Multi-moment risk, hedge fund short-selling & the business cycle

(This version June 12th 2017)

François-Éric Racicot\textsuperscript{a,*}

et

Raymond Théoret\textsuperscript{b}

\textsuperscript{a} Telfer School of Management, University of Ottawa, 55 Laurier Avenue East, Ottawa, Ontario; Groupe de recherche en finance appliquée (GReFA), University of Sherbrooke; Chaire d’information financière et organisationnelle, ESG-UQAM; CGA-Canada Accounting and Governance Research Center (CGA-AGRC).

\textsuperscript{b} Université du Québec (Montréal), École des sciences de la gestion, 315 est Ste-Catherine, R2915, Montréal, Québec; Chaire d’information financière et organisationnelle, ESG-UQAM; Université du Québec (Outaouais).

\textsuperscript{*} Corresponding author. Tel: +1 613-562-5800 (4757).
E-mail addresses: racicot@telfer.uottawa.ca (F.-É. Racicot), raymond.theoret@uqam.ca (R. Théoret).

\textsuperscript{†} Acknowledgements: We thank Carol Alexander, Claudia Champagne, Frank Coggins and Jules van Binsbergen for their useful comments on previous versions of this paper.
Multi-moment risk, hedge fund short-selling & the business cycle

Abstract
Using a non-linear VAR setting, we study the asymmetric responses of hedge fund return moments—especially higher moments—to macroeconomic and financial shocks depending on the phase of the business cycle. Similarly to previous papers on hedge fund systematic market risk (beta), we find that hedge funds do monitor their return co-skewness and co-kurtosis. The response of their return moments to a VIX shock—our indicator of macroeconomic and financial uncertainty—is particularly important, hedge funds reducing their beta and co-kurtosis and increasing their co-skewness following a (positive) VIX shock. Our findings also suggest that hedge fund short-selling activities are hampered by an increase in market volatility. However, short-sellers and futures strategies can capture positive payoffs during crises due to their positive return co-skewness and negative co-kurtosis. We conclude that VIX shocks contribute to increase systemic risk in the hedge fund industry.

Risque multi-moment, ventes à découvert par les fonds de couverture et cycle économique

Résumé
En recourant à une approche basée sur un VAR non-linaire, nous examinons les réactions asymétriques des moments des rendements offerts par les fonds de couverture—et plus spécialement les moments supérieurs—à des chocs macroéconomiques et financiers selon la phase du cycle économique. En lien avec les articles précédents sur le risque systématique des fonds de couverture (bêta), nous établissons que ces fonds monitorent la co-asymétrie et le co-leptokurtisme de leurs rendements. La réponse des moments reliés à la distribution des rendements des fonds de couverture à un choc de volatilité des marchés (VIX)—i.e., notre indicateur d’incertitude macroéconomique et financière—est particulièrement importante. En effet, les fonds de couverture réduisent leur bêta et leur co-leptokurtisme et accroissent leur co-asymétrie à la suite d’un choc positif causé par le VIX. Nos résultats suggèrent également que les ventes à découvert effectuées par les fonds sont obstruées par une hausse du VIX. Toutefois, les stratégies de ventes à découvert et de contrats à terme peuvent engendrer des cash-flows positifs en période de crise en raison de leur co-asymétrie positive et de leur co-leptokurtisme négatif. Nous concluons en montrant que des chocs dus au VIX contribuent à accroître le risque systémique dans l’industrie des fonds de couverture.

Mots-clés : Fonds de couverture; risque multi-moment; VAR non-linaire; cycle économique; risque systémique.
Classification JEL : C13, C58, G11, G23.

1. Introduction

Downside risk is an important dimension of portfolio selection. In this respect, return higher moments—i.e., skewness and kurtosis—are the main drivers of this kind of risk, which is associated with tail risk (Xiong and Idzorek, 2011). Since the beginnings of the 1970s, many theoretical works have been devoted to the role of higher moments in the construction of optimal portfolios1 (Samuelson, 1970; Rubinstein, 1973; Kraus and Litzenberger, 1976; Friend and Westerfield, 1980; Scott and Hovarth, 1980; Sears and Wei, 1985; Fang and Lai, 1997). They analyze the role of higher moments in the utility

---

1 These theoretical developments have given rise to some asset pricing models like the four-moment CAPM.
function of a representative investor. At the empirical level, models show how investors trade-off return moments in order to construct their optimal portfolios (e.g., Desmoulin-Lebeault, 2006; Berg and van Rensburg, 2008; Davies et al., 2009; Harvey et al., 2010; Xiong and Idzorek, 2011). These studies often rely on the minimization of a synthetic measure of risk which embeds higher moments to show that investors tend to avoid negatively skewed assets and attribute lower weights to assets embedding a high level of kurtosis. However, these papers often neglect the fact that skewness and kurtosis are two very interrelated moments (Wilkins, 1944; MacGillivray and Balanda, 1988; Schopflocher and Sullivan, 2005). They also tend to overlook the dynamic or time aspects related to the trade-off between higher moments when selecting an optimal portfolio.

In this study, we contribute to the econometric works on the role of return higher moments in portfolio selection by proposing a VAR (vector autoregressive) model which aims at analyzing the reaction of hedge fund multi-moments to external shocks—i.e., macroeconomic and financial shocks. To the best of our knowledge, we are the first to perform this kind of study. Hedge fund strategies are particularly relevant to capture the impact of higher moments in portfolio selection since their portfolio managers rely heavily on derivatives, an obvious source of return skewness and kurtosis. Our basic model is based on an underpinning developed by Beaudry et al. (2001) and Baum et al. (2002, 2004, 2009) which appears well-suited to study the dynamic co-movements between macroeconomic and financial risk and uncertainty, on the one hand, and our measures of hedge fund risk, on the other hand—i.e., beta, co-skewness and co-kurtosis. The resulting empirical model is first estimated with a straightforward linear VAR and then with a non-linear version which allows for asymmetries between economic expansions and recessions (Auerbach and Gorodnichenko, 2012; Bachman and Sims, 2012). Indeed, previous studies have depicted many asymmetries in the behavior of financial institutions dependent on the stance of the business cycle (Bali et al., 2014; Calmès and Théoret, 2014; Lambert and Plantania, 2016; Namvar et al., 2016; Racicot and Théoret, 2016; Stafylas et al., 2016).

Similarly to Bali et al. (2014), Lambert and Plantania (2016) and Racicot and Théoret (2016) who demonstrate that hedge funds monitor their market beta over the business cycle, one of our main findings is to show that this result also holds for higher moments. Hedge funds thus manage their multi-moment risk over the business cycle—i.e., their behavior with respect to risk and uncertainty is forward-looking. This result is valid for the two hedge fund databases experimented in this paper—i.e., the EDHEC and GAI databases. In this respect, hedge funds’ return moments interact very closely across the business cycle. Moreover, their multi-moment risk varies over the stance of the business cycle. Indeed, hedge funds tend to increase their beta and co-kurtosis and decrease their co-skewness in expansion—i.e., they display a more aggressive risk profile. The reverse is true in recession, whereby they are involved in a deleveraging process (Billio et al., 2012; Santos and Veronesi, 2016). Among the hedge fund risk measures, the beta is the most cyclical and all these measures are very sensitive to the VIX—an indicator

---

2 For instance, Scott and Hovarth (1980) find that investors derive a positive utility from positive odd moments—i.e., positive expected return and positive skewness—but dislike even moments—i.e., variance and kurtosis.

3 According to Hübner et al. (2015), the use of leverage and financial derivatives, and the option-like nature of hedge fund managers’ compensation contracts contribute to the negative skewness and high kurtosis of many hedge fund strategies’ return distributions. See also Stafylas et al., 2016.

4 Similarly to the beta which represents a stock systematic market risk, the relevant measures of tail risk are co-skewness and co-kurtosis since one portion of the risk associated with skewness and kurtosis—i.e., idiosyncratic risk—is diversifiable and therefore not priced on financial markets.
of market expectation of near-term volatility. In other respects, focusing on hedge fund strategies involved in increasing order of short-selling—i.e., long-short, equity market neutral and short-sellers—we find that short sellers are well positioned to capture positive payoffs at the start of a financial crisis, displaying negative co-kurtosis and positive co-skewness (Jurczenko et al., 2006). However, their co-skewness decreases and their co-kurtosis increases following a VIX shock. A rise in market volatility thus seems to be detrimental to short-selling transactions (Lambert and Plantania, 2016).

Finally, we examine the evolution of systemic risk in the hedge fund industry using once more the device proposed by Beaudry et al. (2001). We find that strategies’ beta, co-skewness and co-kurtosis cross-sectional dispersions decrease after a (positive) VIX shock in recession—i.e., the main factor affecting hedge fund multi-moment risk in the framework of our study. The behavior of hedge funds with respect to risk thus becomes more homogenous in recession, which supports Beaudry et al. (2001) conjecture. Hence, systemic risk tends to increase in the hedge fund industry in recession (Shleifer and Vishny, 2010; Wagner, 2008, 2010; Calmès and Théoret, 2014; Racicot and Théoret, 2016). In expansion, the response of the three cross-sectional dispersions to a VIX shock differs—i.e., the behavior of hedge funds becomes more heterogeneous with respect to beta but remains homogenous with respect to co-skewness and co-kurtosis. In other words, hedge fund higher moments are more sensitive to crises than to the stance of the business cycle by itself (Hespeler and Loiacono, 2015).

This paper is organized as follows. Section 2 exposes our methodology. Section 3 presents the stylized facts related to our two hedge fund databases, the EDHEC and the GAI databases. Relying on the four-moment CAPM, Section 4 examines the relative weights of higher moments in the explanation of strategies’ returns. Section 5 reports our VAR results while Section 6 focuses on systemic risk in the hedge fund industry. Section 7 concludes.

2. Methodology

2.1 Computing time-varying measures of beta, co-skewness, and co-kurtosis

Similarly to the beta which is the keystone of the two-moment CAPM, the concepts of co-skewness and co-kurtosis originate from the four-moment CAPM (Rubinstein, 1973; Kraus and Litzenberger, 1976; Friend and Westerfield, 1980; Scott and Hovarth, 1980; Sears and Wei, 1985; Fang and Lai, 1997). The seminal Euler equation on the pricing of financial assets helps put together these various dimensions of risk. It is expressed as (Cochrane, 2005):

\[ E[m_{1,t}R_{1,t} | \Omega] = 1 \] (1)

In Eq.(1), \( m_{1,t} = \beta \frac{u'(c_{1,t})}{u'(c_{t})} \) is the representative agent’s intertemporal marginal rate of substitution between present and future consumption; \( \beta \) is this agent’s discount factor; \( u'(c_{1,t}) \) is his marginal utility

---

4 Not to be confounded with systematic risk which is linked to the correlation of a portfolio return with the market return. Systemic risk is concerned with the co-dependence of financial institutions’ risks and not with the individual risk of these institutions (Anginer et al., 2014).
of consumption at time \( t+1 \); \( \mathcal{R}_{t+1} \) is the gross rate of return on the financial asset we want to price and \( \Omega_t \) is the information set available to the representative agent at the time of his portfolio decision.

If the assumptions of the CAPM are satisfied—i.e., if the return distribution is Gaussian or completely characterized by its first two moments, or if the representative agent’s utility function is quadratic—\( m_{t+1} \) can be written as a linear function of the market return (Desmoulins-Lebeault, 2006):

\[
m_{t+1} = a + b_t \mathcal{R}_{mt+1}
\]  

(2)

where \( \mathcal{R}_{mt+1} \) is the return on the stock market portfolio.

However, if the assumptions associated with the CAPM do not hold—especially if the return distribution is non-Gaussian—the relation between \( m_{t+1} \) and \( \mathcal{R}_{mt+1} \) is nonlinear. Assume that \( m_{t+1} \) may be written as the following cubic polynomial of \( \mathcal{R}_{mt+1} \):

\[
m_{t+1} = a + b_t \mathcal{R}_{mt+1} + c_t \mathcal{R}_{mt+1}^2 + d_t \mathcal{R}_{mt+1}^3
\]  

(3)

We then obtain the four-moment CAPM asset pricing model that may be expressed as follows (Fang and Lai, 1997):

\[
E(R_i) - r_f = \beta_i \text{Cov}(R_i, \mathcal{R}) + \beta_{i2} \text{Cov}(R_i^2, \mathcal{R}) + \beta_{i3} \text{Cov}(R_i^3, \mathcal{R})
\]  

(4)

where \( E(R_i) \) is the expected value of return \( i \); \( r_f \) is the risk-free rate and \( \text{Cov}(\cdot) \) is the operator of covariance. The unscaled beta, co-skewness and co-kurtosis of the asset which is priced are defined as \( \text{Cov}(R_i, \mathcal{R}) \), \( \text{Cov}(R_i^2, \mathcal{R}) \), and \( \text{Cov}(R_i^3, \mathcal{R}) \), respectively. As usual, the risk associated with \( R_i \) is thus seen as co-movements between this return and the stock market return (unscaled beta), its square (unscaled co-skewness) and its cube (unscaled co-kurtosis), respectively. According to Fang and Lai (1997), the cubic market model consistent with the four-moment CAPM is:

\[
R_i = \alpha_i + \beta_i \mathcal{R}_{mt} + \gamma_i \mathcal{R}_{mt}^2 + \delta_i \mathcal{R}_{mt}^3 + \xi_i
\]  

(5)

We will rely on Eq.(5) to estimate the relative importance of higher moments in the explanation of \( R_i \).

In Eq.(4), covariances must be scaled to arrive at relative measures of risk. The well-known definition of the beta of asset \( i \) is:

\[
\text{beta}_i = \frac{\text{Cov}(R_i, \mathcal{R})}{\text{Var}(R_i)}
\]  

(6)

which is the scaling of the first Cov(.) term on the RHS of Eq.(4). The two other covariance expressions in this equation give rise to co-skewness and co-kurtosis, respectively:

\[
\text{co-skewness}_i = \frac{\text{Cov}(R_i^2, \mathcal{R})}{\left[\text{Var}(R_i)\right]^{1.5}}
\]  

(7)

\[
\text{co-kurtosis}_i = \frac{\text{Cov}(R_i^3, \mathcal{R})}{\left[\text{Var}(R_i)\right]^2}
\]  

(8)

To make our three measures of risk time-varying, we rely on the multivariate GARCH (MGARCH, Bollerslev et al., 1988). The simple system used to implement this procedure writes as follows:
\[
\begin{align*}
 f(\mathbf{y}, \beta) &= \varepsilon_t \quad (9)
\end{align*}
\]

In Eq.(9), \( \mathbf{y} \) is a vector of endogenous variables and \( \varepsilon_t \) is a vector of possibly serially correlated disturbances. Each equation of the system has its simplest expression: \( \mathbf{y}_t = \text{constant} + \varepsilon_t \). In our framework, the vector \( \mathbf{y}_t \) takes the form:

\[
\mathbf{y}_t = \begin{bmatrix}
R_y & R_{\text{mc}} & R_{\text{me}}^2 & R_{\text{me}}^0
\end{bmatrix}^\prime. 
\]

The aim of this exercise is to find an estimate of the vector of parameters \( \beta \) which is then used to compute the conditional covariance and variance measures appearing in equations (6), (7), and (8), respectively.

The MGARCH models the variances and covariances of the error term in Eq.(9). In the case of a MGARCH(1,1) model, the conditional covariance \( \langle h_{ij} \rangle \) associated with the variables \( i \) and \( j \) may be written as follows (Mills, 1993):

\[
\text{cov}_{ijt} = h_{ij} = c_{ij} + a_{ij} \varepsilon_{it-1} \varepsilon_{jt-1} + b_{ij} h_{ijt-1} \quad (10)
\]

\( h_{ijt} \) is thus an element of the 4 x 4 conditional variance-covariance matrix located at its \( i^{th} \) line and \( j^{th} \) column. For each period \( t \), the diagonal elements of this 4 x 4 estimated matrix are the conditional variances of our four variables and the off-diagonal elements are the conditional covariances. This matrix can be estimated using the VEC algorithm (Bollerslev et al., 1988) or the BEKK algorithm (Engle and Kroner, 1995). In this study, we adopt the BEKK algorithm since it is a more parsimonious approach in terms of the number of parameters to estimate.

2.2 The financial model

2.2.1 Theoretical framework

To study the behavior of the strategies’ betas and their associated co-skewness and co-kurtosis, we rely on an underpinning derived from a signal extraction problem first experimented by Lucas (1973), modified by Beaudry et al. (2001) and transposed to the financial sector by Baum et al. (2002, 2004, 2009), Quagliariello (2007, 2008, 2009), Yu and Sharaiha (2007), Calmès and Théoret (2014), Caglayan and Xu (2016), and Racicot and Théoret (2016). This kind of device relates a return moment to the first moments of risk factors—i.e., the level of economic and financial variables—and to the second moments of these factors, as gauged by their conditional variances (volatility). The first moments are measures of risk while the second moments gauge uncertainty.

The model used in this study thus writes:

\[
y_t = \theta_0 + \mathbf{u}_t \theta_1 + \sigma_t^2 \theta_2 + \theta_3 \mathbf{y}_{t-1} + \varepsilon_t \quad (11)
\]

In Eq. (11), \( \mathbf{y} \) stands for a strategy beta, or for its return co-skewness and co-kurtosis; \( \mathbf{u}_t \) is the vector of the first moments of the macroeconomic and financial variables proxying for risk; \( \sigma_t^2 \) is the corresponding vector of their conditional covariances proxying for uncertainty and \( \varepsilon_t \) is the innovation.

Actually, Eq.(11) is part of a canonical model aiming at studying the behavior of investors in times of rising uncertainty. In this respect, Beaudry et al. (2001) and Baum et al. (2002, 2004, 2009) have
computed the optimal share of a risky asset \( w_{it}^{ra} \) in an investor’s portfolio using a model which maximizes the investor’s expected utility subject to portfolio risk. They obtain the following expression for the variance of \( w_{it}^{ra} \)—i.e., the cross-sectional dispersion of the share of the risky asset in the investors’ portfolios:

\[
\forall i, \forall t, \quad \text{var}(w_{it}^{ra}) = \frac{\sigma_{it}^2 + \sigma_{it}^2}{\varphi^2 \sigma_{it}^4}
\]

(12)

where \( \varphi \) is the degree of risk aversion of the representative investor.

This variance is based upon the imperfect signal: \( S_{it} = \epsilon_{it} + \nu_i \), which enables the investor to formulate a forecast for \( \epsilon_{it} \)—i.e., the innovation of the risky asset return. However, this signal is disturbed by the conditional variance \( \sigma_{it}^2 \), which accounts for macroeconomic uncertainty. The derivative of Eq. (12) with respect to macroeconomic uncertainty is thus:

\[
\forall i, \forall t, \quad \frac{\partial \text{var}(w_{it}^{ra})}{\partial \sigma_{it}^2} = -\frac{1}{\varphi^2} \left( \frac{2\sigma_{it}^2}{\sigma_{it}^2} + \frac{1}{\sigma_{it}^4} \right) < 0
\]

(13)

Eq. (13) is another relationship which we test in Section 6. It asserts that the behavior of investors becomes more homogenous in times of rising macroeconomic uncertainty—i.e., the more macroeconomic uncertainty increases, the more investors’ portfolios become similar in terms of asset allocation. Racicot and Théoret (2016) have already tested this hypothesis on the cross-sectional dispersion of the hedge fund strategies’ market betas. Consistent with Eq.(13), they find that this dispersion decreases when macroeconomic uncertainty increases. In this study, we postulate that the cross-sectional dispersion of strategies’ co-skewness and co-kurtosis also decreases in times of rising macroeconomic uncertainty. Our study allows identifying the factors which are at the source of this herd-like behavior. This issue is crucial since a decrease in the cross-sectional dispersion of risk measures during crises leads to a rise in systemic risk in the financial system (Shleifer and Vishny, 2010; Wagner, 2008, 2010; Calmès and Théoret, 2014; Racicot and Théoret, 2016).

2.2.2 Empirical formulation of the model: the Chen et al. (1986) model

As justified later, we rely on the Chen et al. (1986) model to specify ours\(^7\). Its final expression is:

\[
y_t = \lambda_0 + \lambda_i.gprod + \lambda.credit\_spread + \lambda.\text{term}\_\text{spread} + \lambda.VIX + \xi_t
\]

(14)

where \( y_t \) are our measures of multi-moment risk; \( gprod \) is the industrial production growth rate; \( credit\_spread \) is the spread between BBB and AAA corporate bond yields; \( term\_\text{spread} \) is the spread between the ten-year interest rate and the three-month Treasury bills rate, and \( VIX \) measures the volatility of the U.S. stock market\(^8\).

---

\(^7\) i.e., the identification of the explanatory variables in Eq.(11).

\(^8\) Table 4 reports the list of the risk and uncertainty indicators experimented in this study and explains how they are built.
The Chen et al. (1986) model comprises four variables: the industrial production growth, the credit spread, the term spread and the inflation rate. As explained by these authors, the industrial production growth is related to the payoffs (cash-flows) of the asset being priced and the three other variables are associated with its discount factor. In our model, we have substituted the VIX for the inflation rate. First, because over our sample period, inflation is not a matter of concern as it was when Chen et al. (1986) conducted their study. Second, since we select the Lucas (1973) underpinning (Eq. (11)) as our general framework to implement our study, our model must include factors accounting for macroeconomic and financial uncertainty. Moreover, given its high level of volatility, the significance of the inflation rate was usually quite weak in the Chen et al. (1986) estimations or at least lower than the other included explanatory variables. Finally, since we run our model with VARs, its formulation ought to be parsimonious since degrees of freedom decrease quickly with the number of endogenous variables in this kind of procedure.

Chen et al. (1986) discuss the signs of the explanatory variables included in their model in terms of risk premia. They thus rely on a long-term (equilibrium) framework to analyze these signs. In contrast to Chen et al. (1986), we rely on a dynamic setting to explain the signs of the variables included in Eq. (14)—i.e., we cast our model in a short-term perspective. In this framework, dynamic hedging strategies play an important role. In this respect, we consider that the sign of \( gprod \) is positive in normal times—i.e., hedge funds take more systematic risk in economic expansion. Therefore, the beta and co-kurtosis should increase following a rise in \( gprod \) in normal times while co-skewness should decrease. However, in recession, hedge funds may hedge totally or partially the impact of this adverse state on their performance. Hence, hedge funds should reduce their risk exposure to the business cycle in downturns by relying on short-selling or on structured products. In this respect, the presence of VIX in Eq. (14) is of great interest. When VIX increases, stock returns drop according to the Black (1976) leverage effect. If a hedge fund does not react to this rise in market volatility, its level of risk automatically increases—i.e., its beta and co-kurtosis increase whereas its co-skewness decreases. In this case, the beta and co-kurtosis co-move positively with the VIX in recession, while the co-skewness co-moves negatively. However, hedge funds can decrease their exposures and even reverse their signs by buying insurance through hedging strategies. In the best scenario, hedge funds adjust their risk position such that their beta and co-kurtosis respond negatively to VIX in recession, while their co-skewness responds positively. In normal times, hedge funds should adopt a more aggressive risk profile—i.e., the exposure of their beta and co-kurtosis to VIX might be positive and the exposure of their co-skewness might be negative. Hedge funds may thus "buy volatility" in expansion—i.e., through structured products like straight straddles or lookback straddles (Fung and Hsieh, 1997, 2001, 2002, 2004; Fieldhouse, 2013; Hespeler and Loiacono, 2015).

---

8 In principle, the device given by Eq. (11) should associate with each included first moment of a macroeconomic or financial variable the corresponding second moment (Huizinga, 1993; Quagliariello, 2007, 2008, 2009; Calmès and Théoret, 2014; Bacinò and Théoret, 2016). For example, if we include the industrial production growth (first moment) in the equation, we should add its conditional variance (second moment). However, as documented in Section 5.1, the VIX seems representative of all the conditional variance series examined in our study. Moreover, a VAR model ought to be parsimonious. Obviously, including our whole set of first and second moments (Table 4) in this kind of procedure will lead to unsatisfactory results.

9 Note that we also experimented with the inflation rate but the results were not conclusive.

10 According Chen et al. (1986), the sign of \( gprod \) should be positive. Indeed, a positive risk premium is required to insure against systematic production risks. A positive premium is also required to hedge against an increase in the credit spread. Actually, an increase in the credit spread is associated with a rise of uncertainty in their model or with an increase in risk aversion attributable to a jump in corporate bankruptcies. The explanation given to justify the sign of the term spread—which they predict negative—is more complex.
Lambert and Plantania, 2016). Hedging strategies thus play an important role in explaining the slopes of the exposures of our measures of risk to the external sources of macroeconomic and financial uncertainty.

We can transpose this argument to the credit spread which measures the degree of investors’ risk aversion in our model. In recession, the exposures of the measures of hedge fund risk to this factor should decrease or at least should be less positive than in normal times. In this respect, Lambert and Plantania (2016) argue that in their hedge fund regime switching model of beta exposures\(^{12}\), the credit spread—considered as a measure of credit risk—should have a positive sign in expansion and a negative sign in recession. Indeed, in expansion, hedge funds should buy the return spread since the risk of such an operation is less than in recession\(^{13}\). In other respects, a decrease in the term spread usually signals an upcoming recession (Clinton, 1994–1995; Ang et al., 2006; Wheelock and Wohar, 2009). Therefore, measures of hedge fund risk should decrease after this drop in the term spread, which suggests a positive exposure of beta and co-kurtosis to the term spread and a negative exposure for co-skewness. However, the term spread may embed other dimensions of macroeconomic and financial risk. In this respect, Lambert and Plantania (2016) provide another interpretation of the role of the term spread for explaining hedge funds’ beta exposures to this factor. Indeed, the term spread may also be viewed as an indicator of liquidity risk\(^{14}\). In such a scenario, an increase in the term spread may induce hedge fund to reduce their risk exposure in recession since rising liquidity risk is then an impediment to short-selling transactions, among others. However, in expansion, similarly to the credit spread, hedge funds may buy the term spread—i.e., increase their exposure to the term spread\(^{15}\).

In this article, we focus particularly on three strategies involved in various degrees of short-selling activities. By increasing order of the weight of short-selling in their business lines, we select long-short, equity market neutral and short-sellers\(^{16}\). Having one of the highest positive betas in the hedge fund industry, the short-selling activities of the long-short strategy are moderate since it maintains a net long position in the long-run. In contrast, the equity market neutral strategy tries to hedge market systematic risk in the long-run. The target of its market beta is thus close to zero. Short-sellers are the most involved in short-selling transactions. Their market beta—which is always negative—may even exceed one in absolute value. Focusing on short-selling transactions thus allows us to see what impact short-selling may have on hedge fund performance along the business cycle. For instance, we expect that short-sellers should perform better during downturns\(^{17}\) and thus offer good opportunities of portfolio diversification during bad times.

---

\(^{12}\) Compared to our approach, Lambert and Plantania (2016) focus on the first two moments of hedge fund return distribution. They examine how the conditional betas of key variables which explain hedge fund returns—like, the market risk premium, SMB and HML—are explained by macroeconomic and financial uncertainty while relying on three regimes.

\(^{13}\) For instance, they can sell CDS (credit default swaps) to capture the credit spread.

\(^{14}\) When the liquidity of financial markets decreases—i.e., when bid-ask spreads increase—investors should buy short-term bonds and sell long-term bonds, which rises the term spread. More precisely, investors have a preference for liquidity (Tobin, 1958). When this preference increases—i.e., in times of crisis—their demand for short-term bonds increases and their demand for long-term bonds decreases, which increases the term spread.

\(^{15}\) See also Campbell et al. (1997) and Veronesi (2010) for other views on the predictive power of the term spread.

\(^{16}\) Short-selling also holds an important share in the operations of the futures strategy.

\(^{17}\) i.e., when the marginal utility of consumption is at its peak (Cochrane, 2005).
2.3 The VAR model

2.3.1 The specification of the linear VAR model

We first rely on a straightforward VAR analysis to document the interactions between business cycles and financial fluctuations, on the one hand, and the moments of hedge fund strategies, on the other hand. Assuming that hedge funds ought to anticipate the impact of external shocks on their measures of risk—i.e., market beta, co-skewness and co-kurtosis—we identify the former set of variables as the “external shocks” to the hedge fund industry, while the latter set is interpreted as “internal” shocks. We compute the impulse response functions (IRF) of our three moments concomitantly with the other IRFs of the variables appearing on the RHS of our basic model (Eq. (14)).

Assume the following k-dimensional structural VAR (Sims, 1980):

\[
P_t = A_{11}y_{t-1} + A_{12}y_{t-2} + \ldots + A_{1p}y_{t-p} + \varepsilon_t
\]

(15)

with \( y_t = [y_{t1}, \ldots, y_{tk}]' \)—i.e., the set of endogenous variables included in the VAR model; \( P \) is of dimension \((k \times k)\), and \( E(\varepsilon_t \varepsilon_t') = \Sigma \).

The reduced-form of Eq. (15) is obtained by multiplying it by \( P^{-1} \), i.e.,

\[
y_t = P^{-1}A_{11}y_{t-1} + P^{-1}A_{12}y_{t-2} + \ldots + P^{-1}A_{1p}y_{t-p} + P^{-1}\varepsilon_t = B_{11}y_{t-1} + B_{12}y_{t-2} + \ldots + B_{1p}y_{t-p} + \mu_t
\]

(16)

The structural shocks \( \varepsilon_t \) can thus be retrieved from reduced form shocks \( \mu_t \) by resorting to \( P^{-1}\mu_t = \varepsilon_t \). The matrix \( P \)—that makes the shocks orthogonal—is usually obtained using the Cholesky factorization (Judge et al., 1988). However, the matrix \( P \) is not unique since it depends on the ordering of the shocks, from the most exogenous to the most endogenous. Since it is difficult to perform this classification in the context of our study, we rely on the generalized impulse response procedure that circumvents this problem. It is presented in the next section.

The coefficients of the IRF functions over the horizon \( \{1, 2, \ldots, h\} \) can be computed recursively, the recursive equation used to compute the IRF coefficients (\( \theta_h \)) being (Kilian and Kim, 2011):

\[
\theta_h = \Phi_h P^{-1} = \sum_{s=1}^{h} \Phi_{h-s} B_s P^{-1}
\]

(17)

with \( \Phi_0 = I_k \). For instance, \( \theta_1 = B_1 P^{-1} \), \( \theta_2 = (B_1^2 + B_2) P^{-1} \), \( \theta_3 = (B_1^3 + B_1B_2 + B_2B_1 + B_3) P^{-1} \), and so on. If the VAR includes only one lag for each endogenous variable—i.e., if \( p=1 \)—we then have: \( \theta_1 = B_1 P^{-1} \), \( \theta_2 = (B_1^2) P^{-1} \), \( \theta_3 = (B_1^3) P^{-1} \), and so on. In this case, the coefficients of the IRFs can be viewed as multipliers of the individual structural shocks (Judge et al., 1988).

In the framework of our study, the vector \( y \) appearing on the LHS of the reduced form equation (Eq. (16)) includes, for each strategy, its market beta, co-skewness or co-kurtosis, on the one hand, and the variables which appear on the RHS of our basic model as given by Eq. (14), on the other hand.

2.3.2 The identification method of the structural shocks: the generalized impulse response procedure

---

18 See, for instance, Judge et al. (1988) and Kilian and Kim (2011) for a presentation of the VAR estimation procedure.
If $\Sigma$ (Eq. (15)) is not diagonal, the Cholesky factorization that is used to compute the IRF coefficients changes with the ordering of the variables. The generalized impulse procedure allows to circumvent this problem (Koop et al., 1996; Pesaran and Shin, 1997, 1998). This procedure is based on the definition of an impulse response as the difference between two forecasts (Hamilton, 1994):

$$ IRF(t,h,d,\Omega_{t-1}) = E(Y_{t+h}|d = e_j, \Omega_{t-1}) - E(Y_{t+h}|d = 0, \Omega_{t-1}) $$

where $d$ is a vector containing the experimental shocks and $\Omega_{t-1}$ is the information set available at time $t-1$. As argued by Pesaran and Shin (1998), an impulse response is the result of a “conceptual experiment” in which the time profile of the impact of a vector of shocks $d' = (e_{t1}, e_{t2}, ..., e_{tk})'$ hitting the economy at time $t$ is compared with a baseline profile at time $t+n$ whereby $d = 0$. To implement the generalized impulse procedure, Eq. (18) is modified as follows:

$$ IRF(t,h,d_j,\Omega_{t-1}) = E(Y_{t+h}|d_j = e_j, \Omega_{t-1}) - E(Y_{t+h}|d = 0, \Omega_{t-1}) $$

Therefore, rather than shocking all elements of the vector $d$ as in Eq. (18), only one of its elements is shocked, say $e_j$. The other shocks are computed using the historical distribution of the errors. More precisely, Koop et al. (1996) have shown that:

$$ E(e_i|d_j = e_j) = \left(\sigma_{ij}, \sigma_{i2}, ..., \sigma_{ik}\right) \sigma_{jj}^{-1} d_j $$

The other shocks are thus retrieved by exploiting the structure of the historical covariances between $e_j$ and the innovations of the other endogenous variables $\left(\sigma_{ij}\right)$. Compared to (17), the generalized impulse function is given by:

$$ IRF_{e_j} = \sigma_{jj}^{1/2} \Phi_k \Sigma e_j $$

where $e_j$ is a $k \times 1$ vector with unity as its $j^{th}$ element and 0 elsewhere. $j$ is usually equal to one—i.e., it corresponds to the first equation of the VAR. Since, in contrast to the orthogonalized impulse responses, the generalized responses are invariant to the reordering of variables, the latter do not coincide with the former only for $j=1^n$. The generalized impulse responses are thus unique and take into account the historical pattern of correlations among shocks (Pesaran and Shin, 1997, 1998).

2.3.3 Introducing asymmetries (nonlinearities) in the VAR model

As largely documented in Section 2.2, there is evidence that the behavior of hedge fund strategies with respect to risk is state-dependent. Actually, many studies find significant asymmetries in the behavior of hedge funds according to the state of the business cycle, hedge funds being more risk-averse in recessions than in expansions (Sabbaghi, 2012; Racicot and Théoret, 2013, 2015, 2016; Bali et al., 2014; Lambert and Plantania, 2016). There is thus evidence that the measures of hedge fund risk analyzed in this study—i.e., beta, co-skewness and co-kurtosis—respond less smoothly to macroeconomic and

---

19 i.e., for the first equation of the VAR whose innovation is shocked.
financial shocks in recessions or crises than in normal times (Lo, 2001; Chen and Liang, 2007; Racicot and Théoret, 2013; Bali et al., 2014).

In this paper, we rely on STVAR (smooth transition vector autoregressive model) to allow for different responses in recession and expansion (Auerbach and Gorodnichenko, 2012). This method is akin to a Markov regime switching regression (Goldfeld and Quandt, 1973; Hamilton, 1989, 2005). However, instead of having only two values for probabilities—zero or one—as in the Markov regime switching regression, the STVAR procedure allows for smooth transition probabilities from one regime to the next. According to Auerbach and Gorodnichenko (2012), the STVAR uses more information by exploiting the variation in the probability of being in a particular regime. In recessions, the STVAR thus works with a larger set of observations than the Markov regime switching regression, which leads to more stable coefficients.

The general form of the STVAR may be written as follows:

$$ y_t = f(z_t) B_r(L) y_{t-1} + \left[1 - f(z_t)\right] B_e(L) y_{t-1} + \xi_t \quad (22) $$

where $y_t$ is the vector of endogenous variables; $B_r(L)$ is the matrix of coefficients in recessions associated with lagged endogenous variables; $B_e(L)$ is the matrix of coefficients in expansions associated with lagged endogenous variables. $f(z_t)$ is defined as follows:

$$ f(z_t) = \frac{e^{-\gamma z_t}}{1 + e^{-\gamma z_t}}, \quad \gamma > 0 \quad (23) $$

i.e., a logistic function parameterized by $\gamma$.

In Eq. (23), $z_t$ is an index built using a backward-looking moving average on a coincident economic indicator, say GDP growth. This moving average is transformed to have a mean of 0 and a standard deviation of one, i.e.,

$$ z_t = \frac{\text{ma}_d \text{ln}(GDP) - \mu_{\text{ma}_d \text{ln}(GDP)}}{\sigma_{\text{ma}_d \text{ln}(GDP)}} \quad (24) $$

where ma_dln(GDP) is a moving average of GDP growth, $\mu_{\text{ma}_d \text{ln}(GDP)}$ is its mean, and $\sigma_{\text{ma}_d \text{ln}(GDP)}$ is its standard deviation. The length of the moving average and the value of $\gamma$ are chosen to match the observed frequencies of U.S. recessions (Bachmann and Sims, 2012).

The cyclical function $f(z_t)$ is bounded between 0 and 1. It thus may be interpreted as the probability to be in a recession. For instance, when $z_t$ is very negative—i.e., lower than -0.9—$f(z_t)$ tends to 1: the economy is then in deep recession. In fact, we may consider that the economy has plunged in recession when $f(z_t) \geq 0.8$. Conversely $1 - f(z_t)$ may be viewed as the probability to be in an expansion. In this respect, when $z$ is very positive—i.e., higher than 0.9—$\left[1 - f(z_t)\right]$ tends towards 0:

\begin{itemize}
  \item Jawadi and Khanniche (2012) rely on the smooth transition regression method (STR), and not on a STVAR as in our study, to analyze the asymmetries in the pattern of hedge fund returns.
  \item Bachmann and Sims (2012) adopt an alternative specification to this equation in which $z_t$ and $z_t^2$ multiply $y_{t-1}$ in their VAR system.
  \item Auerbach and Gorodnichenko (2012) and Bachman and Sims (2012) select a seven-quarter moving average for GDP growth and a value of 1.5 for $\gamma$.
\end{itemize}
the economy is then in a strong expansion. Finally, Auerbach and Gorodnichenko rely on the Monte Carlo Markov Chain method to estimate Eq. (22).\\footnote{See Auerbach and Gorodnichenko (2012) for a description of this econometric procedure.}

### 2.4 Methodological problems

#### 2.4.1 A possible endogeneity issue

One may object that the fact that return moments respond favourably to external shocks is not necessarily an evidence that hedge funds manage their risk exposure. Indeed, there may be a reverse causality between hedge fund asset holdings and return characteristics like skewness and kurtosis: do holdings cause return characteristics or do return characteristics cause holdings? It may seem plausible to argue that only if asset characteristics cause asset holdings may we infer that there is something special in hedge fund holding choices and how they change their holdings in response to external variables.

During crises, if hedge funds do not react to adverse shocks, holdings will effectively cause return characteristics. Hedge fund risk exposure, as measured by their co-moments, will increase. For instance, their market beta will respond positively to the VIX if hedge funds do not manage their risk exposure. However, if their beta decreases, there is evidence that hedge funds manage their risk position. One may object that this favourable change in hedge fund beta following a VIX shock may be due to the use of derivatives. However, even in this case, hedge funds must manage optimally their risk position to reduce their risk exposure with derivatives. Derivatives do not provide insurance against all risks. They may even increase risk in some circumstances. In this instance, many researchers question the efficiency of derivatives in reducing the exposure of financial institutions to risk (e.g., Demsetz and Strahan, 1997).

In fact, we implicitly tackle this possible endogeneity issue by relying on the following criterion which is largely accepted in our kind of literature (e.g., Brown et al., 2014; Lambert and Plantania, 2016; Racicot and Théoret, 2016). If risk exposure increases following an adverse shock—e.g., a VIX shock—we may then infer that holdings cause asset characteristics. If not, we may reverse the causality—i.e., return characteristics cause holdings, and in this case we may conclude that hedge funds manage their exposure to risk as measured by co-moments.

Moreover, in this article, we focus on systematic risk as measured by the market beta, co-skewness and co-kurtosis. Hence, idiosyncratic risk embedded in financial assets is removed to conduct our analysis. Idiosyncratic risk is not controllable by itself, which is not the case for systematic risk. The endogeneity problem seems to apply mainly to “gross” return moments which are not corrected for idiosyncratic risk. This problem should be much less important when we experiment only with systematic risk as in our study.

#### 2.4.2 An errors-in-variables problem
Most of the variables we rely on to construct our VAR systems are *generated variables*—i.e., they are transformations of other existing time series. For instance, many of the indicators of macroeconomic and financial uncertainty we use are computed with multivariate GARCH processes. Pagan (1984, 1986) has studied the biases caused by this kind of variables when running OLS regressions on which VAR are based. According to his simulations, relying on generated variables does not lead to inconsistency at the level of the coefficients but the t-tests associated with the estimated coefficients are invalid. Pagan (1984, 1986) suggests to tackle this kind of endogeneity issue by resorting to an IV method like two-stage least squares or GMM. The generated variables are then purged from their endogeneity by regressing them on instruments.

There is no simple way to tackle this errors-in-variables problem in a VAR analysis. However, all the variables in our VAR systems are endogenous, which mitigates this problem. Moreover, all the variables included in our VAR are regressed on lagged values of the complete set of variables in our system. These lagged values of variables may be considered as instruments which reduce the endogeneity problem due to the presence of generated variables.

### 3. Stylized facts

#### 3.1 Data

Data on hedge fund returns are drawn from the databases managed by Greenwich Alternative Investment (GAI)\(^{24}\) and EDHEC\(^{25}\). GAI manages one of the oldest hedge fund databases, containing more than 13,500 records of hedge funds as of March 2010. Returns provided by the database are net of fees. The EDHEC database is managed by EDHEC-Risk Institute, Liège (Belgium)\(^{26}\). Our datasets run from January 1997 to June 2016, for a total of 234 observations. These datasets include the returns of ten comparable strategies which are described in Table 1. Moreover, the GAI dataset comprises a weighted general index while our benchmark for the EDHEC dataset corresponds to the fund of funds index. Moreover, the data used to build our indicators of macroeconomic and financial risk and uncertainty are drawn from the FRED database, a dataset managed by the Federal Reserve Bank of St.-Louis.

There are many biases which must be addressed when using hedge fund data, the major one being the survivorship bias—i.e., a bias which is created when a database only reports information on operating funds (Cappoci and Hübner, 2004; Fung and Hsieh, 2004; Patton et al., 2015). This bias is accounted for in the GAI database as index returns for periods since 1994 include defunct funds\(^{27}\). Other biases which are tackled for in the GAI database are the self-selection bias and the early reporting bias\(^{28}\) (Capocci and Hübner, 2004; Fung and Hsieh, 2004).

#### 3.2 Descriptive statistics

\(^{24}\) GAI’s database website is [here](http://www.greenwichai.com).
\(^{25}\) EDHEC’s database website is [here](http://www.edhec-risk.com).
\(^{26}\) The address of the EDHEC Risk Institute: Rue Louvrex 14, Bldg N1, 4000 Liège, Belgium.
\(^{27}\) Source: Greenwich Alternative Investment website (2016).
\(^{28}\) Other problems related to hedge fund returns are due to illiquidity and the practice of return smoothing (Pástor and Stambaugh, 2003; Getmansky et al., 2004). The problems may lead to an underestimation of risk in the hedge fund industry. In this article, as explained earlier, we account for return smoothing and illiquidity by adding an autoregressive term in our estimations. See also Amihud (2002).
Figure 1 compares the returns of the strategies we select to perform this study and the returns of some other key strategies for the two databases. We note that the return of the GAI weighted composite index (GI) displays a behavior which is very close to the fund of funds index (FOF), so we select this index as the benchmark for the EDHEC database. The three strategies we mainly focus in this study—i.e., long-short (LS), equity market neutral (EMN) and short-sellers (SS)—also display remarkably similar returns in the two databases. Surprisingly, the futures (FUT, GAI) and Commodity Trading Advisor (CTA, EDHEC) returns are strongly correlated\(^{29}\). This may be due to the fact that the CTA strategy is much involved in futures markets, especially commodities markets. And even if the quants of macro strategies have a priori different expertise, this strategy delivers very similar returns in the two databases.

Table 2 provides the descriptive statistics of our two databases. During our sample period, the return of the GAI weighted composite index (0.65% monthly) is lower than the stock market return (0.72% monthly). In this respect, the GAI weighted composite return shows a clear tendency to decrease since 1988\(^{30}\), which is less the case for the stock market return (Figure 2)\(^{31}\).

In order to better understand the link between hedge fund returns and higher moments, Figure 2 provides the cyclical behavior of the GAI weighted composite index and of the returns of strategies which are greatly involved in short-selling transactions—i.e., short-sellers and futures. During downturns, the hedge fund weighted composite return tends to decrease, but its drop is usually lower than the stock market return\(^{32}\). Note that the hedge fund general index has clearly underperformed the stock market one since the end of the subprime crisis. However, two strategies succeed in delivering positive returns in both samples during downturns: short-sellers and futures\(^{33}\) (Figure 2). During economic expansions, short-sellers usually provide negative returns—which are related to their negative beta\(^{34}\)—while futures continue to deliver positive returns, albeit lower. As shown later, these patterns are closely linked to the higher moments of the short-selling strategies.

According to Table 2, the average stock market skewness, at -0.65, is lower than the one of the GAI general index (0.08). This suggests that there are more negative outliers in the stock market than in the hedge fund industry\(^{35}\). However, kurtosis is higher for hedge funds. The strategies which have the highest positive skewness are: short-sellers, futures and macro. But this advantage may be compensated by higher kurtosis—as for short-sellers. The strategy having the highest tail risk—i.e., low skewness and high kurtosis—is fixed income. Being greatly involved in the mortgage-backed securities market, it was severely hit by the subprime crisis.

\(^{29}\) In fact, the returns of the CTA and futures strategies tend to behave as long straddles (Huber and Kaiser, 2004; Stafylas et al., 2016).

\(^{30}\) The data used to construct this Figure come from the quarterly GAI database.

\(^{31}\) Akay et al. (2013) also find evidence of a decline in hedge fund strategies’ returns, especially after the market crash in 2000. According to Figure 2, this decline has started before.

\(^{32}\) This behavior may be due to the practice of return smoothing in the hedge fund industry.

\(^{33}\) This behavior may be due to the practice of return smoothing in the hedge fund industry.

\(^{34}\) This behavior may be due to the practice of return smoothing in the hedge fund industry.

\(^{35}\) Once more, this may be related to the return smoothing practice in the hedge fund industry.
Turning to systematic measures of skewness and kurtosis, we note in Table 2 that co-skewness of the hedge fund general index (GAI) is negative, which suggests that this co-moment is usually a source of risk for hedge funds. However, three strategies display a positive and high level of co-skewness—i.e., short-sellers, futures and macro—. This suggests that these strategies are quite dynamic in terms of their trade-off between higher moments. In other respects, co-kurtosis is quite different from one strategy to the next. As expected, the equity market neutral strategy has the lowest level of co-kurtosis in both samples while the long-short and the event driven strategies display the highest levels. Interestingly, co-kurtosis is negative and high in absolute value for two strategies: short-sellers and futures. This means that when the cube of the market return decreases—i.e., in falling financial markets—the return delivered by these strategies increases. Figure 3 also shows that strategies’ skewness and kurtosis co-move negatively—i.e., strategies which display the lowest skewness tend to have the highest kurtosis. Risk associated with higher moments thus tends to compound itself. We observe a similar co-movement between strategies’ co-skewness and co-kurtosis.

It is well-known that, for asymmetric distributions, skewness and kurtosis are highly interrelated (MacGillivray and Balanda, 1988). Importantly, when arbitraging between skewness and kurtosis, hedge funds are constrained by the following lower statistical bound for kurtosis which links it to the squared value of skewness (Wilkins, 1944):

$$\text{kurtosis} \geq 1 + \text{skewness}^2 \quad (25)$$

This lower bound thus establishes a quadratic relationship between skewness and kurtosis—i.e., an unavoidable trade-off between these two moments (Figure 3). Eq.(25) is valid for all densities whose third and fourth moments are defined (Schopflocher and Sullivan, 2005). It shows that if hedge funds are in search of a higher skewness—which is advantageous from the viewpoint of risk—they will have to accept a higher level of kurtosis which grows with the square of skewness. This relationship is consistent with the behavior of skewness and kurtosis in the hedge fund industry (Figure 3).

As regards of beta, we note in Table 2 that its mean level is relatively low for hedge funds, being equal to 0.35 for the GAI weighted composite return over the sample period. The fixed income and equity market neutral strategies have the lowest beta while the long-short strategy displays the highest one. The strategies with the highest beta standard deviation are short-sellers and futures—an other indication that these strategies are very dynamic in the management of risk. Moreover, there is a strong positive co-movement between beta and co-kurtosis in both databases (Figure 3). This relationship will be documented further in the section devoted to VARs.

Finally, Table 2 reports the correlation between strategies’ moments. We note that the correlation between co-skewness and co-kurtosis is usually negative and quite high in absolute value, as if

---

35 I.e., the same strategies having the highest skewness.
37 Note that hedge funds may temporarily loosen this relationship by getting involved in return smoothing, a current practice in the hedge fund industry (Kietzmann et al., 2004; Brown et al., 2012; Bali et al., 2014).
38 In turbulent dispersions, there exists the following quadratic relationship between skewness (S) and kurtosis (K): $K = AS^2 + B$, where A and B are empirically fitted constants (Schopflocher and Sullivan, 2005).
these higher moments could substitute for each other \(^{39}\). For instance, this correlation is equal to -0.85 for the GAI general index and to -0.81 for the EDHEC fund of funds index. For most of the strategies, the correlation between co-skewness and co-kurtosis exceeds -0.85. It even exceeds -0.90 for the distressed, event-driven, futures, long-short, mergers and short-sellers strategies. A negative correlation between co-skewness and co-kurtosis implies that when co-skewness decreases, co-kurtosis tends to increase. Therefore, two “bad” risks increase at the same time. However, the short-sellers and futures strategies display a negative co-kurtosis. As shown later, a negative correlation between these two moments is actually at the advantage of these strategies in market turmoil (Jurczenko et al., 2006). In contrast, the equity market neutral and the macro strategies display a positive correlation between co-skewness and co-kurtosis. For these strategies, there is thus a trade-off between the risks associated with co-skewness and co-kurtosis.

In other respects, there is usually a positive correlation between a strategy’s market beta and its co-kurtosis. Therefore, when co-kurtosis increases, systematic risk—as measured by the market beta—also tends to increase. This correlation is moderate for the benchmarks, which seems to result from a diversification effect. It is also very low for the short-sellers and moderate for the equity market neutral strategy, suggesting that their short-selling transactions loosen the positive link between the market beta and co-kurtosis. However, for some strategies—especially distressed, event-driven, long-short, and mergers—the positive correlation between the market beta and co-kurtosis is quite strong. In contrast, this correlation is negative for the futures strategy. Therefore, when its co-kurtosis increases, its beta decreases, which suggests that this strategy succeeds quite well in arbitraging systematic and fat-tail risks.

To get a better grasp on the significance of the concepts of co-skewness and co-kurtosis, Figure 4 relates hedge fund returns to the square \((\text{mkt}^2)\) and the cube \((\text{mkt}^3)\) of the stock market return \(^{40}\). During downturns, according to the Black (1976) leverage effect, \(\text{mkt}^2\)—a rough measure of the volatility of the stock market—tends to increase. During these episodes, the hedge fund weighted composite index tends to decrease. Given the definition of co-skewness provided by Eq. (7), the co-skewness of the weighted index return thus deteriorates during bad times, which adds to the risk of hedge funds. We note a similar behavior for the long-short strategy. The pattern of the equity market neutral strategy returns is also similar, but the return of this strategy is much less volatile than the weighted and long-short returns. Moreover, the co-skewness of the market neutral strategy has decreased less during the subprime crisis than during the tech-bubble crisis. In contrast, the returns of the futures strategy, and especially the returns of the short-sellers strategy, tend to rise when \(\text{mkt}^2\) increases. For these strategies, co-skewness is positive during downturns, which contributes to reduce their risk during bad times (Jurczenko et al.,

3.3 Cyclical co-movements between hedge fund returns, mkt\(^2\) and mkt\(^3\)

In this respect, MacGillivray and Balanda (1988) discuss the substitution between skewness and kurtosis. Figure 4 establishes this relationship for the GAI database. However, the results for the EDHEC database are essentially the same. Note that we discuss here the numerator of the co-skewness and co-kurtosis ratios given by Eqs. (7) and (8). We will examine the cyclical behavior of the scaled higher moments in the next subsection.
As regards of the co-movements between hedge fund returns and $mkt$, note that $mkt$ tends to decrease and become negative during stock market downturns. Figure 4 shows that when $mkt$ drops, the returns of the hedge fund weighted composite index, of the long-short and, to a lower extent, of the equity market neutral strategies also decrease. Given the definition of co-kurtosis provided by Eq.(8), this measure of risk is thus positive for these returns. However, as evidenced by Figure 4, a decrease in $mkt$ leads to an increase in the returns of the short-sellers and futures strategies. The co-kurtosis of these strategies is thus negative during downturns, which again contributes to reduce the risk of these strategies during bad times. In this respect, according to Jurczenko et al. (2006), strategies which exhibit positive co-skewness and negative co-kurtosis (with respect to the market portfolio) will tend to perform the best when the market portfolio becomes more volatile and thus experiences significant losses. These strategies—i.e., futures (or CTA) and short-sellers—will capture positive payoffs in falling markets, whereby most other hedge fund strategies, displaying negative co-skewness and positive co-kurtosis during market turmoil, will then exhibit severe negative payoffs. Finally, we note in Figure 4 that $mkt$ and $mkt'$ are relatively stable and low during expansions, which also corresponds to low and stable co-movements between hedge fund returns, on the one hand, and $mkt$ and $mkt'$, on the other hand, during these periods.

3.4. Cyclical monitoring of risk associated with beta, co-skewness and co-kurtosis

Even though their performance deteriorates following adverse shocks, hedge funds can mitigate their impact by reducing their exposure to these sources of risk. In this respect, Figure 5 reports the cyclical behavior of the betas, co-skewness and co-kurtosis of the return series studied in Figure 4. We note that the beta of the GAI general index decreases during downturns, which suggests that hedge funds try to reduce their market systematic risk when they are hit by adverse shocks. More importantly, their behavior is forward looking in the sense that their beta begins to decrease before downturns. Actually, if hedge funds behave optimally over the business cycle, they search a solution to a stochastic Bellman equation which takes the form $J_t(\cdot) = \max_{u} \left\{ f_t(\cdot) + \beta E\left[J_{t+1}(\cdot)\right]\right\}$, where $u$ is the vector of feedback control variables; $\beta$ is a discount factor, $f(\cdot)$ is the hedge fund objective function—i.e., profits, utility of profits, value added or any other criteria which they aim at maximizing; $E(\cdot)$ is the expected value operator, and $J_t(\cdot)$ is a recursive device (value function) that embeds the constraints of the problem and which is used to find an optimal solution. This maximizing behaviour is thus obviously forward-looking since $J_t(\cdot)$

\footnote{Indeed, $mkt'$ is the product of $mkt$ and $mkt$. $mkt$ being always positive, the sign of $mkt'$ depends on $mkt$. Since $mkt$ tends to decrease and to become negative during stock market downturns, $mkt'$ follows the same pattern.}

\footnote{According to Jurczenko et al. (2006), these strategies embedded with such higher moments act as skewer enhancers and kurtosis reducers during market turmoil.}

\footnote{Or act as if they were searching for such a solution.}
depends on $E[J_{t+1}(.)]^{44}$.

We note the same pattern for the betas of the long-short and equity market neutral strategies. Short-sellers—which maintain a negative beta across the whole business cycle—also reduce their market systematic risk during crises in the sense that their beta decreases in absolute value. However, the beta of the futures strategy turns from positive to negative during downturns, suggesting that this strategy positions itself to benefit from the drop in the stock market. This behavior requires good forecasting skills, to say the least.

Turning to higher moments, Figure 5 shows that the general index co-skewness has increased and that its co-kurtosis has decreased during the subprime crisis, which suggests that hedge funds were involved in reducing their higher moment risk. This behavior is less clear during the tech-bubble crisis whereby co-skewness tends to decrease. We observe the same pattern for the higher moments of the long-short strategy. However, the equity market neutral strategy displayed some difficulties in controlling its higher moment risk during the subprime crisis while its co-skewness and co-kurtosis evolved adversely during the tech-bubble crisis.

As regards short-sellers, we note that they were particularly well positioned at the start of the subprime crisis to capture positive payoffs in times of market turmoil, their co-skewness being at its maximum over our sample period and their co-kurtosis being at its minimum$^{45}$ (Jurczenko et al., 2006). During the crisis, in line with their beta, they fine-tuned their higher moment positions, reducing their co-skewness and increasing their co-kurtosis, perhaps because they were expecting a reversal of the financial markets$^{46}$. However, their behavior was different during the tech-bubble crisis while their higher moment risk was quite stable. The co-skewness and co-kurtosis of the futures strategy—which is also greatly involved in short-selling—obey to the same pattern$^{47}$.

4. The relevance of higher moments in the explanation of hedge fund returns

To better grasp the relevance of return higher moments in the explanation of the levels of hedge fund returns, we estimate the four-moment CAPM—as given by Eq. (5)—on hedge fund strategies. Panel A of Table 3 provides the OLS estimation of the four-moment CAPM for our two databases. To make the coefficients comparable, Panel B reports the standardized coefficients for each strategy.

The $R^2$ of the equations vary from 0.12 for the futures strategy to 0.61 for the long-short strategy. These $R^2$ usually increase with the estimated value of the market beta. Except for futures, market beta is the most important and significant factor explaining the returns of hedge fund strategies. However, higher moments have also a role to play. In the case of our sample, co-kurtosis, as measured by the standardized coefficient of $mkt^2$, is usually more important than co-skewness, as gauged by the

44 For more details, see Sydsæter et al. (2005), chap. 12.
45 Remind that the co-kurtosis of short-sellers is negative.
46 This change in risk positions may also be partly involuntary, exogenous shocks leading to a decrease in co-skewness and an increase in co-kurtosis.
47 The co-kurtosis of the futures strategy is also negative, which may be explained by its short-selling activities.
standardized coefficient of \( mkt \). When it is significant, the coefficient of \( mkt^2 \) is usually negative, which suggests that hedge fund returns decrease in a volatile stock market. The strategies which are the most hit by co-skewness are mergers\(^{48}\), fixed income and distressed securities. However, two strategies benefit from stock market volatility: futures (GAI and EDHEC) and short-sellers (EDHEC)\(^{49}\). This benefit seems to be linked to the short-selling activities of these strategies.

In other respects, we know that \( mkt \) tends to decrease during downturns. A negative coefficient for a strategy co-kurtosis is then favorable since it means that its return tends to increase in bad times. The futures and macro strategies have negative coefficients for co-kurtosis and these coefficients are, among strategies, the highest in absolute values. These strategies thus seem to manage their positions in order to gain in falling markets. The equity market neutral strategy, which is not sensitive to market volatility, also benefits from a decrease in \( mkt \). In contrast, the returns of the convertibles strategy drop significantly following a decrease in \( mkt \). These results are globally consistent with those obtained by Davies et al. (2009) in the framework of their model aiming at computing hedge fund optimal portfolios.

5. Empirical results

5.1 The selection of uncertainty factors

Table 4 provides the list and the description of the risk factors (first moments) and uncertainty factors (second moments) experimented in this study\(^{50}\). The choice of the risk factors will be made in the next section. In addition to the variables appearing in Table 4, we also considered global uncertainty indicators—i.e., (i) the FRED uncertainty (equity) indicator (FRED_UEQ)\(^{51}\); (ii) the first principal component of four indicators: FRED uncertainty indicator (equity), FRED uncertainty indicator (policy), the news-based baseline and the news-based policy indicators produced by the Economic Policy Uncertainty Group(PC_FRED_NEWS)\(^{52}\); (iii) the first principal component of our conditional variances uncertainty indicators listed in Table 4 (PC_CV).

Among all the uncertainty indicators recorded, the VIX is the most representative (Table 5). Not surprisingly, its correlation with the conditional variance of the return on S&P500 (\( cv_mkt \)) is the highest (0.80). It also has a high correlation (0.76) with the first principal component of our conditional variance uncertainty indicators (PC_CV) and with other global uncertainty indicators like FRED_UEQ (0.64) and PC_FRED_NEWS (0.60). It co-moves tightly with the uncertainty associated with the business cycle (\( cv_gprod \)) and with the uncertainty related to the credit spread (\( cv_creditspread \)).

Figure 6 provides the plots of the VIX compared to other key uncertainty indicators. As

---

\(^{48}\) It is well-known that a volatile stock market is not favorable for mergers. Indeed, merger activity is mainly observed during periods of high economic growth, when the volatility of the stock market is relatively low (Black, 1976).

\(^{49}\) The short-sellers strategy of the GAI database is insensitive to market volatility.

\(^{50}\) We also experimented with the 3-month Treasury bills rate and the ten-year interest rate but the results were not conclusive, these variables displaying a pronounced downward trend during our sample period. The term spread—i.e., the difference between the ten-year and the three-month interest rates—was much more significant.

\(^{51}\) This global indicator of macroeconomic uncertainty is produced by the Federal Reserve Bank of St.-Louis. FRED is the acronym of the database managed by this Federal Reserve Bank.

\(^{52}\) The website of this Group is: [http://www.policyuncertainty.com](http://www.policyuncertainty.com). For details on the indicators produced by this Group, see: Baker et al., 2015.
expected, the VIX tracks closely the conditional variance of the stock market return. It is also very representative of the first principal component of the whole set of our conditional variance uncertainty indicators. Although less tightly associated with PC_FRED_NEWS, the VIX trends in the same direction. In other respects, it tracks quite well the uncertainty associated with the business cycle (cv_gprod) but, in contrast to this indicator, it also reacts to crises unrelated to economic downturns like the European sovereign debt crisis in the aftermath of the subprime crisis. We also note that the conditional variance of the credit spread (cv_credit spread) reacts usually more to crises than cv_gprod. Finally, the VIX also co-moves with the conditional variance of unemployment (cv_unrate) although this indicator is more volatile than the VIX.

In our VAR model, for the sake of parsimony, we thus retain only one indicator of macroeconomic and financial uncertainty—i.e., the VIX—which appears to be very representative of the others.

5.2 The justification of the specification of the financial model (Eq. (14))

Table 6 displays the correlation coefficients between our three return moments—i.e., beta, co-skewness and co-kurtosis—of the GAI general index and the EDHEC fund of funds index with our macroeconomic and financial indicators. Consistent with Figure 3, the correlation between co-skewness and co-kurtosis is high, being -0.83 for the GAI index and -0.82 for the EDHEC one. Moreover, for both databases, the beta and co-kurtosis co-move positively, the correlation between these two variables exceeding 0.40. Second, we note that co-skewness is less correlated with our macroeconomic and financial indicators than the beta and co-kurtosis. For both databases, the credit spread and the term spread are among the indicators the most correlated with beta and co-kurtosis, which justifies their introduction in our basic model (Eq. (14)). In other respects, in addition to gprod, Table 6 shows that we can also select gpayroll or unrate as substitutes to decrypt the cyclicality of our risk measures. Finally, as justified in the previous section, the VIX is the variable we select to account for macroeconomic and financial uncertainty in Eq. (14). Note that the choice of the term spread, the credit spread and the industrial production growth rate is supported by many researchers in the field of hedge funds (Kat and Miffre, 2002; Amenc et al., 2003; Brealy and Kaplanis, 2010; Bali et al., 2014; Lambert and Platania, 2016). Furthermore, Agarwal et al. (2014) and Lambert and Platania (2016) find that the stock market implied volatility (VIX) is an important driver of hedge fund returns and hedge fund exposures to the stock market and Fama and French factors. Finally, Racicot and Théoret (2013, 2014, 2016) find that most hedge fund strategies follow a procyclical behavior with respect to risk, which also justifies the presence of the industrial production growth rate in our model.

53 which are often associated with a rise in credit risk.
54 Indeed, the estimation of a VAR model consumes many degrees of freedom. These degrees of freedom decrease quickly with the number of lagged variables.
55 Table 6 provides the contemporaneous coefficients of correlation between return moments and macroeconomic and financial variables. However, since the return moments series are autoregressive, these coefficients are representative of the correlation between these return moments and the lagged values of macroeconomic and financial variables.
56 The variable gpayroll is a proxy for employment growth. According to Veronesi (2010, chap. 7), gpayroll appears to be the most correlated with the Fed Funds rate among many other employment related variables. Since inflation has been relatively under control since the beginnings of the 1990s, the co-movement between the Fed Funds rate and gpayroll is tight in the 1990s and 2000s.
5.3 Interactions between hedge fund moments

5.3.1 Hedge fund benchmarks

It is well-known that the interactions between the moments of a statistical distribution are important. For instance, as discussed previously, there is a quadratic lower bound linking skewness and kurtosis—i.e., the Wilkins’ (1944) lower bound\(^{35}\). Insofar as hedge fund managers display forecasting skills, they are constrained to trade-off positive odd moments—i.e., return and skewness—against even moments—i.e., variance and kurtosis—, the former being desirable for risk-averse investors and the latter being undesirable (Scott and Hovarth, 1980). In this respect, in their study on hedge fund portfolio selection, Jurczenko et al. (2006) find that when the variance of a portfolio return increases, kurtosis tends to increase\(^{58}\). Minimizing smaller risks also increases bigger risks (Desmoulins-Lebeault, 2006). It is thus impossible to simultaneously maximize skewness and minimize variance and kurtosis subject to a return constraint.

The links between return co-moments are less well-known in the literature. In this respect, using a simple VAR system, Figure 7 plots the interactions between the moments of the GAI general index and the EDHEC fund of funds (FOF) return—chosen as the benchmark for this database—over our sample period. First, we note a strong\(^{59}\) positive and significant interaction between the market beta and co-kurtosis. Therefore, co-kurtosis co-moves positively with beta for both indices, an unfavorable relationship from the point of view of a risk-averter when he increases the beta of his portfolio—i.e., the systematic risk which he bears. Conversely, when a fund deleverages—i.e., in times of market turmoil—its beta and co-kurtosis tend to decrease simultaneously (Billio et al., 2012; Santos and Veronesi, 2016). Second, an increase in co-kurtosis also decreases co-skewness for both indices, a relationship which is akin to the Wilkins’ (1944) lower bound. Conversely, when a fund deleverages, a decrease in co-kurtosis leads to an increase in co-skewness, a desirable co-movement between these two moments in times of crisis\(^{60}\). Note, as argued in this paper, that these co-movements between moments result partly from the strategies followed by hedge fund managers and are not purely exogenous market relationships (Jurczenko et al., 2006; Hübner et al., 2015).

5.3.2 Long-short, equity market neutral and short-sellers strategies

Figure 8 provides the same information as Figure 7 for the three strategies on which we focus in this study—i.e., long-short, equity market neutral and short-sellers. The market beta of the long-short strategy responds positively and very significantly to a co-kurtosis (positive) shock in both databases. The

---

\(^{35}\) In this respect, according to Xiong and Idzorek (2011), a high kurtosis is often associated with more extreme negative skewness. Assets with such higher moments display relatively stable returns during expansions but can produce important negative payoffs in recessions.

\(^{36}\) Jurczenko et al. (2006) argue that it is not possible to decrease kurtosis while controlling for variance.

\(^{58}\) Note that the ordinates of all the IRFs plots of our risk measures are scaled on the respective own shocks of these measures. For instance, the plot of the response of the market beta to co-kurtosis shock is scaled on the plot of the response of this beta to its own shock, which obviously displays the highest amplitude. Thus we can directly gauge the relative importance of an impulse response function by the amplitude (or height) of this response on the plot.

\(^{60}\) For instance, an increase in the share of liquid assets in a portfolio should lead to these changes in higher moments.
response of the equity market neutral strategy’s beta to this shock goes in the same direction, although, as expected, it is lower in amplitude. However, the response of the short-sellers’ beta to a co-kurtosis shock is, although positive, much less tight and significant than for the two other strategies, which seems to stand as an advantage for short-sellers.

Figure 8 reveals more differences in the responses of the strategies’ co-kurtosis to a co-skewness shock. For the long-short strategy, this response is negative and quite significant. As discussed previously, this suggests that the managers of the long-short strategy reduce their higher moment risk during downturns but that they are induced to bear more risk in expansion. In contrast, in both databases, the response of co-kurtosis to a co-skewness shock is positive for the equity market neutral strategy, which suggests that this strategy may have difficulties in controlling its higher moment risk in bad times relatively to the long-short strategy (Figure 5). However, similarly to the beta, these co-movements between co-skewness and co-kurtosis are relatively small compared to those of the long-short strategy. Finally, the short-sellers’ co-kurtosis decreases\(^{61}\) when its co-skewness increases. As mentioned previously, this pattern is peculiar to the short-sellers strategy and constitutes a plus in recession.

5.4 Estimation of the linear VAR model

The reduced form of our linear VAR system is given by Eq. (16). As justified in Section 2.2.2, the vector \(\mathbf{Y}_t\) of endogenous variables is equal to:

\[
\mathbf{Y}_t = \begin{bmatrix} \text{moment}_{ij} \& \text{gprod} \& \text{VIX} \& \text{term\_spread} \& \text{credit\_spread} \end{bmatrix} (26)
\]

where \(\text{moment}_{ij}\) is one of our three measures \(i\) of hedge fund risk—i.e., beta, co-skewness and co-kurtosis—and \(j\) stands for the selected strategies or for the general indices. We thus allow for interactions or feedback effects between all the variables of our canonical model given by Eq. (14). Using the usual information criteria—i.e., the AIC, AIC\(_c\),\(^{62}\) and SIC statistics—we retain three lagged values for the \(\mathbf{Y}_t\) vector for our VAR model.

5.4.1 Hedge fund benchmarks

Figure 9 reports the IRFs of our linear VAR model for the two hedge fund benchmarks—i.e., the weighted composite index for the GAI database and the fund of funds (FOF) index for the EDHEC database, respectively. As expected, an industrial production growth shock induces hedge funds to take more risk as measured by the market beta. Moreover, hedge funds decrease their beta following a (positive) VIX shock—an increase in VIX being associated with falling financial markets. In other respects, a credit spread shock and a term spread shock lead to a significant decrease in the market beta. These patterns are consistent with the mapping of the credit and term spreads to the credit risk and liquidity risk spaces, respectively (Lambert and Plantania, 2016). The reaction of the market beta to the last three shocks seems dominated by risk management policies taking place during economic downturns

\(^{61}\) i.e., increases in absolute value.

\(^{62}\) The AIC\(_c\) is a corrected version of the AIC criterion proposed by Hurvich and Tsay (1993) specifically designed for VARs. See also Jordà (2005).
or financial crises.

Not surprisingly, since there is a positive co-movement between the market beta and co-kurtosis as regards of benchmarks, we observe the same responses of co-kurtosis to the industrial production growth, VIX and credit spread shocks. However, the response of co-kurtosis to VIX is more important and significant. Hedge funds thus seem more concerned by the impact of VIX on their fat-tail risk. In contrast to the market beta, co-kurtosis increases after a term spread shock. Interpreting this indicator as a measure of liquidity risk, we can conjecture that hedge funds experience difficulties in controlling the impact of this kind of risk on the tails of their return distributions.

Turning to co-skewness, we note that this measure of risk responds positively to an industrial production growth shock, suggesting that an increase in economic growth fosters positive return outliers. More importantly, a VIX shock leads to a jump of co-skewness. This may be related to hedging policies aiming at controlling tail risk in periods of rising market volatility. The impact on co-skewness of the two remaining shocks is quite low.

5.4.2 Long-short, equity market neutral and short-sellers strategies

Figures 10 and 11 report the IRFs of our three risk measures for the three strategies we focus on in this study, respectively for the GAI and the EDHEC databases. To facilitate the comparison between our findings, we express the beta and the co-kurtosis of short-sellers in absolute value since they are always negative in our sample.

For both databases, the IRFs of the long-short beta are consistent with the ones of the indices, except for the term spread for which the IRFs slope upwards. It is possible that this strategy experiences some difficulties in controlling liquidity risk, so its beta responds positively to a term spread shock. Similarly to the benchmarks, the beta of the equity market neutral strategy also shows procyclicality but seems to be less responsive to the VIX. An increase in volatility thus seems to harm the functioning of this strategy. Similarly to the long-short strategy, the beta of the equity market neutral strategy responds positively to a term-spread shock.

The short-sellers beta is not very cyclical: its response to the unemployment rate shock is low. Therefore, short-sellers seem to be quite immunized against economic fluctuations. Compared to the other strategies, there is a long delay between a VIX shock and a (significant) decrease in short-sellers beta. Since stock prices usually decrease with a rise in volatility, this delay may correspond to a deliberate move to capture the positive payoffs associated with short-selling. However, short-sellers seem quite involved in credit risk since a credit shock entails a substantial decrease in their beta.

The co-kurtosis of the three strategies is not very procyclical. But once more, it is much related to the VIX. Co-kurtosis decreases following a VIX shock for the long-short and equity market neutral

---

63 For an analysis of market liquidity on hedge fund performance, see Criton and Scaillet (2011).
64 Note that we discuss particularly the results associated with the GAI database in this section, since the IRFs obtained with the EDHEC one are quite comparable.
65 This is not surprising since the share of the long-short strategy is the highest in the GAI weighted index.
66 For the short-sellers strategy, we have selected the unemployment rate rather than the industrial production growth rate as business cycle indicator since short-sellers seem to respond more to the unemployment rate (Lambert and Plantania, 2016).
67 i.e., an important deleveraging.
strategies. This suggests that hedge funds tend to reduce their fat-tail risk with a rise in market volatility. On the side of short-sellers, a VIX shock leads to a substantial decrease in their (negative) co-kurtosis. Indeed, an increase in market volatility impedes short-selling transactions, so they seem to deliberately decrease their co-kurtosis gap (Lambert and Plantania, 2016).

Similarly to co-kurtosis, the co-skewness of the three strategies is not very responsive to a business cycle shock. However, in both databases, a VIX shock induces the long-short strategy to increase substantially its co-skewness. This may correspond to a deliberate move to hedge the impact of an increase in market volatility. In contrast, co-skewness responds negatively to a VIX shock for the equity market neutral strategy, and especially for the short-sellers one, suggesting once more that an increase in market volatility is detrimental to short-selling transactions.

In other respects, regardless of the strategy, co-skewness is not very responsive to a term spread shock. However, the long-short’s co-skewness increases significantly after a credit shock, suggesting that this strategy is quite exposed to this kind of risk and tries to hedge partially the impact of this shock. The other two strategies are less successful in their hedging operations since a credit shock leads to a decrease in their co-skewness.

5.5. Estimation of the asymmetric VAR model

To implement the STVAR, we must compute the function \( f(z_t) \) (Eq. (23)) which allows to identify the episodes of expansion and recession. Auerbach and Gorodnichenko (2012), and Bachman and Sims (2012) rely on GDP growth to construct the \( z \) variable. To identify recessions, they use a smoothing parameter \( \gamma \) equal to 1.5 and a moving average of GDP growth of seven quarters. Since our observations are defined on a monthly basis, we rely on industrial production growth to construct \( z \). After many experiments, we selected the same value for \( \gamma \) and we used a twenty-one-month moving average of the industrial production growth. This calibration provides recession periods which best fitted our priors.

Figure 12 displays the plots of \( z_t \) and \( f(z_t) \) used to run our STVAR system. When \( z_t \leq -0.9 \) — i.e., when the probability of being in recession is equal or greater than 0.8 — the corresponding period is associated with a deep recession (Auerbach and Gorodnichenko, 2012; Bachman and Sims, 2012). Our computations thus allow identifying two recession episodes during our sample period, the first corresponding to the tech-bubble crisis which lasted from August 2001 to September 2002, and the second corresponding to the subprime crisis which stretched from August 2008 to June 2010. These periods do not coincide precisely with the NBER recession periods. For instance, according to the NBER, the subprime crisis lasted from December 2007 to June 2009 (Figure 12). We do not expect that the recession periods provided by a smooth transition function will correspond exactly to the NBER computations. Moreover, the recession periods computed by the NBER are subject to error and do not

---

\[68 \text{i.e., deleverage.} \]

\[69 \text{Increasing the } \gamma \text{ parameter reduces the smoothness of } f(z_t). \text{ For high values of } \gamma, \text{ the probability function } f(z_t) \text{ becomes a step function, taking only two values—0 and 1—as in regime switching econometric models.} \]
necessarily coincide with the ranges established by other researchers. In this respect, Bekaert and Hodrick (2012) range the subprime crisis from 2008 to 2010, a period which is closer to our computations.

To verify the precision of our monthly computations, we also report in Figure 12 the \( f(z_t) \) function based on the U.S. quarterly GDP growth from 1988 to 2016 using the same calibration as Auerbach and Gorodnichenko (2012), and Bachman and Sims (2012). According to the \( f(z_t) \) plot, the subprime crisis lasted from the first quarter of 2008 to the third quarter of 2010, a result which is close to our monthly results. However, according to the plot, the tech-bubble crisis is classified as an economic slowdown rather than as a deep recession.

5.5.1 Hedge fund benchmarks

Figure 13 features the non-linear IRFs of the three risk measures for the benchmarks of both databases—i.e., the weighted general index for the GAI database and the fund of funds index for the EDHEC database.

Among the three risk measures, the response of beta to external shocks is the most asymmetric. Interestingly, beta is procyclical in expansion—i.e., it reacts positively and significantly to a \( g_{prod} \) shock—but it is quite stable (hedged) in recession. Therefore, the representative hedge fund increases its beta in expansion to capture the positive payoffs related to rising economic growth but reduces its systematic risk in recession by hedging its exposure to the stock market\(^7\). Consistent with Lambert and Plantania (2016), the beta decreases substantially in recession following a VIX shock—which suggests an important deleveraging process. In contrast, it increases significantly in expansion after this shock, which suggests that hedge funds “buy” volatility in expansion (Lambert and Plantania, 2016). The asymmetric reaction of the beta to the term spread and especially to the credit spread is in line with our previous arguments.

The representative hedge fund’s co-kurtosis is not significantly procyclical\(^7\). Moreover, there is no obvious asymmetry in the response of co-kurtosis to VIX associated with the phase of the business cycle. A VIX shock induces hedge funds to reduce importantly and significantly their co-kurtosis risk and this reaction does not seem to depend on the phase of the business cycle. It is much more associated with the financial crises which can occur in recession but also in times of expansion like the Asian crisis in 1997-1998 or the European sovereign debt crisis in 2010-2012. In contrast, the response of co-kurtosis to a credit shock is asymmetric, being negative in recession and positive in expansion.

Turning to co-skewness, we note that a \( g_{payroll} \) shock (business cycle shock) impacts significantly co-skewness for the GAI database, suggesting that some strategies are vulnerable to recession in terms of co-skewness risk. Similarly to co-kurtosis, hedge funds reduce their co-skewness risk after a VIX shock and this behavior does not seem to be asymmetric. Moreover, a credit spread shock induce hedge funds to take less higher-moment risk in recession while it leads to an increase in co-

\(^7\) In the absence of hedging operations, the hedge fund beta ought to increase in recession.
\(^7\) For the analysis of co-skewness and co-kurtosis, we have eliminated the term spread shock since these two risk measures are not very sensitive to this external shock.
kurtosis in expansion\textsuperscript{72}.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure14}
\caption{Figure 14}
\end{figure}

\textbf{5.5.2 Long-short, equity market neutral and short-sellers strategies}

The reaction of the betas of our three strategies to a \emph{gprod} shock involves three interesting issues (Figure 14). First, the long-short strategy seems to have some difficulties in controlling its systematic risk in recession—especially in the EDHEC database. Second, the beta of the equity market neutral strategy is quite responsive to a \emph{gprod} shock in expansion—especially in the EDHEC database—suggesting that this strategy adopts deliberately a long position in expansion. Third, the beta of the short-sellers displays relatively low, albeit significant, procyclicality. Following an unemployment rate shock—the business cycle indicator selected for this strategy—its beta decreases in recession and increases in expansion.

A VIX shock also entails a different asymmetric behavior for the three strategies' betas. In contrast to the benchmarks and in both databases, the beta of the long-short strategy decreases both in expansion and recession, which suggests that this strategy is less involved in “volatility buying” than the representative hedge fund. The beta of the equity market neutral strategy tends to adopt the same behavior as the long-short one\textsuperscript{73} while the asymmetric pattern of the short-sellers' beta is more akin to the benchmarks. Finally, the three strategies respond similarly to a credit spread shock and their reaction is close to the benchmarks.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure15}
\caption{Figure 15}
\end{figure}

Turning to co-skewness, we note once more that this measure of risk is quite insensitive to the business cycle for the three strategies (Figure 15). However, the response of strategies’ co-skewness to VIX differs. For the long-short strategy, this measure of risk increases importantly with this shock regardless of the stance of the business cycle. It thus reduces its co-skewness risk substantially after a rise in stock market volatility. The two other strategies are less successful in reducing co-skewness risk. For instance, co-skewness decreases substantially for the EDHEC equity market neutral strategy in recession. For short-sellers, co-skewness decreases significantly in recession and expansion without any obvious asymmetry. The strategies more involved in short-selling thus seem to have difficulties in controlling their co-skewness risk in the presence of a VIX shock.

As regards credit spread shocks, the response of the long-short's co-skewness is the most important. The impact of this shock is positive and higher in recession in both databases. In contrast, the co-skewness of the equity market neutral strategy is not very sensitive to a credit shock, albeit it decreases significantly in recession in the EDHEC database. For short-sellers—especially in the case of the EDHEC database—co-skewness decreases in recession and increases in expansion, a pattern which obeys to the overall cyclical behavior of short-sellers' co-skewness (Figure 5).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure16}
\caption{Figure 16}
\end{figure}

\textsuperscript{72} In expansion, the impact of a credit shock on co-skewness is quite weak.

\textsuperscript{73} Note however that the beta of the equity market neutral strategy tends to increase significantly after a long delay following a VIX shock.
The co-kurtosis of the long-short strategy responds positively to a gprod shock in recession, but a significant response is only observed after a long delay (Figure 16). The co-kurtosis of the equity market neutral strategy is not very sensitive to the business cycle while, for short-sellers, this measure of risk increases\textsuperscript{74} in recession and decreases in expansion following an unemployment rate shock.

Once more, the VIX shock is the one which impacts the most strategies’ co-kurtosis. When this shock occurs, the co-kurtosis of the long-short strategy, and especially of the equity market neutral strategy, decreases substantially without any obvious asymmetry related to the stance of the business cycle. A VIX shock thus induces these strategies to reduce their exposure to fat-tail risk. In contrast, short-sellers are less successful in controlling their co-kurtosis risk in the occurrence of this shock since it increases significantly, both in recession and expansion. As explained earlier, this “constat” seems related to the particularities of this strategy.

The long-short and equity market neutral strategies reduce significantly their co-kurtosis after a credit spread shock in recession. However, the positive impact of this shock on co-kurtosis is not significant in expansion, except for the equity market neutral strategy. In contrast, short-sellers’ co-kurtosis co-moves positively with a credit spread shock in recession and negatively in expansion.

### 6. The cross-sectional dispersions of hedge fund measures of risk

#### 6.1 Stylized facts about cross-sectional dispersions

In this section, we aim at testing whether hedge funds behave homogeneously when macroeconomic and financial uncertainty increases (Eq. (13)). This is an important issue because if financial institutions adopt a homogenous behavior in times of rising uncertainty, systemic risk then increases in the financial system (Beaudry et al., 2001; Baum et al., 2002, 2004, 2009; Wagner, 2007, 2008, 2010; Shleifer and Vishny, 2010; Gennaioli et al., 2011; Calmès and Théoret, 2014; Racicot and Théoret, 2016; Santos and Veronesi, 2016). The hypothesis related to Eq. (13) has already been tested on risk measures associated with the second moment of return distributions—i.e., the standard deviation or the beta (e.g., Racicot and Théoret, 2016)—but, to the best of our knowledge, it has not yet been tested on risk measures associated with the higher moments—i.e., co-skewness and co-kurtosis. In this study, we contribute to fill this gap in the literature.

A first look at the plots of the cross-sectional dispersions of our three measures of hedge fund risk shows that, in both databases, the conjecture given by Eq. (13) seems to hold for the three measures (Figure 17). In line with Racicot and Théoret (2016), the cross-sectional dispersion of the strategies’ betas decreased during the subprime crisis and especially during the tech-bubble crisis, which suggests that a learning process was at play over our sample period. Regarding co-skewness and co-kurtosis and also consistent with our conjecture, we observe, in both databases, a big drop in their respective cross-sectional dispersions during the subprime crisis. During the tech-bubble crisis, the cross-sectional dispersions of these measures were very low, signaling a homogenous behavior for hedge fund strategies.

\textsuperscript{74} Remind that short-sellers’ co-kurtosis is expressed in absolute value.
during this crisis\textsuperscript{75}. We also report the plots of the cross-sectional dispersions excluding the most dynamic (volatile) strategies—i.e., short-sellers and futures. The pattern remains the same\textsuperscript{76}.

Similarly to Hespeler and Loiacono (2015) who identified a hedge fund event in 2004-2005 which increased systemic risk in the hedge fund sector, we also note that the cross-sectional dispersions of strategies’ co-skewness and co-kurtosis decreased during this period, suggesting that the behavior of the strategies became more homogeneous. This hedge fund event was related to the downgrading of the ratings of GM and Ford in 2004-2005, among others, which led to an increase in the CDS\textsuperscript{77} premia—i.e., a signal of rising credit risk to which many strategies are exposed. Similarly to the systemic indicators developed by Hespeler and Loiacono (2015), the cross-sectional dispersions of the higher moments can depict systemic events which are not necessarily associated with a financial crisis.

6.2 STVAR of the cross-sectional dispersions

In this section, we apply our STVAR system (Eq. (22)) to the cross-sectional dispersions of our risk measures in order to decrypt the factors which explain the homogeneous (or heterogeneous) behavior of strategies in recession and expansion. The plots of the IRFs of the cross sectional dispersions of strategies’ betas, co-skewnesses and co-kurtosis for our two databases—GAI and EDHEC—are reported in Figure 18.

Insert Figure 18 here

After a delay, a \textit{gprod} shock increases significantly the beta cross-sectional dispersion, both in recession and expansion. The business cycle by itself thus contributes to the heterogeneity in the behavior of hedge fund strategies. In contrast, a VIX shock decreases this cross-sectional dispersion in recession and increases it in expansion\textsuperscript{78}. The impact of this shock is more important in recession. The stock market volatility thus makes strategies more homogeneous in recession in the sense that most strategies reduce their systematic risk—i.e., deleverage—following this shock (Santos and Veronesi, 2016). In expansion, some strategies “buy” the stock market volatility, which leads to a more heterogeneous behavior. Similarly, a credit spread shock entails an unambiguous decrease in the beta cross-sectional dispersion in recession in both databases. In expansion, the IRFs differ. For the GAI database, we first note a decrease in the beta cross-sectional dispersion followed by an increase, but overall, the impact of a credit spread shock is weak. This shock leads to an increase in the beta cross-sectional dispersion in the EDHEC database and the response is more important.

The reactions of the co-skewness and co-kurtosis cross-sectional dispersions to \textit{external} shocks are similar. In line with the beta, these cross-sectional dispersions increase with a \textit{gprod} shock—especially in recession. However, a VIX shock leads to a significant and important decrease in the higher moment cross-sectional dispersions, both in recession and expansion\textsuperscript{79}. In contrast to the beta cross-sectional

\textsuperscript{75} Looking backward using the GAI’s cross sectional dispersions of co-skewness and co-kurtosis—GAI’s return series being longer than the EDHEC’s ones—we note that these dispersions were trending downward before the tech-bubble crisis.

\textsuperscript{76} However, we note a temporary jump in the GAI’s cross-sectional dispersions during the subprime crisis mainly due to the loss of control of some strategies particularly hit by the collapse of the mortgage-backed securities market—especially fixed income and convertibles.

\textsuperscript{77} i.e., credit default swaps.

\textsuperscript{78} In expansion, the behavior of the beta cross-sectional dispersion of the EDHEC strategies is less clear. It first decreases significantly and then increases significantly.

\textsuperscript{79} Note that this impact is greater in the GAI database.
dispersion, hedge funds do not adopt a more heterogeneous behavior in expansion after a VIX shock, which is the main factor impacting strategies’ multi-moment risk in the framework of our study. Similarly to the beta, a credit shock give rises to a more homogenous behavior in the hedge fund industry in recession in both databases and to a more heterogeneous one in expansion, albeit not significant for the GAI database.

7. Conclusion

Previous studies have shown that the behavior of hedge funds is forward-looking, in the sense that they can control market systematic risk by monitoring macroeconomic and financial risk and uncertainty (Patton and Ramadorai, 2013; Bali et al., 2014; Lambert and Plantania, 2016; Namvar et al., 2016; Racicot and Théoret, 2016). Since hedge funds follow option-like strategies, their behavior is thus essentially dynamic (Fung and Hsieh, 1997, 2001, 2002, 2004; Hübner et al., 2015). However, to the best of our knowledge, there exists no extensive econometric study which analyzes the time series of hedge fund strategies’ higher moments in an holistic perspective. Research in this area mainly focuses on building optimal portfolios by minimizing a global risk criterion accounting for higher moments (e.g., Jurczenko et al., 2006; Berg and van Rensburg, 2008; Davies et al., 2009; Xiong and Idzorek, 2011). In this paper, relying on a linear and nonlinear VAR settings, our main contribution is to show that hedge funds also control their higher moment risk by tracking macroeconomic and financial risk and uncertainty. In this respect, we find that the response of hedge fund strategies to macroeconomic and financial shocks is dependent on the stance of the business cycle.

Regarding our hedge fund benchmarks, we find that the beta is the most asymmetric to the business cycle among return moments, hedge funds increasing their beta during periods of expansion and stabilizing it in recession. The two other higher moment measures of risk seem less sensitive to the business cycle. However, our results indicate that our three measures of hedge fund risk are very responsive to the VIX—i.e., our indicator of macroeconomic and financial uncertainty—both in expansion and recession. In this respect, hedge fund beta tends to display an asymmetric pattern, increasing in expansion and decreasing in recession, suggesting that hedge funds monitor their systematic risk. However, hedge fund co-skewness and co-kurtosis do not exhibit such asymmetry—i.e., co-skewness increases and co-kurtosis decreases with a VIX shock—and this response does not seem to be associated with the phase of the business cycle. The response of higher moments to a VIX shock is thus more related to crises—a jump in the VIX signaling an upcoming crisis—than to the stance of the business cycle by itself.

In this study, we also examine how the intensity of short-selling activities can impact the behavior of hedge funds. Compared to the long-short strategy, strategies more involved in short-selling—i.e., equity market neutral and short-sellers—seem to have difficulties in controlling their co-skewness risk following market volatility or credit shocks. Short-selling operations may thus be hampered by this kind of shocks (Lambert and Plantania, 2016). However, similarly to the futures

---

80 Which suggests a deliberate reduction of risk.
strategy, short-sellers are well positioned at the start of financial crises to capture positive payoffs. They can thus stand as skewness enhancers and kurtosis reducers (Jurczenko et al., 2006). In other respects, we also rely on our VAR framework to analyze the asymmetric pattern of systemic risk in the hedge fund industry. Our principal finding is that VIX shocks make the behavior of hedge fund strategies more homogenous regardless of the stance of the business cycle while economic growth fosters less systemic risk.

Finally, the strong linkages between hedge fund higher co-moments, on the one hand, and the tight co-movements between beta and co-kurtosis, on the other hand, may give credit to Markowitz (2012) who argued recently that, despite its neglect of higher moments, his mean-variance theory was continuing to do quite a good job61. These tight co-movements we observe between moments also support cross-sectional studies on stock returns which find that tail risk has a small role to play in the determination of returns, systematic risk being their main driver (e.g., Bali et al., 2012).

References


---

61 Which seems to justify the acronym that is still used to label the mean-variance approach to portfolio selection—i.e., MPT (Modern Portfolio Theory).


Table 1 List of the hedge fund strategies

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>convertible (CV)</td>
<td>Managers take a long position in convertibles and short simultaneously the stock of companies having issued these convertibles in order to hedge a portion of the equity risk.</td>
</tr>
<tr>
<td>Distressed securities (DS)</td>
<td>Managers buy equity and debt at deep discounts issued by firms facing bankruptcy.</td>
</tr>
<tr>
<td>Event driven (ED)</td>
<td>Managers follow a multistrategy event driven approach.</td>
</tr>
<tr>
<td>Equity market neutral (EMN)</td>
<td>Managers aim at obtaining returns with low or no correlation with equity and bond markets. They exploit pricing inefficiencies between related equity securities.</td>
</tr>
<tr>
<td>Fixed income (FI)</td>
<td>Managers follow a variety of fixed income strategies like exploiting relative mispricing between related sets of fixed income securities. They invest in MBS, CDO, CLO and other structured products.</td>
</tr>
<tr>
<td>Fund of funds (FOF)</td>
<td>Managers invest in many strategies</td>
</tr>
<tr>
<td>Futures (FUT)</td>
<td>Manager utilize futures contracts to implement directional positions in global equity, interest rate, currency and commodity markets. They rely on leveraged positions to increase his return.</td>
</tr>
<tr>
<td>Long-short (LS)</td>
<td>Managers invest simultaneously on both the long and short sides of the equity market. Unlike the equity market neutral strategy, they maintain a long position. Their beta can thus exceed substantially the one of the hedge fund weighted composite indices.</td>
</tr>
<tr>
<td>Macro (MACRO)</td>
<td>These funds have a particular interest for macroeconomic variables. They take positions according to their forecasts of these variables. Managers rely on quantitative models to implement their strategies. They rely extensively on leverage and derivatives.</td>
</tr>
<tr>
<td>Mergers (MERGER)</td>
<td>These funds may purchase the stock of a company being acquired and simultaneously sell the stock of his bidder. They hope to profit from the spread between the current price of the acquired company and its final price.</td>
</tr>
<tr>
<td>Short sellers (SS)</td>
<td>Managers take advantage of declining stocks. Short-selling consists in selling a borrowed stock in the hope of buying it at a lower price in the short-run. Managers’ positions may be highly leveraged.</td>
</tr>
</tbody>
</table>

Table 2 Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>CV</th>
<th>DS</th>
<th>ID</th>
<th>EMN</th>
<th>FI</th>
<th>FUT</th>
<th>LS</th>
<th>MACRO</th>
<th>MERGER</th>
<th>SS</th>
<th>GI</th>
<th>FOF</th>
<th>MKT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return</td>
<td>Gai</td>
<td>EDHEC</td>
<td>Gai</td>
<td>EDHEC</td>
<td>Gai</td>
<td>EDHEC</td>
<td>Gai</td>
<td>EDHEC</td>
<td>Gai</td>
<td>EDHEC</td>
<td>Gai</td>
<td>EDHEC</td>
<td>Gai</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0063</td>
<td>0.0048</td>
<td>0.0069</td>
<td>0.0071</td>
<td>0.0071</td>
<td>0.0066</td>
<td>0.0054</td>
<td>0.0050</td>
<td>0.0060</td>
<td>0.0045</td>
<td>0.0061</td>
<td>0.0048</td>
<td>0.0073</td>
</tr>
<tr>
<td>Median</td>
<td>0.0081</td>
<td>0.0034</td>
<td>0.0100</td>
<td>0.0091</td>
<td>0.0090</td>
<td>0.0088</td>
<td>0.0047</td>
<td>0.0055</td>
<td>0.0070</td>
<td>0.0057</td>
<td>0.0040</td>
<td>0.0034</td>
<td>0.0100</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.0704</td>
<td>0.0691</td>
<td>0.0570</td>
<td>0.0504</td>
<td>0.0890</td>
<td>0.0442</td>
<td>0.0670</td>
<td>0.0253</td>
<td>0.0347</td>
<td>0.0365</td>
<td>0.1080</td>
<td>0.0691</td>
<td>0.1180</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.1936</td>
<td>-0.0543</td>
<td>-0.0777</td>
<td>-0.0836</td>
<td>-0.0820</td>
<td>-0.0886</td>
<td>-0.0337</td>
<td>-0.0587</td>
<td>-0.0800</td>
<td>-0.0867</td>
<td>-0.0710</td>
<td>-0.0543</td>
<td>-0.0819</td>
</tr>
<tr>
<td>St.Dev.</td>
<td>0.0213</td>
<td>0.0237</td>
<td>0.0176</td>
<td>0.0177</td>
<td>0.0207</td>
<td>0.0175</td>
<td>0.0111</td>
<td>0.0082</td>
<td>0.0114</td>
<td>0.0122</td>
<td>0.0274</td>
<td>0.0237</td>
<td>0.0270</td>
</tr>
<tr>
<td>Skewness</td>
<td>-4.7338</td>
<td>0.1793</td>
<td>-0.8471</td>
<td>-1.3076</td>
<td>-0.3611</td>
<td>-1.4087</td>
<td>1.1480</td>
<td>-2.2952</td>
<td>-3.5643</td>
<td>-3.8251</td>
<td>0.4366</td>
<td>0.1793</td>
<td>0.0389</td>
</tr>
<tr>
<td>Bêta</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>0.1542</td>
<td>0.1589</td>
<td>0.2562</td>
<td>0.2892</td>
<td>0.3705</td>
<td>0.3306</td>
<td>0.1236</td>
<td>0.0863</td>
<td>0.0822</td>
<td>0.0586</td>
<td>0.0372</td>
<td>0.0381</td>
<td>0.5125</td>
</tr>
<tr>
<td>St.Dev.</td>
<td>0.1180</td>
<td>0.0662</td>
<td>0.1050</td>
<td>0.1252</td>
<td>0.0683</td>
<td>0.1461</td>
<td>0.0525</td>
<td>0.0444</td>
<td>0.0421</td>
<td>0.0497</td>
<td>0.1314</td>
<td>0.1106</td>
<td>0.0871</td>
</tr>
<tr>
<td>Co-skewness (cs)</td>
<td>mean</td>
<td>0.0206</td>
<td>-0.0288</td>
<td>-0.1788</td>
<td>-0.2210</td>
<td>-0.1616</td>
<td>-0.1943</td>
<td>0.0262</td>
<td>0.0310</td>
<td>-0.0481</td>
<td>-0.0819</td>
<td>0.3875</td>
<td>0.1813</td>
</tr>
<tr>
<td>Co-kurtosis (ck)</td>
<td>mean</td>
<td>0.1195</td>
<td>0.0404</td>
<td>0.1219</td>
<td>0.1528</td>
<td>0.1098</td>
<td>0.1358</td>
<td>0.0311</td>
<td>0.0395</td>
<td>0.0800</td>
<td>0.0584</td>
<td>0.3047</td>
<td>0.1306</td>
</tr>
<tr>
<td>ρ(beta,ck)</td>
<td>0.14</td>
<td>0.71</td>
<td>0.93</td>
<td>0.95</td>
<td>0.62</td>
<td>0.97</td>
<td>0.52</td>
<td>0.35</td>
<td>0.36</td>
<td>0.22</td>
<td>-0.60</td>
<td>-0.52</td>
<td>0.58</td>
</tr>
<tr>
<td>ρ(beta,cs)</td>
<td>-0.46</td>
<td>-0.45</td>
<td>-0.85</td>
<td>-0.95</td>
<td>-0.64</td>
<td>-0.97</td>
<td>-0.08</td>
<td>-0.26</td>
<td>-0.59</td>
<td>-0.09</td>
<td>0.70</td>
<td>0.56</td>
<td>-0.57</td>
</tr>
<tr>
<td>ρ(ck,cs)</td>
<td>-0.15</td>
<td>-0.42</td>
<td>-0.90</td>
<td>-0.98</td>
<td>-0.98</td>
<td>-0.98</td>
<td>0.44</td>
<td>0.39</td>
<td>0.10</td>
<td>-0.90</td>
<td>-0.93</td>
<td>-0.90</td>
<td>-0.90</td>
</tr>
</tbody>
</table>

Notes: The acronyms of the strategies are reported in Table 1. The conditional beta, co-skewness and co-kurtosis are computed using the multivariate GARCH procedure, as explained in Section 2.1. St.-Dev. stands for standard deviation. ρ(x, y) designates the correlation between x and y.
Table 3 Estimation of the four-moment CAPM for hedge fund strategies' returns

Panel A

OLS coefficients

<table>
<thead>
<tr>
<th></th>
<th>c</th>
<th>mkt</th>
<th>mkt₁</th>
<th>mkt₂</th>
<th>ar(1)</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GAI</td>
<td>EDHEC</td>
<td>GAI</td>
<td>EDHEC</td>
<td>GAI</td>
<td>EDHEC</td>
</tr>
<tr>
<td>CV</td>
<td>0.0064</td>
<td>0.0066</td>
<td>0.05</td>
<td>0.04</td>
<td>-0.14</td>
<td>-0.38</td>
</tr>
<tr>
<td></td>
<td>3.43</td>
<td>5.09</td>
<td>1.63</td>
<td>2.76</td>
<td>-0.31</td>
<td>-1.48</td>
</tr>
<tr>
<td>DS</td>
<td>0.0072</td>
<td>0.0064</td>
<td>0.28</td>
<td>0.26</td>
<td>-1.24</td>
<td>-0.21</td>
</tr>
<tr>
<td></td>
<td>2.95</td>
<td>4.51</td>
<td>6.18</td>
<td>7.07</td>
<td>-2.69</td>
<td>-0.68</td>
</tr>
<tr>
<td>ED</td>
<td>0.0059</td>
<td>0.0065</td>
<td>0.38</td>
<td>0.29</td>
<td>-1.02</td>
<td>-1.16</td>
</tr>
<tr>
<td></td>
<td>3.70</td>
<td>3.59</td>
<td>6.65</td>
<td>10.07</td>
<td>-2.17</td>
<td>-2.11</td>
</tr>
<tr>
<td>EMN</td>
<td>0.0041</td>
<td>0.0040</td>
<td>0.15</td>
<td>0.10</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>2.28</td>
<td>3.20</td>
<td>7.71</td>
<td>6.89</td>
<td>0.14</td>
<td>0.28</td>
</tr>
<tr>
<td>FI</td>
<td>0.0078</td>
<td>0.0054</td>
<td>0.07</td>
<td>0.08</td>
<td>-0.87</td>
<td>-0.82</td>
</tr>
<tr>
<td></td>
<td>6.70</td>
<td>3.84</td>
<td>2.11</td>
<td>2.13</td>
<td>-3.05</td>
<td>-2.68</td>
</tr>
<tr>
<td>FUT</td>
<td>0.0004</td>
<td>0.0013</td>
<td>0.30</td>
<td>0.35</td>
<td>1.78</td>
<td>1.40</td>
</tr>
<tr>
<td></td>
<td>0.17</td>
<td>0.68</td>
<td>3.34</td>
<td>4.00</td>
<td>2.62</td>
<td>2.04</td>
</tr>
<tr>
<td>LS</td>
<td>0.0051</td>
<td>0.0051</td>
<td>0.56</td>
<td>0.41</td>
<td>-1.07</td>
<td>-0.88</td>
</tr>
<tr>
<td></td>
<td>2.85</td>
<td>2.86</td>
<td>8.64</td>
<td>11.04</td>
<td>-2.04</td>
<td>-1.97</td>
</tr>
<tr>
<td>MACRO</td>
<td>0.0020</td>
<td>0.0043</td>
<td>0.41</td>
<td>0.28</td>
<td>0.05</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>1.09</td>
<td>3.56</td>
<td>3.18</td>
<td>8.02</td>
<td>0.11</td>
<td>-0.19</td>
</tr>
<tr>
<td>MERGER</td>
<td>0.0058</td>
<td>0.0063</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.85</td>
<td>-0.92</td>
</tr>
<tr>
<td></td>
<td>4.58</td>
<td>5.10</td>
<td>2.46</td>
<td>4.05</td>
<td>-2.05</td>
<td>-2.38</td>
</tr>
<tr>
<td>SS</td>
<td>0.0022</td>
<td>0.0034</td>
<td>-0.96</td>
<td>-0.95</td>
<td>-0.04</td>
<td>1.93</td>
</tr>
<tr>
<td></td>
<td>1.21</td>
<td>1.09</td>
<td>-12.19</td>
<td>-8.34</td>
<td>-0.08</td>
<td>2.02</td>
</tr>
<tr>
<td>GI</td>
<td>0.0052</td>
<td>0.0042</td>
<td>0.39</td>
<td>0.29</td>
<td>-0.85</td>
<td>-0.95</td>
</tr>
<tr>
<td></td>
<td>2.63</td>
<td>2.65</td>
<td>8.39</td>
<td>9.10</td>
<td>-2.04</td>
<td>-2.18</td>
</tr>
</tbody>
</table>
Panel B

Standardized coefficients

<table>
<thead>
<tr>
<th></th>
<th>mkt</th>
<th>mkt$^2$</th>
<th>mkt$^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GAI</td>
<td>EDHEC</td>
<td>GAI</td>
</tr>
<tr>
<td>CV</td>
<td>0.08</td>
<td>0.09</td>
<td>-0.01</td>
</tr>
<tr>
<td>DS</td>
<td>0.62</td>
<td>0.58</td>
<td>-0.15</td>
</tr>
<tr>
<td>ED</td>
<td>0.73</td>
<td>0.65</td>
<td>-0.11</td>
</tr>
<tr>
<td>EMN</td>
<td>0.56</td>
<td>0.49</td>
<td>0.01</td>
</tr>
<tr>
<td>FI</td>
<td>0.24</td>
<td>0.25</td>
<td>-0.17</td>
</tr>
<tr>
<td>FUT</td>
<td>0.43</td>
<td>0.58</td>
<td>0.14</td>
</tr>
<tr>
<td>LS</td>
<td>0.83</td>
<td>0.79</td>
<td>-0.09</td>
</tr>
<tr>
<td>MACRO</td>
<td>0.78</td>
<td>0.74</td>
<td>0.01</td>
</tr>
<tr>
<td>MERGER</td>
<td>0.40</td>
<td>0.48</td>
<td>-0.19</td>
</tr>
<tr>
<td>SS</td>
<td>-0.75</td>
<td>-0.78</td>
<td>0.00</td>
</tr>
<tr>
<td>GI</td>
<td>0.77</td>
<td>0.72</td>
<td>-0.09</td>
</tr>
</tbody>
</table>

Notes: This Table reports the estimation of Eq. (5) for each strategy and for the benchmarks (gi). The acronyms of the strategies are reported in Table 1. c stands for the constant and mkt is the monthly return on the S&P500. ar(1) is an autoregressive term of order 1 which accounts for the practice of return smoothing in the hedge fund industry. For an explanatory variable, the standardized coefficient in Panel B is the corresponding coefficient of Panel A multiplied by $\frac{\sigma_i}{\sigma_y}$ —i.e., the ratio of the standard deviation of the explanatory variable and the standard deviation of the dependent variable.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description and construction</th>
<th>Variable</th>
<th>Description and construction</th>
</tr>
</thead>
<tbody>
<tr>
<td>credit_spread</td>
<td>Spread between BBB and AAA corporate bond yields</td>
<td>cv_creditspread</td>
<td>The conditional variance of the credit spread. It is the conditional variance of the innovation of an AR(2) process applied to the credit spread. This conditional variance is built with an EGARCH(1,1) process.</td>
</tr>
<tr>
<td>inf</td>
<td>The inflation rate. It is equal to log(CPI/CPI(-4)).</td>
<td>cv_inf</td>
<td>The conditional variance of inflation. It is the conditional variance of the innovation of an AR(6) process applied to inflation. This conditional variance is built using an EGARCH(1,1) process.</td>
</tr>
<tr>
<td>gpayroll</td>
<td>The non-farm payroll growth rate. It is equal to log(payroll/payroll(-4))*100.</td>
<td>cv_gpayroll</td>
<td>The conditional variance of the growth of non-farm payroll. It is the conditional variance of the innovation of an AR(2) process applied to the payroll growth. The conditional variance is built using an EGARCH(1,1) process.</td>
</tr>
<tr>
<td>gprod</td>
<td>The industrial production growth rate. It is equal to log(prod/prod(-4))*100.</td>
<td>cv_gprod</td>
<td>The conditional variance of the industrial production growth. It is the conditional variance of an AR(6) process applied to the industrial production growth. The conditional variance is built using an EGARCH(1,1) process.</td>
</tr>
<tr>
<td>mkt</td>
<td>The rate of return on the S&amp;P500.</td>
<td>cv_mkt</td>
<td>The conditional variance of the return of the S&amp;P500. It is the conditional variance of an AR(6) process applied to the return on the S&amp;P500. The conditional variance is built using an EGARCH(1,1) process.</td>
</tr>
<tr>
<td>output_gap</td>
<td>The output gap. To obtain the output gap, we detrend the logarithm of the industrial production time series with the Hodrick-Prescott filter. The resulting residuals constitute the output gap.</td>
<td>cv_outputgap</td>
<td>The conditional variance of the output gap. It is the conditional variance of an AR(2) process applied to the output gap. The conditional variance is built using an EGARCH(1,1) process.</td>
</tr>
<tr>
<td>term_spread</td>
<td>Spread between the ten-year interest rate and the 3-month Treasury bills.</td>
<td>cv_termspread</td>
<td>The conditional variance of the term spread. It is the conditional variance of an AR(2) process applied to the term spread. The conditional variance is built using an EGARCH(1,1) process.</td>
</tr>
<tr>
<td>unrate</td>
<td>Unemployment rate.</td>
<td>cv_unrate</td>
<td>The conditional variance of the unemployment rate. It is the conditional variance of an AR(6) process applied to the unemployment rate. The conditional variance is built using an EGARCH(1,1) process.</td>
</tr>
</tbody>
</table>

Table 5 Correlation matrix between the indicators of macroeconomic and financial uncertainty

<table>
<thead>
<tr>
<th>Probability</th>
<th>VIX</th>
<th>FRED_UEQ</th>
<th>PC_FRED_NEWS</th>
<th>cv_credit</th>
<th>cv_inf</th>
<th>cv_mkt</th>
<th>cv_outputgap</th>
<th>cv_gpayroll</th>
<th>cv_gprod</th>
<th>cv_termspread</th>
<th>cv_unrate</th>
<th>PC_CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FRED_UEQ</td>
<td>0.64</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC_FRED_NEWS</td>
<td>0.60</td>
<td>0.69</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_creditspread</td>
<td>0.63</td>
<td>0.18</td>
<td>0.46</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_inf</td>
<td>0.22</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.47</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_mkt</td>
<td>0.80</td>
<td>0.58</td>
<td>0.52</td>
<td>0.60</td>
<td>0.28</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_outputgap</td>
<td>0.37</td>
<td>0.18</td>
<td>0.22</td>
<td>0.41</td>
<td>0.37</td>
<td>0.22</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_gpayroll</td>
<td>0.27</td>
<td>0.12</td>
<td>0.16</td>
<td>0.19</td>
<td>0.19</td>
<td>0.28</td>
<td>0.20</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_gprod</td>
<td>0.60</td>
<td>0.20</td>
<td>0.34</td>
<td>0.82</td>
<td>0.54</td>
<td>0.54</td>
<td>0.66</td>
<td>0.22</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_termspread</td>
<td>0.40</td>
<td>0.42</td>
<td>-0.01</td>
<td>-0.02</td>
<td>0.03</td>
<td>0.34</td>
<td>0.05</td>
<td>0.12</td>
<td>0.13</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cv_unrate</td>
<td>0.47</td>
<td>0.22</td>
<td>0.45</td>
<td>0.64</td>
<td>0.33</td>
<td>0.44</td>
<td>0.29</td>
<td>0.11</td>
<td>0.68</td>
<td>0.13</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>PC_CV</td>
<td>0.76</td>
<td>0.36</td>
<td>0.48</td>
<td>0.86</td>
<td>0.61</td>
<td>0.76</td>
<td>0.59</td>
<td>0.36</td>
<td>0.91</td>
<td>0.22</td>
<td>0.71</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes FRED_UEQ: the FRED uncertainty indicator; PC_FRED_NEWS: the first principal component of the two uncertainty indicators published by FRED and two other uncertainty indicators produced by the Economic Policy Uncertainty group; PC_CV: the first principal component of our conditional variances uncertainty indicators listed in Table 4. The acronyms of the other indicators are reported in Table 4.
Table 6 Correlation between moments and macroeconomic (financial) indicators

<table>
<thead>
<tr>
<th></th>
<th>beta</th>
<th></th>
<th>co-skewness</th>
<th></th>
<th>co-kurtosis</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GAI</td>
<td>EDHEC</td>
<td>GAI</td>
<td>EDHEC</td>
<td>GAI</td>
<td>EDHEC</td>
</tr>
<tr>
<td>beta</td>
<td>1.00</td>
<td>1.00</td>
<td>-0.28</td>
<td>-0.21</td>
<td>0.41</td>
<td>0.45</td>
</tr>
<tr>
<td>co-skewness</td>
<td>-0.28</td>
<td>-0.21</td>
<td>1.00</td>
<td>1.00</td>
<td>-0.83</td>
<td>-0.82</td>
</tr>
<tr>
<td>co-kurtosis</td>
<td>0.41</td>
<td>0.45</td>
<td>-0.83</td>
<td>-0.82</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>credit_spread</td>
<td>-0.51</td>
<td>-0.37</td>
<td>0.12</td>
<td>0.03</td>
<td>-0.36</td>
<td>-0.32</td>
</tr>
<tr>
<td>inf</td>
<td>0.21</td>
<td>0.07</td>
<td>0.07</td>
<td>0.01</td>
<td>0.13</td>
<td>0.12</td>
</tr>
<tr>
<td>gpayroll</td>
<td>0.57</td>
<td>0.53</td>
<td>-0.20</td>
<td>-0.08</td>
<td>0.40</td>
<td>0.37</td>
</tr>
<tr>
<td>gprod</td>
<td>0.40</td>
<td>0.26</td>
<td>-0.05</td>
<td>0.07</td>
<td>0.22</td>
<td>0.18</td>
</tr>
<tr>
<td>mkt</td>
<td>-0.01</td>
<td>-0.03</td>
<td>0.13</td>
<td>0.08</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>output_gap</td>
<td>0.26</td>
<td>0.33</td>
<td>-0.15</td>
<td>-0.15</td>
<td>0.23</td>
<td>0.25</td>
</tr>
<tr>
<td>term_spread</td>
<td>-0.49</td>
<td>-0.53</td>
<td>0.30</td>
<td>0.27</td>
<td>-0.32</td>
<td>-0.25</td>
</tr>
<tr>
<td>unrate</td>
<td>-0.41</td>
<td>-0.38</td>
<td>0.20</td>
<td>0.17</td>
<td>-0.28</td>
<td>-0.22</td>
</tr>
<tr>
<td>cv_creditspread</td>
<td>-0.28</td>
<td>-0.14</td>
<td>0.01</td>
<td>-0.06</td>
<td>-0.22</td>
<td>-0.22</td>
</tr>
<tr>
<td>cv_inf</td>
<td>-0.02</td>
<td>0.08</td>
<td>-0.19</td>
<td>-0.28</td>
<td>0.05</td>
<td>0.09</td>
</tr>
<tr>
<td>cv_gpayroll</td>
<td>-0.08</td>
<td>-0.04</td>
<td>0.02</td>
<td>0.06</td>
<td>-0.14</td>
<td>-0.16</td>
</tr>
<tr>
<td>cv_gprod</td>
<td>-0.31</td>
<td>-0.15</td>
<td>0.01</td>
<td>-0.06</td>
<td>-0.21</td>
<td>-0.20</td>
</tr>
<tr>
<td>cv_mkt</td>
<td>-0.35</td>
<td>-0.29</td>
<td>0.16</td>
<td>0.11</td>
<td>-0.48</td>
<td>-0.49</td>
</tr>
<tr>
<td>cv_outputgap</td>
<td>-0.11</td>
<td>-0.02</td>
<td>0.10</td>
<td>-0.08</td>
<td>-0.05</td>
<td>-0.06</td>
</tr>
<tr>
<td>cv_termspread</td>
<td>0.10</td>
<td>-0.09</td>
<td>0.17</td>
<td>0.34</td>
<td>-0.35</td>
<td>-0.49</td>
</tr>
<tr>
<td>cv_unrate</td>
<td>-0.40</td>
<td>-0.29</td>
<td>0.13</td>
<td>0.09</td>
<td>-0.29</td>
<td>-0.28</td>
</tr>
<tr>
<td>VIX</td>
<td>-0.32</td>
<td>-0.26</td>
<td>0.28</td>
<td>0.31</td>
<td>-0.60</td>
<td>-0.62</td>
</tr>
</tbody>
</table>

Notes: The acronyms of the variables are reported in Table 4. The variables which are retained in this study are in bold.

Figures

Figure 1 Comparison of GAI and EDHEC monthly returns
Notes: The acronyms of the strategies are reported in Table 1. GI stands for the GAI weighted composite index and FOF, for the EDHEC fund of funds index.

**Figure 2** Hedge fund returns and the stock market return

GAI general index
Notes: Returns are expressed as a twelve-month moving average. The trends are computed using the Hodrick-Prescott filter. Shaded areas represent recession episodes.

Figure 3 Interactions between hedge fund beta, skewness and kurtosis

Skewness—kurtosis (scatter diagrams)

GAI

EDHEC

Wilkin's theoretical lower bound
Notes: These Figures are scatter diagrams of moments of the strategies included in the GAI and EDHEC databases, respectively. The Wilkin's theoretical lower bound is explained in Section 3.2.
**Figure 4** Cyclical co-movements between hedge fund returns and \( mkt \), \( mkt' \)

**Hedge fund strategies' returns and \( mkt \)**

<table>
<thead>
<tr>
<th>General index</th>
<th>Long-short</th>
<th>Equity market neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Graph" /></td>
<td><img src="image2" alt="Graph" /></td>
<td><img src="image3" alt="Graph" /></td>
</tr>
<tr>
<td><img src="image4" alt="Graph" /></td>
<td><img src="image5" alt="Graph" /></td>
<td><img src="image6" alt="Graph" /></td>
</tr>
</tbody>
</table>

**Short-sellers**

<table>
<thead>
<tr>
<th>General index</th>
<th>Long-short</th>
<th>Equity market neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image7" alt="Graph" /></td>
<td><img src="image8" alt="Graph" /></td>
<td><img src="image9" alt="Graph" /></td>
</tr>
<tr>
<td><img src="image10" alt="Graph" /></td>
<td><img src="image11" alt="Graph" /></td>
<td><img src="image12" alt="Graph" /></td>
</tr>
</tbody>
</table>

**Futures**

<table>
<thead>
<tr>
<th>General index</th>
<th>Long-short</th>
<th>Equity market neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image13" alt="Graph" /></td>
<td><img src="image14" alt="Graph" /></td>
<td><img src="image15" alt="Graph" /></td>
</tr>
<tr>
<td><img src="image16" alt="Graph" /></td>
<td><img src="image17" alt="Graph" /></td>
<td><img src="image18" alt="Graph" /></td>
</tr>
</tbody>
</table>

**Hedge fund strategies' returns and \( mkt' \)**

<table>
<thead>
<tr>
<th>General index</th>
<th>Long-short</th>
<th>Equity market neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image19" alt="Graph" /></td>
<td><img src="image20" alt="Graph" /></td>
<td><img src="image21" alt="Graph" /></td>
</tr>
<tr>
<td><img src="image22" alt="Graph" /></td>
<td><img src="image23" alt="Graph" /></td>
<td><img src="image24" alt="Graph" /></td>
</tr>
</tbody>
</table>

**Short-sellers**

<table>
<thead>
<tr>
<th>General index</th>
<th>Long-short</th>
<th>Equity market neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image25" alt="Graph" /></td>
<td><img src="image26" alt="Graph" /></td>
<td><img src="image27" alt="Graph" /></td>
</tr>
<tr>
<td><img src="image28" alt="Graph" /></td>
<td><img src="image29" alt="Graph" /></td>
<td><img src="image30" alt="Graph" /></td>
</tr>
</tbody>
</table>

**Futures**

<table>
<thead>
<tr>
<th>General index</th>
<th>Long-short</th>
<th>Equity market neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image31" alt="Graph" /></td>
<td><img src="image32" alt="Graph" /></td>
<td><img src="image33" alt="Graph" /></td>
</tr>
<tr>
<td><img src="image34" alt="Graph" /></td>
<td><img src="image35" alt="Graph" /></td>
<td><img src="image36" alt="Graph" /></td>
</tr>
</tbody>
</table>

**Notes:** \( mkt \) is the return on the S&P500. Returns are expressed as a twelve-month moving average. Shaded areas represent recession episodes.

**Figure 5** Cyclical behavior of beta, co-skewness and co-kurtosis

\( \beta \)
Notes: The conditional beta, co-skewness and co-kurtosis are computed using the multivariate GARCH procedure, as explained in Section 2.1. Shaded areas represent recession episodes.

Figure 6 VIX and other indicators of economic uncertainty
Notes: PC_FRED_NEWS: the first principal component of the two uncertainty indicators published by FRED and two other uncertainty indicators produced by the Economic Policy Uncertainty group; PC_CV: the first principal component of our conditional variances uncertainty indicators listed in Table 4. The acronyms of the other indicators are reported in Table 4.
Figure 7 Interactions between beta, co-skewness and co-kurtosis shocks of the general index

Panel A
Gai general index

Panel B
EDHEC fund of funds (FOF)
In this standard VAR, $Y_i = \begin{bmatrix} \text{beta} & \text{co-skewness} & \text{co-kurtosis} \end{bmatrix}'$, where $i$ is the return index. Each endogenous variable comprises three lags. The shaded area encloses the 95% confidence interval.
Figure 8: Interactions between beta, co-skewness and co-kurtosis shocks of strategies involved in different degrees of short-selling

<table>
<thead>
<tr>
<th>Beta</th>
<th>Co-kurtosis shock</th>
<th>Co-skewness shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAI</td>
<td>EDHEC</td>
<td>EDHEC</td>
</tr>
<tr>
<td>Long-short</td>
<td>Co-kurtosis shock</td>
<td>Co-skewness shock</td>
</tr>
<tr>
<td></td>
<td>GAI</td>
<td>EDHEC</td>
</tr>
<tr>
<td></td>
<td>EDHEC</td>
<td>EDHEC</td>
</tr>
<tr>
<td>Equity market neutral</td>
<td>Co-kurtosis shock</td>
<td>Co-skewness shock</td>
</tr>
<tr>
<td></td>
<td>GAI</td>
<td>EDHEC</td>
</tr>
<tr>
<td></td>
<td>EDHEC</td>
<td>EDHEC</td>
</tr>
<tr>
<td>Short-sellers</td>
<td>Co-kurtosis shock</td>
<td>Co-skewness shock</td>
</tr>
<tr>
<td></td>
<td>GAI</td>
<td>EDHEC</td>
</tr>
<tr>
<td></td>
<td>EDHEC</td>
<td>EDHEC</td>
</tr>
</tbody>
</table>

Notes: In this standard VAR, $Y_t = [\beta_t, co-skewness_t, co-kurtosis_t]$, where $i$ is the return index. Each endogenous variable comprises three lags. The shaded area encloses the 95% confidence interval. The shaded area encloses the 95% confidence interval.
Figure 9 Linear impulse response functions: general index moments

Beta
GAI
gprod shock VIX shock term_spread shock credit_spread shock

EDHEC

Co-skewness
GAI

EDHEC

Notes: The IRFs are computed using Eq. (26) with three lags. The shaded area encloses the 95% confidence interval.

Co-kurtosis
GAI
Notes: The IRFs are computed using Eq. (26) with three lags. The shaded area encloses the 95% confidence interval.
Figure 10 Linear impulse responses of the moments of three GAI strategies

<table>
<thead>
<tr>
<th>gprod shock</th>
<th>VIX shock</th>
<th>Beta</th>
<th>term_spread shock</th>
<th>credit_spread shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-short</td>
<td>0.05</td>
<td>-0.03</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Equity market neutral</td>
<td>0.06</td>
<td>0.04</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Short-sellers</td>
<td>0.07</td>
<td>0.05</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Co-skewness</td>
<td>Long-short</td>
<td>0.05</td>
<td>-0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Equity market neutral</td>
<td>0.06</td>
<td>0.04</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Short-sellers</td>
<td>0.07</td>
<td>0.05</td>
<td>0.04</td>
<td>0.02</td>
</tr>
</tbody>
</table>

53
Notes: The IRFs are computed using Eq. (26) with three lags. The shaded area encloses the 95% confidence interval.
Figure 11 Linear impulse responses of the moments of three EDHEC strategies

<table>
<thead>
<tr>
<th>Strategy Type</th>
<th>Beta</th>
<th>VIX Shock</th>
<th>Term Spread Shock</th>
<th>Credit Spread Shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-short</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equity market neutral</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short-sellers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Co-skewness</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long-short</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equity market neutral</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short-sellers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Co-kurtosis
Long-short

Equity market neutral

Short-sellers

Notes: The IRFs are computed using Eq. (26) with three lags. The shaded area encloses the 95% confidence interval.

Figure 12 Components of STVAR: $z_t$ and $f(z_t)$

U.S. industrial production (monthly growth rate)

$f(z_t)$: smooth transition probability of being in recession
Notes: $z_t$ and $f(z_t)$ are computed using Eq. (24) and Eq. (23), respectively. The selected cyclical indicator used to construct the scaled variable $z$ is the U.S. industrial production growth for monthly data and the U.S. GDP growth for quarterly data.
Figure 13 Nonlinear impulse response functions: general index moments

**Beta**

<table>
<thead>
<tr>
<th>GAI</th>
<th>EDHEC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recession</td>
<td>Recession</td>
</tr>
<tr>
<td>Expansion</td>
<td>Expansion</td>
</tr>
</tbody>
</table>

**Shocks: gprod**

<table>
<thead>
<tr>
<th>Beta</th>
<th>VIX</th>
<th>Term spread</th>
<th>Credit spread</th>
<th>Co-skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
</tr>
<tr>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
</tr>
</tbody>
</table>

**VIX**

<table>
<thead>
<tr>
<th>Beta</th>
<th>VIX</th>
<th>Term spread</th>
<th>Credit spread</th>
<th>Co-skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
</tr>
<tr>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
</tr>
</tbody>
</table>

**Term spread**

<table>
<thead>
<tr>
<th>Beta</th>
<th>VIX</th>
<th>Term spread</th>
<th>Credit spread</th>
<th>Co-skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
</tr>
<tr>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
</tr>
</tbody>
</table>

**Credit spread**

<table>
<thead>
<tr>
<th>Beta</th>
<th>VIX</th>
<th>Term spread</th>
<th>Credit spread</th>
<th>Co-skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
</tr>
<tr>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
</tr>
</tbody>
</table>

**Co-skewness**

<table>
<thead>
<tr>
<th>Beta</th>
<th>VIX</th>
<th>Term spread</th>
<th>Credit spread</th>
<th>Co-skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
<td>GAI</td>
</tr>
<tr>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
<td>Expansion</td>
<td>Recession</td>
</tr>
</tbody>
</table>
Notes: The IRFs are estimated with the STVAR—i.e., Eq. (22). $\mathbf{Y}_t = \left[ \beta_{\text{prod}} \ gprod \ VIX \ term\_spread \ credit\_spread \right]$ for the beta and $\mathbf{Y}_t = \left[ \text{moment}_a \ gprod \ VIX \ credit\_spread \right]$ with moment being equal to co-skewness or co-kurtosis. The shaded area encloses the 95% confidence interval.
Figure 14: Nonlinear impulse response functions of beta: three strategies involved in short-selling at different degrees

<table>
<thead>
<tr>
<th>Beta</th>
<th>Shocks: gprod</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAI long-short</td>
<td>EDHEC long-short</td>
</tr>
<tr>
<td>recession</td>
<td>recession</td>
</tr>
<tr>
<td>expansion</td>
<td>expansion</td>
</tr>
</tbody>
</table>

GAI equity market neutral

EDHEC equity market neutral

GAI short-sellers

EDHEC short-sellers

VIX

GAI equity market neutral

EDHEC equity market neutral

GAI short-sellers

EDHEC short-sellers
Credit shock

GAI long-short

recession

expansion

EDHEC long-short

recession

expansion

GAI equity market neutral

EDHEC equity market neutral

GAI short-sellers

EDHEC short-sellers

Notes: The IRFs are estimated with the STVAR — i.e., Eq. (22). \( Y = \beta gprod VIX credit \). The shaded area encloses the 95% confidence interval.

Figure 15 Nonlinear impulse response functions of co-skewness: three strategies involved in short-selling at different degrees

Co-skewness

gprod

recession

expansion

GAI long-short

EDHEC long-short

GAI equity market neutral

EDHEC equity market neutral
Notes: The IRFs are estimated with the STVAR—i.e., Eq. (22). $\mathbf{Y}_t = \left[ \text{co skewness}, \quad \text{gprod}, \quad \text{VIX}, \quad \text{credit spread} \right]$. The shaded area encloses the 95% confidence interval.

**Figure 16** Nonlinear impulse response functions of co-kurtosis: three strategies involved in short-selling at different degrees.
VIX

recession expansion recession expansion
GAI long-short EDHEC long-short

GAI equity market neutral EDHEC equity market neutral

GAI short-sellers EDHEC short-sellers

recession expansion Credit shock expansion
GAI long-short EDHEC long-short

GAI equity market neutral EDHEC equity market neutral
Notes: The IRFs are estimated with the STVAR—i.e., Eq. (22). \( Y_t = \left[ \text{co-kurtosis}_t, \text{gprod}_t, \text{VIX}_t, \text{credit\_spread}_t \right] \). The shaded area encloses the 95% confidence interval.

**Figure 17** Cross-sectional dispersions of beta, co-skewness and co-kurtosis: EDHEC and GAI databases

**Beta**

**All strategies**

- EDHEC cross-sectional dispersion: all strategies
- GAI cross-sectional dispersion: all strategies

**Excluding futures and short-sellers**

- EDHEC cross-sectional dispersion: excluding FUT and SS
- GAI cross-sectional dispersion: excluding FUT and SS

**Co-skewness**

- EDHEC cross-sectional dispersion: all strategies
- GAI cross-sectional dispersion: all strategies

**Co-kurtosis**

- EDHEC cross-sectional dispersion: all strategies
- GAI cross-sectional dispersion: all strategies
The beta cross-sectional dispersion at time $t$ is the standard deviation of the strategies' conditional betas observed at $t$. The cross-sectional dispersions of the higher moments are computed using the same procedure. Shaded areas represent recession episodes.

**Figure 18** Nonlinear impulse response functions of beta, co-skewness and co-kurtosis cross-sectional dispersions: EDHEC and GAI databases
Notes: The IRFs are estimated with the STVAR—i.e., Eq. (22). $Y_t = [\text{cross\_sectional\_dispersion}, \ gprod, \ \text{VIX}, \ \text{credit\_spread}]^\top$, where $j$ stands for the moment. The shaded area encloses the 95% confidence interval.