0.89	1.26	3.49	7.18
	t_beta_S&P	8.07	8.82	8.67	8.49	12.62	11.27	9.31	11.49	11.49	6.65	-0.47
	contrib_alpha	2.26	1.67	4.01	4.46	3.15	5.91	7.96	6.49	8.84	15.37	13.11
	contrib_CR	10.52	8.33	5.75	5.02	3.73	1.83	1.10	-1.76	-2.31	-6.96	-17.48
	contrib_S&P500	0.72	0.83	1.05	0.88	1.01	0.93	0.82	1.18	1.09	0.69	-0.03

Panel D: Long/Short Equity Funds with Low Net Exposure (LLNE)

		low	2	3	4	5	6	7	8	9	high	H-L
	beta_CR	-0.054	-0.039	-0.063	-0.038	-0.009	-0.001	0.021	0.020	0.036	0.048	0.10
	Return (% p.a.)	13.93	11.09	11.43	7.08	12.48	3.49	3.28	3.86	5.70	0.68	-13.26
FH7 Model Coefficients	FH7 Alpha (% p.a.)	9.52	8.80	5.28	3.69	10.47	1.04	-0.22	3.05	2.55	0.11	-9.41
	t_alpha	4.67	3.25	1.83	1.35	5.46	0.66	-0.06	1.10	0.68	0.04	-4.63
BKT Model Coefficients	BKT Alpha (% p.a.)	0.34	3.47	-0.24	-0.23	9.28	0.97	3.25	4.82	8.65	4.23	3.89
	beta_CR	-0.054	-0.039	-0.063	-0.038	-0.009	-0.001	0.021	0.020	0.036	0.048	0.10
	beta_S&P500	0.221	0.074	-0.323	0.027	0.213	0.077	0.279	0.145	-0.184	0.170	-0.05
	beta_SCMLC	0.145	0.136	0.017	0.179	0.116	0.077	0.303	0.070	-0.049	0.143	0.00
	beta_BD10RET	0.010	-0.116	0.033	0.073	-0.104	-0.064	-0.161	-0.089	-0.134	-0.161	-0.17
	beta_BAAMTSY	-0.176	-0.089	-0.012	-0.124	-0.223	0.026	-0.345	-0.155	0.156	-0.155	0.02
	beta_PTFSBD	-0.015	-0.010	-0.051	0.003	0.014	-0.016	-0.021	0.007	-0.011	0.009	0.02
	beta_PTFSFX	0.003	-0.025	0.012	-0.015	-0.010	-0.007	-0.007	-0.029	-0.005	-0.026	-0.03
	beta_PTFSCOM	0.018	0.001	0.014	0.017	0.023	0.021	0.027	0.021	0.041	0.031	0.01
	t_alpha	0.13	0.94	-0.07	-0.06	3.54	0.48	0.59	1.34	1.61	1.13	2.79
	t_beta_CR	-4.70	-2.11	-2.43	-1.57	-0.67	-0.05	0.89	0.78	1.58	1.75	3.34
	t_beta_S&P	5.11	1.21	-4.10	0.40	4.86	1.77	3.21	1.90	-2.15	2.02	-2.51
	contrib_alpha	0.34	3.47	-0.24	-0.23	9.28	0.97	3.25	4.82	8.65	4.23	3.89
	contrib_CR	9.32	5.18	5.48	3.85	1.15	0.06	-3.53	-1.75	-6.19	-4.11	-13.43
	contrib_S&P500	0.52	-0.07	1.56	-0.09	-0.45	-0.41	0.66	-0.77	-0.43	-0.62	-1.15

Table VI: FH and BKT Model Regression Coefficients by Investment Objective

In this table, we report, by hedge fund category, regression coefficients for individual hedge funds that are sorted by their BKT correlation risk beta into deciles t-statistics. Column 3 reports results for decile 1, which contains individual hedge funds with the lowest correlation risk beta. Column 12 reports results for decile 10, which contains funds with the highest correlation risk beta. Rows 1 and 6 report the BKT model correlation risk beta. Row 2 reports the average absolute return per year. Rows 3 to 4 report FH model results. Rows 5 to 16 report BKT model results. Rows 14 to 16 report t-statistics for several BKT model betas. Rows 17 to 19 report the contribution of alpha and several BKT model betas to the total absolute return. Alpha and hedge funds returns are annualized and expressed in a percentage format. The sample period is from January 1996 to December 2008. Panels A and B report results for investment objectives Merger Arbitrage and Option Strategies, respectively.

Panel A: Merger Arbitrage

		low	2	3	4	5	6	7	8	9	high	H-L
	beta_CR	-0.036	-0.012	-0.028	-0.007	-0.010	0.000	-0.004	-0.008	-0.007	-0.006	0.03
	Return (% p.a.)	13.70	8.39	6.66	7.86	5.11	9.14	7.33	5.79	6.06	6.04	-7.66
FH7 Model Coefficients	FH7 Alpha (% p.a.)	9.22	4.63	0.53	4.06	1.87	5.38	3.52	2.33	2.30	1.26	-7.96
	t_alpha	3.66	5.62	0.20	4.60	1.49	4.26	3.26	1.56	1.85	0.58	-3.08
BKT Model Coefficients	BKT Alpha (% p.a.)	3.11	2.53	-4.92	2.95	0.18	5.40	2.82	1.02	1.06	0.08	-3.04
	beta_CR	-0.036	-0.012	-0.028	-0.007	-0.010	0.000	-0.004	-0.008	-0.007	-0.006	0.03
	beta_S&P500	0.087	0.075	0.179	0.085	0.048	0.089	0.129	0.014	0.122	0.062	-0.02
	beta_SCMLC	-0.016	0.077	0.205	0.037	0.049	0.050	0.029	0.062	0.066	0.122	0.14
	beta_BD10RET	0.207	-0.014	-0.082	0.003	-0.079	-0.008	0.000	0.012	-0.008	-0.031	-0.24
	beta_BAAMTSY	0.926	0.071	0.134	0.063	-0.039	-0.048	0.076	0.205	0.091	0.196	-0.73
	beta_PTFSBD	0.008	-0.010	-0.029	-0.007	0.000	-0.010	-0.003	0.006	-0.005	-0.007	-0.02
	beta_PTFSFX	-0.008	0.007	-0.007	0.002	-0.005	0.000	0.001	-0.001	-0.005	-0.005	0.00
	beta_PTFSCOM	-0.009	-0.010	0.005	-0.008	-0.003	-0.003	-0.009	0.001	0.001	-0.009	0.00
	t_alpha	0.88	2.18	-1.23	2.33	0.10	2.98	1.82	0.48	0.60	0.02	-1.61
	t_beta_CR	-2.40	-2.53	-1.80	-1.24	-1.31	0.01	-0.63	-0.86	-0.97	-0.46	2.93
	t_beta_S&P	1.54	4.05	3.21	4.23	1.68	3.09	5.24	0.43	4.33	1.35	-0.89
	contrib_alpha	3.11	2.53	-4.92	2.95	0.18	5.40	2.82	1.02	1.06	0.08	-3.04
	contrib_CR	6.20	2.14	5.64	1.13	1.72	-0.02	0.71	1.32	1.25	1.22	-4.98
	contrib_S&P500	0.21	0.18	1.18	0.20	0.11	0.21	0.30	0.03	0.29	0.38	0.18

Panel B: Options

		low	2	3	4	5	6	7	8	9	high	H-L
	beta_CR	-0.145	-0.085	-0.069	-0.009	0.016	-0.001	0.024	0.069	0.088	0.096	0.24
	Return (% p.a.)	20.74	21.58	18.80	12.29	10.91	6.64	7.59	8.44	20.39	11.83	-8.91
FH7 Model Coefficients	FH7 Alpha (% p.a.)	16.18	18.33	13.97	7.53	6.30	1.75	3.59	5.31	17.49	8.25	-7.92
	t_alpha	4.13	5.65	3.91	1.56	1.83	0.62	1.30	1.18	4.17	2.36	-1.77
BKT Model Coefficients	BKT Alpha (% p.a.)	-8.38	3.80	2.33	6.02	8.97	1.56	7.59	17.06	32.43	24.45	32.82
	beta_CR	-0.145	-0.085	-0.069	-0.009	0.016	-0.001	0.024	0.069	0.088	0.096	0.24
	beta_S&P500	0.135	-0.012	0.243	0.509	0.112	0.091	0.046	0.552	0.176	0.431	0.30
	beta_SCMLC	0.035	0.153	0.086	0.387	-0.004	-0.069	0.061	0.132	-0.139	0.043	0.01
	beta_BD10RET	0.261	0.148	0.152	0.321	0.330	0.324	0.146	-0.144	-0.101	0.036	-0.23
	beta_BAAMTSY	0.528	0.404	-0.019	-0.345	0.422	0.514	-0.010	0.169	-0.151	0.074	-0.45
	beta_PTFSBD	0.012	0.034	0.006	0.022	0.001	0.031	-0.004	0.058	0.031	0.018	0.01
	beta_PTFSFX	-0.020	-0.026	-0.002	0.013	0.008	0.011	-0.007	-0.019	0.008	-0.035	-0.01
	beta_PTFSCOM	-0.021	0.015	0.027	-0.030	-0.055	0.009	0.002	0.030	-0.034	-0.006	0.01
	t_alpha	-1.72	0.87	0.47	0.87	1.82	0.39	1.92	2.70	5.61	5.24	4.05
	t_beta_CR	-7.05	-4.66	-3.28	-0.30	0.76	-0.07	1.41	2.60	3.61	4.85	7.20
	t_beta_S&P	1.75	-0.17	3.08	4.61	1.44	1.41	0.74	5.51	1.92	5.82	1.02
	contrib_alpha	-8.38	3.80	2.33	6.02	8.97	1.56	7.59	17.06	32.43	24.45	32.82
	contrib_CR	24.94	14.67	11.82	1.53	-2.72	0.19	-4.06	-11.94	-15.17	-16.45	-41.38
	contrib_S&P500	0.32	-0.02	0.57	1.20	0.27	0.21	0.11	1.31	0.42	1.02	0.70

Table VII: The Cross-section of Hedge Fund Excess Returns and Correlation Risk Exposure

This table reports estimates for the risk premia on the market index and the Fung and Hsieh (2004) factors and the correlation risk factor (CR). In Panel A, we report results for the market and the correlation risk factor (Model I). In Panel B, we report results for the BKT eight-factor model. The estimation methods are OLS, WLS and GLS versions of the (Fama-MacBeth) two-pass regression methodology. t-statistics are in brackets. t-statistics in columns four to six are calculated using standard errors based Shanken (1992) errors-in-variables (EIV) adjustment. The cross-sectional regressions are based on 27 portfolios (tercile portfolios based on sthe market, correlation risk and size factor betas). The sample period is January 1996 to Dec 2008.

Panel A: Model 1 (Correlation Risk and Market Risk)

				With Shanken's Correction		
	OLS	WLS	GLS	OLS	WLS	GLS
Intercept	0.54	0.51	0.47	0.54	0.51	0.47
tstat	(4.37)	(3.98)	(4.99)	(3.81)	(3.45)	(4.26)
Correl Risk	-8.16	-8.40	-8.61	-8.16	-8.40	-8.61
tstat	-(3.16)	-(3.33)	-(4.39)	-(2.83)	-(2.98)	-(3.95)
Mkt Risk	0.47	0.57	0.22	0.47	0.57	0.22
tstat	(.77)	(.93)	(.47)	(.71)	(.84)	(.43)

Panel B: Model 2 (Correlation risk factor and FH(2004)

				With Shanken's Correction		
	OLS	WLS	GLS	OLS	WLS	GLS
Intercept	0.61	0.58	0.55	0.61	0.58	0.55
tstat	(4.7)	(4.52)	(4.86)	(3.8)	(3.69)	(3.94)
Correl Risk	-7.48	-7.55	-8.49	-7.48	-7.55	-8.49
tstat	-(3.04)	-(3.03)	-(3.8)	-(2.57)	-(2.58)	-(3.24)
Mkt Risk	0.04	0.17	-0.06	0.04	0.17	-0.06
tstat	(.06)	(.29)	-(.12)	(.05)	(.25)	-(.11)
SCMBC	0.32	0.28	0.24	0.32	0.28	0.24
tstat	(.52)	(.46)	(.46)	(.44)	(.4)	(.4)
BD10RET	-0.77	-0.74	-0.34	-0.77	-0.74	-0.34
tstat	-(2.01)	-(1.96)	-(1.01)	-(1.69)	-(1.66)	-(.86)
BAAmTSY	-0.10	-0.09	-0.03	-0.10	-0.09	-0.03
tstat	-(.44)	-(.39)	-(.15)	-(.38)	-(.34)	-(.13)
PTFSBD	-0.57	-0.49	0.51	-0.57	-0.49	0.51
tstat	-(.16)	-(.14)	(.16)	-(.14)	-(.12)	(.14)
PTFSFX	4.46	4.30	3.73	4.46	4.30	3.73
tstat	(1.03)	(1.)	(.98)	(.85)	(.83)	(.82)
PTFSCOM	1.66	2.10	-1.15	1.66	2.10	-1.15
tstat	(.55)	(.7)	-(.41)	(.46)	(.58)	-(.34)

Table VIII: Return Decomposition of Equally-Weighted Hedge Fund Index Returns

This table reports alpha and beta coefficiencts of equally-weighted hedge fund index returns for different investment objectives (see Table 2 for abbreviations). Panel A reports results based on the seven-factor Fung-Hsieh model. The columns show the annualized hedge fund index return, the annualized alpha, the betas and the t-statistics of the alpha and betas. Panel B reports the alphas for the BKT 8-factor model. For simplicity, we report the betas and their t-statistics for the equity market return and the correlation risk proxy only. The sample period is January 1996 to December 2008.

Panel A: FH -7 Model Alpha and Betas

	All	ALNE	LSE	LLNE	EL	EMN	OPT	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL	MF
HF ret (% p.a.)	7.23	7.29	9.25	6.98	7.66	3.88	10.86	7.33	5.30	4.00	2.24	1.65	7.30	8.67	3.30	8.35	6.74
Alpha (% p.a.)	6.41	7.15	8.83	6.66	6.86	3.61	10.27	6.73	4.71	3.86	1.73	1.27	6.27	7.20	2.91	7.00	5.95
Beta SNP	0.24	0.10	0.41	0.13	0.66	0.06	0.25	0.22	0.13	0.11	0.07	0.12	0.24	0.55	0.19	0.01	-0.01
Beta SCM	0.14	0.11	0.28	0.10	0.38	0.03	0.03	0.15	0.10	0.06	0.04	0.06	0.11	0.18	0.13	0.05	-0.02
Beta BD10RET	0.07	-0.02	-0.03	-0.07	-0.05	0.00	0.14	-0.03	-0.06	-0.02	0.05	0.06	0.13	-0.04	-0.03	0.21	0.03
Beta BAAmTSY	0.10	-0.04	-0.19	-0.14	0.02	-0.09	0.09	0.17	0.46	0.10	0.28	0.51	-0.08	0.48	0.11	0.05	0.12
Beta PTFSBD	0.01	-0.01	0.00	-0.02	0.00	-0.01	0.02	-0.02	-0.03	0.00	-0.01	0.00	0.01	-0.03	-0.01	0.03	-0.01
Beta PTFSFX	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.01	0.00	0.00	0.04	0.04
Beta PTFSCOM	0.02	0.02	0.01	0.02	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.02	0.00	0.01	0.06	0.01
t-stat Alpha	6.08	5.42	6.02	3.96	4.42	3.96	6.41	6.14	3.50	4.49	2.18	0.99	4.68	2.41	2.18	3.11	5.40
t-stat SNP	10.60	3.67	13.04	3.66	20.10	2.92	7.28	9.63	4.73	6.00	4.42	4.37	8.48	8.63	6.87	0.23	-0.55
t-stat SCM	5.92	3.81	8.70	2.61	11.27	1.57	0.85	6.50	3.46	3.37	2.47	2.05	3.86	2.78	4.32	1.05	-1.00
t-stat BD10RET	1.58	-0.47	-0.54	-1.03	-0.74	-0.04	2.20	-0.70	-1.15	-0.56	1.73	1.26	2.43	-0.32	-0.55	2.37	0.70
t-stat BAAmTSY	1.66	-0.53	-2.23	-1.38	0.18	-1.73	0.98	2.61	5.86	2.07	6.04	6.83	-1.02	2.76	1.38	0.36	1.87
t-stat PTFSBD	0.97	-1.07	-0.17	-1.60	0.26	-1.38	2.53	-3.13	-3.94	-0.78	-2.72	-0.47	1.44	-1.64	-1.03	2.35	-0.82
t-stat PTFSFX	2.07	-1.28	-0.47	-0.35	-0.45	0.95	-0.48	0.50	0.31	-0.04	-1.55	-1.95	1.89	0.25	-0.44	3.67	6.45
t-stat PTFSCOM	2.82	2.04	0.93	2.31	1.00	0.66	-0.34	0.78	0.64	-0.65	0.87	-0.37	2.71	0.01	1.56	4.39	1.20
adj R^2	55.92	16.96	62.96	12.90	81.58	4.35	33.31	61.36	53.81	37.43	48.86	51.46	38.42	51.33	40.04	32.20	23.87

Panel B: BKT

	All	ALNE	LSE	LLNE	EL	EMN	OPT	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL	MF
HF ret (% p.a.)	7.23	7.29	9.25	6.98	7.66	3.88	10.86	7.33	5.30	4.00	2.24	1.65	7.30	8.67	3.30	8.35	6.74
Alpha (% p.a.)	4.59	4.94	5.71	4.38	5.84	2.38	9.03	4.81	4.54	2.24	1.47	-0.68	4.55	8.88	0.54	2.45	4.96
Beta CR	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.01	0.00	-0.01	-0.01	0.01	-0.01	-0.03	-0.01
Beta SNP	0.22	0.09	0.38	0.11	0.65	0.05	0.24	0.21	0.13	0.10	0.07	0.10	0.23	0.56	0.18	-0.03	-0.02
Beta SCM	0.14	0.11	0.28	0.10	0.38	0.03	0.03	0.15	0.10	0.06	0.04	0.06	0.11	0.18	0.13	0.05	-0.02
Beta BD10RET	0.07	-0.02	-0.03	-0.07	-0.04	0.00	0.14	-0.03	-0.06	-0.02	0.05	0.07	0.13	-0.04	-0.03	0.22	0.03
Beta BAAmTSY	0.09	-0.05	-0.20	-0.14	0.01	-0.10	0.09	0.16	0.46	0.10	0.28	0.50	-0.09	0.49	0.10	0.03	0.12
Beta PTFSBD	0.01	-0.01	0.00	-0.02	0.00	-0.01	0.02	-0.02	-0.03	0.00	-0.01	0.00	0.01	-0.03	-0.01	0.03	-0.01
Beta PTFSFX	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.01	0.00	0.00	0.04	0.04
Beta PTFSCOM	0.02	0.02	0.01	0.02	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.01	0.06	0.01
t-stat Alpha	3.06	2.63	2.75	1.82	2.62	1.82	3.93	3.09	2.35	1.83	1.29	-0.37	2.38	2.07	0.28	0.77	3.14
t-stat CR	-1.69	-1.64	-2.10	-1.33	-0.64	-1.32	-0.75	-1.72	-0.12	-1.86	-0.32	-1.49	-1.25	0.55	-1.74	-1.99	-0.87
t-stat SNP	9.34	2.85	11.55	2.94	18.49	2.26	6.51	8.43	4.36	4.98	4.00	3.56	7.48	8.23	5.83	-0.50	-0.83
t-stat SCM	5.96	3.83	8.80	2.62	11.25	1.58	0.85	6.55	3.44	3.40	2.46	2.06	3.87	2.78	4.35	1.06	-1.00
t-stat BD10RET	1.63	-0.43	-0.50	-1.00	-0.72	-0.01	2.21	-0.67	-1.14	-0.52	1.74	1.30	2.46	-0.34	-0.51	2.43	0.72
t-stat BAAmTSY	1.55	-0.64	-2.39	-1.48	0.13	-1.82	0.92	2.50	5.81	1.95	5.98	6.73	-1.11	2.79	1.26	0.23	1.80
t-stat PTFSBD	0.87	-1.19	-0.32	-1.69	0.21	-1.47	2.48	-3.26	-3.92	-0.91	-2.73	-0.57	1.36	-1.59	-1.16	2.23	-0.87
t-stat PTFSFX	2.13	-1.24	-0.43	-0.32	-0.43	0.98	-0.46	0.55	0.32	0.00	-1.54	-1.92	1.93	0.24	-0.39	3.75	6.47
t-stat PTFSCOM	2.62	1.85	0.69	2.14	0.92	0.50	-0.42	0.59	0.62	-0.86	0.82	-0.54	2.56	0.07	1.36	4.18	1.096
adj R^2	56.47	17.90	63.79	13.35	81.51	4.83	33.11	61.87	53.50	38.45	48.55	51.86	38.66	51.10	40.86	33.54	23.75

Table IX: Robustness to Liquidity Factor

This table reports alpha and beta coefficiencts of hedge fund index returns for different investment objectives. Panel A reports results based on the baseline eight-factor BKT model. The columns show the annualized hedge fund index return, the annualized alpha, the BKT beta and the t-statistics of the alpha and BKT betas. Panel B reports the alphas of an augemented BKT model that also includes the Fontaine and Garcia (2008) liquidity risk factor. Panel C reports the alphas of an augemented BKT model that also includes the Pastor and Stambaugh (2003) tradable liquidity risk factor. The sample period is January 1996 to Dec 2008.

Panel A: BKT

	All	ALNE	LSE	LLSE	EL	EMN	OPTS	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL
HF ret (% p.a.)	6.23	14.16	8.77	15.30	5.34	1.97	4.91	7.07	7.45	3.84	1.80	1.99	6.37	6.86	2.89	8.07
Alpha (% p.a.)	3.47	4.25	5.20	3.36	3.96	1.18	1.49	3.25	8.90	2.00	-0.25	-0.68	2.37	9.64	0.56	2.19
Beta CR	-0.01	-0.06	-0.02	-0.07	0.00	0.00	-0.02	-0.02	0.02	-0.01	-0.01	-0.01	-0.02	0.03	-0.01	-0.03
Beta SNP	0.19	0.14	0.33	0.15	0.61	0.02	0.08	0.23	0.10	0.12	0.07	0.27	0.19	0.48	0.20	0.01
Beta SCM	0.12	0.09	0.26	0.09	0.26	-0.02	0.04	0.12	0.01	0.08	0.05	0.18	0.10	0.15	0.13	0.04
Beta BD10RET	0.10	-0.06	-0.01	-0.10	0.09	0.03	0.03	-0.04	-0.03	-0.02	0.10	0.16	0.18	0.06	0.02	0.21
Beta BAAmTSY	0.08	-0.13	-0.29	-0.28	0.09	0.01	-0.08	0.28	0.58	0.09	0.28	0.37	0.04	0.45	0.08	0.07
Beta PTFSBD	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.04	-0.05	-0.01	-0.02	0.00	0.00	-0.03	-0.02	0.03
Beta PTFSFX	0.01	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.00	0.02
Beta PTFSCOM	0.02	0.03	0.01	0.04	0.02	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.04
t-stat Alpha	2.17	1.20	2.11	0.71	2.03	0.82	0.76	1.18	2.73	1.48	-0.18	-0.30	1.12	2.36	0.28	0.79
t-stat CR	-1.65	-3.73	-1.77	-3.44	0.00	-0.36	-2.13	-1.39	1.10	-1.62	-1.28	-1.11	-1.78	1.53	-1.14	-2.47
t-stat SNP	7.35	2.54	8.50	1.98	19.59	1.02	2.43	5.19	1.92	5.52	3.19	7.50	5.56	7.46	6.31	0.12
t-stat SCM	4.82	1.70	6.88	1.31	8.85	-1.13	1.31	2.95	0.13	3.84	2.10	5.22	3.04	2.35	4.25	0.88
t-stat BD10RET	2.21	-0.57	-0.13	-0.78	1.59	0.71	0.63	-0.57	-0.28	-0.44	2.46	2.53	3.13	0.55	0.35	2.68
t-stat BAAmTSY	1.18	-0.93	-2.87	-1.46	1.15	0.24	-1.04	2.51	4.38	1.69	4.86	4.04	0.51	2.69	0.97	0.63
t-stat PTFSBD	0.20	-0.59	-0.41	-0.24	-0.05	-1.45	-0.44	-3.73	-3.37	-1.99	-2.53	-0.22	-0.11	-2.02	-1.94	2.64
t-stat PTFSFX	1.23	-0.25	-0.56	-0.12	-1.43	0.44	-0.78	0.40	0.38	-0.17	-0.34	-1.10	1.45	-0.28	-0.03	2.53
t-stat PTFSCOM	2.39	1.72	1.32	1.82	2.14	0.96	2.37	0.71	0.95	-0.49	0.50	-0.47	2.17	0.48	1.58	3.04
adj R^2	44.84	17.68	47.40	12.79	81.81	-0.80	9.33	43.21	25.66	41.79	37.98	57.02	31.34	44.77	39.74	25.04

Panel B: BKT + Fontaine and Garcia (2008) Liquidity Factor

	All	ALNE	LSE	LLSE	EL	EMN	OPTS	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL
HF ret (% p.a.)	6.23	14.16	8.77	15.30	5.34	1.97	4.91	7.07	7.45	3.84	1.80	1.99	6.37	6.86	2.89	8.07
Alpha (% p.a.)	3.46	-2.44	0.09	-7.46	2.39	1.66	0.40	5.25	14.51	-0.96	0.27	0.50	3.03	15.79	1.22	4.27
Beta CR	-0.01	-0.05	-0.01	-0.06	0.00	0.00	-0.02	-0.02	0.01	-0.01	-0.01	-0.01	-0.02	0.02	-0.01	-0.03
Beta SNP	0.19	0.13	0.32	0.13	0.61	0.02	0.07	0.23	0.11	0.11	0.07	0.27	0.19	0.49	0.20	0.01
Beta SCM	0.12	0.09	0.26	0.10	0.26	-0.02	0.04	0.12	0.00	0.08	0.04	0.18	0.10	0.14	0.13	0.04
Beta BD10RET	0.10	-0.05	-0.01	-0.09	0.09	0.03	0.04	-0.05	-0.03	-0.01	0.10	0.16	0.18	0.06	0.02	0.21
Beta BAAmTSY	0.08	-0.05	-0.22	-0.14	0.11	0.01	-0.07	0.26	0.51	0.13	0.27	0.36	0.04	0.37	0.07	0.05
Beta PTFSBD	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.04	-0.05	-0.01	-0.02	0.00	0.00	-0.04	-0.02	0.03
Beta PTFSFX	0.01	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.00	0.02
Beta PTFSCOM	0.02	0.02	0.01	0.03	0.02	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.04
Beta Liq	0.00	0.03	0.02	0.05	0.01	0.00	0.00	-0.01	-0.02	0.01	0.00	-0.01	0.00	-0.03	0.00	-0.01
t-stat Alpha	1.59	-0.51	0.03	-1.19	0.90	0.85	0.15	1.40	3.30	-0.53	0.14	0.16	1.06	2.87	0.46	1.13
t-stat CR	-1.62	-3.41	-1.42	-3.06	0.14	-0.41	-2.01	-1.49	0.80	-1.25	-1.33	-1.18	-1.81	1.27	-1.18	-2.56
t-stat SNP	7.29	2.35	8.36	1.76	19.40	1.05	2.35	5.24	2.11	5.35	3.21	7.51	5.55	7.63	6.29	0.20
t-stat SCM	4.81	1.77	7.04	1.40	8.86	-1.14	1.32	2.93	0.08	3.97	2.08	5.19	3.02	2.32	4.22	0.85
t-stat BD10RET	2.21	-0.52	-0.08	-0.72	1.61	0.70	0.65	-0.59	-0.33	-0.38	2.44	2.51	3.11	0.51	0.34	2.66
t-stat BAAmTSY	1.13	-0.34	-2.17	-0.73	1.34	0.13	-0.83	2.19	3.73	2.32	4.55	3.72	0.40	2.15	0.83	0.39
t-stat PTFSBD	0.20	-0.55	-0.36	-0.18	-0.03	-1.45	-0.43	-3.75	-3.44	-1.97	-2.53	-0.24	-0.12	-2.07	-1.94	2.61
t-stat PTFSFX	1.22	-0.22	-0.54	-0.09	-1.42	0.43	-0.77	0.39	0.36	-0.14	-0.34	-1.10	1.44	-0.31	-0.04	2.52
t-stat PTFSCOM	2.38	1.61	1.20	1.70	2.09	0.97	2.32	0.76	1.07	-0.64	0.52	-0.44	2.18	0.58	1.60	3.08
t-stat Liq	0.01	2.08	2.29	2.55	0.87	-0.37	0.61	-0.79	-1.89	2.43	-0.40	-0.57	-0.34	-1.65	-0.37	-0.82
adj R^2	44.47	19.51	48.88	15.93	81.78	-1.40	8.94	43.07	26.93	43.66	37.63	56.82	30.92	45.42	39.38	24.87

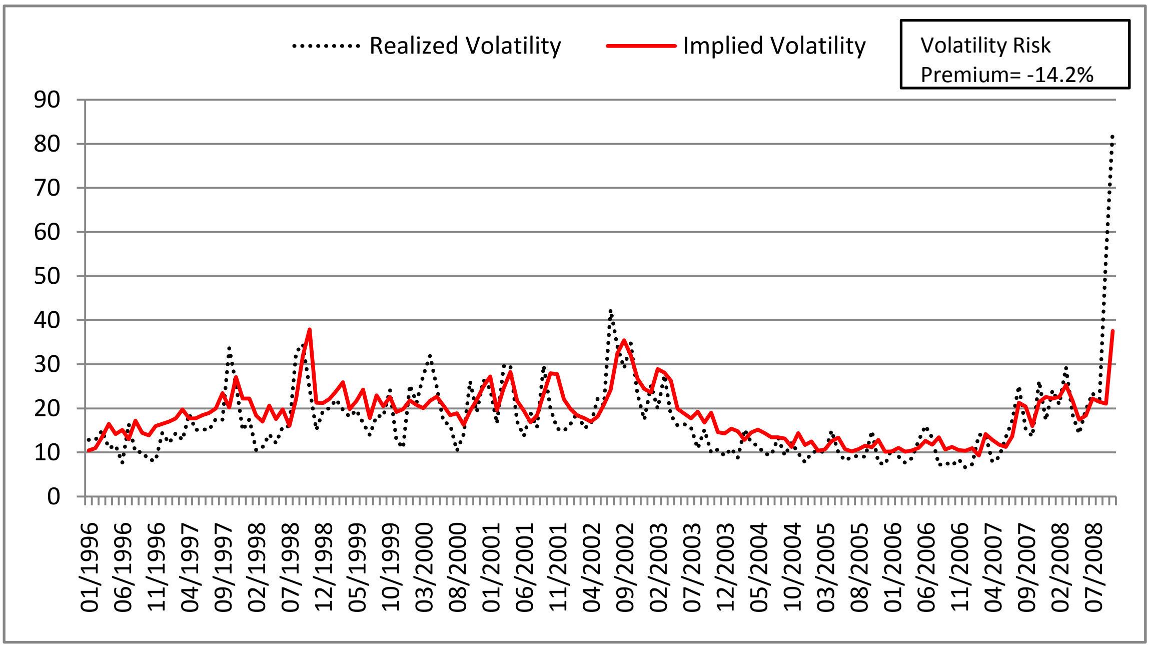
Panel C: BKT + Pastor and Stambaugh (2003) Liquidity Factor

	All	ALNE	LSE	LLSE	EL	EMN	OPTS	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL
HF ret (% p.a.)	6.23	14.16	8.77	15.30	5.34	1.97	4.91	7.07	7.45	3.84	1.80	1.99	6.37	6.86	2.89	8.07
Alpha (% p.a.)	3.28	5.55	5.64	5.30	3.85	1.03	1.63	3.17	7.03	1.94	-0.44	-0.79	2.05	8.94	0.41	2.18
Beta CR	-0.01	-0.05	-0.02	-0.06	0.00	0.00	-0.02	-0.02	0.01	-0.01	-0.01	-0.01	-0.02	0.03	-0.01	-0.03
Beta SNP	0.18	0.16	0.34	0.17	0.61	0.02	0.08	0.23	0.07	0.12	0.07	0.27	0.18	0.47	0.19	0.01
Beta SCM	0.12	0.09	0.26	0.10	0.26	-0.02	0.04	0.12	0.00	0.08	0.04	0.18	0.10	0.14	0.13	0.04
Beta BD10RET	0.10	-0.06	-0.01	-0.11	0.09	0.03	0.03	-0.04	-0.02	-0.02	0.10	0.16	0.18	0.06	0.02	0.21
Beta BAAmTSY	0.07	-0.09	-0.27	-0.22	0.09	0.01	-0.08	0.28	0.52	0.09	0.28	0.37	0.03	0.42	0.07	0.07
Beta PTFSBD	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.04	-0.05	-0.01	-0.02	0.00	0.00	-0.04	-0.02	0.03
Beta PTFSFX	0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.01	0.00	0.01	0.00	0.00	-0.01	0.01	0.00	0.00	0.02
Beta PTFSCOM	0.02	0.03	0.01	0.04	0.02	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.04
Beta Liq	0.01	-0.09	-0.03	-0.13	0.01	0.01	-0.01	0.01	0.12	0.00	0.01	0.01	0.02	0.05	0.01	0.00
t-stat Alpha	1.98	1.52	2.21	1.10	1.90	0.70	0.81	1.11	2.12	1.39	-0.30	-0.34	0.94	2.12	0.20	0.76
t-stat CR	-1.69	-3.55	-1.67	-3.24	-0.03	-0.40	-2.08	-1.39	0.83	-1.63	-1.33	-1.12	-1.84	1.44	-1.16	-2.44
t-stat SNP	7.05	2.80	8.43	2.29	19.00	0.90	2.42	5.02	1.40	5.33	3.00	7.26	5.29	7.12	6.07	0.11
t-stat SCM	4.79	1.77	6.89	1.39	8.80	-1.15	1.32	2.94	0.03	3.81	2.07	5.19	3.00	2.31	4.22	0.87
t-stat BD10RET	2.22	-0.62	-0.16	-0.84	1.59	0.72	0.62	-0.57	-0.21	-0.43	2.47	2.53	3.14	0.57	0.36	2.67
t-stat BAAmTSY	1.05	-0.63	-2.66	-1.10	1.07	0.15	-0.95	2.42	3.88	1.61	4.65	3.91	0.38	2.50	0.88	0.62
t-stat PTFSBD	0.16	-0.46	-0.34	-0.10	-0.08	-1.48	-0.42	-3.72	-3.61	-1.99	-2.55	-0.24	-0.16	-2.07	-1.95	2.61
t-stat PTFSFX	1.27	-0.41	-0.64	-0.31	-1.39	0.48	-0.80	0.40	0.65	-0.15	-0.28	-1.06	1.50	-0.20	0.00	2.50
t-stat PTFSCOM	2.39	1.71	1.31	1.82	2.14	0.96	2.36	0.71	0.98	-0.49	0.50	-0.47	2.17	0.49	1.58	3.03
t-stat Liq	0.47	-1.43	-0.69	-1.61	0.23	0.40	-0.28	0.11	2.27	0.17	0.50	0.19	0.58	0.67	0.30	0.02
adj R^2	44.55	18.27	47.21	13.72	81.70	-1.39	8.76	42.83	27.71	41.41	37.66	56.73	31.03	44.57	39.36	24.53

Figure 1: Implied and Realized Volatility for Individual and Index Options

Panel A of this figure shows the implied and realized volatility for the S&P500 based on index options. The y-axis shows volatility in percent per year. Panel B shows the average implied and realized volatility for the S&P500 constituent stocks. The results are based on the 30 most liquid individual options associated with the 30 largest S&P500 constituents. We also report the difference between the realized and the implied volatility, which we label, volatility risk premium in each of the panels.

Panel A: Implied versus Realized Volatility of S&P500 Index



Panel B: Average Implied versus Realized Volatility of Individual Names

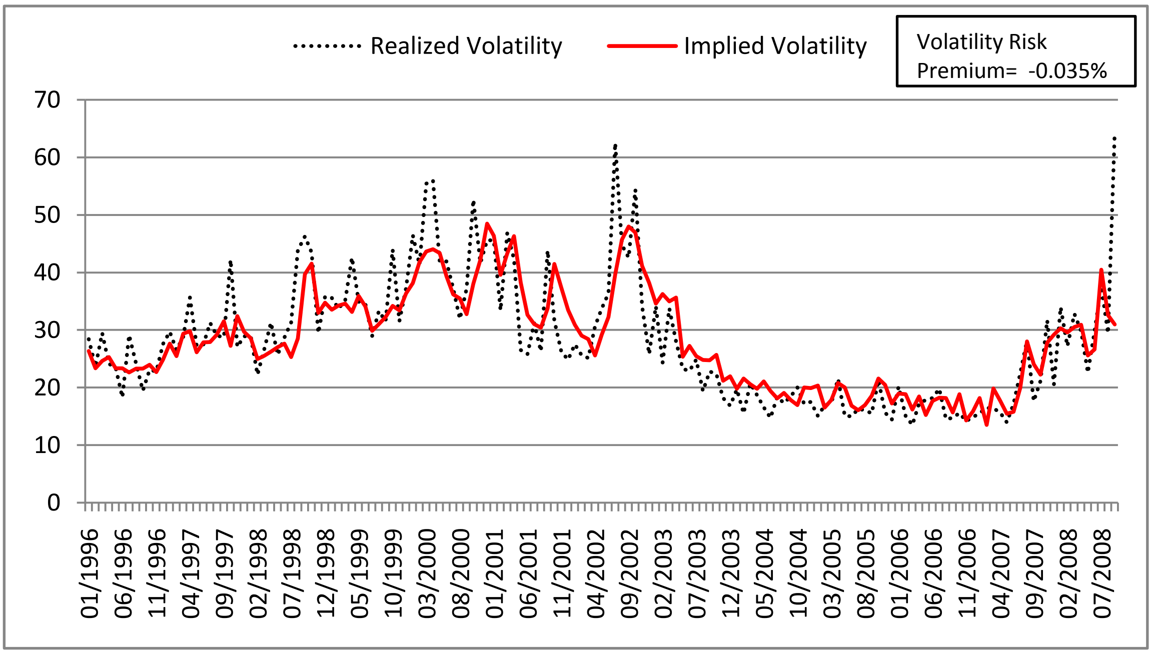
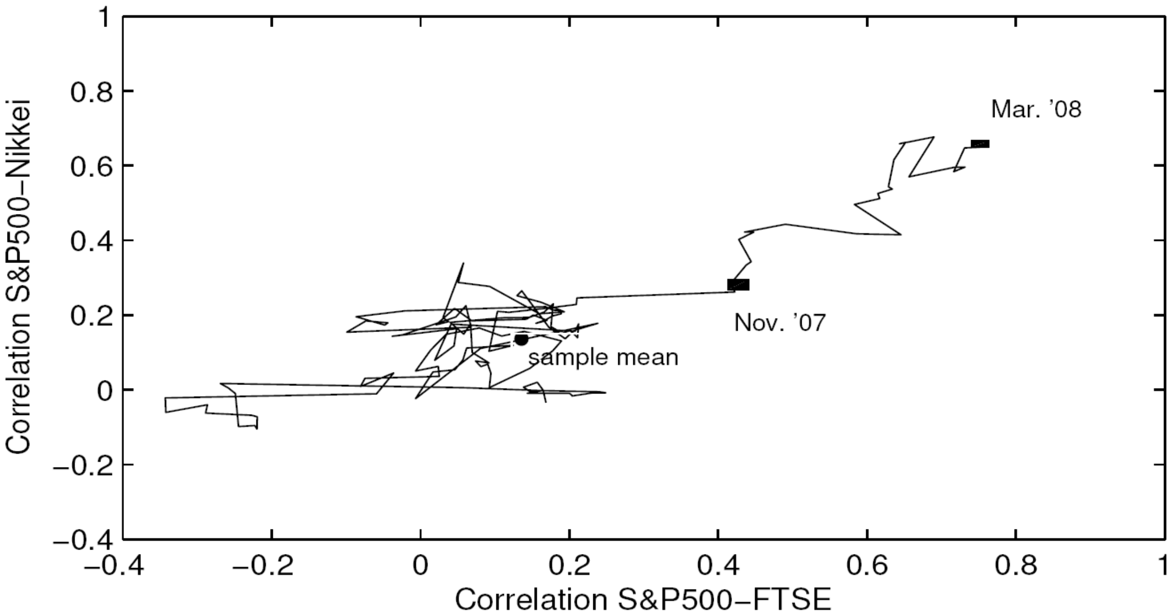


Figure 2: Correlation Risk and Market Events Across Equity Markets and Asset Classes

Panel A shows the S&P500-FTSE100 correlation and the S&P500-Nikkei correlation computed with weekly returns, using overlapping windows of quarterly length. Correlations reported are from 2004 until April 2008. Panel B shows the implied daily correlations on mezzanine tranches (7Y, 10-22 bp) in North America (CDX) and Europe (iTraxx). Reported correlations are from April 2004 to April 2008.

Panel A: S&P500-FTSE 100 correlation and S&P500-Nikkei correlation



Panel B: Implied daily correlations on mezzanine tranches in North America and Europe

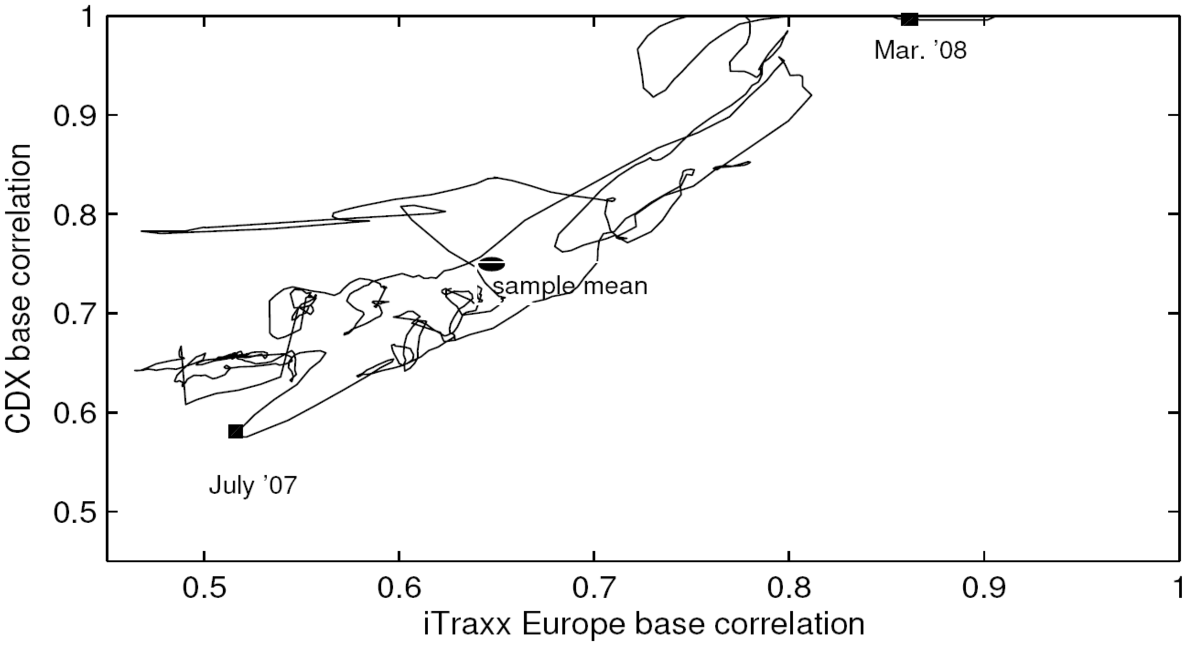


Figure 3: Implied and Realized Correlation from Correlation Swap Quotes

This figure shows the six-month moving average of the implied (IC_MA) and the realized correlation (RC_MA) from correlation swaps quotes. The data is based on the period January 1996 to December 2008.

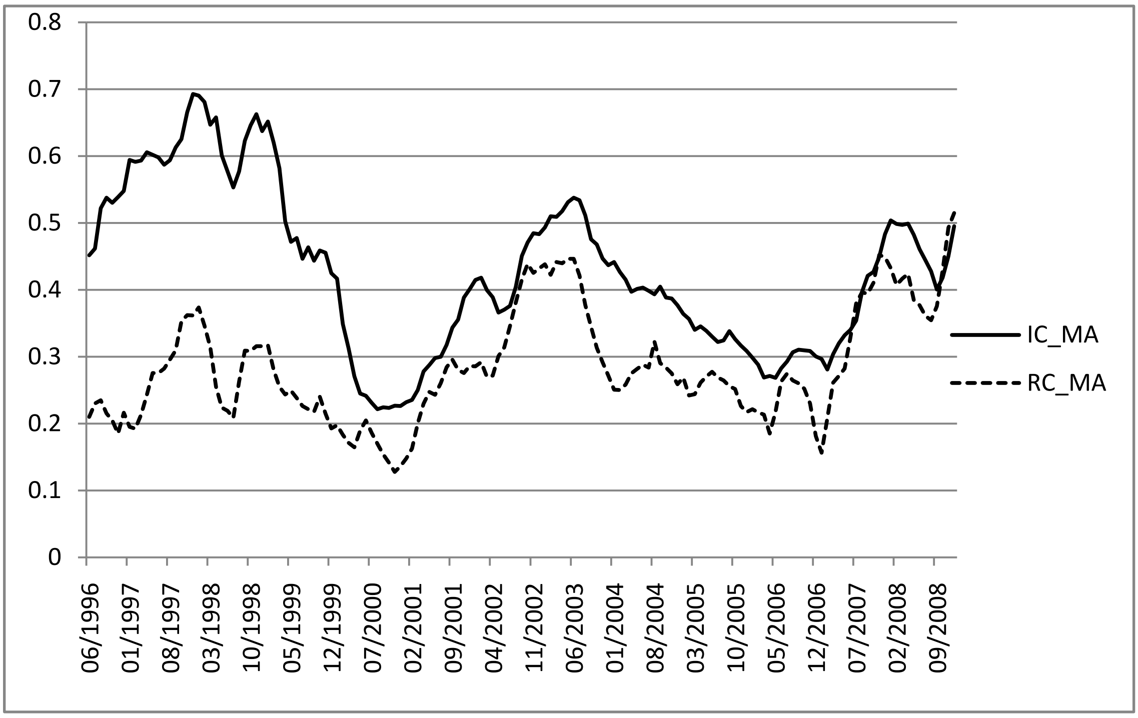


Figure 4: Hedge Fund Taxonomy

This figure illustrates the classification of hedge fund categories according to their risk properties (as often found in industry classifications).

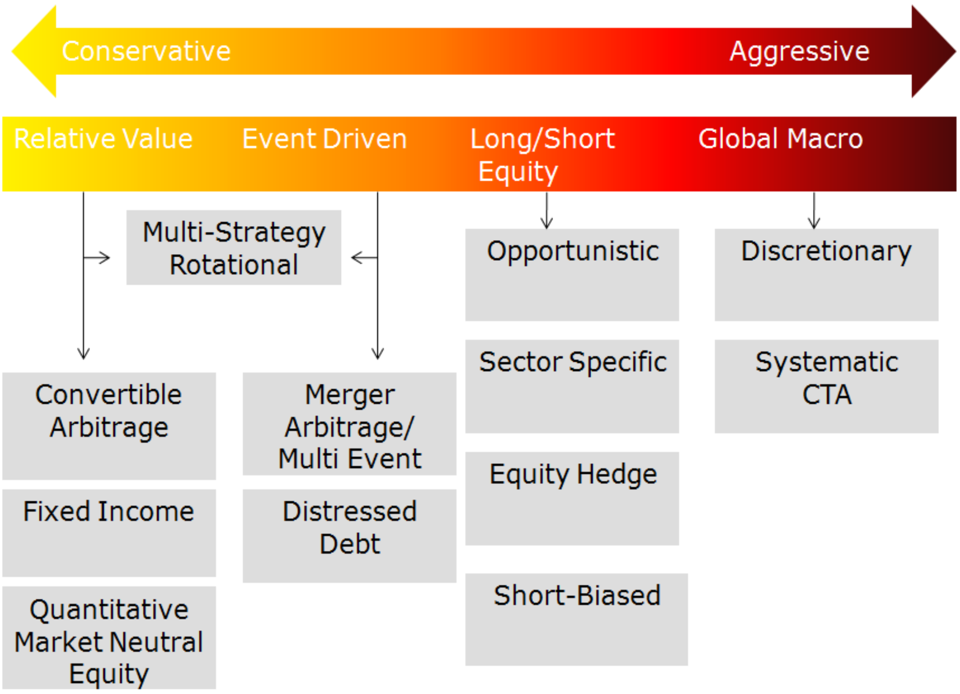


Figure 5: Moving Average Plot of Correlation Risk Premium and S&P500 Return

This figure plots the 12-month moving average of the return of the correlation swap (based on correlation swap market quotes and abbreviated CR_MA) and the S&P500 return (S&P_RF_MA) over time. The sample period is from April 2000 to March 2008.

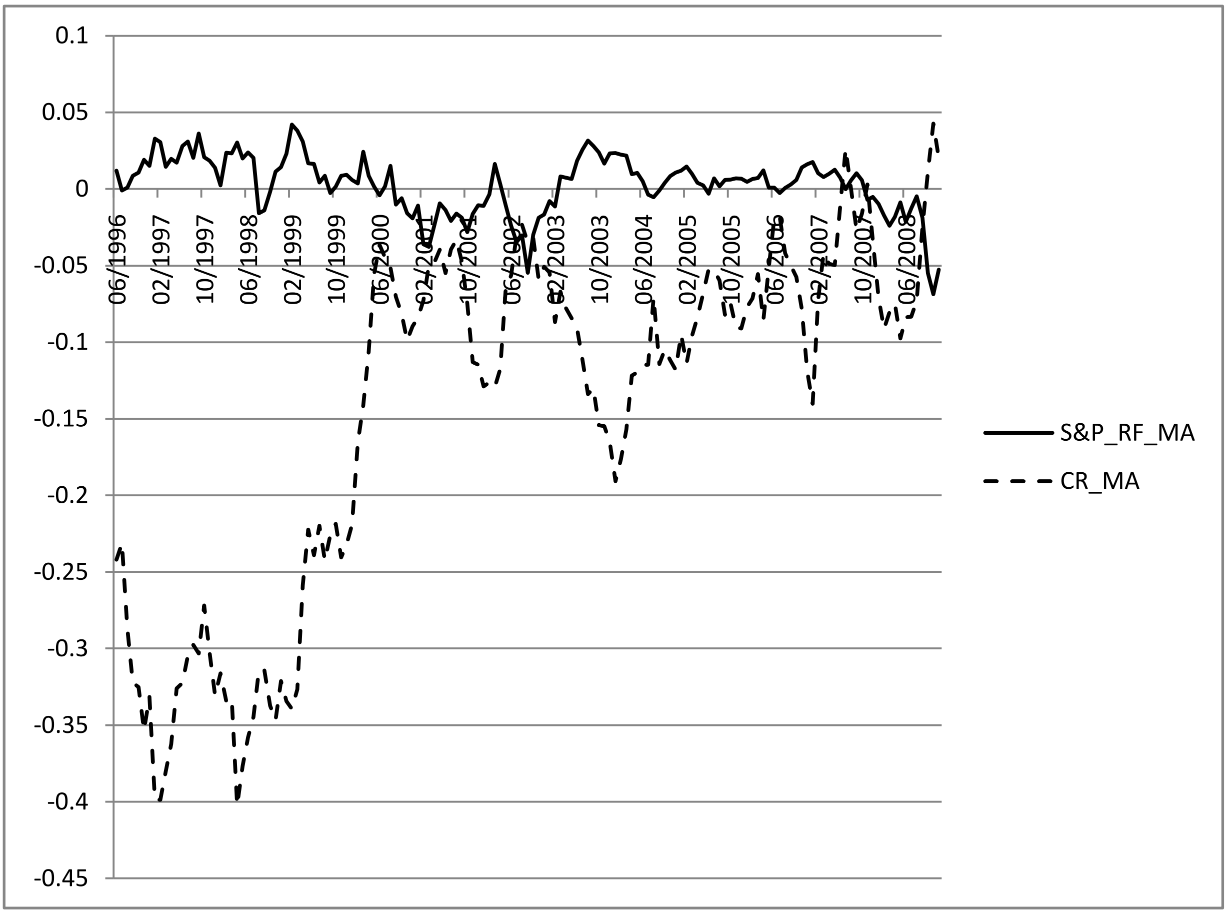


Figure 6: Drawndowns and Correlation Risk Exposure

In this figure, we plot the maximum drawdown for decile portfolios sorted based on funds' beta with respect to realized correlation. The 'low' portfolio has the lowest, that is the most negative, beta, while the 'high' portfolio has the highest, that is the most positive beta. A negative beta with respect to correlation implies that when correlation increases a fund's return decreases. Funds in the low correlation portfolio have the most negative exposure to correlation risk. Maximum drawdown (MDD) is the sum of the longest sequence of consecutive losses. It is measured in percent per month. The solid line (MDD) plots the cross-sectional average maximum drawdown of funds in each decile. The dashed line (MDD EW) plots the maximum drawdown of an equal weighted portfolio of the funds in each decile. The betas are calculated using data from January 1996 until December 2008.