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What do we know about the risk and return characteristics of hedge funds?

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ABSTRACT This article gives an overview of the risk and return characteristics of hedge funds. Analyzing the extensive research on hedge funds during the past two decades, this article discusses the style-specific risks of hedge funds, reviews the findings on the statistical properties of hedge funds and assesses the research on nonlinear, regime-dependent risks of hedge funds. Asset-based style factor models and regime-switching models both suggest that several (but not all) hedge fund strategies exhibit nonlinear, option-like payoffs. In recent empirical studies, financial economists argue that hedge funds are exposed to considerable credit, liquidity and bankruptcy risks in periods of stress in financial markets and that a widespread fraud problem may exist in the widely unregulated hedge fund industry.

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INTRODUCTION

The extensive academic research on hedge funds reflects the increasing importance of hedge funds for financial markets and has important implications for investors, policymakers and the public debate on hedge funds. On the basis of a review of 651 peer-reviewed articles on hedge funds published in the period 1990–2011, this article summarizes the key empirical and theoretical findings on the risk and return characteristics of hedge funds.¹ Concentrating

on the main findings and implications of the vast research on hedge funds during the past two decades, this article discusses asset-based style (ABS) factor models and style-specific risks in Chapter 2, reviews the academic research on the statistical properties of hedge funds in Chapter 3 and provides an overview of the research on nonlinear risks of hedge funds in Chapter 4.

The publication by Fung and Hsieh in 1997 was the first important milestone in the academic research on hedge funds. Hedge funds

apply a wide range of dynamic trading strategies, which differ dramatically from mutual funds. Fung and Hsieh (1997a) first notice that the risk of hedge funds predominantly depends on the dynamic trading strategy (or style), which hedge funds implement instead of the asset classes in which they invest. Extending the work of Sharpe (1992), Fung and Hsieh (1997a) propose a factor model including not only traditional asset class factors but also so-called ABS factors capturing the style-specific risk and return characteristics of different hedge fund strategies. Following Fung and Hsieh (1997a), a large number of empirical studies have been written on style-specific risks of hedge funds. Among others, Fung and Hsieh (1997a), Agarwal and Naik (2004), Mitchell and Pulvino (2001), Fung and Hsieh (2001, 2002b, 2004a, b), Dor *et al* (2006), Jaeger (2005), Kuenzi and Shi (2007), Racicot and Théoret (2008) and Agarwal *et al* (2011b) formulate ABS factor models to explain the style-specific risks of hedge funds. Section ‘Style-specific risks: ABS factor models’ summarizes the academic research on style-specific risks of hedge funds and ABS factor models.

There are many salient features about the statistical properties of hedge fund return series that are now well documented. Brooks and Kat (2002), Kat (2003), Lamm (2003), Brulhart and Klein (2005) and Eling (2006) document that hedge funds exhibit fat-tailed distributions. In addition, a large number of studies find statistical biases in hedge fund data bases including Park (1995), Fung and Hsieh (1997b, 2000a), Liang (2000, 2001), Amin and Kat (2003a), Malkiel and Saha (2005) and Fung and Hsieh (2009). Recent research finds empirical evidence that hedge funds are engaged in return smoothing and other fraudulent activities. The empirical

evidence presented in Getmansky *et al* (2004), Bollen and Pool (2008, 2009), Viebig and Poddig (2010a) and Agarwal *et al* (2011a) suggests that a widespread fraud phenomenon may exist in the largely unregulated hedge fund industry. Section ‘Academic research analyzing the statistical properties of hedge funds’ reviews the academic research on the statistical properties of hedge funds.

Although hedge funds promise their clients to generate returns uncorrelated with traditional asset classes, a growing amount of studies show that correlation estimates greatly underestimate the exposures of hedge funds to traditional asset classes. Asness *et al* (2001), Chan *et al* (2006) and Agarwal *et al* (2011b) analyze the exposures of hedge funds to traditional asset class factors in different market regimes.

Fung *et al* (2008) apply breakpoint analysis to study different factor loadings conditional on time periods. They test for the presence of structural breaks in hedge fund risk exposures and find that September 1998 and March 2000 are major structural breaks associated with the Long-Term Capital Management (LTCM) crisis in 1998 and the peak of the Internet bubble in early 2000. Among others, Jorion (2000) and Till (2008) analyze the collapses of LTCM and Amaranth in periods of extreme stress in financial markets. Among others, Fung and Hsieh (2000b, 2002b), Garbaravicius and Dierick (2005), and Stulz (2007) argue that a failure of one or more large hedge funds could have far-reaching implications for financial market stability. Billio *et al* (2010) apply regime-switching models to study the effects of financial crises on hedge fund risk. They find that traditional risk factor models substantially underestimate the risk of hedge funds during periods of crises. Bollen and Whaley (2009)

employ optimal changepoint regressions and find that ignoring time-varying risk exposures of hedge funds leads to incorrect risk and return estimates. Section 'Regime-dependent, nonlinear risks of hedge funds' discusses the academic literature on the regime-dependent risk characteristics of hedge funds, with particular reference to the risks of hedge funds in regimes of extreme stress in financial markets.

STYLE-SPECIFIC RISKS: ABS FACTOR MODELS

Hedge funds implement dynamic trading strategies and are free to shift between asset classes. As hedge funds typically do not employ buy-and-hold strategies, traditional benchmarks are not appropriate for understanding the risk and return characteristics of hedge funds. An extensive literature has documented that hedge funds exhibit nonlinear, option-like payoffs relative to the returns of traditional asset classes. ABS factors are designed to create a new set of benchmarks capturing the nonlinear, strategy-specific payoff profiles of hedge fund strategies. The goal of the ABS approach is to construct linear regression models explaining the returns of hedge funds, R_t , where the nonlinear, option-like payoff profile of hedge funds is contained in the style factors, $SF_{i,t}$ (Fung and Hsieh, 2002a):

$$R_t = \alpha + \sum_i \beta_i SF_{i,t} + \varepsilon_t \quad (1)$$

The term β_i represents the factor loadings or sensitivities to the style factors. The idea of ABS factor models is to identify style factors, $SF_{i,t}$, capturing the nonlinear, strategy-specific risk and return characteristics of hedge funds while preserving the linear relation between fund returns and the explanatory factors of the model.

Fung and Hsieh (1997a) first notice that the risk of hedge funds predominantly depends on the dynamic trading strategy (or style), which hedge funds implement instead of the asset classes in which they invest. Extending Sharpe's (1992) style analysis, they find that the trading strategy describing how long and short positions are traded over time is a dominant source of risk of hedge funds. They apply principal component analysis to determine dominant hedge fund styles and find that style factors explain a substantial portion of the return variation of hedge funds. Fung and Hsieh (1997a, 2001) argue that trend-following strategies can be replicated by long straddle positions on US equities. A long straddle position involves going long both a call and a put on the same underlying with the same strike price and the same expiration date. Trend-following funds implement dynamic trading strategies involving frequent adjustments of position sizes.

Trend-following funds buy when asset prices rise and sell when asset prices decline. The strategy is similar to delta hedging strategies for options. Replicating the risk and return profile of trend-following funds with a long straddle position makes intuitively sense as straddles and trend-following funds both generate large gains if the underlying increases or falls severely.

ABS factors aim to convert nonlinear relationships (between the returns on the hedge fund strategy and the returns on the underlying asset class) into linear relationships (between the returns on the hedge fund strategy and the returns on the option-based factors). Empirical results by Agarwal and Naik (2004) confirm that the use of option-based factors substantially increases the explanatory power of linear factor models when analyzing hedge fund returns.

Mitchell and Pulvino (2001) analyze a large number of mergers between 1963 and 1998. In a cash merger, the arbitrageur simply buys the target company's stock after a merger is announced. In a stock merger, the arbitrageur buys the target's stock and sells short the stock of the acquirer to capture the arbitrage spread. Mergers often involve complex deal structures. Mitchell and Pulvino (2001) calculate daily returns of 4750 merger transactions where the arbitrageur's investment is straightforward. Using the total market equity value of the target company as weighting factor, they construct a 'Value-weighted Average Return Series (VWRA)' capturing the strategy-specific risk and return characteristics of merger arbitrage funds. They demonstrate that the VWRA benchmark captures the nonlinear payoff profile of merger arbitrage funds. Mitchell and Pulvino (2001) find that merger arbitrage returns are positively correlated with equity market returns in severely depreciating markets but uncorrelated with market returns in flat and appreciating markets. In addition, they show that merger arbitrage strategies can be replicated by a long position in a risk-free bond and a short position in put options on a broad equity index such as the S&P 500 Index.

Since the publications of Fung and Hsieh (1997a, 2001) and Mitchell and Pulvino (2001), a large number of articles and working papers have been written on strategy-specific hedge fund risks. Table 1 gives an overview of selected studies proposing ABS factor models to explain the return variation of hedge funds (Tancar and Viebig, 2008). Fung and Hsieh (2002b) argue that the performance of fixed-income arbitrage hedge funds implementing trend-following strategies on spreads can be replicated by an option-based factor. Fixed-income arbitrage

hedge funds often implement convergence trades by taking long positions in cheap assets and short positions in more expensive but otherwise similar assets. Fixed-income arbitrage hedge funds realize arbitrage profits when the spreads between the two assets revert. According to Fung and Hsieh (2002b), convergence trading strategies on spreads can be modeled as short positions in lookback straddles since convergence trading strategies on spreads are the opposite of trend-following strategies on spreads. In addition, Fung and Hsieh (2002b) find that fixed-income arbitrage funds exhibit considerable exposures to convertible bond/Treasury spreads, high-yield bond/Treasury spreads, mortgage securities/Treasury spreads and emerging market bond/Treasury spreads. They argue that increases in credit spreads represent a common source of risk in fixed-income arbitrage and warn that leveraged fixed-income arbitrage strategies can potentially destabilize markets when extreme events occur.

Agarwal and Naik (2004) show that hedge funds exhibit option-like payoffs and suffer large losses during market downturns. Using the excess returns on traditional asset classes and the returns of puts and calls on these asset classes as risk factors, Agarwal and Naik (2004) construct a flexible, piecewise linear multi-factor model capturing the option-like payoffs of hedge funds:

$$R_p = \alpha + \beta_1 R_m + \beta_2 \max(R_m - k_1, 0) + \beta_3 \max(R_m - k_2, 0) + \beta_4 \max(k_1 - R_m, 0) + \beta_5 \max(k_2 - R_m, 0) + \varepsilon \quad (2)$$

R_p and R_m represent the returns on a hedge fund portfolio and the returns on the market, respectively. β_i and k_j denote the factor loadings and the strike prices of the options. The option-based model shown in equation (2) can easily be

Table 1: ABS-factors used in empirical studies

<i>Study</i>	<i>Strategy</i>	<i>Maximum R² (%)</i>	<i>Model components</i>
Fung and Hsieh (1997a)	All	70.0	Factor analysis is used to extract five dominant style factors representing five qualitative style categories (Systems/Opportunistic, Global/Macro, Value, Systems/trend Following, Distressed), option-based factors
Fung and Hsieh (2001)	Managed futures	60.7	Three Lookback straddles (bonds, currencies, commodities)
Mitchell and Pulvino (2001)	Merger arbitrage	42.4	Value-weighted portfolio of long announced targets and short the acquirers
Fung and Hsieh (2002a)	All	89.0	Zurich Capital Markets Trend-Follower index, option-based trend-following factor, traditional asset-class factors
Fung and Hsieh (2002b)	Fixed income arbitrage	79.0	Long position in Baa corporate bonds, short position on 10-year Treasury bonds, also swap, mortgage and yield-curve spreads
Agarwal and Naik (2004)	Equity-oriented hedge funds	91.6	Buy-and-hold, option-based factors, spread factors (HML, SMB), momentum factor
Fung and Hsieh (2004a)	Funds of hedge funds	84.0	S&P500, Wilshire 1750 Small Cap – Wilshire 750 Large Cap, change in Fed 10-year constant maturity yield, change in spread between Moody's Baa yield and portfolio of lookback straddles on bond futures, portfolio of lookback straddles on currency futures, portfolio of lookback straddles on commodity futures.
Fung and Hsieh (2004b)	L/S Equity	87.1	Fama-French three factor model, Carhart momentum factor
Capocci and Hübner (2004)	All	92.0	Fama-French HML, Carhart momentum factor, credit spread factors
	Convertible arbitrage	13.7	Equally weighted and capitalization-weighted portfolio of convertible bonds, hedged equity risk

Table 1 continued

<i>Study</i>	<i>Strategy</i>	<i>Maximum R² (%)</i>	<i>Model components</i>
Jaeger (2005)	All (index)	88.5	Small-cap spread, High-Yield spread, Value spread, CPPI on S&P500, Merger Fund, BXM index (covered call writing on the S&P500) and the SGFI index (trend following futures)
Dor <i>et al</i> (2006)	All	87.6	Wilshire 5000, CBOE Volatility Index, US SMB, US HML, EM Telecom Index
Kuenzi and Shi (2007)	L/S Equity	—	S&P500, SMB, HML, volatility factors
Racicot and Théoret (2008)	All	93	S&P500, SMB, HML, momentum factor, 1-month short put on the S&P500
Agarwal <i>et al</i> (2011b)	Convertible arbitrage	62.6	Volatility arbitrage (delta-neutral long gamma position, hedged credit and interest rate risk), credit arbitrage (hedged equity and interest rate risk), and positive carry (delta-neutral position, positive interest income, hedged equity risk)
Buraschi <i>et al</i> (2011)	All	—	Failure to account for differences in correlation risk exposures may lead to an overestimation of performance and an underestimation of risk.
Patton and Ramadorai (2011)	All	—	Patton and Ramadorai (2011) use high-frequency conditioning variables to explain the return variation of hedge funds.

extended to a model with an arbitrary number of buy-and-hold factors and option-based factors. Agarwal and Naik (2004) show that allowing for nonlinear risk characteristics is important while analyzing hedge funds. Linear factor models greatly underestimate the tail-risks of hedge funds. Agarwal and Naik (2004) find that equity-related hedge funds exhibit significant exposures to Fama and French's (1992, 1993) HML and SMB factors and Carhart's (1997) momentum factor.

Several empirical studies suggest that spreads between asset classes explain a large proportion of the return variation of hedge funds. Fung and Hsieh (2004b) apply the linear 3-factor Fama and French (1992, 1993, 1995, 1996) model to explain the variation in returns of long/short equity hedge funds. According to Fama and French, the expected return on a portfolio of stocks $E(r_p)$ in excess of the risk-free rate r_f can be explained by the expected return of a well-diversified market portfolio in excess of the risk-free rate ($F_1 = E(r_m) - r_f$), the expected return spread between small capitalization and large capitalization stocks ($F_2 = \text{SMB}$), and the expected return spread between high book-to-market (value) and low book-to-market (growth) stocks ($F_3 = \text{HML}$):

$$[E(r_p) - r_f] = \alpha_p + \beta_{p,1}[E(r_m) - r_f] + \beta_{p,2}E(\text{SMB}) + \beta_{p,3}E(\text{HML}) + \varepsilon \quad (3)$$

The terms $\beta_{p,1}$, $\beta_{p,2}$ and $\beta_{p,3}$ represent the factor sensitivities or loadings to the three explanatory factors of the model. Applying the Fama and French (1992, 1993, 1995, 1996) model, Fung and Hsieh (2004b) find that the excess return on the market and the spread between small cap and large cap stocks are

important risk factors for long/short equity hedge funds. According to Fung and Hsieh (2004b), the HML factor is not statistically significant. They introduce a Carhart (1997) momentum factor, which is statistically significant but does not add much additional explanatory power. Fung and Hsieh (2004b) document that spread factors can be used to extract portable α s from long/short equity hedge funds. In several studies, financial economists apply modified versions of the Fama and French model to explain the return variation of long/short equity hedge funds (for example, Capocci and Hübner, 2004; Kuenzi and Shi, 2007; Racicot and Théoret, 2008).

Kuenzi and Shi (2007) extend the Fama and French model by adding a volatility factor. They argue that the implicit volatility of 3-month at-the-money call and put options represents the best volatility factor to explain the return variation of equity-related hedge funds. Among others, Dor *et al* (2006) use the CBOE Volatility Index (VIX) as volatility factor, a widely used measure of market risk often referred to as 'investor fear gauge' (Whaley, 2009). Racicot and Théoret (2008) argue that high α s estimated by factor models are often due to inappropriate or omitted factors or other specification errors in models. In addition to the three factors suggested by Fama and French (1992, 1993, 1995, 1996) and a momentum factor, they use the returns of a short put on the S&P 500 Index whose volatility is the VIX to account for the option-like payoffs of hedge funds.

Agarwal *et al* (2011b) explain how ABS factors can be constructed to explain the performance of convertible arbitrage hedge funds. Analyzing US Dollar- and Japanese Yen-denominated convertible bonds, they construct a rule-based ABS factor capturing the performance of

convertible arbitrage hedge funds. Convertible arbitrage hedge funds typically buy convertible bonds and hedge the equity risk by shorting the shares of the convertible bond issuer. Agarwal *et al* (2011b) argue that convertible arbitrage funds are important intermediaries providing funding to convertible bond issuers. Using daily returns from the convertible bond and stock markets, Agarwal *et al* (2011b) compute an ABS factor assuming that convertible arbitrage funds take long positions in convertible bonds and short positions in the shares of the convertible bond issuer. They find that their rule-based ABS factor explains a large proportion of the return variation of convertible arbitrage hedge funds. The empirical evidence provided by Agarwal *et al* (2011b) suggests that convertible arbitrage strategies are highly sensitive to extreme market events.

The goal of ABS models is to construct linear regression models to explain the return variation of hedge funds. ABS factor models are an attractive modeling choice as the linear relation between fund returns and explanatory factors is preserved. The nonlinearity between traditional asset class returns and hedge fund returns is contained in the style factors of the ABS model. Generally, four different groups of ABS factors can be differentiated: rule-based factors, option-based factors, spread factors and volatility factors. Although empirical research suggests that adding ABS factors substantially increases the explanatory power of linear factor models, several limitations of ABS factor models need to be mentioned.

First, unlike traditional asset class factors, ABS factors cannot be observed in the markets. Constructing and maintaining ABS factors is often time consuming. Second, a substantial amount of the variation in hedge fund returns

cannot be explained by ABS factors. Further research is required to better understand the systematic risks of hedge fund strategies. Third, the choice of ABS factors is often arbitrary in nature. Today no convincing formal model or theory exists to identify ABS factors (Fung and Hsieh, 2002a). Brown and Goetzmann (2003), Maillet and Rousset (2003), Dor *et al* (2006), Baghai-Wadji *et al* (2006), Gibson and Gyger (2007) present empirical evidence for style drift of hedge funds. ABS factor models are designed to capture the strategy-specific risk and return characteristics of hedge fund strategies. Investors who allocate capital to individual hedge funds should be aware that hedge funds often do not consistently follow a replicable, predefined trading strategy but shift between different styles.

Last but not least, like traditional factor models, ABS factor models usually assume that risk exposures are constant. Buraschi *et al* (2011) find that correlation risk exposures account for a large part of the return variation of hedge funds. Investors who do not account for correlation risk exposures tend to overestimate the performance and underestimate the risk of hedge funds. Buraschi *et al* (2011) show that hedge funds with low net exposures often suffer large losses when correlations unexpectedly increase. Correlation risk exposure is an important risk for hedge fund investors. Patton and Ramadorai (2011) use high frequency conditioning variables to model hedge fund risk exposures. They argue that hedge funds exhibit time-varying risk exposures and tend to cut risk exposures during periods of stress in financial markets. ABS factor models may underestimate hedge fund risks when ignoring time-varying exposures to option-based risk factors and other ABS factors.

ACADEMIC RESEARCH ANALYZING THE STATISTICAL PROPERTIES OF HEDGE FUNDS

Most research on hedge funds has been conducted using monthly return data as most hedge funds only report monthly track records to database vendors such as Hedge Fund Research (HFR), Tremont Advisory Shareholder Services (TASS), Morgan Stanley Capital International, Barclays Global Investors (BGI) and the Center for International Securities and Derivatives Markets (CISDM). Empirical studies on hedge funds should be treated with care as hedge funds are for the most part unregulated entities that are not obliged to periodically publish return data.

Since the early work by Park (1995), it has been well documented that hedge fund databases contain measurement biases. New hedge funds are often seeded with capital coming from the managers' friends and relatives. If the track record is satisfactory, hedge fund managers often decide to report information to a database to attract capital from outside investors. When hedge funds report return information to a database for the first time, data vendors usually include the complete return history in their databases. This creates the possibility of an instant history or backfilling bias. Empirical studies show that the returns reported by data vendors are upward biased as data vendors backfill historical returns. Fung and Hsieh (2000a) estimate an instant history bias of 1.4 per cent per year for hedge funds. Edwards and Caglayan (2001) find that average hedge fund returns during the first year of existence are 1.17 per cent higher than average hedge fund returns in following years. Malkiel and Saha (2005) analyze the returns of hedge funds, which

reported information to the TASS database and find that the backfilled returns exceeded the contemporaneously reported, not backfilled returns on average by over 5 per cent per year over the period 1994–2003. The backfilling bias was most pronounced in the early years (1994–1995) when the number of backfilled returns exceeded the number of contemporaneously reported returns.

Another important measurement bias that has been well documented in empirical studies is referred to as survivorship bias. Data vendors usually only include the returns of hedge funds currently reporting information to the database (survivors) into performance calculations and exclude the returns of funds which stopped reporting information to the database (dead, defunct or graveyard funds). A high attrition rate leads to a high survivorship bias if funds dissolve for poor performance. Fung and Hsieh (1997b) argue that commodity trading advisors (CTA) dissolve more frequently than mutual funds and find that the difference between the returns of surviving CTA funds and all CTA funds averages 3.48 per cent per year over the period 1989–1995. Fung and Hsieh (2000a) estimate that the survivorship bias in hedge funds is 3.0 per cent per year over the 1994–1998 period. Liang (2000) argues that the survivorship bias in hedge fund returns exceeds 2 per cent per annum and that the size of the survivorship bias differs across hedge fund styles. Liang (2001) finds that the annual survivorship bias of hedge funds was 2.43 per cent from 1990 to mid-1999. Amin and Kat (2003a) present evidence that the survivorship bias in hedge fund returns is on average 2 per cent per annum but can be as high as 4–5 per cent per annum for small, young and leveraged hedge funds, which have on average higher attrition rates. According to Malkiel and Saha

(2005), the difference in mean returns between live hedge funds and all hedge funds is on average 4.42 per cent per annum over the 1996–2003 period.

The main reason for the high survivorship bias in hedge fund databases is the high attrition rate. Gregoriou (2002) finds that one half of all hedge funds die within 5.5 years of first reporting. Brown *et al* (2001) present empirical evidence that survival of hedge funds is a function of performance, excess volatility and fund age. Funds lagging industry benchmarks, funds taking excessive risks and recently launched hedge funds are less likely to survive. Although high performance fees may theoretically lead to moral hazard, Ackermann *et al* (1999) and Brown *et al* (2001) argue that hedge fund termination is a strong motive for hedge funds to control risk. Little evidence exists that hedge funds increase risks to take advantage of asymmetric performance contracts. Fung and Hsieh (2009) assume that the attrition rate and the survivorship bias may have been increased recently because of the unprecedented capital flows out of hedge funds during the financial crisis 2007–2009.

The selection of hedge funds contained in a database is not necessarily representative for the complete universe of hedge funds available for investment. Fung and Hsieh (2000a) rightly point out that the selection bias cannot be measured accurately as long as a large amount of hedge funds do not disclose return information to data vendors. According to Fung and Hsieh (2009), close to 40 per cent of the top 100 single hedge funds in the 2008 annual ranking by Institutional Investor do not report return information to four major databases (BGI, HFR, CISDM, TASS) analyzed by the authors. Fung and Hsieh (2009) argue that hedge funds

sometimes stop reporting return information to one database or switch their reporting from one database to another. Hedge fund databases are neither similar in their scope and coverage nor necessarily representative for the entire hedge fund industry.

Several studies explore the statistical properties of hedge fund returns. Brooks and Kat (2002), Anson (2002b), Kat (2003), Lamm (2003) and Brulhart and Klein (2005) analyze monthly hedge fund returns and conclude consistently that return distributions of hedge funds exhibit negative skewness and positive excess kurtosis. Empirical studies suggest that hedge fund returns do not follow a normal distribution. Anson (2002a) argues that symmetric performance measures like the Sharpe ratio are not suitable performance measures for hedge funds generating asymmetric, option-like returns. Eling (2006) calculates Jarque and Bera (1987) statistics for 10 CSFB/Tremont hedge fund indices over the January 1994–December 2004 period and concludes that 9 out of 10 indices deviate significantly from the normal distribution at the 99 per cent level of confidence. Investors should assume that hedge funds generate extreme returns more frequently than the normal distribution suggests.

Amin and Kat (2003b) conclude that adding hedge funds to a portfolio of stocks and bonds is not a free lunch. Allocating capital to hedge funds improves a portfolio's mean-variance characteristics at the cost of a lower skewness and higher kurtosis. Amin and Kat (2003c) argue that investing in single hedge funds is not efficient. They find that the inefficiency cost of individual hedge funds can be diversified away by investing in a diversified portfolio of hedge funds. As the returns of hedge funds exhibit weak relationships with the returns of other asset

classes, they recommend investing at least 10 per cent of a portfolio in hedge funds.

The empirical studies by Boyson *et al* (2006) and Li and Kazemi (2007) are among the few studies that analyze not only monthly hedge fund returns, but also daily hedge fund return data. Boyson *et al* (2006) apply binomial and multinomial logit models of contagion to explore whether extreme movements in equity, fixed income and currency markets are contagious to hedge funds. They conclude that there is no evidence of contagion from equity, fixed income and currency markets to hedge funds, except for weak evidence of contagion for one single daily hedge fund style index. However, Boyson *et al* (2006) find evidence that extreme adverse movements in one hedge fund style index are contagious to other hedge fund strategy indices. Li and Kazemi (2007) test for the presence of asymmetries in conditional correlations between hedge fund returns and returns on stock and bond indices in up and down markets. Using the symmetry tests documented in Ang and Chen (2002) and Hong *et al* (2007), they formally test for asymmetry. They argue that correlations between hedge fund returns and market returns are symmetric in rising and falling markets and conclude that there is no empirical evidence in support of contagion between hedge funds and traditional asset classes. Unfortunately, the studies by Boyson *et al* (2006) and Li and Kazemi (2007) both do not include the period 2007–2009 in which returns of traditional asset classes and hedge funds collapsed simultaneously. Although previous researchers applying logit models of contagion and tests for the presence of asymmetries have argued that there is nonempirical evidence in support of contagion between equities and hedge funds Viebig and

Poddig (2010b) find that a statistically significant volatility spillover effect exists between equities and several hedge fund strategies during periods of extreme stress in equity markets. Applying Vector Autoregressive models, they find that the dependencies between several hedge fund strategies and equities increased substantially during the recent financial crisis in 2007–2009. Extreme value theory and copula theory are appropriate modeling choices to capture extreme returns and asymmetric dependence structures of hedge fund strategies during periods of extreme stress in financial markets (Viebig and Poddig, 2010c).

The empirical evidence that hedge fund returns are severely distorted by instant history biases, survivorship biases and selection biases is widely accepted. Getmansky *et al* (2004), Bollen and Pool (2008, 2009), Viebig and Poddig (2010a) and Agarwal *et al* (2011a) suggest that return series of hedge funds are not only distorted by statistical biases, but also by a widespread misreporting phenomenon. Agarwal *et al* (2011a) argue that hedge fund investors face a principal–agent conflict like shareholders of corporate firms. Hedge funds only voluntarily submit return information to databases. Most hedge funds do not disclose their holdings to investors. As a result, hedge fund investors make investment decisions under incomplete and asymmetric information. High performance-linked incentive fees, typically 20 per cent of the annual fund performance, tend to align interests between investors and hedge fund managers. However, high incentive fees may not only motivate managers to act on behalf of their investors but may also induce some managers to misreport returns in order to earn higher compensation. Schneeweis *et al* (2006) find that hedge funds tend to time the release of return

information. Comparing the performance of hedge funds reporting early in the monthly reporting cycle with the performance of hedge funds reporting later in the reporting cycle, they find that poorly performing managers tend to delay reporting returns. More recently, researchers find that hedge funds not only tend to time the release of return information, but may also be engaged in return smoothing and other fraudulent activities.

Hedge fund managers have an interest to smooth returns in order to attract and retain investors. Return smoothing behavior leads to lower volatility and higher Sharpe ratios. Asness *et al* (2001) and Getmansky *et al* (2004) present empirical evidence that hedge fund returns are often highly serially correlated. Getmansky *et al* (2004) argue that although several potential explanations for serial correlation in hedge fund returns exist, the high serial correlation in hedge fund returns most likely stems from illiquidity and smoothed returns. They present a linear regression model that can help to distinguish between systematic illiquidity and idiosyncratic return smoothing behavior. Bollen and Pool (2008) investigate whether the serial correlation is related to the likelihood that fund managers are engaged in fraudulent activities. They find that high serial correlation is a leading indicator for fraud. Funds investigated for fraud by the SEC more likely exhibit higher positive serial correlations than other funds.

Bollen and Pool (2009) observe that the number of small gains significantly exceeds the number of small losses reported by hedge funds. They argue that the discontinuity in the pooled distribution of monthly hedge fund returns may result from hedge funds temporarily overstating returns. Bollen and Pool (2009) find that the discontinuity is not present three months before

an audit. The study by Bollen and Pool (2009) suggests that hedge funds deliberately avoid reporting losses. Viebig and Poddig (2010a) complement the literature on possible misreporting by hedge funds. They show that the likelihood of observing positive outliers in the first 3-month period after a new hedge fund is launched is significantly larger than the likelihood of observing positive outliers in any later 3-month period at the 99 per cent level of confidence. As the statistically significant concentration of positive outliers during the first 3-month period does not disappear after controlling for risk, they conclude that hedge funds actively jump-start newly launched funds to attract capital from investors and argue that the concentration of positive outliers during the first 3-month period can result from both legal and illegal trading behavior.

Agarwal *et al* (2011a) observe that hedge fund returns during December are significantly higher than hedge fund returns during the rest of the year. They find that risk-based explanations do not fully explain the 'December spike' in hedge fund returns and argue that hedge funds may inflate December returns by underreporting returns earlier in the year and by borrowing from January returns in the next year. The latter can be achieved, for example, by placing large buy orders in illiquid securities at the end of December to artificially inflate prices. The empirical evidence presented by Agarwal *et al* (2011a) indicates that some hedge funds may not accurately value securities.

Taken together, the empirical evidence presented by Getmansky *et al* (2004), Bollen and Pool (2008, 2009), Viebig and Poddig (2010a) and Agarwal *et al* (2011a) suggests that some hedge funds may purposefully misreport returns to attract capital flows and to increase fee

income. Regulators and investors are concerned that hedge funds deliberately misreport returns. The academic literature, in fact, suggests that a widespread misreporting phenomenon may exist in the largely unregulated hedge fund industry.

Table 2 summarizes the research on the statistical properties of hedge funds. Three important implications can be drawn. First, the available data on hedge funds are severely distorted by backfilling biases, survivorship biases and selection biases. Second, hedge funds typically exhibit negative skewness and positive excess kurtosis. The Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965) and Mossin (1966), the Arbitrage Pricing Theory (APT) by Ross (1976) and other capital pricing models assuming that returns are normally distributed do not adequately capture the asymmetric, option-like return profiles of hedge funds. Third, recently published academic research on hedge funds suggests that a widespread misreporting phenomenon may exist in the largely unregulated hedge fund industry. Some hedge funds may deliberately be engaged in return smoothing and other fraudulent activities.

REGIME-DEPENDENT, NONLINEAR RISKS OF HEDGE FUNDS

This Section reviews the literature analyzing the nonlinear, regime-dependent risks of hedge funds. In several studies, financial researchers analyze the dynamic behavior of hedge fund returns over time. In light of the unprecedented losses of hedge funds during the financial crisis 2008–2009, these studies are of particular interest for investors who want to better understand the risks of hedge funds in periods of

extreme stress in financial markets. Recent empirical work suggests that return series of hedge funds exhibit dramatic breaks, associated with financial crises. It seems that hedge funds behave quite differently during financial crises, when volatility increases and liquidity dissipates in global financial markets, than in less volatile periods. Table 3 gives an overview of studies discussing the regime dependent, nonlinear risks of hedge funds.

Asness *et al* (2001) analyze 10 equity hedge fund indices in bull and bear markets over the January 1994–September 2000 period. They find that traditional β and correlation estimates greatly understate the exposures of hedge funds to equity markets. They argue that hedge fund returns are not synchronous with market returns as hedge funds price their securities, intentionally or unintentionally, with a lag. Using not only contemporaneous but also lagged returns as explanatory variables to account for the smoothing effect, Asness *et al* (2001) find that hedge funds exhibit significant exposures to the equity market in up and down markets. Investors often allocate capital to hedge funds to diversify risks. The positive diversification effects that investors desire from hedge funds vanish, when lagged β models are applied to estimate more accurate market exposures.

Spurgin *et al* (2001) present empirical evidence that the null hypothesis of constant correlation between hedge fund returns and traditional asset returns can be rejected for most hedge fund strategies with a high degree of confidence. As the exposures of hedge funds are not constant over time, financial economists have applied regime-switching models to account for nonlinearity in hedge fund returns (Viebig *et al*, 2011a). Threshold models aim to capture nonlinearity by stepwise linearization.

Table 2: Selected studies analyzing the statistical properties of hedge funds

Study	Key findings
Park (1995), Fung and Hsieh (1997b, 2000a), Liang (2000, 2001), Edwards and Caglayan (2001), Amin and Kat (2003a), Malkiel and Saha (2005) Ackermann <i>et al</i> (1999), Brown <i>et al</i> (2001)	Hedge fund return data are significantly influenced by backfilling, survivorship and selection biases. Hedge fund survival is a function of performance, excess volatility and fund age. Despite high performance fees, there is little evidence that hedge funds take excess volatility to increase short-term profits, as the threat of termination is a strong motive to control risk. The median survival lifetime of hedge funds is only 5.5 years. Assets under management, redemption periods, performance fee, leverage, monthly returns and minimum purchase influence the survival lifetime of hedge funds.
Gregoriou (2002)	Monthly returns of hedge funds exhibit negative skewness and positive excess kurtosis. Hedge funds generate extreme returns more frequently than the normal distribution suggests. Traditional performance measures like the Sharpe ratio, which assume that returns that are normally distributed, are not suitable for hedge funds.
Anson (2002a, b), Brooks and Kat (2002), Kat (2003), Lamm (2003) and Brulhart and Klein (2005), Eling (2006)	Investing in hedge funds is not a free lunch. Allocating capital to hedge funds improves a portfolio's mean variance characteristics at the cost of a lower skewness and a higher kurtosis. The inefficiency cost of investing in single hedge funds can be diversified away by investing in a diversified portfolio of hedge funds.
Amin and Kat (2003b, c)	There is no evidence of contagion from traditional asset classes to hedge funds. Unlike Li and Kazemi (2007), Boyson <i>et al</i> (2006) find evidence that extreme adverse movements in one hedge fund style index are contagious to other hedge fund strategy indices. Viebig and Poddig (2010b) show that a statistically significant contagion effect exists between equities and several hedge fund strategies during the financial crisis 2007–2009.

Schneeweis <i>et al</i> (2006)	Hedge funds tend to time the release of return information. Poorly performing managers tend to delay reporting returns.
Asness <i>et al</i> (2001), Getmansky <i>et al</i> (2004), Bollen and Pool (2008)	Hedge funds exhibit a high degree of serial correlation, which possibly results from illiquidity and smoothed returns. Bollen and Pool (2008) show that funds investigated for fraud by the SEC more likely exhibit high conditional serial correlations than other funds.
Bollen and Pool (2009)	Bollen and Pool (2009) detect a significant discontinuity in the pooled distribution of monthly hedge fund returns. Hedge funds report small gains more frequently than small losses. The discontinuity possibly results from temporarily overstated returns.
Agarwal <i>et al</i> (2011a)	Managerial incentives in hedge fund contracts and managerial discretion matter. Hedge funds with greater managerial incentives, higher levels of managerial ownership and a higher degree of managerial discretion tend to generate higher returns.
Viebig and Poddig (2010a)	Viebig and Poddig (2010a) complement the literature on possible misreporting by hedge funds. They find that hedge funds actively jump-start newly launched funds to attract capital from investors in the first 3-month period.
Agarwal <i>et al</i> (2011a)	Hedge fund returns during December are significantly higher than hedge fund returns from January to November (December spike). Hedge funds possibly inflate December returns.

Table 3: Selected Studies analyzing the nonlinear, regime-dependent risks of hedge funds

<i>Study</i>	<i>Key finding</i>
Asness <i>et al</i> (2001)	Traditional β and correlation estimates greatly understate the exposures of hedge funds to equity markets. Hedge fund returns are not synchronous with market returns as hedge funds price their securities with a lag. Hedge funds exhibit significant exposures to the equity market in up and down markets.
Spurgin <i>et al</i> (2001)	The correlations between hedge fund returns and equity market returns are not constant over time.
Fung <i>et al</i> (2004a), Fung <i>et al</i> (2008), Agarwal <i>et al</i> (2011b)	Correlations typically increase when equity markets decline severely. September 1998 and March 2000 associated with the LTCM crisis and the peak of the Internet are major structural break points for hedge funds. Factor exposures of hedge funds are not constant over time. Hedge funds are sensitive to extreme market events. The explanatory power increases when regime-switching models instead of traditional multi-factor models are applied accounting for structural changes in factor loadings.
Bollen and Whaley (2009)	Changepoint regression models generally have a higher explanatory power than models assuming that parameters are constant over time. Over 40 per cent of live hedge funds experience statistically significant shifts in risk exposure. α s from constant regression models are misleading measures of abnormal performance.
Chan <i>et al</i> (2006)	The probabilities of being in a regime of high volatility or a regime of low expected returns are not constant over time. Hedge funds face complex nonlinear risks. Extreme market events can cascade into a financial crisis, when large losses erode the capital base of highly leveraged hedge funds, liquidity in financial market dissipates, and correlations increase. A definitive assessment whether hedge funds increase systemic risks, however, requires data that are not available.
Jorion (2000), Till (2008)	The size and the concentration of the risk positions of LTCM and Amaranth were inappropriate for the level of their capital base. Relying on short-term history, LTCM severely underestimated its risk. The failures of LTCM and Amaranth both illustrate the 'death spiral' that highly leveraged hedge funds face when large losses suddenly erode the capital base, and risk positions cannot be closed economically.

Eichengreen <i>et al</i> (1998), Fung and Hsieh (2000b), Garbaravicius and Dierick (2005), Stulz (2007)	Hedge funds provide liquidity and tend to reduce market inefficiencies. There is little evidence that hedge funds use positive feedback strategies and cause market prices to deviate from economic fundamentals. A failure of one or more hedge funds could lead to far-reaching implications for prime brokers and other counterparties of hedge funds and financial market stability. The counterparty risks and the market impact of hedge funds cannot be estimated reliably as hedge funds are not obliged to report risk positions to regulators. As a result, no analysis exists that reliably quantifies the social costs and benefits of hedge funds.
Khandani and Lo (2007)	The unprecedented losses of quantitative long/short equity hedge funds during the week of 6 August 2007, potentially result from quantitative hedge funds or proprietary trading desks reducing risk exposures. Volatility can escalate when hedge funds are forced to cover large long or short positions to reduce risks.
Brunnermeier (2009)	Hedge funds and other leveraged investors are exposed to extreme liquidity and credit risks in periods of distress. During periods of stress in financial markets, it becomes more difficult for hedge funds to obtain funding and to raise money by selling assets. Loss spirals and margin spirals can amplify financial crises.
Billio <i>et al</i> (2010)	Hedge funds are exposed to extreme liquidity, credit and volatility risks during financial crises. Traditional factor models overestimate the diversification benefits of hedge funds. Hedge funds are exposed to a common latent risk factor potentially related to margin spirals, runs on hedge funds, massive redemptions, credit freezes, market-wide panic and interconnectedness between financial markets.

Tong and Lim (1980) originally introduced threshold models to account for, among other things, cyclical phenomena in time series data. Threshold models are multi-stage factor models with the transition between them depending on an indicator variable τ :

$$R_t = \begin{cases} \alpha_t^I + \sum_{n=1}^N \beta_n^I F_{nt} + \varepsilon_t^I, & \text{if } \tau > \eta \\ \alpha_t^{II} + \sum_{n=1}^N \beta_n^{II} F_{nt} + \varepsilon_t^{II}, & \text{if } \tau \leq \eta \end{cases} \quad (4)$$

$\alpha^I, \alpha^{II}, \beta^I, \beta^{II}$, and $\varepsilon^I, \varepsilon^{II}$ represent the parameters and the error terms of the model with $n = 1, \dots, N$ factors F_n . The parameter η specifies the switching rule for the indicator variable τ . Threshold models can be used to analyze hedge fund returns conditional on different ‘regimes’ or ‘states of the worlds’. If the returns of a broad market index are used as indicator variable τ , a two-stage model can be constructed to explore the returns of hedge funds in an up-market regime ($\tau > 0$) and a down-market regime ($\tau < 0$).

Regime-switching models have become popular among financial economists as many financial time series occasionally exhibit breaks in their behavior. Regime-switching models are more flexible than traditional linear regression models. The two-stage multi-factor model shown in equation (4) can easily be generalized to a multi-stage, multi-factor model. With a growing number of degrees of freedom, however, the danger of overfitting the return series increases. Return series of hedge funds are generally short, as hedge funds typically only report monthly return information. If a regime-switching model becomes excessively complex, it may describe noise rather than a systematic relationship between hedge fund returns and the explanatory variables of the model. Statistical

models that have been overfit often have high in-sample R^2 but poor out-of-sample predictive power.

Several empirical studies suggest that hedge fund returns behave differently in regimes of stress in financial markets. Liang (2001) analyzes the performance of hedge funds from 1990 to mid-1999 and finds that hedge funds increased substantially during the 10-year bull period, but were severely affected during the LTCM crisis 1998. Fung and Hsieh (2004a) apply a multi-factor model and test the stability of the factor β s. They find that September 1998 and March 2000 associated with the LTCM crisis and the peak of the Internet bubble are major break points in time series of hedge funds. Fung *et al* (2008) use a modified version of the Chow (1960) test to systematically test for break points in hedge fund data. Using breakpoint analysis to study factor loadings conditional on time periods, they find that September 1998 and March 2000 are important structural breaks. Taking time-varying exposures into account is of great importance when analyzing the risk and return characteristics of hedge funds. Hedge funds are significantly exposed to time-varying factor risks. Fung and Hsieh (2004a) are the first to observe that extreme market events trigger structural break points in hedge fund return series. According to Fung and Hsieh (2004a), the exposures of hedge funds to the S&P500 index decreased substantially after the LTCM debacle and the end of the Internet bubble possibly because of a reduction of risk during bear markets. They present evidence that hedge funds dynamically adjust risk exposures in response to changing market conditions. Factor loadings of hedge funds are not constant over time.

Analyzing hedge fund data covering the period 1994–2005, Bollen and Whaley (2009)

study changes in risk exposures of hedge funds. Assuming that hedge fund exposures may undergo discrete shifts, Bollen and Whaley (2009) formulate a changepoint regression model as follows:

$$\begin{aligned} R_t &= \alpha_0 + \beta_0^T F_t + \varepsilon_t \quad \text{for } t = 1, \dots, T\pi \\ R_t &= \alpha_0 + \alpha_1 + (\beta_0^T + \beta_1^T) F_t + \varepsilon_t \\ &\quad \text{for } t = T\pi + 1, \dots, T \end{aligned} \quad (5)$$

π with $0 < \pi < 1$ denotes a single unknown changepoint. The changepoint regression model can be used to test whether the parameters change over time. If the null hypothesis $H_0: \alpha_1 = \beta_1 = 0$ can be rejected, the parameters undergo structural change. The changepoint regression model shown in equation (5) assumes that hedge fund exposures to underlying factors undergo discrete shifts. Bollen and Whaley (2009) also apply a stochastic β model, assuming that hedge fund exposures are unobserved state variables that follow a first-order autoregressive process and revert to a long-run mean over time. They find that the explanatory power of the changepoint regression model is generally higher than the explanatory power of the stochastic β model. Analyzing a large sample of hedge funds included in the CISDM and the TASS databases, Bollen and Whaley (2009) find that over 40 per cent of the live hedge funds in their sample experience statistically significant shifts in risk exposures.

Agarwal *et al* (2011b) investigate the impact of extreme market events such as the LTCM crisis on convertible arbitrage hedge funds. They formulate a structural break model to account for the LTCM crisis. The explanatory power increases dramatically when structural break models are applied instead of traditional multi-factor models. In the post-LTCM crisis,

the factor exposures of convertible arbitrage decline on average possibly because of an increase in risk aversion after a period of extreme stress in financial markets. The study suggests that accounting for structural changes arising from extreme market events leads to an increase in explanatory power as convertible arbitrage strategies are sensitive to extreme market events such as the LTCM crisis.

Chan *et al* (2006) apply a regime-switching model to estimate the probabilities of being in a state of high volatility and a state of low expected returns. The probability of being in a regime of high volatility or low expected returns is not constant over time. The study confirms that hedge funds face nonlinear, option-like risks. According to Chan *et al* (2006), market events such as the Russian debt crisis 1998 can cascade into a financial crisis, when large losses erode the capital base of highly leveraged hedge funds, liquidity in financial market dissipates and correlations increase simultaneously. A definitive assessment whether hedge funds increase the systemic risk in financial markets, however, requires data on the degree of net leverage, counterparty exposures and other information that is currently not available.

Similar to Chan *et al* (2006), several studies ask whether hedge funds increase the systemic risk in financial markets. Eichengreen *et al* (1998) analyze the impact of hedge funds on the Asian currency crisis in 1997. They argue that hedge funds like other market participants were surprised by the speed of the Asian currency crisis in 1997 and were relatively late to build positions against the Thai Baht. They find no evidence that hedge funds play a singular role in herding in financial markets and argue that hedge funds are generally less inclined than mutual funds to engage positive feedback trading

amplifying market movements. Using empirical techniques, Fung and Hsieh (2000b) estimate the impact of hedge funds over a set of extreme market events from the stock market crash in 1987 to the Asian currency crisis in 1997. They find that hedge funds probably exerted market impact during the ERM crisis in 1992 and the European bond market rally 1993/1994, but did not exert substantial market impact during the stock market crash of 1987, the Mexican peso crisis of 1994 and the Asian currency crisis of 1997. Fung and Hsieh (2000b) find no evidence of hedge funds implementing positive feedback strategies and conclude that there is little evidence that hedge funds systematically cause market prices to deviate from economic fundamentals. They point out that it is almost impossible to quantify the market impact of hedge funds directly as hedge funds are not obliged to report positions to regulators. Stulz (2007) argues that no analysis exists that reliably quantifies the social costs and benefits of hedge funds. According to Stulz (2007), the hedge fund industry plays an important role in providing liquidity and reducing market inefficiencies. On the other hand, he argues that large trades by hedge funds can increase liquidity risks and volatility risks and warns that a collapse of a hedge fund could create risks to financial institutions if the fund is large enough.

Fung and Hsieh (2002b) also warn that leveraged fixed-income trades can destabilize financial markets when extreme events like the Russian debt crisis occur. Schneeweis *et al* (2005) find that a systematic relationship between leverage and volatility exists. Strategies with lower volatility typically employ higher leverage. Using the Sharpe ratio to measure risk-adjusted performance, they find that there is

little evidence of a systematic relationship between leverage and risk-adjusted performance.

Garbaravicius and Dierick (2005) argue that the failure of highly leveraged hedge funds could have far-reaching implications for prime brokers and other counterparties of hedge funds and financial market stability. In August 1998, LTCM's balance sheet included over US\$125 billion in assets. With less than \$5 billion in equity capital, the high level of assets translated into a leverage ratio of over 25:1. Following the Russian debt moratorium on 17 August 1998, LTCM suffered large losses when investors took a 'flight to quality' and credit spreads increased. When large losses eroded the fund's capital base, credit arrangement became more rigid, and assets could not be liquidated economically, the Federal Reserve Bank of New York initiated a consortium of 14 private financial institutions that injected capital into the fund and took over control of LTCM to avoid a default (Jorion, 2000). Amaranth, a multi-strategy hedge fund, lost 65 per cent of its assets with concentrated bets in the energy markets in little over a week in September 2006. Till (2008) argues that the size and the concentration of Amaranth's risk positions were too large for the equity capital employed. Nick Maounis, CEO and President of Amaranth Group, explains the collapse of Amaranth as follows (Maounis, 2006):

... In September 2006, a series of unusual and unpredictable market events caused the Fund [...] to incur dramatic losses while the markets provided no economically viable means of exiting those positions. Despite all of our efforts, we were unable to close out the exposures in the public markets. [...] As news of our losses began to sweep through the markets, our already

limited access to market liquidity quickly dissipated. [...] Furthermore, several significant counterparties had informed Amaranth [...], they would not be comfortable in continuing to extend credit to us. Without the liquidity required to meet margin calls over the coming days, those and other counterparties would likely exercise termination rights under the Fund's various financing and trading agreements, [...] We had not expected that we would be faced with a market that would move so aggressively against our positions without the market offering any ability to liquidate positions economically. [...] But sometimes, even the highly improbable happens. That is what happened in September. ...

The statement illustrates that highly leveraged hedge funds are substantially exposed to market risks, liquidity risks and credit risks in periods of distress in financial markets, when losses erode the capital base, risk positions cannot be closed economically in illiquid markets, and previously flexible credit arrangements suddenly become more rigid. Khandani and Lo (2007) investigate the unprecedented losses of quantitative long/short equity hedge funds during the week of 6 August 2007. They argue that volatility in financial markets can increase when large hedge funds or proprietary desks are forced to cover large long and short positions to reduce risks.

According to Billio *et al* (2010), the poor performance of hedge funds in periods of extreme stress in financial markets is possibly related to margin spirals, runs on hedge funds, redemption pressures, credit freeze, market-wide panic and interconnectedness between financial

institutions. When leveraged investors suffer losses eroding their capital base, they are forced to deleverage by selling assets. A loss spiral occurs when asset sales depress prices further and force leveraged investors to deleverage by selling more assets and so on. In periods of distress, counterparty risks increase, and lenders typically restrict their lending. Loss cycles can be reinforced by margin spirals when increases in margin requirements force leveraged investors to reduce their leverage ratios (Brunnermeier, 2009; Brunnermeier and Pedersen, 2009).

Academic research on hedge funds suggests that risk exposures of hedge funds are not constant over time. Hedge funds are exposed to extreme market risks, liquidity risks and credit risks in periods of extreme distress in financial markets. Several academic studies warn that a collapse of a highly leveraged hedge fund could potentially destabilize financial markets. The mechanisms causing the failure of hedge funds in regimes of extreme stress in financial markets are well understood today. A reliable assessment of whether hedge funds increase systemic risks in financial markets requires information on risk positions, net leverage and interactions with banks, which is not available as hedge funds are not obliged to report these information to regulators.

CONCLUSION

In the past decade, extensive research has been published exploring the risk and return characteristics of hedge funds, which has important implications for investors, regulators and future research. Fung and Hsieh (1997a) first present empirical evidence that the risk of hedge funds predominantly depends on the trading

strategy or style followed by hedge funds. An extensive number of studies confirm their finding that hedge funds exhibit nonlinear, option-like payoffs relative to the returns of traditional asset classes. ABS factor models are based on the assumption that hedge funds following the same trading strategy exhibit similar risk and return characteristics. ABS factor models preserve the linear relationship between hedge fund returns and the explanatory variables of the model. The nonlinearity between asset class returns and hedge fund returns is contained in the ABS factors. Financial economists have proposed option-based factors, rule-based factors, spread factors and volatility factors to explain the return variation of hedge funds. The explanatory power of multi-factor models increases substantially when ABS factors are applied capturing the strategy-specific risk and return characteristics of hedge funds.

Several studies show that hedge funds exhibit positive excess kurtosis and negative skewness. The CAPM, the APT and other theoretical models assuming that returns are normally distributed do not adequately capture the tail risks of hedge funds. The number of extreme returns in hedge fund time series is substantially larger than the normal distribution suggests. Traditional mean-variance analysis tends to overestimate the diversification benefits of investing in hedge funds. It has been well documented that hedge fund data are severely distorted by instant history biases, survivorship biases and selection biases. Although it is widely accepted that hedge funds are prone to measurement biases, recently published studies suggest that some hedge funds may intentionally misreport returns to attract capital flows and to increase fee income. The academic literature suggests that a widespread misreporting

phenomenon may exist in the largely unregulated hedge fund industry. Some hedge funds are possibly engaged in return smoothing and other fraudulent activities.

Hedge funds implement dynamic trading strategies and are significantly exposed to time-varying factor risks. Regime-switching models can be used to analyze the dynamic return behavior of hedge funds over time. Although the construction of ABS factor models and regime-switching models differs, the economic implications of both methodologies are consistent. ABS factor models and regime-switching models both suggest that several (but not all) hedge fund strategies exhibit nonlinear, option-like payoffs. Recent research on nonlinear, regime-dependent risks of hedge funds reveals that several hedge fund strategies are exposed to considerable credit, liquidity and bankruptcy risks in periods of stress in financial markets. In several studies, financial economists warn that the failure of one or more hedge funds could destabilize financial markets when extreme market events occur.

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NOTES

1. This is an updated version of Viebig *et al* (2011b) discussing the risk and return characteristics of hedge funds in German language. We analyzed a large sample of 651 peer-reviewed articles on hedge funds downloaded from JSTOR, EBSCO HOST and other databases.

REFERENCES

- Ackermann, C., McEnally, R. and Ravenscraft, D. (1999) The performance of hedge funds: Risk, return, and incentives. *The Journal of Finance* 54(3): 833–874.
- Agarwal, V., Daniel, N.D. and Naik, N.Y. (2009) Role of managerial incentives and discretion in hedge fund performance. *The Journal of Finance* 64(5): 2221–2256.
- Agarwal, V., Daniel, N.D. and Naik, N.Y. (2011a) Do hedge funds manage their reported returns? *The Review of Financial Studies* 24(10): 3281–3320.
- Agarwal, V., Fung, W.F., Loon, Y.C. and Naik, N.Y. (2011b) Risk and return in convertible arbitrage: Evidence from the convertible bond market. *Journal of Empirical Finance* 18(2): 175–194.
- Agarwal, V. and Naik, N.Y. (2004) Risks and portfolio decisions involving hedge funds. *The Review of Financial Studies* 17(1): 63–98.
- Amin, G.S. and Kat, H.M. (2003a) Welcome to the dark side: Hedge fund attrition and survivorship bias over the period 1994–2001. *The Journal of Alternative Investments* 6(1): 57–73.
- Amin, G.S. and Kat, H.M. (2003b) Stocks, bonds, and hedge funds. *The Journal of Portfolio Management* 29(4): 113–120.
- Amin, G.S. and Kat, H.M. (2003c) Hedge fund performance 1990–2000: Do the ‘money machines’ really add value? *Journal of Financial and Quantitative Analysis* 38(2): 251–274.
- Ang, A. and Chen, J. (2002) Asymmetric correlations of equity portfolios. *Journal of Financial Economics* 63(3): 443–494.
- Anson, M.J.P. (2002a) Symmetrical performance measures and asymmetrical trading strategies: A cautionary example. *The Journal of Alternative Investments* 5(1): 81–85.
- Anson, M.J.P. (2002b) An examination of hedge fund return distribution. In: B.R. Bruce (ed.) *Hedge Fund Strategies, A Global Outlook*. New York, NY: Institutional Investor, pp. 14–27.
- Asness, C., Krail, R. and Liew, J. (2001) Do hedge funds hedge? *The Journal of Portfolio Management* 28(1): 6–19.
- Baghai-Wadji, R., El-Berry, R., Klocker, S. and Schwaiger, M. (2006) Changing investment styles: Style creep and style gaming in the hedge fund industry. *Intelligent Systems in Accounting, Finance and Management* 14(4): 157–177.
- Billio, M., Getmansky, M. and Pelizzon, L. (2010) Crises and Hedge Fund Risk. University Ca’ Foscari of Venice, Department of Economics Research Paper Series No. 10–08; UMASS-Amherst Working Paper; Yale ICF Working Paper No. 07–14. Available at SSRN: <http://ssrn.com/abstract=1130742> or doi:10.2139/ssrn.1130742, accessed 18 July 2010.
- Bollen, N.P.B. and Pool, V.K. (2008) Conditional return smoothing in the hedge fund industry. *Journal of Financial and Quantitative Analysis* 43(2): 267–298.
- Bollen, N.P.B. and Pool, V.K. (2009) Do hedge fund managers misreport returns? Evidence from the pooled distribution. *The Journal of Finance* 64(5): 2257–2288.
- Bollen, N.P.B. and Whaley, R.E. (2009) Hedge fund risk dynamics: Implications for performance appraisal. *The Journal of Finance* 64(2): 985–1035.
- Boyson, N.M., Stahel, C.W. and Stulz, R.M. (2006) Is There Hedge Fund Contagion? National Bureau of Economic Research, NBER Working Paper Series, Working Paper 12090.
- Brooks, C. and Kat, H.M. (2002) The statistical properties of hedge fund index returns and their implications for investors. *The Journal of Alternative Investments* 5(2): 26–44.
- Brown, S.J. and Goetzmann, W.N. (2003) Hedge funds with style. *The Journal of Portfolio Management* 29(2): 101–112.
- Brown, S.J., Goetzmann, W.N. and Park, J. (2001) Careers and survival: Competition and risk in the hedge fund and CTA industry. *The Journal of Finance* 56(5): 1869–1886.
- Brulhart, T. and Klein, P. (2005) Faulty hypotheses and hedge funds. *Canadian Investment Review* 18(2): 6–13.
- Brunnermeier, M.K. (2009) Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives* 23(1): 77–100.
- Brunnermeier, M.K. and Pedersen, L.H. (2009) Market liquidity and funding liquidity. *Review of Financial Studies* 22(6): 2201–2238.
- Buraschi, A., Kosowski, R. and Trojani, F. (2011) When there is no place to hide – correlation risk and the cross-section of hedge fund returns. Available at SSRN: <http://ssrn.com/abstract=1639984> or doi:10.2139/ssrn.1639984, accessed 12 July 2011.
- Capocci, D. and Hübner, G. (2004) Analysis of hedge fund performance. *Journal of Empirical Finance* 11(1): 55–89.
- Carhart, M.M. (1997) On persistence in mutual performance. *The Journal of Finance* 52(1): 57–82.
- Chan, N., Getmansky, M., Haas, S.M. and Lo, A.W. (2006) Do hedge funds increase systemic risk? *Federal Reserve Bank of Atlanta, Economic Review* 91(4): 49–80.
- Chow, G.C. (1960) Tests of equality between sets of coefficients in two linear regressions. *Econometrica* 28: 591–605.
- Dor, A.B., Dynkin, L. and Gould, T. (2006) Style analysis and classification of hedge funds. *The Journal of Alternative Investments* 9(2): 10–29.
- Edwards, F.R. and Caglayan, M.O. (2001) Hedge fund performance and manager skill. *The Journal of Futures Markets* 21(11): 1003–1028.
- Eichengreen, B., Mathieson, D., Chanda, B., Jansen, A., Kodres, L. and Sharma, S. (1998) Hedge Funds and Financial Market Dynamics. International Monetary Fund, Washington DC, Occasional Paper 166.

- Eling, M. (2006) Autocorrelation, bias and fat tails: Are hedge funds really attractive investments? *Derivatives Use, Trading & Regulation* 12(1/2): 1–20.
- Fama, E.F. and French, K.R. (1992) The cross-section of expected stock returns. *The Journal of Finance* 47(2): 427–465.
- Fama, E.F. and French, K.R. (1993) Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1): 3–56.
- Fama, E.F. and French, K.R. (1995) Size and book-to-market factors in earnings and returns. *The Journal of Finance* 50(1): 131–155.
- Fama, E.F. and French, K.R. (1996) Multifactor explanations of asset pricing anomalies. *The Journal of Finance* 51(1): 55–84.
- Fung, W. and Hsieh, D.A. (1997a) Empirical characteristics of dynamic trading strategies: The case of hedge funds. *The Review of Financial Studies* 10(2): 275–302.
- Fung, W. and Hsieh, D.A. (1997b) Survivorship bias and investment style in the returns of CTAs. *Journal of Portfolio Management* 24(1): 30–41.
- Fung, W. and Hsieh, D.A. (2000a) Performance characteristics of hedge funds and commodity funds: Natural vs spurious biases. *Journal of Financial and Quantitative Analysis* 35(3): 291–307.
- Fung, W. and Hsieh, D.A. (2000b) Measuring the market impact of hedge funds. *Journal of Empirical Finance* 7(1): 1–36.
- Fung, W. and Hsieh, D.A. (2001) The risk in hedge fund strategies: Theory and evidence from trend followers. *The Review of Financial Studies* 14(2): 313–341.
- Fung, W. and Hsieh, D.A. (2002a) Asset-based style factors for hedge funds. *Financial Analysts Journal* 58(5): 16–27.
- Fung, W. and Hsieh, D.A. (2002b) Risk in fixed-income hedge fund styles. *The Journal of Fixed Income* 12(2): 6–27.
- Fung, W. and Hsieh, D.A. (2004a) Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal* 60(5): 65–80.
- Fung, W. and Hsieh, D.A. (2004b) Extracting portable alphas from equity long/short hedge funds. *Journal of Investment Management* 2(4): 57–75.
- Fung, W. and Hsieh, D.A. (2009) Measurement biases in hedge fund performance data: An update. *Financial Analysts Journal* 65(3): 1–3.
- Fung, W., Hsieh, D.A., Naik, N.Y. and Ramodara, T. (2008) Hedge funds: Performance, risk and capital formation. *The Journal of Finance* 63(4): 1777–1803.
- Garbaravicius, T. and Dierick, F. (2005) Hedge Funds and their Implication for Financial Market Stability. European Central Bank, Frankfurt, Occasional Paper Series 34.
- Getmansky, M., Lo, A.W. and Makarov, I. (2004) An economic model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics* 74(3): 529–609.
- Gibson, R. and Gyger, S. (2007) The style consistency of hedge funds. *European Financial Management* 13(2): 287–308.
- Gregoriou, G.N. (2002) Hedge fund survival lifetimes. *Journal of Asset Management* 3(3): 237–252.
- Hedge Fund Research (HFR). (2009) HFR Global Hedge Fund Industry Report. Year End 2008.
- Hong, Y., Tu, J. and Zhou, G. (2007) Asymmetries in stock returns: Statistical tests and economic evaluation. *The Review of Financial Studies* 20(5): 1547–1581.
- Jaeger, L. (2005) Factor Modelling and Benchmarking of Hedge Funds: Are Passive Investments in Hedge Funds Possible? Partners Group: Research Paper.
- Jarque, C.M. and Bera, A.K. (1987) A test for normality of observations and regression residuals. *International Statistical Review* 55(2): 163–172.
- Jorion, P. (2000) Risk management lessons from long-term capital management. *European Financial Management* 6(3): 277–300.
- Kat, H.M. (2003) 10 things that investors should know about hedge funds. *The Journal of Wealth Management* 5(4): 72–81.
- Khandani, A.E. and Lo, A.W. (2007) What happened to the quants in August 2007? *Journal of Investment Management* 5(4): 29–78.
- Kuenzi, D.E. and Shi, X. (2007) Asset based style analysis for equity strategies: The role of the volatility factor. *The Journal of Alternative Investments* 10(1): 10–23.
- Lamm, R.M. (2003) Asymmetric returns and optimal hedge fund portfolios. *The Journal of Alternative Investments* 6(2): 9–21.
- Li, Y. and Kazemi, H. (2007) Conditional properties of hedge funds: Evidence from daily returns. *European Financial Management* 13(2): 211–238.
- Liang, B. (2000) Hedge funds: The living and the dead. *Journal of Financial and Quantitative Analysis* 35(3): 309–326.
- Liang, B. (2001) Hedge fund performance: 1990–1999. *Financial Analysts Journal* 57(1): 11–18.
- Lintner, J. (1965) Security prices, risk, and maximal gains from diversification. *The Journal of Finance* 20(4): 587–615.
- Maillet, B. and Rousset, P. (2003) Classifying hedge funds with Kohonen maps: A first attempt. In: C. Lesage and M. Cottrell (eds.) *Connectionist Approaches in Economics and Management Sciences, Series Advances in Computational Management Science*, Vol. 6. Kluwer Academic Publishers, pp. 233–259.
- Malkiel, B.G. and Saha, A. (2005) Hedge funds: Risk and return. *Financial Analysts Journal* 61(6): 80–88.
- Maounis, N. (2006) Remarks by Nick Maounis, President, Chief Executive Officer and Chief Investment Officer

- Amaranth Group Inc. Investor Conference Call: 22 September, 2PM ET.
- Mitchell, M. and Pulvino, T. (2001) Characteristics of risk and return in risk arbitrage. *The Journal of Finance* 56(6): 2135–2175.
- Mossin, J. (1966) Equilibrium in a capital asset market. *Econometrica* 34(4): 768–783.
- Park, J.M. (1995) Managed futures as an investment set. Dissertation, Columbia University.
- Patton, A.J. and Ramadorai, T. (2011) On the high-frequency dynamics of hedge fund risk exposures. Available at SSRN: <http://ssrn.com/abstract=1874668> or doi:10.2139/ssrn.1874668, accessed 14 December 2011.
- Racicot, F.-É. and Théoret, R. (2008) Integrating volatility factors in the analysis of the hedge fund alpha puzzle. *Journal of Asset Management* 10(1): 37–62.
- Ross, S.A. (1976) The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13(3): 341–360.
- Schneeweis, T., Martin, G., Kazemi, H. and Karavas, V. (2005) The impact of leverage on hedge fund risk and return. *The Journal of Alternative Investments* 7(4): 10–21.
- Schneeweis, T., Spurgin, R. and Waksman, S. (2006) Early reporting effects on hedge funds and CTA returns. *The Journal of Alternative Investments* 9: 30–45.
- Sharpe, W.F. (1964) Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance* 19(3): 425–442.
- Sharpe, W.F. (1992) Asset allocation: Management style and performance measurement. *The Journal of Portfolio Management* 18(2): 7–19.
- Spurgin, R., Martin, G. and Schneeweis, T. (2001) A method of estimating changes in correlation between assets and its application to hedge fund investment. *The Journal of Asset Management* 1(3): 217–230.
- Stulz, R. (2007) Hedge funds: Past, present and future. *The Journal of Economic Perspectives* 21(2): 175–194.
- Tancar, R. and Viebig, J. (2008) Alternative beta applied – an introduction to hedge fund replication. *Financial Markets and Portfolio Management* 22(3): 259–279.
- Till, H. (2008) Amaranth lessons thus far. *The Journal of Alternative Investments* 10(4): 82–98.
- Tong, H. and Lim, K.S. (1980) Threshold autoregression, limit cycles and data. *Journal of the Royal Statistical Society* 42(3): 245–292.
- Viebig, J. and Poddig, T. (2010a) The jump-start effect in return series of long/short equity hedge funds. *Journal of Derivatives & Hedge Funds* 16(3): 191–211.
- Viebig, J. and Poddig, T. (2010b) Does a contagion effect exist between equity markets and hedge funds in periods of extreme stress in financial markets? *The Journal of Alternative Investments* 13(2): 78–103.
- Viebig, J. and Poddig, T. (2010c) Modelling extreme returns and asymmetric dependence structures of hedge fund strategies using extreme value theory and copula theory. *The Journal of Risk* 13(2): 23–55.
- Viebig, J., Poddig, T. and Papanastasiou, P. (2011a) Regime-dependent nonlinear analysis of hedge funds. *The Journal of Alternative Investments* 13(4): 53–72.
- Viebig, J., Poddig, T. and Tancar, R. (2011b) Risiken von Hedgefonds: Forschungsansätze und Erkenntnisse der aktuellen Kapitalmarktforschung. *Kredit und Kapital* 44(2): 279–310.
- Whaley, R.E. (2009) Understanding the VIX. *The Journal of Portfolio Management* 35(3): 98–105.