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

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Using a novel data set on correlation swaps, we study the relation between correlation risk, hedge fund characteristics, and their risk-return profile. We find that the ability of hedge funds to create market-neutral returns is often associated with a significant exposure to correlation risk, which helps to explain the large abnormal returns found in previous models. We also estimate a significant negative market price of correlation risk, which accounts for the cross-section of hedge fund excess returns. Finally, we detect a pronounced nonlinear relation between correlation risk exposure and the tail risk of hedge fund returns. (*JEL* D9, E3, E4, G11, G14, G23)

This paper analyzes the relation between correlation risk exposures, hedge fund characteristics, and the cross-sectional profile of individual hedge funds' risk and return.

Correlation risk arises because of an unexpected change in the correlation of the returns between different assets or asset classes, which can be linked to an adverse evolution of portfolio diversification opportunities. A suboptimal exposure to correlation risk in a managed portfolio can generate undesired properties, such as a low hedging effectiveness against the risks of some

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portfolio components and/or an undesired degree of underdiversification. Faced with time-varying diversification opportunities, risk-averse investors might prefer trading strategies with higher payoffs in states of low diversification benefits and be willing to pay a premium for assets that have higher payouts when the correlation among some asset returns or asset classes is large. Krishnan, Petkova, and Ritchken (2009a, 2009b), for instance, present empirical evidence that time-varying stock and stock-bond correlations are linked to a systematic risk that is priced in the cross-section of stock returns.

Although correlation risk is an important concern for the development of investment strategies in general, it can be a special concern for hedge funds for a number of reasons. First, a key feature of hedge funds is that they follow an investment mandate with an absolute return objective, that is, a return uncorrelated with the whole market (Ineichen 2002). To achieve this objective, they reduce market beta, often making use of a variety of long-short arbitrage strategies with low net exposure, typically requiring assumptions on the dynamics of hedge ratios and market betas to implement the risk immunization. When correlations are not constant, such strategies can generate a potential additional exposure to correlation shocks, because time-varying hedge ratios and market betas are not observable in reality and have to be estimated based on explicit or implicit correlation assumptions.[1]

Second, hedge funds' legal structure grants them contractual flexibility, such as lock-ups for investors, whose legal rights are those of a limited partner, as opposed to those of a retail client. These features allow the prime broker to grant special funding conditions to hedge funds, under which they can implement strategies that are not accessible to, for example mutual funds. The funding role played by prime brokers implies a potentially fragile capital structure. As the 2007–2008 experience shows, when prime brokers increase hedge funds' collateral requirements and mandate haircuts in response to a more acute counterparty risk during systemic crisis events, they also tend to force a deleveraging of funds' arbitrage positions. Given the relatively small number of prime brokers, it has been argued that such effects can have implications for the systematic nature of correlation shocks.[2]

Third, in contrast to mutual funds, hedge funds can trade options and derivatives, which expose them directly to correlation and volatility shocks. A growing body of literature has documented that, on average, option-implied volatilities and correlations are larger than are realized volatilities and correlations. This difference is interpreted as a (negative) risk premium for bearing market volatility and correlation risk, respectively (see

[1] For instance, Khandani and Lo (2007) report that during the week of August 6, 2007, many market-neutral Long/Short Equity funds experienced unprecedented losses, ranging from −5% to −30% per month. They suggest that the risk reallocation after the Bear Stearns debacle induced large shocks in asset correlations that precipitated into heavy losses for these funds.

[2] A large body of 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; Engle and Sheppard 2006; among others).

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Bakshi and Kapadia 2009; Bollen and Whaley 2004; Carr and Wu 2009; Driessen, Maenhout, and Vilkov (DMV) 2009; among others). Therefore, a hedge fund performance evaluation framework abstracting from these risk factors can potentially produce misspecified models of risk-adjusted returns.

To measure exposure to correlation risk, we collect a time-series of market prices for the average correlation of S&P 500 stocks, using a unique data set of actual correlation swap quotes. Because the correlation swap rate equals the forward price of the average S&P 500-realized correlation, correlation swaps provide a natural traded proxy for the price of correlation risk. Based on an extended eight-factor specification, which incorporates standard risk factors used in the literature together with our correlation risk proxy, we then study the relation between correlation risk exposures and the cross-sectional profile of individual hedge funds risks and returns.

First, we find that hedge funds as an industry are exposed to correlation risk. When studying correlation risk exposures conditional on funds' investment objective, we document that broad classes of funds, such as Long-Short Equity, Option Trader, Funds of Funds, and Managed Futures, have a significant negative exposure to correlation risk. Such an exposure can explain a substantial fraction of hedge fund returns and can imply economically relevant corrections in funds risk-adjusted performance, relative to benchmark performance attribution models in the literature. These classes of funds often have a lower risk-adjusted performance, after accounting for correlation risk exposure. For instance, the annualized risk-adjusted performance of Long-Short Equity, Option Trader, and Managed Futures funds becomes insignificant, falling from 4.64%, 8.98%, and 6.05% to 2.80%, 3.91%, and 0.95%, respectively, when a correlation risk factor is added to the benchmark Fung-Hsieh (FH; 2004) seven-factor model. Indeed, more than 40% of the classes of funds with a statistically significant alpha with respect to the benchmark FH model have an insignificant alpha after controlling for correlation risk exposure.

Second, individual hedge fund returns sorted with respect to their correlation risk beta can imply an economically large variation in risk-adjusted performance, after controlling for individual leverage effects, exposure to pure variance risk and other standard hedge fund risk factors in the literature. For instance, the difference between the annualized alphas of the top and bottom decile portfolios sorted with respect to their correlation risk exposure is only 0.23% in the benchmark FH model. In contrast, the largest difference in alphas with respect to a valuation framework extended by the correlation risk factor is about 4.84%. We also find that correlation risk exposure explains in most cases the largest fraction of the average return of funds that are more short correlation, indicating that it might also systematically explain substantial differences of average returns across funds.

Third, with a two-pass Fama-Macbeth (1973) approach, we test whether correlation risk, measured by the return of a correlation swap, is priced in the cross-section of hedge fund returns. We consider an extended FH eight-factor

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performance evaluation framework that additionally includes our correlation risk proxy and estimate a significant negative correlation risk premium that ranges between −2.61% and −4.27% (−3.15% and −2.07%), on a monthly basis, using the BarclayHedge (TASS) database.[3] These risk premia suggest that funds with large negative correlation risk exposure have higher returns on average. In contrast, we find no significant evidence that other standard hedge fund risk factors or pure market variance risk are priced in the cross-section of hedge fund returns.

Fourth, we document an asymmetric U-shaped relation between correlation risk exposure and tail risk in the cross-section of hedge fund returns. We find that portfolios of funds with (negative) correlation risk betas in the bottom deciles, that is, sellers of insurance against unexpected deteriorations in diversification opportunities, typically have the largest maximum drawdowns. For instance, in the period between January 1996 and June 2012, we find that the maximum drawdown of an equal-weighted portfolio of funds in the decile with the most negative correlation risk beta is about 55% on a monthly basis. In contrast, the maximum drawdown of a portfolio of funds in the deciles with a small absolute correlation risk beta is only about 20%, whereas the maximum drawdown of the decile portfolio with the largest (positive) correlation risk beta is about 40%. This evidence indicates that hedge funds with negative correlation risk exposure tend to suffer large losses more frequently at similar times. Often this occurs during economic crises when correlations increase, thus making correlation risk a nondiversifiable factor in the cross-section of hedge fund returns.

Finally, our results are robust to the use of alternative databases, such as BarclayHedge and TASS, to the use of equal-weighted, instead of value-weighted indexes, to extended benchmarks that include liquidity, credit, or pure market volatility risk factors, to individual fund characteristics, such as self-reported leverage, and to alternative proxies of correlation risk based on option factor-mimicking portfolios.[4] The results are also robust to the use of either WLS or GLS estimators, which have different finite sample properties (Shanken and Zhou 2007).

Our work borrows from different streams of the literature on hedge funds, portfolio choice, and derivatives pricing. First, we complement the literature on hedge fund performance and risk evaluation (see Agarwal and Naik 2004; Bollen and Whaley 2009; Ding et al. 2010; Fung and Hsieh 1997, 2001, 2004; Patton and Ramadorai 2013; among others). In contrast to mutual funds, a number of empirical studies have documented a positive alpha in hedge fund returns. Our results indicate that part of this evidence can be biased by the

[3] The first estimate refers to weighted least squares (WLS) and the second one to generalized least squares (GLS) estimators.

[4] Aragon (2007), Sadka (2010), and Teo (2011) find that liquidity helps explain cross-sectional differences in hedge fund returns.

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misspecification of performance attribution models not considering correlation risk: negative exposure to this source of risk systematically reduces ceteris paribus the hedge fund alphas implied by such models. Our findings are also distinct from those of Bondarenko (2004) and Agarwal, Bakshi, and Huij (2008). These authors focus on the time series of hedge funds index returns, whereas we provide evidence at the individual fund level, controlling for individual characteristics in a large panel of individual funds. We document the key economic role of correlation risk exposures for the cross-section of hedge fund returns and show that it is different from the one of volatility risk exposures.

Second, our findings are related to the optimal portfolio choice literature. Buraschi, Porchia, and Trojani (2010) show that the optimal hedging demand against unexpected changes in correlations can be a nonnegligible fraction of the myopic portfolio, often dominating the pure volatility hedging demand. In related work, Leippold, Egloff, and Wu (2010) find that the dynamic optimal portfolio with index variance swaps is very different from the one of an investor who can invest only in the index and the riskless asset. Detemple, Garcia, and Rindisbacher (2010) use factor regression models with option-like risk factors and no-arbitrage principles to identify the market price of hedge funds risk, the volatility of hedge fund returns, and the correlation between hedge fund and market returns. Our findings are consistent with this literature, as correlation risk emerges as a factor in the return characteristics of hedge fund portfolios.

Finally, our work is also related to the literature that investigates variance and correlation risk premia in equity options (see Buraschi and Jackwerth 2001; Bakshi and Kapadia 2009; Duarte and Jones 2007; Carr and Wu 2009; DMV 2009; among others). These papers document the systematic differences between implied and realized index correlations (volatilities) that give rise to a negative correlation (volatility) risk premium. Nonzero volatility and correlation risk premia are also consistent with the intuition of theoretical economic models. Drechsler and Yaron (2011) provide theoretical arguments for the emergence of a market volatility risk premium in an economy with time-varying macroeconomic uncertainty. Buraschi, Trojani, and Vedolin (2013) show that negative volatility and correlation risk premia are consistent with a general equilibrium model with heterogenous beliefs. They also find empirical evidence that volatility and correlation risk premia are more negative in periods of increased uncertainty or diversity in beliefs.

The rest of the paper is structured as follows. Section 1 discusses the choice of our hedge fund databases and the main properties of correlation swap data. Section 2 reviews the basic hedge fund return decomposition methodology, defines the risk factor for correlation/variance risk, and addresses computational aspects. Section 3 reports and discusses the empirical results, and Section 4 concludes. The Online Appendix summarizes additional empirical evidence, data information, and robustness checks.

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1. Data

Our main survivorship bias-free hedge fund return data is from the BarclayHedge database, which contains net-of-fee hedge fund returns from 1996 to June 2012.[5] After applying a range of data filters and excluding funds of funds, our sample includes 13,930 individual hedge funds.

Compared with other popular commercial hedge fund databases, such as TASS, a useful property of the BarclayHedge database for our analysis is that it provides information about individual fund's short and long exposure. Net exposure is defined as the ratio of the dollar value of the net long and short positions over the NAV of the fund. A fund net exposure can be interpreted as a measure of the directional market exposure that resides "unhedged" in a hedge fund portfolio.[6] Therefore, it can be used to gain economic insight into the origins and the potentially different role of correlation risk across funds with different degrees of directional market exposures. We use net exposure information to 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 with self-reported net exposure below 30% in June 2012. The second subgroup consists of Long-Short Equity (LSE) funds with net exposure below 30%. We label these funds LLNE.

Overall, the most represented hedge fund categories in our data are Long/Short Equity (1,728), Equity Long (1,395), Managed Futures (3,891), Equity Market Neutral (443), Macro (436), and Option Trader (397). Class ALNE has 1,044 funds and there are 584 funds in class LLNE. Funds of Funds (4,667) is also well represented in our data. Although we consider them when studying aggregate exposures to correlation risk, we disregard them in our cross-sectional analysis, to avoid well-known biases documented in the literature.[7] Panel A of Table 1 reports summary diagnostics for all funds and investment objectives, on which we focus.

Which investment objectives do funds with low net exposure tend to have? We find that more than 50% of the 1,044 low net exposure funds belong to the Long-Short Equity category (584 funds), providing some support to the self-declared investment objective. We also see in Table 2 that a value-weighted index of all funds (all funds with low net exposure, ALNE) has an annualized average return of 6.88% (6.49%). About 68% (62%) of this return is deriving from an annualized alpha of 4.65% (4.05%) with respect to the benchmark

[5] The sample period is determined by the availability of Optionmetrics data, which are available from January 1996 and onward.

[6] We assume for simplicity that long and short positions are balanced along dimensions, such as style, capitalization, and industry.

[7] Funds of funds are typically excluded in performance persistence tests, because they tend to generate a persistently low performance, implying a potentially biased evidence of performance persistence for individual funds (Kosowski, Naik, and Teo 2007). Moreover, funds of funds consist of individual hedge funds. Therefore, to avoid double counting, we focus on individual funds in our cross-sectional tests. In results available upon request we find that our conclusions are unchanged when funds of funds are included.

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Table 1
Summary statistics of hedge funds returns

Panel A: Summary statistics for hedge fund excess returns

Investment objective	ALL (except FoF)	All LNE (ALNE)	Long/ Short Equity (LSE)	Low Net Exposure (LLNE)	Equity Long (EL)	Equity Market Neutral (EMN)	Options Trader (OPT)	Event Driven (ED)	Distressed Securities (DS)	Merger Arbitrage (MA)	Fixed Income (FI) Relative Value	Convertible Arbitrage (CA)	Macro (MAC)	Emerging Markets (EMG)	Funds of Funds (FOF)	Multistrategy (MUL)	Managed Futures
# Funds	13,930	1,044	1,728	584	1,395	443	397	344	199	129	267	292	436	1,230	4,667	355	3,891
Mean	0.57	0.54	0.59	0.50	0.57	0.29	0.88	0.64	0.55	0.39	0.44	0.45	0.64	0.77	0.38	0.63	0.62
SD	1.76	2.09	2.20	2.16	3.48	1.20	2.56	2.46	1.74	1.10	1.49	2.44	2.25	4.64	2.09	1.22	3.00
Skew	−0.11	−0.20	0.13	−0.03	−0.81	−0.30	0.26	−2.10	−1.11	−1.28	−1.57	−1.64	0.25	−1.07	−0.81	−1.39	0.45
Kurt	3.23	5.10	4.50	4.96	4.47	4.11	5.61	13.58	5.98	7.24	9.04	11.91	5.62	8.22	6.61	8.51	3.21
Min	−5.89	−6.46	−5.62	−7.34	−13.51	−3.87	−8.09	−15.96	−6.96	−5.14	−7.39	−14.23	−9.29	−21.40	−9.28	−6.12	−5.66
Med	0.52	0.73	0.62	0.51	1.19	0.31	0.64	0.91	0.69	0.50	0.63	0.52	0.44	1.35	0.36	0.75	0.38
Max	5.16	8.46	9.25	7.68	7.94	3.45	9.39	7.54	4.30	2.94	4.72	7.24	8.83	15.98	6.63	3.56	10.37
Alpha	0.48	0.43	0.46	0.39	0.30	0.24	0.82	0.50	0.47	0.33	0.40	0.30	0.55	0.50	0.26	0.58	0.65
Beta	0.21	0.27	0.31	0.25	0.64	0.11	0.12	0.32	0.19	0.15	0.09	0.34	0.20	0.64	0.27	0.11	−0.06
SR	0.33	0.26	0.27	0.23	0.16	0.24	0.34	0.26	0.32	0.36	0.30	0.18	0.28	0.17	0.18	0.52	0.21
TM	2.35	1.57	1.45	1.55	0.47	2.07	6.77	1.54	2.47	2.19	4.33	0.91	2.77	0.78	0.96	5.24	−11.06
Msq	1.76	1.45	1.50	1.32	1.00	1.35	1.84	1.45	1.72	1.90	1.63	1.10	1.57	1.02	1.09	2.66	1.21

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.	29.40	−5.74	−4.79	−4.36	−9.01	−2.91	−0.81	−8.78	−6.36	−3.61	−4.97	−11.50	−2.76	−16.76	−7.49	−5.97	−2.04
2007/July	13.50	−0.06	0.61	1.00	−1.09	0.99	−0.11	0.64	1.80	0.62	0.67	−0.04	1.16	2.96	0.86	0.01	−1.63
2007/Feb.	24.40	0.22	1.04	0.97	0.34	1.18	−0.85	1.09	2.09	1.42	0.80	1.37	0.17	1.99	1.27	0.70	−2.20
2006/May	9.00	−1.67	−2.59	−2.36	−3.01	0.33	−1.61	−0.99	1.17	0.44	0.64	0.39	−2.45	−4.84	−1.24	−0.58	−1.40
2005/Oct.	12.70	−1.06	−1.45	−0.22	−2.75	−0.42	0.84	−2.34	−0.45	−1.29	0.90	−0.14	−2.02	−2.18	−1.47	−0.29	−0.09

This table reports summary statistics for monthly value-weighted hedge fund index excess returns of seventeen hedge funds categories (Panel A) and the performance of different hedge fund styles in crisis months (Panel B). The first row in Panel A reports results for a value-weighted average of all hedge funds, including all investment objectives in the database, but 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 %. LSE Low Net Exposure (LLNE) funds are Long/Short Equity (LSE) funds that are reported to have a net long/short exposure below 30%. The value-weights are rebalanced every month based on the fund's assets under management. Returns are expressed in percent per month. The sample period is January 1996 to June 2012. Rows 2 to 8 report the mean, standard deviation, skewness, kurtosis, minimum, median, and maximum of monthly index returns. Rows 9 to 13 report alpha and beta coefficients (with respect to the S&P 500), the Sharpe Ratio (SR), the Treynor's measure (TM), and the M-squared measure. Panel B reports monthy returns for hedge fund indexes and benchmark factors in recent stock market crisis months. Panel B reports the returns (in percent) of the correlation risk factor and of different fund styles in crisis months.

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seven-factor FH performance attribution model. Similarly, a value-weighted index of LSE funds (LSE funds with low net exposure) has an average return of 7.09% (5.99%), a market beta of 0.3 (0.23), and a fraction of 65% (61%) of this return ascribed to the fund's FH alpha.

Are these large alpha contributions to fund returns due exclusively to fund skill, or are they rather the consequence of an inappropriate measurement of some of the implicit risks of the trading strategies used by hedge funds? A preliminary unconditional analysis indicates that the average low net exposure fund can have a larger tail risk than the average fund, with a VaR of \$3.15 million for the first class, which is almost double the VaR of \$1.74 million for the second class.[8] As motivated in the introduction, funds with a low net exposure, applying long/short strategies to reduce market beta, could tend to generate a larger exposure to unexpected shocks in correlation among assets than more directional funds. Therefore, whether exposure to correlation risk can capture some of the cross-sectional differences in hedge funds risk-return trade-off is a relevant question, which needs to be addressed.

To measure correlation risk and exposure to it, we collect market prices for the average correlation of S&P 500 stocks in the sample period April 2000 to June 2012, using a unique data set of actual correlation swaps obtained from the leading market maker for these contracts (a major international bank). As detailed more precisely in Section 2.2 and in the Online Appendix, a correlation swap is a contract that pays the difference between the realized correlation in a basket of assets, over a given investment horizon, and the so-called correlation swap rate. The net payoff is settled in cash at the expiration of the contract, so that the correlation swap rate is the forward price of the realized correlation of the constituents in the basket. Because the cost at initiation of the swap is zero, this payoff is the excess return of a traded asset, which provides an ideal variable to control for correlation risk in the context of a performance attribution model. Our correlation swap data consists of daily implied and realized correlation quotes for one-month maturity contracts on the average correlation of S&P 500 stocks. Implied correlation swap quotes are constructed to correspond to the midpoint of the bid and the ask price of the correlation swap.[9]

Beyond the availability of net exposure information, the use of the BarclayHedge database is motivated by a number of useful features, with respect to other commercial databases, such as TASS, Eurekahedge, HFR, or Morningstar. First, as documented in Joenväärä, Kosowski, and Tolonen (2012), the BarclayHedge database has the largest number of funds and the highest percentage of dead funds, thus making it least likely to suffer from survivorship bias. Second, it has the lowest percentage (11%) of missing Assets under Management (AuM) information and the longest AuM time series,

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8 We estimate VaR using a simple parametric 95% Value-at-Risk, based on a hypothetical \$100 million portfolio invested in the value-weighted indexes.

9 The Online Appendix provides further detailed information.

making it more appropriate for studying value-weighted hedge fund returns. For comparison, the percentage of missing AuM information in the TASS database is about 34%.

Joenväärä, Kosowski, and Tolonen (2012) also document that, despite the small overlap of funds in BarclayHedge and TASS, these databases are similar with respect to a number of other important properties, including the evidence of performance persistence in individual hedge fund returns. Therefore, to check the robustness of our results, we estimate hedge funds individual correlation risk exposures and the market price of correlation risk also using the TASS database.

2. Methodology

In this section, we present the methodology we use 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 to include the return of a long correlation swap position. We then discuss the construction of the proxy for the return of a correlation swap, using direct correlation swap quotes for the period April 2000 to June 2012, and synthetic correlation swap quotes, implied by the cross-sections of option prices of S&P 500 index and individual stock options, in the period from January 1996 to March 2000.

2.1 Hedge fund return decomposition

The literature on hedge fund performance attribution takes into account the unique nature of hedge fund strategies. It extends benchmark performance attribution regressions with variables capturing either (1) priced risk dimensions that help explain risk premia or (2) other variables that correlate with realized hedge fund returns, even though these might not give rise to a priced source of risk in the traditional sense.

Our starting benchmark is the standard FH seven-factor model, in which hedge fund's returns $r_{i,t}$ are decomposed into their risk-adjusted performance component (α_i) and the return components associated with the factor exposure (β_i^k) of each risk factor. To capture a potential link among hedge fund returns, hedge fund business styles, and exposure to correlation risk, we extend the FH factor model by the return of a long correlation swap position, denoted by CR_t. We call, for brevity, the resulting eight-factor model the BKT benchmark model:

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

where $r_{i,t}$ is the monthly return on portfolio i in excess of the one-month Treasury-bill return; $SNPMRF$ is the S&P 500 excess return; $SCMLC$ is

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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 definition and construction of the correlation swap return CR_t is discussed in the sections that follow. Additional details are provided in the Online Appendix.

2.2 Construction of correlation and volatility risk factors

Market proxies for correlation (variance) risk should replicate the excess return of a payoff proportional to the realized correlation (variance) risk over the relevant investment horizon. Correlation (variance) swaps are claims with payoffs proportional to the difference of the realized stock market correlation (variance) and the price of the realized stock market correlation (variance). Therefore, swap quotes make the market price of correlation and variance risk readily observable and their payoff is a natural proxy for the excess return of a static investment strategy, creating a pure exposure to correlation (variance) risk over a given investment period.

When correlation and variance swap market quotes are not directly available, the price of variance and correlation can be estimated from the price of a standard static-replicating portfolio investing in a continuum of liquid out-of-the-money index and individual equity options. Correlation swaps help to benchmark the monthly reporting of hedge fund returns with respect to the return of a static long correlation swap, whereas option factor-mimicking portfolios for correlation risk, such as dispersion portfolios, imply a more unbalanced holding period, for example, because index options expire on the Saturday after the third Friday of each month.[10] Similarly, buying options with maturities above one month and selling them before expiration, captures changes in implied volatility, less precisely isolating the volatility or correlation risk premia on the given reporting period. Moreover, dynamic factor-mimicking portfolios for correlation risk require a dynamic delta and vega hedging, with model-dependent hedging ratios that can generate undesired residual exposures to market or volatility shocks.

The correlation swap market was created in the early 2000s by banks interested in hedging the correlation risk embedded in their structuring books. Before the creation of this market, banks were trading correlation by using dispersion portfolios. Correlation swaps allowed banks to manage correlation risk more directly. However, correlation swaps are, unlike options, over-the-counter-derivatives that can embed a rent for the intermediary or a potential premium for illiquidity. Thus, the correlation risk premium implied

[10] A dispersion trading strategy typically involves short positions in index options and long positions in individual options. Dispersion trading is designed to take advantage of relative value differences in implied volatilities between an index and a basket of component stocks.

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by correlation swaps can underestimate the actual correlation risk premium in the market.

2.2.1 Correlation swaps and correlation risk factor. Correlation swap contracts are becoming increasingly popular and are the natural vehicle to hedge unexpected changes in the average pairwise correlation of a predetermined basket of assets. A swap buyer pays implied correlation at the maturity T of the contract, that is, the correlation swap rate $SC_{t,T}$ and receives the correlation $RC_{t,T}$, realized from the initiation to the maturity of the contract. Because the initial price of the correlation swap is zero, the correlation swap rate equals the arbitrage free price of the realized correlation, that is, its risk neutral expected value:

$$SC_{t,T} = \mathbb{E}_t^{\mathbb{Q}}[RC_{t,T}], \tag{2}$$

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

$$CR_{t,T} := L \cdot (RC_{t,T} - SC_{t,T}). \tag{3}$$

Empirically, this spread is typically negative on average, which is strong support for the hypothesis of a negative unconditional correlation risk premium:

$$CRP_{t,T} = \mathbb{E}^{\mathbb{P}}\left[RC_{t,T}\right] - \mathbb{E}^{\mathbb{Q}}\left[RC_{t,T}\right] = \mathbb{E}^{\mathbb{P}}\left[RC_{t,T}\right] - SC_{t,T} < 0\,, \tag{4}$$

where $\mathbb{P}$ is the physical (statistical) probability measure. Such a negative risk premium can arise because states of large average stock market correlations are states of low diversification opportunities, in which, in equilibrium, risk-averse investors are forced to bear a larger amount of nondiversifiable risk. Because a long position in a correlation swap provides insurance against unexpected deteriorations in diversification opportunities, its average excess return, the correlation risk premium, is negative. Similarly, a short correlation swap implies a positive exposure to unexpected deteriorations in diversification opportunities, which is compensated ex ante by a positive correlation risk premium.

A useful property of the BKT model in Equation (1) is that all right-hand-side variables represent the return of a tradable asset, thus allowing us to obtain a market-based factor model in which the regression intercept has the interpretation of a risk-adjusted measure of abnormal return. In our empirical BKT performance attribution regression, we construct the return RC_t of a long correlation swap in the time period from April 2000 to June 2012 directly from swap market quotes. In the period from January 1996 to March 2000, correlation swap quotes are not available. Therefore, we use a time series that is based on a synthetic replication of correlation and index variance swap rates, by computing

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swap rates from the price of a static replicating portfolio consisting of liquid out-of-the-money index and individual equity options, following Bakshi, Kapadia, and Madan (2003) and DMV (2009). The Online Appendix provides details on our synthetic computation of correlation and variance swap rates.

2.2.2 Main empirical features of correlation and volatility risk proxies. The median monthly payoff of a variance swap on the S&P 500 index variance is -18.5% squared in our sample, whereas the median monthly payoff of a correlation swap on the average correlation of S&P 500 stocks is -7.3% (see Table A1 of the Online Appendix).[11] Consistent with the literature (see, e.g., Bakshi and Kapadia 2009) the unconditional correlation risk premium of S&P 500 stocks in our sample is a large fraction (about 40%) of the total S&P 500 index volatility risk premium. This finding is confirmed by the fact that the estimated average volatility risk premium of individual stocks is also small and not statistically significant in our sample period: when we consider the thirty most liquid constituents of the S&P 500 index, their average implied volatility is 31.6% and their average realized volatility is 32.6%, implying a statistically insignificant average individual volatility risk premium.

From the perspective of an unconditional mean variance investor, short correlation and variance swaps have been quite attractive investment strategies in our sample period: the annualized Sharpe ratio of a short correlation (index variance) swap in our sample is about 0.55 (0.47), which is more than six times larger than the Sharpe ratio of 0.09 deriving from a simple investment in the S&P 500 index. Correlation and variance swaps imply a quite different risk profile not only in terms of their mean-variance properties, but also with respect to the higher order moments of their payoffs: whereas short variance swap positions imply payoffs with large tail risk and a pronounced nonnormality, correlation swaps imply payoffs with a more moderate unconditional skewness and kurtosis (see again Table A1 of the Online Appendix). These simple statistics highlight the distinct role of correlation and variance risk in producing return components with different (unconditional) risk-return profile. Interestingly, the proxies of correlation and index variance risk also feature different time series and persistence properties: whereas correlation swaps imply returns with significant autocorrelations at lags of 1–4 months, the returns of index variance swaps are less autocorrelated.[12]

Another interesting property of the returns of correlation swaps is an apparent nonlinearity with respect to aggregate stock market shocks, which suggests a

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[11] In the sample period 1996–2003, DMV (2006) estimate a monthly average realized correlation of 28.6% and a monthly average implied correlation of 46.7%, implying an unconditional correlation risk premium of -18.1% per month. For their sample period, we obtain a monthly correlation risk premium of -9.2%, implied by an average realized correlation of 27.5% and an average implied correlation of 36.7%.

[12] For instance, the first three autocorrelations of the correlation (variance) risk proxy are 0.32, 0.18, and 0.21 (0.26, -0.07, and 0.04), respectively. The confidence intervals are 0.14 given the sample size of 198 observations.

potentially increased role of correlation risk in explaining hedge fund returns, during periods of market or financial distress. For instance, the returns of S&P 500 correlation swaps were 29.4%, 17.5%, and 12.6% per month in September, October, and November 2008, as a consequence of extraordinarily high levels of average realized stock correlations, thus reminding investors and proprietary trading desks that shorting correlation swaps is a risky strategy rather than an arbitrage opportunity.

Although large positive returns of correlation swaps tend to be positively related to aggregate market losses during phases of market distress, it is important to realize that the sample correlation between S&P 500 index and correlation swap returns is only −50% on a monthly basis, indicating that correlation shocks generate a nonredundant source of risk with respect to aggregate market shocks. This feature implies that correlation risk is a potentially relevant risk factor also for hedge fund portfolios consisting of market-neutral positions. Moreover, the large correlation swap returns of 8.7% and 29.4% in August 2007 and September 2008 also suggest a potential link between correlation risk exposures and hedge fund returns. A value-weighted index of all Low Net Exposure Funds (Long-Short Equity funds) produced a large monthly loss of −1.1% (−1.4%) and −5.61% (−4.79%), respectively, in those months.

Useful features of correlation risk exposures for explaining hedge fund returns emerge when considering distinct hedge fund categories. Table 2, Panels B and C, shows that correlation risk exposures across aggregate hedge fund categories can be significant for classes of funds that include, for example, funds with low net exposure and long-short equity funds, funds of funds, managed futures funds, and funds that explicitly follow option strategies. Because correlation risk exposures are tightly linked to the nonlinear risk profile of correlation shocks, it is a natural hypothesis that they might also explain some features of the cross-section of hedge fund returns. For instance, in the crisis month September 2008 (October 2008), which was a very negative month for most of the hedge fund industry, we find that while a portfolio of the decile of funds with the highest positive correlation risk beta generated a return of −1 (+20)%, the portfolio of the decile of funds with the lowest negative correlation risk beta suffered a negative return of −6% (−5%).

3. Empirical Findings

In this section, we study systematically the empirical relation between correlation risk and hedge funds risk-return profile. Hedge fund trading styles are very heterogeneous. Therefore, even though hedge fund returns might often indicate a significant exposure to correlation and variance risk at the index level, the degree to which these risks explain individual fund returns in the time series might strongly depend on the characteristics of each hedge fund strategy. Cross-sectional heterogeneities in correlation risk exposures might

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Table 2
Return decomposition of hedge fund index returns

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.)	6.88	6.49	7.09	5.99	6.83	3.43	10.51	7.64	6.60	4.71	5.31	5.39	7.67	9.30	4.56	7.54	7.45
IR (p.a.)	0.29	0.22	0.27	0.18	0.13	0.16	0.29	0.24	0.32	0.35	0.22	0.11	0.23	0.10	0.10	0.53	0.19
Alpha (% p.a.)	4.65	4.05	4.64	3.66	2.53	2.12	8.98	5.09	4.83	3.31	3.28	2.07	5.35	4.03	1.79	6.53	6.05
Beta S&P	0.20	0.25	0.30	0.23	0.59	0.11	0.11	0.23	0.10	0.12	0.02	0.24	0.21	0.48	0.22	0.06	0.04
Beta SCM	0.10	0.20	0.22	0.19	0.24	−0.03	0.04	0.09	0.08	0.06	0.03	0.14	0.21	0.17	0.11	0.03	0.04
Beta BD10RET	0.15	0.11	0.08	0.12	0.08	0.09	0.06	−0.05	−0.04	0.05	0.18	0.17	0.19	0.08	0.12	0.00	0.34
Beta BAAmTSY	0.19	0.14	0.10	0.14	0.22	0.08	0.12	0.32	0.29	0.14	0.36	0.49	0.04	0.67	0.30	0.22	0.09
Beta PTFSBD	0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.02	−0.04	−0.03	−0.01	−0.02	−0.01	−0.01	−0.04	−0.02	−0.01	0.02
Beta PTFSFX	0.02	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.05
Beta PTFSCOM	0.02	0.01	0.01	0.01	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.04
t-stat Alpha	4.03	3.12	3.73	2.50	1.90	2.30	4.13	3.41	4.45	4.91	3.10	1.55	3.21	1.43	1.38	7.40	2.65
t-stat S&P	8.97	9.55	12.15	7.96	22.33	6.22	2.53	7.74	4.81	8.88	0.99	9.15	6.45	8.64	8.67	3.30	0.89
t-stat SCM	3.83	6.45	7.62	5.44	7.65	−1.60	0.85	2.61	2.98	3.63	1.20	4.29	5.24	2.53	3.71	1.53	0.75
t-stat BD10RET	3.27	2.20	1.54	2.05	1.50	2.39	0.64	−0.81	−0.90	1.80	4.30	3.25	2.80	0.75	2.39	0.01	3.69
t-stat BAAmTSY	3.64	2.42	1.74	2.14	3.60	1.84	1.20	4.78	5.82	4.67	7.46	8.07	0.48	5.30	5.14	5.59	0.92
t-stat PTFSBD	−0.28	−1.25	−0.96	−0.82	−1.39	−2.59	−1.65	−4.29	−5.19	−2.96	−3.40	−1.07	−0.99	−2.41	−2.18	−1.65	1.44
t-stat PTFSFX	3.14	0.59	1.46	0.40	0.92	2.10	0.79	1.75	1.12	1.78	−0.81	−0.08	0.98	0.56	1.48	0.15	4.31
t-stat PTFSCOM	2.45	1.28	1.18	1.25	0.45	1.41	2.22	−0.11	0.49	−0.55	0.27	−0.38	1.91	−0.28	1.48	−0.12	2.59
Adj. R^2	44.71	50.00	58.75	40.70	81.13	24.65	6.62	52.51	49.38	51.89	34.60	61.23	29.35	52.68	49.99	32.06	25.14

(*continued*)

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Table 2
Continued

Panel B: BKT eight-factor model

	All	ALNE	LSE	LLNE	EL	EMN	OPT	ED	DS	MA	FI	CA	MAC	EMG	FOF	MUL	MF
HF ret (% p.a.)	6.88	6.49	7.09	5.99	6.83	3.43	10.51	7.64	6.60	4.71	5.31	5.39	7.67	9.30	4.56	7.54	7.45
IR (p.a.)	0.13	0.10	0.14	0.06	0.05	0.13	0.12	0.15	0.19	0.27	0.18	0.03	0.13	0.08	0.01	0.43	0.03
Alpha (% p.a.)	2.38	2.00	2.80	1.35	1.08	1.96	3.91	3.72	3.30	2.99	3.02	0.60	3.45	3.50	0.11	6.09	0.95
Beta CR	−0.03	−0.03	−0.02	−0.03	−0.02	0.00	−0.07	−0.02	−0.02	0.00	0.00	−0.02	−0.03	−0.01	−0.02	−0.01	−0.07
Beta S&P	0.17	0.21	0.27	0.20	0.57	0.11	0.03	0.21	0.08	0.11	0.02	0.22	0.18	0.47	0.20	0.05	−0.04
Beta SCM	0.10	0.20	0.22	0.19	0.24	−0.03	0.04	0.09	0.08	0.06	0.03	0.13	0.21	0.17	0.11	0.03	0.04
Beta BD10RET	0.16	0.12	0.08	0.13	0.08	0.09	0.07	−0.04	−0.03	0.05	0.18	0.18	0.19	0.09	0.13	0.00	0.36
Beta BAAmTSY	0.16	0.12	0.07	0.11	0.20	0.07	0.05	0.30	0.27	0.14	0.35	0.47	0.01	0.67	0.28	0.22	0.03
Beta PTFSBD	0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.02	−0.04	−0.03	−0.01	−0.02	−0.01	−0.01	−0.04	−0.02	−0.01	0.02
Beta PTFSFX	0.02	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.05
Beta PTFSCOM	0.02	0.01	0.01	0.01	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.02	−0.01	0.01	0.00	0.03
t-stat Alpha	1.85	1.36	1.99	0.82	0.71	1.85	1.63	2.17	2.67	3.85	2.47	0.40	1.81	1.08	0.07	5.99	0.37
t-stat CR	−3.56	−2.81	−2.63	−2.81	−1.92	−0.30	−4.27	−1.62	−2.50	−0.83	−0.44	−1.93	−2.01	−0.33	−2.29	−0.86	−4.07
t-stat S&P	7.04	7.78	10.24	6.30	19.83	5.56	0.70	6.47	3.46	7.80	0.73	7.67	5.15	7.76	7.11	2.68	−0.78
t-stat SCM	3.90	6.53	7.70	5.50	7.68	−1.60	0.84	2.60	2.99	3.62	1.19	4.29	5.26	2.52	3.73	1.52	0.73
t-stat BD10RET	3.56	2.39	1.71	2.23	1.61	2.39	0.89	−0.73	−0.78	1.84	4.31	3.37	2.92	0.77	2.54	0.06	4.05
t-stat BAAmTSY	3.15	1.99	1.33	1.71	3.28	1.76	0.57	4.49	5.44	4.48	7.29	7.72	0.16	5.17	4.78	5.38	0.30
t-stat PTFSBD	−0.05	−1.08	−0.80	−0.65	−1.27	−2.56	−1.44	−4.20	−5.08	−2.90	−3.36	−0.94	−0.86	−2.38	−2.05	−1.59	1.76
t-stat PTFSFX	3.32	0.67	1.55	0.48	0.97	2.10	0.93	1.80	1.20	1.80	−0.80	−0.04	1.03	0.56	1.55	0.17	4.58
t-stat PTFSCOM	2.13	1.00	0.91	0.97	0.25	1.36	1.86	−0.28	0.23	−0.64	0.22	−0.59	1.70	−0.31	1.24	−0.21	2.25
Adj. R^2	47.90	51.75	60.00	42.78	81.40	24.29	14.37	52.91	50.74	51.81	34.32	61.78	30.45	52.45	51.08	31.97	30.82

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Table 2
Continued

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.)	7.18	6.86	7.48	6.37	7.30	3.60	10.66	7.98	6.83	4.89	5.36	5.63	7.92	9.94	4.87	7.70	7.76
IR (p.a.)	0.15	0.12	0.14	0.06	0.05	0.17	0.17	0.20	0.24	0.32	0.21	0.10	0.10	0.14	0.10	0.41	0.03
Alpha (% p.a.)	3.06	2.82	2.96	1.66	1.25	2.75	6.24	5.42	4.62	3.84	3.96	2.47	3.00	6.84	2.33	6.51	1.07
Beta CR	−0.03	−0.03	−0.03	−0.03	−0.02	0.00	−0.06	−0.02	−0.02	0.00	0.00	−0.02	−0.03	0.00	−0.02	0.00	−0.07
Beta VW IVR	−0.11	−0.13	0.02	−0.02	0.02	−0.16	−0.55	−0.36	−0.29	−0.17	−0.23	−0.42	0.17	−0.67	−0.48	−0.06	0.00
Beta S&P	0.16	0.21	0.27	0.19	0.56	0.10	0.01	0.20	0.07	0.11	0.01	0.21	0.19	0.46	0.18	0.05	−0.05
Beta SCM	0.10	0.19	0.22	0.19	0.24	−0.04	0.02	0.08	0.07	0.05	0.02	0.12	0.21	0.15	0.10	0.03	0.04
Beta BD10RET	0.15	0.12	0.09	0.13	0.09	0.08	0.04	−0.06	−0.05	0.04	0.17	0.16	0.20	0.04	0.10	0.00	0.36
Beta BAAmTSY	0.14	0.09	0.08	0.11	0.21	0.04	−0.05	0.23	0.21	0.10	0.31	0.39	0.04	0.52	0.19	0.20	0.04
Beta PTFSBD	0.00	0.00	0.00	0.00	−0.01	−0.01	−0.02	−0.04	−0.03	−0.01	−0.02	0.00	−0.01	−0.04	−0.01	−0.01	0.03
Beta PTFSFX	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.05
Beta PTFSCOM	0.02	0.01	0.01	0.01	0.00	0.01	0.02	0.00	0.00	0.00	0.00	−0.01	0.02	−0.01	0.01	0.00	0.03
t-stat Alpha	2.13	1.72	1.89	0.90	0.74	2.31	2.32	2.82	3.35	4.43	2.88	1.45	1.40	1.88	1.43	5.66	0.38
t-stat CR	−3.56	−2.80	−2.83	−2.98	−2.14	−0.25	−4.00	−1.31	−2.15	−0.62	−0.22	−1.72	−2.00	−0.05	−2.01	−0.68	−4.25
t-stat VW IVR	−0.76	−0.80	0.13	−0.12	0.12	−1.35	−2.02	−1.84	−2.08	−1.97	−1.68	−2.46	0.78	−1.81	−2.93	−0.54	0.01
t-stat S&P	6.70	7.42	9.99	6.02	19.46	5.14	0.31	6.07	3.10	7.30	0.42	7.07	5.19	7.37	6.57	2.60	−0.95
t-stat SCM	3.75	6.32	7.69	5.45	7.67	−1.81	0.46	2.24	2.61	3.23	0.89	3.83	5.28	2.15	3.24	1.39	0.75
t-stat BD10RET	3.35	2.22	1.75	2.23	1.68	2.07	0.47	−1.06	−1.12	1.48	3.94	2.92	2.96	0.35	1.99	−0.08	4.01
t-stat BAAmTSY	2.39	1.36	1.27	1.49	2.97	0.88	−0.50	2.95	3.69	2.92	5.48	5.56	0.50	3.53	2.79	4.30	0.34
t-stat PTFSBD	0.43	−0.60	−0.23	−0.10	−0.68	−2.10	−1.20	−3.96	−4.85	−2.50	−3.20	−0.54	−0.82	−2.17	−1.60	−1.54	2.22
t-stat PTFSFX	3.47	0.82	1.73	0.69	1.16	2.28	1.10	1.80	1.20	1.91	−0.72	0.20	0.89	0.60	1.77	0.08	4.78
t-stat PTFSCOM	2.15	1.00	0.91	0.95	0.20	1.33	1.77	−0.23	0.34	−0.71	0.24	−0.69	1.78	−0.32	1.28	−0.14	2.25
Adj. R^2	48.60	51.78	60.26	42.78	81.56	24.20	15.69	52.92	51.09	52.03	34.80	62.62	30.36	52.73	52.94	31.57	32.38

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%. LSE Low Net Exposure (LLNE) funds are Long/Short Equity (LSE) funds that are reported to have a net long/short exposure below 30%. 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), Multistrategy (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 information ratio and FH alpha, the FH betas, and the t-statistics of the FH alpha and betas. Panel B reports the alphas for the BKT eight-factor model. Panel C is based on a nine-factor model that includes the BKT model factors and a value-weighted index of individual options variance risk factor (VW Indiv. VR). For Panels A and B (Panel C) the sample period is January 1996 to June 2012 (February 2012).

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also be responsible for systematic differences in hedge-fund-expected returns, indicating that correlation risk is priced in the cross-section of hedge fund returns.

We start by characterizing correlation risk exposures at the aggregate (index) level for different hedge fund trading styles. Second, to highlight the implications for benchmark performance attribution frameworks, such as the FH seven-factor model, we map differences in the correlation risk exposure of sorted fund portfolios to differences in their risk-adjusted performance. Third, to quantify the relative importance of different risk factors for hedge fund returns, we address the cross-sectional link between correlation risk exposures and the excess returns of sorted fund portfolios. Fourth, we provide a motivation for the economic origins of correlation risk exposures in hedge fund returns, by documenting a potential relation among the degree of fund net exposures, the degree of correlation risk exposure, and the betas with respect to more standard risk factors, such as market or credit risk. Fifth, using the two-pass Fama-Macbeth regression methodology, we estimate the factor risk premium of correlation risk, and we test whether correlation risk is priced in the cross-section of hedge fund returns. Finally, motivated by the nonlinearity of correlation risk with respect to aggregate market shocks in periods of financial distress, we highlight an asymmetric U-shaped cross-sectional dependence between correlation risk exposures and nonlinear measures of hedge fund risk, such as maximum drawdowns.

3.1 Hedge fund index returns and correlation risk exposures

Table 2, Panels A and B, reports estimated alpha and beta coefficients of hedge fund index returns, across investment objectives, for the FH performance attribution model and for the BKT model, respectively. Panel C presents results with respect to the BKT performance attribution model extended by a risk factor for aggregate variance risk; details about the definition and construction of the aggregate variance risk factor are provided in the Online Appendix.

The third row of Table 2, Panel A, highlights quite large and significant FH alphas, at the index level, for almost all hedge fund categories. For instance, the estimated FH alpha of 4.65% (4.05%) for a value-weighted index of all funds (all LNE funds) is responsible for a fraction of about 68% (62%) of the index average return. For fund categories, such as Long-Short Equity, Option Trader, and Managed Futures, the fraction of the fund's average return ascribed to the FH fund's alpha is as large as 65%, 85%, and 81%, respectively. In terms of number of funds (Assets Under Management), these categories represent about 43% (53%) of the whole universe in the BarclayHedge database.

Panel B of Table 2 shows that in general the estimated alpha with respect to the BKT model is lower than in Panel A, in some cases by a large extent, and is often not statistically significant. For instance, among the fourteen fund categories with a significant alpha in Panel A, more than half have an insignificant alpha in Panel B, when correlation risk exposures are considered. We also find that

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an aggregate value-weighted index of all funds has a statistically significant negative correlation risk beta at the 1% level, and an index of All Low Net Exposure funds also implies a very significant negative correlation risk beta at the 1% level. In the last case, the estimated alpha in Panel B is not statistically significant and is about 50% lower than in Panel A. These findings are a first hint of the fact that neglecting correlation risk in the estimation of funds risk-return profile can potentially produce important biases, which can be especially large for long-short funds characterized by a low directional market exposure.

A finer stratification across investment styles helps to more clearly identify hedge fund strategies with particular exposure to correlation risk. For instance, Long/Short Equity (LSE), Options Trader (OPT), Managed Futures (MF), and Funds of Funds (FOF) have a negative correlation risk beta t-statistic equal to −2.63, −4.27, −4.07, and −2.29, respectively. These categories represent more than 50% of the whole universe in the BarclayHedge database (in terms of AuM).

A closer comparison of Panels A and B in Table 2, shows that significant negative exposures to correlation risk often imply large economic differences in the estimated risk-adjusted performance across investment styles. For instance, the correlation risk t-statistic of −2.81, −2.63, −4.27, and −4.07 for all LNE funds, Long-Short Equity, Option Trader and Managed Futures funds, respectively, implies a large difference of −2.05%, −1.84%, −5.07%, and −5.11% in risk-adjusted performance, relative to the FH model. This is a second indication that neglecting correlation risk exposures can imply a substantial overestimation of funds' actual risk-adjusted performance, especially for hedge funds that are short correlation.

In Table 2, Panel C, we consider results for the BKT performance evaluation model extended by a risk factor for market variance, in order to isolate the potentially distinct implications of correlation and variance risk for different hedge fund categories. We find that the significant correlation risk exposures of funds that are short correlation in Panel B are largely unaffected by the introduction of a value-weighted individual variance risk proxy in the BKT model, showing that our results are robust to variance risk. In particular, in most cases funds with a significant short correlation risk exposure have no significant exposure to variance risk.[13] Because Low Net Exposure (ALNE) funds are associated with strategies from all investment objectives, our results show the potential relevance of correlation risk for explaining the time series of returns of this class of funds, which are characterized by a lower volatility and market beta than are long-only strategies.

[13] As in Panel B of Table 2, a significant negative exposure to correlation risk arises in Panel C of Table 2 for, for example, Long/Short Equity (LSE) funds, Option Trader (OPTS), Funds of Funds (FOF), and Managed Futures (MF), which have correlation risk beta t-statistics of −2.83, −4.00, −2.01 and −4.25, respectively. Similarly, the correlation risk beta t-statistic of low net exposure funds (ALNE) is −2.80 and the one of long-short equity funds with low net exposure (LLNE) is −2.98.

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We find that variance risk exposure explains the returns of hedge fund classes in a different way than does correlation risk exposure. For instance, the variance risk beta $t-$statistic is significant for Convertible Arbitrage funds (t-statistic of -2.46) and Distressed Securities (t-statistic of -2.08), which are often directional in nature. In many cases, hedge fund strategies with significant exposure to variance risk have no significant exposure to correlation risk. Moreover, investment objectives with low net exposure have no significant exposure to variance risk, but they feature a significant negative correlation risk exposure.[14]

In summary, our results show that correlation and variance risk are conceptually separate risk factors with distinct implications for the returns of different hedge fund strategies and categories. This finding challenges the common wisdom that volatility, more than correlation, is the key risk to control for in modeling hedge fund returns, independently of the investment strategy. The usual argument goes as follows. Hedge fund managers have convex incentives (2% fees plus 20% of performance) and a payoff profile similar to that of a call option. Therefore, in equilibrium they tend to be long volatility. However, this argument is incomplete. Panageas and Westerfield (2009) show that hedge fund managers engage 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 chooses a bounded portfolio, despite the option-like character of her compensation. When the horizon is not finite, the fund manager cares also about the continuation value of her call option, which is a perpetually renewed option. This continuation value is a key disciplining device that prevents the manager from taking unbounded risk, thereby creating the incentive to mitigate risk. A second reason why in practice hedge fund managers might dislike large volatility exposures is their reliance on prime brokers for leverage and securities lending. In an intertemporal context, fund managers fear the removal of leverage and other services after a sequence of excessive drawdowns. Hedge funds receive capital from two counterparties: the investor and the prime broker. While the incentive structure is convex with respect to the investor perspective, it is concave with respect to the prime broker and the investor.[15] It follows that hedge fund manager's aversion to volatility can lead them to seek risk mitigation through hedging with long-short positions, thus potentially exposing the fund to correlation risk.

3.2 The cross-section of individual correlation risk exposures

The previous analysis is based on aggregate index return information. In this section, we consider individual hedge funds and study more systematically the

[14] These findings are consistent with the results for the TASS database, collected in Table A9 of the Online Appendix.

[15] Even if a fund manager could impose a "gate" to prevent the investor to redeem, a fund cannot "gate" the prime broker to force liquidation of funds' positions and seize collateral; see also Healy and Lo (2009) on gates and hedge fund illiquidity.

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cross-sectional link between their expected excess returns and correlation risk exposures.

3.2.1 Sorting by correlation risk exposure. We sort individual hedge fund returns into decile portfolios according to each fund's exposure to correlation risk. Because the recent hedge fund literature highlights a potential time-variation in factor betas (e.g., Patton and Ramadorai 2013), we apply a dynamic sorting procedure that allows individual hedge fund factor betas to vary through time.

We can model a time-variation in factor betas, simply by specifying them as a function of a relevant set of conditioning variables observed at time $t-1$ (see Pastor and Stambaugh 2003, among others). This approach requires assumptions about the set of relevant instruments for capturing a time-variation in factor betas, making the conclusions potentially dependent on the chosen instruments. A more robust approach can sort hedge fund returns based on historical factor betas alone. We follow this approach in the sequel.

At the end of each year, we identify hedge funds with at least thirty-six observations of monthly returns continuing through the current year end. For each fund, we estimate its historical correlation risk beta, by running the regression in the BKT model based on the most recent thirty-six monthly observations. At the end of each year, funds are then sorted according to their historical correlation risk beta t-statistic into ten equal-weighted portfolios.[16] This portfolio formation procedure uses information available only as of the formation date and avoids potential look-ahead biases in the estimation of hedge fund factor betas. Monthly postranking portfolio returns are computed for the following year, after which the estimation/formation procedure is repeated. The postranking portfolio returns are linked across years, giving rise to a single return series for each decile portfolio, covering the period from January 1999 to June 2012.

Table 3, reports the characteristics of the postranking betas of the ten decile portfolios in our data set. The postranking betas are estimated by estimating for each decile portfolio the BKT regression model, using data from the whole sample period from January 1999 to June 2012.

The pattern in postranking correlation risk betas and associated t-statistics is monotone, and we find in Panel A of Table 3 that sorting on historical t-statistics generates a useful degree of dispersion in postranking correlation risk betas. Indeed, the postranking beta for correlation risk ranges from a minimum of -0.06 for the bottom decile to a maximum of 0.00 for the top decile. Moreover, the high-minus-low spread portfolio, which goes long (short) the top (bottom) decile portfolio, implies a statistically significant correlation risk beta of 0.06.

[16] For the first three years of observations we assume a constant correlation risk beta, as historical betas are not available for the first thirty-five months of our hedge fund return time series.

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Table 3
Properties of portfolios sorted on correlation risk

	Decile portfolio										
	Low	2	3	4	5	6	7	8	9	High	H-L
Panel A: Postranking correlation risk betas											
beta_CR	−0.06	−0.04	−0.04	−0.03	−0.02	−0.02	−0.02	−0.01	−0.01	0.00	0.06
t_beta_CR	−4.97	−4.39	−3.88	−3.74	−2.78	−1.89	−1.77	−1.38	−0.68	0.29	3.86
Panel B: Additional Properties											
beta_S&P500	0.17	0.21	0.25	0.30	0.32	0.30	0.29	0.29	0.26	0.23	0.05
beta_SCMLC	0.07	0.12	0.15	0.18	0.20	0.19	0.16	0.19	0.16	0.10	0.02
beta_BD10RET	0.07	0.11	0.08	0.08	0.13	0.09	0.07	0.11	0.07	0.07	0.01
beta_BAAMTSY	0.12	0.18	0.21	0.24	0.26	0.29	0.23	0.27	0.25	0.23	0.13
beta_PTFSBD	0.00	0.00	0.00	0.00	−0.01	0.00	0.00	0.00	0.00	0.00	0.00
beta_PTFSFX	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00
beta_PTFSCOM	0.03	0.02	0.02	0.01	0.01	0.01	0.00	0.00	0.01	0.01	−0.02
t_beta_S&P500	5.12	7.37	9.19	11.41	12.78	12.20	11.54	11.05	9.63	8.25	1.20
t_beta_SCMLC	2.03	3.91	5.10	6.37	7.24	7.21	5.82	6.55	5.39	3.15	0.49
t_beta_BD10RET	1.20	2.09	1.49	1.75	2.77	1.98	1.48	2.20	1.32	1.41	0.08
t_beta_BAAMTSY	1.69	3.01	3.51	4.38	5.05	5.65	4.32	4.78	4.32	3.99	1.34
t_beta_PTFSBD	0.31	−0.51	0.25	0.24	−0.93	−0.22	−0.10	0.38	0.30	0.06	−0.24
t_beta_PTFSFX	1.94	2.08	2.49	2.62	3.04	3.32	2.75	2.74	3.17	2.99	0.40
t_beta_PTFSCOM	2.85	2.77	2.48	1.03	1.48	1.85	−0.10	0.46	1.32	0.68	−1.70

This table reports betas and their t-statistics for decile portfolios of individual hedge funds. Each year, from January 1999 to 2011, all funds are sorted into equal-weight decile portfolios based on their BKT correlation risk beta t-statistic, calculated using the previous thirty-six monthly returns. Column 2 reports results for decile 1, which contains individual hedge funds with the most 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 11 reports results for decile 10, which contains funds with the highest correlation risk beta. The last column reports the difference between the high and the low portfolio. Rows 1 and 2 in Panel A report the BKT model correlation risk beta and its t-statistic. Panel B reports additional properties of the decile portfolios, such as the betas and the beta t-statistics of the other factors in the BKT model. The Fung and Hsieh (2004) factors are the S&P 500 return minus the risk-free rate (S&P 500), the Wilshire small cap minus large cap return (SCMLC), the change in the constant maturity yield of the U.S. ten-year Treasury bond adjusted for the duration of the ten-year bond (BD10RET), the change in the spread of Moody's BAA bond over ten-year Treasury bond appropriately adjusted for duration (BAAMTSY), the bond PTFS (PTFSBD), the currency PTFS (PTFSFX), and the commodities PTFS (PTFSCOM), where PTFS is the primitive trend-following strategy.

Panel B of Table 3 provides additional details on the properties of the decile portfolios sorted by historical correlation risk t-statistics. We observe an increasing tendency, from the low to the top decile portfolios, for the postranking betas of the market and size risk factors: market (size) postranking betas range from a minimum of 0.17 (0.07) for the bottom decile portfolio to a value of 0.23 (0.10) for the top decile portfolio. These cross-sectional differences imply a high-minus-low spread portfolio with a positive, but statistically, insignificant exposure to both market and size.

Overall, we find that the sorted decile portfolios with the most negative correlation risk exposures are also those with the smallest directional exposures to the standard market and size risk factors. This finding suggests that the broad hedge fund practice of reducing directional exposures with long-short portfolio positions may actually create in a number of cases an additional exposure to correlation shocks.

A key question is whether cross-sectional differences in exposures to correlation risk, market risk, or other risk factors are systematically linked to

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an economically relevant variation in individual fund excess returns and risk-adjusted performance measures. The results in Table 3 indicate that risk factors like market, size, and correlation risk can be often significant in explaining the time-series variation of the returns of decile portfolios. For instance, estimated market and size betas are significant for all decile portfolios in Panel B of Table 3, whereas correlation risk betas are significant for seven decile portfolios in Panel A of Table 3. However, these findings do not imply per se that these risk factors need to be priced in the cross-section of hedge fund returns, as large cross-sectional variations in factor exposures might be simply linked to small differences in excess returns.

Economic intuition suggests that correlation risk is related to systematic market-wide shocks that can affect the diversification potential of a large number of assets. Therefore, it could appear as a systematic risk factor, in addition to the standard Fama-French factors, in the cross-section of hedge fund returns. We address this topic in more detail in the following sections.

3.2.2 Hedge fund alphas and return decompositions. If correlation risk is priced in the cross-section of hedge funds, then a relevant portion of the return component left unexplained by the standard FH risk factors should be systematically related to the fund exposure to correlation risk. A direct way to investigate this is by comparing the alpha of hedge fund returns estimated using the FH performance attribution framework and using the BKT model, respectively. Because the last model extends the FH setting by a single correlation risk proxy, this comparison provides an indication of the fraction of FH alpha that can be explained by a (time-series) exposure to correlation shocks. Panel A of Table 4 collects the FH and BKT model alphas estimated for the ten decile portfolios of Table 3.

First, we find that the annualized postranking FH alphas of all decile portfolios are positive, large, and strongly statistically significant. Although the cross-sectional pattern of the FH alphas is slightly U-shaped, the differences between decile portfolios are not significant. On average, the fraction of expected hedge fund portfolio return left unexplained by the FH factors is large: whereas the average annualized alpha of the decile portfolios is about 4% on a yearly basis, the average annualized decile portfolio return is about 7.6%.

When we additionally control for correlation risk in the BKT model, the estimated postranking alphas are systematically lower than in the FH model, in some cases by a large amount. The average alpha across decile portfolios is only 2%, and the individual alphas of the decile portfolios are not significant from zero, at the 1% level, in six cases. These findings challenge the interpretation of positive risk-adjusted performance measures estimated by traditional risk factor specifications that do not incorporate an exposure to correlation risk.

The BKT alphas in Table 4 provide additional insight on the sign of a correlation risk premium in the cross-section of hedge fund returns. The BKT

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Table 4
Alphas of equally weighted portfolios sorted on correlation betas

	Decile portfolio									
	Low	2	3	4	5	6	7	8	9	High
Panel A: All funds										
Alpha before and after controlling for correlation risk										
FHAlpha (% p.a.)	4.37	3.26	3.73	3.77	2.84	3.36	4.08	4.19	4.80	4.59
t_alpha	2.66	2.32	2.81	3.03	2.45	2.92	3.47	3.41	3.82	3.59
BKT Alpha (% p.a.)	−0.03	−0.10	0.90	1.20	1.03	2.13	2.90	3.22	4.31	4.81
t_alpha	−0.02	−0.06	0.61	0.87	0.78	1.62	2.16	2.28	2.97	3.25
Economic contribution of each factor										
contrib_CR	4.87	3.72	3.14	2.85	2.01	1.37	1.31	1.07	0.55	−0.23
contrib_S&P500	0.88	1.09	1.30	1.52	1.62	1.54	1.49	1.50	1.34	1.17
contrib_SCMLC	0.09	0.15	0.19	0.22	0.24	0.24	0.20	0.23	0.20	0.12
contrib_BD10RET	0.27	0.41	0.28	0.31	0.46	0.33	0.25	0.39	0.24	0.26
contrib_BAAMTSY	0.28	0.42	0.47	0.55	0.61	0.68	0.53	0.62	0.57	0.54
contrib_PTFSBD	−0.05	0.08	−0.04	−0.03	0.12	0.03	0.01	−0.05	−0.04	−0.01
contrib_PTFSFX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
contrib_PTFSCOM	0.04	0.04	0.03	0.01	0.02	0.02	0.00	0.01	0.02	0.01
Panel B: Long/Short Equity										
Alpha before and after controlling for correlation risk										
FH7 Alpha (% p.a.)	3.23	2.27	3.57	3.83	4.95	6.00	5.93	5.70	6.65	6.52
t_alpha	1.76	1.48	2.40	2.75	3.55	3.78	3.53	3.49	4.19	4.48
BKT Alpha (% p.a.)	−0.61	−0.27	1.55	1.93	3.80	4.52	4.37	4.54	6.21	6.19
t_alpha	−0.30	−0.15	0.92	1.22	2.37	2.49	2.27	2.41	3.39	3.68
Economic contribution of each factor										
contrib_CR	4.26	2.80	2.24	2.10	1.28	1.64	1.73	1.29	0.50	0.36
contrib_S&P500	1.40	1.82	1.78	1.96	1.71	1.81	2.18	1.76	1.76	1.63
contrib_SCMLC	.31	0.28	0.33	0.29	0.31	0.35	0.48	0.36	0.31	0.20
contrib_BD10RET	−0.09	−0.08	−0.11	0.23	0.21	0.18	0.24	−0.14	0.14	0.08
contrib_BAAMTSY	−0.05	0.15	0.22	0.32	0.19	0.35	0.05	0.14	0.38	0.04
contrib_PTFSBD	0.30	0.27	−0.01	0.12	0.14	−0.10	−0.12	−0.10	−0.16	−0.23
contrib_PTFSFX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
contrib_PTFSCOM	0.03	0.01	0.03	0.02	0.01	0.01	−0.01	0.00	0.01	−0.01
Panel C: Long/Short Equity with Low Net Exposure (LLNE)										
Alpha before and after controlling for correlation risk										
FH7 Alpha (% p.a.)	2.55	4.25	4.12	4.53	6.20	5.18	3.50	3.88	5.73	2.74
t_alpha	0.79	1.62	2.05	2.09	2.94	2.79	1.88	1.53	2.14	1.11
BKT Alpha (% p.a.)	−0.98	1.67	1.37	1.64	2.21	3.88	1.75	1.79	5.55	4.37
t_alpha	−0.27	0.55	0.60	0.67	0.94	1.82	0.82	0.61	1.80	1.54
Economic contribution of each factor										
contrib_CR	3.90	2.87	3.04	3.20	4.42	1.45	1.94	2.32	0.21	−1.80
contrib_S&P500	0.61	1.22	1.31	0.69	0.51	0.72	1.35	1.12	0.98	0.62
contrib_SCMLC	0.03	0.05	0.15	0.26	0.19	0.27	0.29	0.59	0.64	0.20
contrib_BD10RET	−0.68	−0.69	−0.08	0.69	0.79	0.68	0.40	0.69	0.32	0.02
contrib_BAAMTSY	0.27	0.52	0.08	0.53	0.41	0.35	0.10	0.11	0.17	0.48
contrib_PTFSBD	0.67	−0.04	−0.09	0.03	0.29	0.26	−0.07	0.11	0.02	0.30
contrib_PTFSFX	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
contrib_PTFSCOM	0.04	−0.01	0.01	0.02	0.05	0.00	0.03	0.03	0.01	0.04

This table reports properties of equal-weighted decile portfolios of individual hedge funds. The portfolios are formed as described in the legend of Table 3. Column 2 reports results for decile 1, which contains individual hedge funds with the most negative correlation risk beta. Column 11 reports results for decile 10, which contains funds with the highest correlation risk beta. Rows 1 and 2 (3 and 4) of each panel report the Fung-Hsieh (BKT) model alphas. Rows 5 to 12 of each panel report the economic contribution of each factor to the total average return of the portfolio. This is measured as the risk exposure times the factor average return. Alpha and hedge funds returns are annualized and expressed in a percentage format. The sample period is from January 1996 to June 2012. Panel A reports results for all funds, whereas Panels B and C report results for Long/Short Equity Funds and Long/Short Equity Funds with Low Net Exposure, respectively.

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alphas are almost monotonically increasing from the bottom to the top decile, which is an indication of a positive contribution of negative correlation risk exposures to the total average return. For instance, whereas for the bottom decile the alpha drops from 4.37% in the FH model to −0.03% in the BKT model, in the top decile it actually rises slightly from 4.59% to in the FH model to 4.81% in the BKT model.

The largest reductions of FH alphas in Table 4 are in a one-to-one relation with the large negative correlation risk exposures in the bottom deciles of Table 3. Indeed, we find that larger negative correlation risk exposures generate larger positive contributions of correlation risk to the fund average returns. For instance, whereas the annualized economic contribution of correlation risk to the total return is 4.87% and 3.72% in the two bottom deciles, it is only 0.55% and −0.23% in the two top deciles.

3.2.3 Investment objectives. The economic contributions of correlation risk to fund returns are often larger than those of standard risk factors, such as market risk and size, despite the fact that these risk factors are very significant in the return time series. For instance, in Panel A of Table 4 the largest contribution to the fund return of an exposure to size risk is only 0.24% on a yearly basis, for the fifth decile portfolio. Similarly, the contribution of an exposure to market risk is only 0.88% and 1.09% in the two bottom decile portfolios. This is an additional indication that standard risk factors might fail to explain a subset of the cross-section of hedge fund returns, especially for funds that might try to reduce directional exposures to market risk using, for example, long-short trading strategies.

Panels B and C of Table 4 more directly address this last intuition, by focusing on LSE funds (one of the largest subset of individual hedge funds by investment objective) and LLNE funds. The results confirm that correlation risk exposures can imply economically relevant differences in fund risk-adjusted performance. For instance, in Panel B of Table 4, the FH alpha of LSE funds is significant at the 1% level for eight decile portfolios. However, after controlling for correlation risk exposures, only six portfolios have a statistically significant alpha. Importantly, the absolute contribution of correlation risk exposures to the average fund return in Panel B (Panel C) is largest for four (nine) of the decile portfolios. Intuitively, this last result might follow from the broad objective of LSE funds to reduce directional exposures to market risk, using long-short strategies that can generate a potentially unexpected exposure to correlation shocks.

Table A4 of the Online Appendix considers additional styles in more detail, including Option Trader (OPT), Managed Futures (MF), and Fund of Funds, three fund categories with a significant correlation risk exposure at the aggregate level. We again find that the BKT alphas of these funds are systematically lower than in the FH model and are not significant for Option Trader and Funds of Funds. Also for these classes of funds, the economic contribution of

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correlation risk exposures to the fund return often dominates the one of other standard risk factors. For the OPT and MF fund categories, estimated market risk exposures are in most cases not statistically significant, whereas for Fund of Funds they are highly statistically significant. This last finding might not be surprising, given the flexibility intrinsic in Fund of Funds strategies, but it further stresses the limits of exclusively using the traditional hedge fund risk factors for performance attribution purposes.

In summary, the large contribution of correlation risk exposures to the average returns in the cross-section of fund decile portfolios supports the null hypothesis that correlation risk is priced in the cross-section of hedge fund returns. Because decile portfolios with a negative correlation risk exposure tend to be associated with a larger positive contribution to the fund average return, the natural hypothesis is that the correlation risk premium is negative and more substantial for the returns of funds with lower directional market exposures. These features are consistent with the intuition that an increase in the payoff of correlation swaps is linked to adverse states of potentially deteriorated diversification opportunities, often related to distinct phases of the economic cycle, or different periods of market-wide distress and recovery, which are undesirable for the representative investor.

3.2.4 Net exposure. The findings in Section 3.1 document a significant negative correlation risk beta at the index level, for LSE funds and for funds with low net exposures (ALNE). This evidence is consistent with the results for individual hedge funds in Sections 3.2 and 3.2.3, in which large negative correlation risk betas are obtained for funds and styles, implying a low directional exposure to market risk and other standard risk factors.

In contrast to mutual fund portfolios, a low directional exposure and small market betas are typical characteristics of many hedge fund strategies, such as, for example, long-short equity. These features are motivated by the absolute return target followed by hedge fund managers, who can exploit the degrees of freedom in their mandate to reduce directional market exposures, often making use of long-short investment strategies. If correlations are stochastic, however, long-short strategies can have the undesired effect of creating an additional exposure to correlation risk. Our previous results tend to support this hypothesis. This is an important difference relative to, for example, mutual funds, because it suggests that a major characteristic of hedge fund portfolios, low directional exposures, is intrinsically related to a more pronounced role of correlation risk for assessing hedge fund risk-adjusted returns.

To study in more detail the relation between correlation risk and residual market exposure in hedge fund returns, we use the self-reported net exposure information provided by the BarclayHedge database and sort individual funds into quintiles of net exposure. Ideally, we would like to implement a dynamic sorting procedure, similar to the approach in Section 3.2. Unfortunately, this is not possible because net exposure information is not available at an annual

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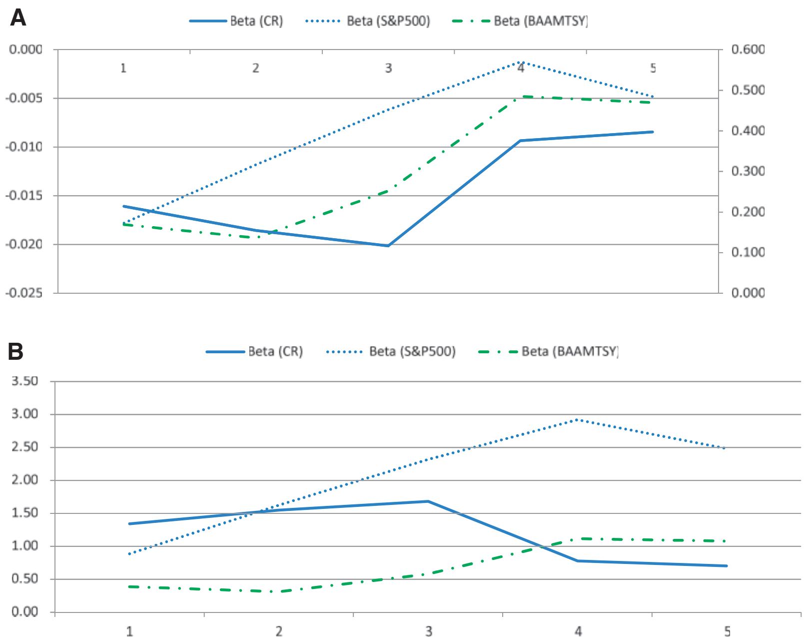

Figure 1
Correlation risk beta as function of net exposure
This figure shows the relationship between the correlation risk beta and net exposure based on Table A5. For comparison, we also report the market risk and credit spread betas. Individual hedge funds are sorted into quintiles based on their net exposure reported to the BarclayHedge database. Panel A reports the betas as a function of net exposure. The solid line shows the correlation risk beta (y-axis on the left). The dashed and dashed-dotted line show the market and size betas, respectively (y-axis on the right). Panel B reports the contribution of each correlation risk, market risk, and credit spread exposure to the total return in percent per year. The data is based on the period January 1996 to June 2012.

frequency over an extended period of time. Thus, we construct the next exposure quintiles based on the information provided in June 2012. For each quintile portfolio, we then estimate the BKT model, using the full sample of returns from January 1996 to June 2012.

Panel A of Figure 1 shows that, as net exposure increases across quintile portfolios, the betas for correlation, market, and credit risk increase quite steadily, indicating that directional exposures increase with self-reported fund net exposures, consistent with intuition.

The betas for the standard risk factors are all positive. In contrast, the correlation risk betas are negative and large in absolute value for the three bottom quintiles, whereas they are less negative and about half as large for the two top quintiles. This pattern supports our conjecture of a link between funds degree of net exposure and correlation risk exposure. Panel B of Figure 1 quantifies the contribution of each factor exposure to the average return of each quintile portfolio. We find that correlation risk exposure is the most important return determining factor for low net exposure funds. Its contribution to fund

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returns is larger than the one of market risk for the bottom quintile portfolio, and for the three bottom quintiles, it is larger than the one of credit risk. The return contribution of correlation risk is positive for the funds in the bottom quintiles, but it turns negative for the top decile, consistent with the changing sign of the correlation risk betas across net exposure quintiles.

Overall, these findings support the hypothesis that correlations risk is a useful risk dimension for correctly capturing the risk-return profile of hedge fund portfolios with low directional market exposures. Although such a dimension might not contribute as strongly to the returns of long-only portfolios, such as, for example, mutual fund portfolios, it appears to play a role for measuring correctly risk-adjusted returns of long-short portfolios with low net exposure, as it is typically the case for many hedge funds. This provides supporting evidence to the conjecture that although simple long-short strategies may mechanically reduce exposure to traditional risk factors, they may also tend to generate exposure to correlation risk. Because the correlation risk premium appears to be significantly negative, this finding helps to explain the cross-sectional pattern in excess returns and FH alphas.

3.3 Using the cross-section to estimate the price of correlation risk

This section tests whether correlation risk is priced in the cross-section of hedge fund returns. A nonzero price of correlation risk has important implications for the interpretation of return decompositions implied by hedge fund performance attribution models. If a risk factor is priced, the excess return generated by exposure to that factor is an equilibrium compensation for a source of nondiversifiable risk that a hedge fund is, explicitly or implicitly, taking. In contrast, several hedge fund factors proposed in the literature, such as, for example, the returns on rolling exchange rates and commodity indexes, aim at explaining the time series of hedge fund returns. These variables are unsystematic benchmarks unrelated to priced sources of non diversifiable risk. It follows that quantifying the price of correlation risk can help to better identify skill and risk premia in the cross-section of hedge fund returns, thus improving the efficient allocation of risky capital within the industry.

3.3.1 Sorting and estimation methods. To investigate whether hedge fund expected excess returns are systematically explained by their correlation risk exposures, we again adopt a straightforward portfolio-based approach, in order to create a universe of funds with sufficiently disperse betas with respect to the traded correlation (CR) and market ($SNPMRF$) risk factors in the BKT model. We sort funds with respect to the exposure to the market risk factor.[17] At the same time, we allow all factor betas to change over time.

[17] We obtain qualitatively similar results when sorting funds with respect to the exposure to the correlation risk factor.

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We borrow from Pastor and Stambaugh (2003) and identify at the end of each year the funds with at least thirty-six observations of monthly returns continuing through the current year end. For each fund, we then estimate the historical betas for market risk, running the regression in model (1) based on the most recent thirty-six monthly observations. At the end of each year, we sort funds, according to their historical t-statistics with respect to the market risk factor, into seventy-five equal-weighted portfolios. Monthly postranking portfolio returns are then computed for the following year, after which the estimation/formation procedure is repeated. Finally, the postranking portfolio returns are linked across years, giving rise to seventy-five return series, covering the period from January 1996 to June 2012.

Using the seventy-five sorted portfolios, we estimate the correlation risk premium and test whether correlation risk is priced in the cross-section of hedge fund returns using a Fama-Macbeth (1973) approach. We proceed in two steps: First, we estimate hedge fund betas in the BKT model for each of the seventy-five time series of sorted portfolio returns. Second, we then investigate the ability of cross-sectional differences in correlation risk exposures to explain the cross-sectional variation of expected excess returns across the seventy-five hedge fund portfolios.

More precisely, let $Y_t = [f_t', R_t']'$, where f_t is the vector of K factors at time t in the BKT model in Equation (1), which includes our traded correlation factor, and R_t is the vector of returns on the $N = 75$ fund portfolios at time t. Using this notation, the BKT model reads:

$$R_t = \beta_0 + B f_t + \epsilon_t, \tag{5}$$

where β_0 is a $N \times 1$ vector of constants; B a $N \times K$ matrix of factor betas; and ϵ_t a $N \times 1$ vector of return shocks. Because all components of vector f_t correspond to the return of a traded portfolio, the returns of the N sorted fund portfolios are priced by the return sensitivities to these factors:

$$E(R_t) = \beta_0 + B\lambda,$$

where $E(\cdot)$ denotes unconditional expectations, and λ is a $K \times 1$ vector of factor risk premia. Our main interest in this section is to quantify the price of risk and test the economic and statistical significance of the risk premium associate to CR_t.

Denoting the sample moments of Y_t by

$$\widehat{\mu} := \begin{bmatrix} \widehat{\mu}_1 \\ \widehat{\mu}_2 \end{bmatrix} := \frac{1}{T}\sum_{t=1}^{T} Y_t \ ; \ \widehat{V} := \begin{bmatrix} \widehat{V}_{11} & \widehat{V}_{12} \\ \widehat{V}_{21} & \widehat{V}_{22} \end{bmatrix} := \frac{1}{T}\sum_{t=1}^{T} (Y_t - \widehat{\mu})(Y_t - \widehat{\mu})',$$

we estimate matrix B of betas in model (5), using the time series of portfolio monthly returns from January 1996 to June 2012. The matrix of betas estimated from this first-pass time-series regression is given by $\widehat{B} = \widehat{V}_{21}\widehat{V}_{11}^{-1}$. Based on our seventy-five triple-sorted portfolios, we find that almost all market and size

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postranking betas, as well as about 90% of the correlation risk postranking betas, are statistically significant.

In the second pass of the methodology, we run a cross-sectional regression of $\widehat{\mu}_2$ on $\widehat{X}=\left[1_N, \widehat{B}\right]$ and estimate the vector of factor risk premia λ in model (5). Given a suitable symmetric and positive definite weighting matrix W, parameter λ is estimated by:

$$\widehat{\lambda}_W=\left(\widehat{X}' W \widehat{X}\right)^{-1} \widehat{X}' W \widehat{\mu}_2. \tag{6}$$

We apply different choices of the weighting matrix, implying distinct asymptotic standard errors, in order to verify the robustness of our results with respect to the finite-sample properties of estimator (6) and the well-known errors-in-variables (EIV) problem in two-step least squares procedures.[18] Precisely, we make use of GLS and WLS estimators that are robust to a potential error correlation and heteroscedasticity. Shanken and Zhou (2007) compare by Monte Carlo simulation the finite-sample properties of several WLS, GLS, GMM, and ML estimators, showing that GLS estimators have desirable properties in small samples and are preferable to GMM estimators, at least in their CAPM specifications. ML estimators, although asymptotically efficient under a correctly specified model, are slightly less precise than GLS estimators in small samples or in presence of nonnormalities. Given these findings, we rely on GLS and WLS estimators to interpret our results. Finally, given the evidence in Chen and Kan (2004) that EIV problems can be relevant for second-step GLS-type t-statistics, we also report GLS and WLS t-statistics based on Shanken (1992)'s asymptotic correction.

3.3.2 The price of correlation risk. Table 5 (6) reports the Fama-Macbeth estimates $\widehat{\lambda}_W$ in Equation (6) for GLS and WLS estimators, using the BarclayHedge (TASS) database. For comparison purposes, we report results for two different factor models. First, using a simple augmented-CAPM model with $K=2$ factors, given by the market index return and the return of our correlation swap (Model 1). Second, using $K=8$ factors in the BKT model, given by the seven FH risk factors and the return of our correlation swap (Model 2).

Using GLS estimators, we estimate a negative market price of correlation risk with respect to models 1 and 2, both with and without Shanken's asymptotic correction. The point estimate for the correlation factor risk premium is highly statistically significant, with t-statistics of -4.14 and -4.06, respectively, in each model.[19] In contrast, the GLS point estimates for other well-known

[18] The EIV problem has a number of potential consequences in two-step least squares procedures. First, if standard errors do not include information that beta coefficients are measured with error, the implied t-statistics might overstate the precision of the risk premium estimates. Second, different estimators might have substantially different properties when the linear factor model is misspecified, either because of a missing factor or because of a latent nonlinearity. Finally, least squares estimators of risk premia in the second step might be biased in finite samples.

[19] The t-statistics after Shanken's correction are -4.06 and -3.92, respectively.

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Table 5
The cross-section of hedge fund excess returns and correlation risk exposures

Panel A: Model 1 (Correlation risk and market risk)

			With Shanken's correction	
	GLS	WLS	GLS	WLS
Intercept	0.10	0.16	0.10	0.16
t-stat	(3.74)	(2.31)	(3.47)	(2.17)
Correl risk	−4.33	−4.54	−4.33	−4.54
t-stat	−(4.14)	−(2.7)	−(4.06)	−(2.58)
Mkt risk	−0.02	0.57	−0.02	0.57
t-stat	−(0.07)	(1.41)	−(0.07)	(1.38)

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

	GLS	WLS	GLS	WLS
Intercept	0.10	0.18	0.10	0.18
t-stat	(3.74)	(3.4)	(3.32)	(3.09)
Correl risk	−4.27	−2.61	−4.27	−2.61
t-stat	−(4.06)	−(1.9)	−(3.92)	−(1.79)
Mkt risk	0.01	0.39	0.01	0.39
t-stat	(0.04)	(1.06)	(0.04)	(1.04)
SCMBC	0.58	0.47	0.58	0.47
t-stat	(2.09)	(1.33)	(2.05)	(1.26)
BD10RET	−0.04	−0.36	−0.04	−0.36
t-stat	−(0.19)	−(1.33)	−(0.19)	−(1.24)
BAAmTSY	−0.03	−0.08	−0.03	−0.08
t-stat	−(0.15)	−(0.36)	−(0.14)	−(0.34)
PTFSBD	3.18	2.06	3.18	2.06
t-stat	(2.53)	(1.19)	(2.44)	(1.12)
PTFSFX	2.89	4.79	2.89	4.79
t-stat	(1.82)	(2.11)	(1.74)	(1.98)
PTFSCOM	0.37	2.12	0.37	2.12
t-stat	(0.32)	(1.26)	(0.31)	(1.18)

This table reports estimates for the risk premia on the market index, the Fung and Hsieh (2004) factors and the correlation risk factor (CR). Portfolios are formed based on rolling beta estimates. In Panel A, we report results for the market and the correlation risk factor (Model 1). In Panel B, we report results for the BKT eight-factor model (Model 2). The estimation methods are GLS and WLS versions of the (Fama-MacBeth) two-pass regression methodology. t-statistics are in brackets. t-statistics in Columns 4 to 5 are calculated using standard errors based on Shanken (1992) errors-in-variables (EIV) adjustment. The cross-sectional regressions are based on 75 portfolios (based on a sort using the market betas). Each year from January 1999 to 2011 funds are sorted into these portfolios based on their betas calculated using the previous 36 monthly returns. The sample period is January 1996 to June 2012.

systematic risk factors, such as market risk or credit risk, are relatively small and not significant at standard levels, indicating that these risks are not priced in the cross-section of hedge fund returns.[20]

The GLS point estimates for the correlation factor risk premium from the cross-sectional regressions are large in absolute value. They correspond to an excess return of −4.33% per month with respect to the augmented CAPM model and a return of −4.27% per month with respect to the BKT model. In terms of magnitude, these findings are comparable to the average monthly correlation swap payoff of −6.97% estimated from time-series data. Finally, the results based on the less efficient WLS-estimator are less sharp, but they again support

20 The nonsignificance of the market risk premium might arise because of the relatively small number of monthly observations in our sample, or more likely because many hedge funds successfully implement market-neutral strategies. The size factor is significant for GLS estimates only.

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Table 6
The cross-section of hedge fund excess returns and correlation risk exposures - TASS data

Panel A: Model 1 (Correlation risk and market risk)

			With Shanken's correction	
	GLS	WLS	GLS	WLS
Intercept	0.24	0.18	0.24	0.18
t-stat	(8.3)	(2.21)	(8.14)	(2.14)
Correl risk	−2.42	−3.39	−2.42	−3.39
t-stat	−(2.34)	−(2.1)	−(2.33)	−(2.05)
Mkt risk	0.24	0.48	0.24	0.48
t-stat	(0.7)	(1.17)	(0.7)	(1.16)

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

	GLS	WLS	GLS	WLS
Intercept	0.23	0.22	0.23	0.22
t-stat	(7.76)	(3.8)	(7.18)	(3.33)
Correl risk	−2.07	−3.15	−2.07	−3.15
t-stat	−(1.99)	−(2.17)	−(1.95)	−(1.99)
Mkt risk	0.25	0.38	0.25	0.38
t-stat	(0.73)	(0.99)	(0.72)	(0.95)
SCMBC	−0.47	0.30	−0.47	0.30
t-stat	−(1.63)	(0.85)	−(1.6)	(0.79)
BD10RET	0.06	−0.26	0.06	−0.26
t-stat	(0.34)	−(1.04)	(0.33)	−(0.95)
BAAmTSY	−0.05	−0.16	−0.05	−0.16
t-stat	−(0.31)	−(0.78)	(−0.31)	−(0.72)
PTFSBD	2.94	2.18	2.94	2.18
t-stat	(2.38)	(1.19)	(2.33)	(1.09)
PTFSFX	5.23	6.21	5.23	6.21
t-stat	(3.37)	(2.52)	(3.29)	(2.28)
PTFSCOM	1.35	−0.55	1.35	−0.55
t-stat	(1.16)	−(0.33)	(1.13)	−(0.30)

This table reports estimates for the risk premia on the market index, the Fung and Hsieh (2004) factors and the correlation risk factor (CR). Portfolios are formed based on rolling beta estimates. In Panel A, we report results for the market and the correlation risk factor (Model 1). In Panel B, we report results for the BKT eight-factor model (Model 2). The estimation methods are GLS and WLS versions of the (Fama-MacBeth) two-pass regression methodology. t-statistics are in brackets. t-statistics in Columns 4 to 5 are calculated using standard errors based on Shanken (1992) errors-in-variables (EIV) adjustment. The cross-sectional regressions are based on seventy-five portfolios (based on a sort using the market betas). Each year from January 1999 until January 2012 funds are sorted into these portfolios based on their betas calculated using the previous thirty-six monthly returns. The sample period is January 1996 to June 2012.

the hypothesis of a negative correlation risk premium for the BarclayHedge data, with point estimates of −4.54% and −2.61% that are significant at the 1% level for model 1 and the 10% level for model 2, for all choices of the asymptotic standard errors.

The results using the TASS database again produce evidence of a negative and significant correlation risk premium, using both GLS and WLS estimators, for all choices of the asymptotic t-statistics. Using the GLS (WLS) estimator, the point estimate for the correlation factor risk premium corresponds to a return of −2.07% (−3.15%) per month with respect to the BKT model. Tables A12 and A13 of the Online Appendix also report a significant and negative factor risk premium using the full sample instead of rolling correlation risk betas, for both the BarclayHedge and TASS databases. The estimated factor risk premium for correlation risk in Model 2 is −3.56% and −5.69% (−3.10% and −6.34) using GLS and WLS estimators on BarclayHedge (TASS) data.

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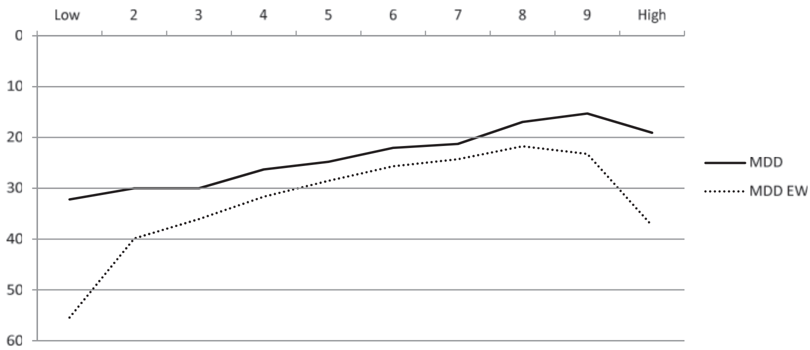

Figure 2
Drawndowns and correlation risk exposure
In this figure, we plot the maximum drawdown for decile portfolios sorted based on funds' beta with respect to correlation risk. The "low" portfolio has the lowest, that is the most negative, beta, whereas the "high" portfolio has the highest, that is, the most positive beta. A negative beta with respect to correlation implies that when correlation increases, a fund's return decreases. Maximum drawdown 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 to June 2012.

3.4 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 comove 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, because 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, that is, the longest consecutive sequence of losses.[21] 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.

Using our sorts of hedge fund returns into decile portfolios based on their correlation risk betas, Figure 2 plots the maximum drawdown of these portfolios across the different deciles.

A negative correlation risk beta means a short correlation position, implying that hedge fund losses tend to increase when correlations rise. Figure 2 shows that portfolio diversification does not help to diversify away correlation risk. Funds with the most negative exposure to correlation risk tend to suffer large drawdowns at the same time, in a much more pronounced way than funds with a nonnegative correlation risk exposure. Indeed, the equally weighted portfolio of funds with the most negative exposure to correlation risk has a maximum

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

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drawdown of about 55%. In contrast, the cross-sectional average maximum drawdown of funds in the decile with the largest positive correlation risk beta is only about 19%, whereas the maximum drawdown of the equally weighted portfolio of funds for that decile is about 39%.

This evidence provides 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 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 avoid large maximum portfolio drawdowns. Second, maximum drawdowns of funds with the 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 important, funds with large negative correlation risk exposure generate large average returns, as we documented in the previous section, but they also more strongly comove 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 long-short strategies and fund of hedge funds cannot find a safe place to hide.

3.5 Robustness checks

We have examined the robustness of our results with respect to (1) the use of equally weighted, instead of value-weighted, indexes, (2) extended performance attribution factor models that include proxies for liquidity risk, and (3) the use of the TASS, instead of the BarclayHedge, database. These results are available in the Online Appendix.

4. Conclusion

In this paper, we analyze the relation between correlation risk exposures, hedge fund characteristics, and the cross-sectional profile of individual hedge funds risk and return. Our empirical study produces a number of novel findings in the literature.

First, broad classes of funds, including Long-Short Equity, Option Trader, Funds of Funds, and Managed Futures funds, imply a significant negative exposure to correlation risk, where correlation risk is proxied by the excess return of a correlation swap for the basket of S&P 500 stocks. This exposure explains an important fraction of hedge fund risk-adjusted performance measures at the index level.

Second, at the individual level, hedge fund returns sorted with respect to their correlation risk beta imply an economically relevant variation in risk-adjusted performance. After controlling for correlation risk, we observe a significant drop in alphas, which are often not significantly different from zero, especially for funds with a negative correlation risk exposure. To a great extent, these

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results reverse the hedge fund performance rankings produced by benchmark valuation frameworks, not including a correlation risk dimension. We also find that correlation exposures tend to be more negative for funds with low directional net exposure. These funds have by design low betas with respect to market risk or other conventional risk factors, and they often imply positive alphas according to traditional risk-adjustment models. We find that a good fraction of those alphas is linked to a positive compensation for the larger negative exposures to correlation risk of these funds.

Third, using a two-pass Fama-Macbeth (1973) approach, we test whether correlation risk is priced in the cross-section of hedge fund returns. In an extended eight-factor performance valuation framework, which incorporates standard risk factors in the literature together with our correlation risk proxy based on the return of a correlation swap, we estimate a significant and negative correlation risk premium of about −4.27% (−2.07%), on a monthly basis, based on the BarclayHedge (TASS) database. Such a premium explains an economically relevant fraction of the cross-sectional variation in excess returns as a compensation for exposure to correlation risk. In contrast, we find no significant evidence that pure market variance risk is priced in the cross-section.

Finally, we detect a U-shaped relation between correlation risk exposure and tail risk in the cross-section of hedge fund returns. We find that portfolios of funds with negative correlation risk beta, that is, sellers of insurance against unexpected deteriorations in diversification opportunities, typically have maximum drawdowns significantly higher than those of portfolios of funds with a small or a positive correlation risk exposure. This is an indication of the fact that hedge funds with negative correlation risk exposure tend to suffer large losses at similar times, for instance when correlations increase during periods of economic crises or market distress, thus making correlation risk a systematic risk factor in the cross-section of hedge fund returns.

Our findings have broad relevance for hedge fund investors, because risk-adjusted (alpha) performance measures ignoring correlation risk tend to implicitly underestimate fund risk, as measured by key hedge fund selection metrics like, for example, maximum drawdowns. Because funds with negative correlation risk betas tend to suffer sudden large losses when correlations unexpectedly increase, monitoring and hedging this risk is key also more generally for hedge fund portfolio risk management.

Finally, although we focus in this paper on correlation risk deriving from unexpected changes in average stock correlation, studying the implications of other potentially relevant forms of correlation risk for hedge fund risk return trade-off, for example, risk linked to variations in stock-bond correlations or in correlations between different exchange rates, would be interesting. For instance, Mueller, Stathopoulos, and Vedolin (2012) show that the cross-section of exchange rate excess returns is systematically explained by exposures to a single correlation risk factor in the exchange rate market. Given the international character of several hedge fund strategies, an interesting avenue of

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research is whether exposure to exchange rate correlation risk can additionally explain some of the risk-return features of the time series and the cross-section of hedge fund returns.

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