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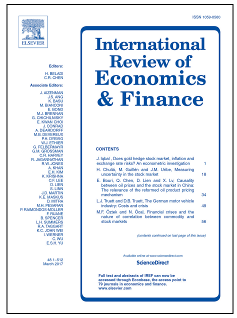

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François-Éric Racicot, Raymond Théoret

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Multi-moment risk, hedging strategies, & the business cycle

François-Éric Racicot[a,*], Raymond Théoret[b]

[a] *Telfer School of Management, University of Ottawa, 55 Laurier Avenue East, Ottawa, Ontario; Affiliate Research Fellow, IPAG Business School, Paris, France.*

[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).*

Abstract

We study the asymmetric responses of hedge fund return moments—especially higher moments as measured by return co-skewness and co-kurtosis—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 seem to monitor their return co-skewness and co-kurtosis. The response of their return moments to VIX shocks—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. Overall, the representative hedge fund tends to behave as an insurance seller in economic expansion and as an insurance buyer in recession or crisis. Finally, VIX shocks contribute to increase systemic risk in the hedge fund industry.

Keywords: Hedge fund; Multi-moment risk; Non-linear VAR; Business cycle; Systemic risk.
JEL classification: C13; C58; G11; G23.

* Corresponding author. Tel: +1 613-562-5800 (4757).

E-mail addresses: racicot@telfer.uottawa.ca (F.-É. Racicot), raymond.theoret@uqam.ca (R. Théoret).

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Abstract

We study the asymmetric responses of hedge fund return moments—especially higher moments as measured by return co-skewness and co-kurtosis—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 seem to monitor their return co-skewness and co-kurtosis. The response of their return moments to VIX shocks—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. Overall, the representative hedge fund tends to behave as an insurance seller in economic expansion and as an insurance buyer in recession or crisis. Finally, VIX shocks contribute to increase systemic risk in the hedge fund industry.

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 portfolios[1] (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 function of a representative investor[2]. At the empirical level, models show how investors trade-off return moments in order to construct their optimal portfolios (e.g., Desmoulins-Lebeault, 2006; Berg and van Rensburg, 2008; Davies, Kat and Lu, 2009;

[1] These theoretical developments have given rise to some asset pricing models like the four-moment CAPM.

[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.

Harvey, Liechty, Liechty and Müller, 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 temporal aspects related to the trade-off between higher moments when selecting an optimal portfolio.

In this study, we contribute to the empirical works on the role of return higher moments in portfolio selection by computing non-linear impulse response functions in order to gauge 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 in a holistic setting. Hedge fund strategies are particularly relevant to capture the impact of higher moments in portfolio selection since their managers rely heavily on derivatives, an obvious source of return skewness and kurtosis[3]. Our article complements the recent paper of Agarwal, Ruenzi and Weigert (2017b) who find that hedge funds seem to monitor a measure of tail risk they developed. However, they were mainly interested in the microstructure of tail-risk timing in the hedge fund industry while our paper focuses on the macroeconomic dynamics of hedge fund risk[4].

Our basic model is based on an underpinning developed by Beaudry, Caglayan and Schiantarelli (2001) and Baum, Caglayan and Ozkan (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

[3] According to Agarwal and Naik (2004) and Stafylas, Andersen and Uddin (2017), the use of leverage and financial derivatives, and the option-like nature of hedge fund managers' compensation contracts, might contribute to the negative skewness and high kurtosis of many hedge fund strategies' return distributions.

[4] However, note that Agarwal, Ruenzi and Weigert (2017b) have correlated their tail risk measure with the global uncertainty indicator developed by Bali, Brown and Caglayan (2014), which is the first principal component of well-known macroeconomic and financial uncertainty indicators. They find a negative correlation. Although the authors do not discuss this result, it may be further evidence that hedge funds do monitor their tail risk.

co-kurtosis[5]. Using this model, we compute nonlinear impulse response functions of our risk measures to macroeconomic and financial shocks which allow depicting asymmetric behavior during economic expansions and recessions (Auerbach and Gorodnichenko, 2012; Bachman and Sims, 2012). Indeed, previous studies have found many asymmetries in the behavior of financial institutions dependent on the stance of the business cycle (Jawadi and Khanniche, 2012; Bali, Brown and Caglayan, 2014; Calmès and Théoret, 2014; Lambert and Plantania, 2016; Namvar, Phillips, Pukthuanthong and Rau, 2016; Racicot and Théoret, 2016; Stafylas, Andersen and Uddin, 2017).

Similarly to Bali, Brown and Caglayan (2014), Lambert and Plantania (2016) and Racicot and Théoret (2016) who find 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 seem to 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, Getmansky and Pellizon, 2012; Santos and Veronesi, 2016). Among the hedge fund risk measures, the beta is the most cyclical and all risk measures are very sensitive to the VIX—an indicator of market expectation of near-term volatility. Our results are consistent with Agarwal, Ruenzi and Weigert (2017b) who find that many hedge fund strategies seem to behave as a short put in expansion and as a (long) put in recession or crisis. Hedge funds thus seem to sell insurance in good times and to reverse this behavior in times of turmoil by buying protection. Our results also support the findings of Huang, Chen and Kato (2017), who argue that

[5] 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.

hedge funds alternate their risk exposures dependent on the market conditions.

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, Maillet and Merlin, 2006). However, a market volatility shock seem detrimental to strategies particularly involved in short sales—i.e., equity market neutral and short-sellers— since it tends to increase their co-skewness risk, especially in recession (Lambert and Plantania, 2016). Moreover, the market neutral strategy is far from being a "hedged" strategy. Consistent with Duarte, Longstaff and Yu (2007) and Patton (2009), it may be risky in times of turmoil since it seems to have difficulties in controlling its higher moment risk. Moreover, our results suggest that its beta is procyclical.

Finally, we examine the evolution of systemic risk[6] in the hedge fund industry using once more the underpinning proposed by Beaudry, Caglayan and Schiantarelli (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, Caglayan and Schiantarelli's (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).

[6] 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, Demirguc-Kunt and Zhu, 2014).

This paper is organized as follows. Section 2 exposes our methodology. Section 3 presents the stylized facts related to our two hedge fund databases—i.e., 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 results regarding the asymmetric impulse response functions 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):

$$E\left[m_{t+1}\Re_{t+1} \middle| \Omega_t \right] = 1 \qquad (1)$$

In Eq.(1), $m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)}$ is the representative agent's intertemporal marginal rate of substitution between present and future consumption; β is this agent's discount factor; $u'(c_{t+1})$ is his marginal utility of consumption at time *t+1*; $\Re_{t+1}$ is the gross rate of return on the financial asset we want to price and Ω_τ 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):

$$m_{t+1} = a + b_t R_{mt+1} \qquad (2)$$

where 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 R_{mt+1} is nonlinear. Assume that m_{t+1} may be written as the following cubic polynomial of R_{mt+1}:

$$m_{t+1} = a + b_t R_{mt+1} + c_t R_{mt+1}^2 + d_t R_{mt+1}^3 \qquad (3)$$

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

$$E(R_i) - r_f = \varphi_1 Cov(R_m, R_i) + \varphi_2 Cov(R_m^2, R_i) + \varphi_3 Cov(R_m^3, R_i) \qquad (4)$$

where $E(R_i)$ is the expected value of return i; r_f is the risk-free rate and $Cov(.)$ is the operator of covariance. The *unscaled* beta, co-skewness and co-kurtosis of the asset which is priced are defined as $Cov(R_m, R_i)$, $Cov(R_m^2, R_i)$, and $Cov(R_m^3, R_i)$, 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:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{mt}^2 + \delta_i R_{mt}^3 + \xi_{it} \qquad (5)$$

We will rely on Eq.(5) to estimate the relative importance of higher moments in the explanation of R_{it}.

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:

$$beta_i = \frac{Cov(R_m, R_i)}{Var(R_m)} \qquad (6)$$

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-kewness and co-kurtosis, respectively:

$$co-skewness_i = \frac{Cov(R_m^2, R_i)}{\left[Var(R_m)\right]^{1.5}} \qquad (7)$$

$$co-kurtosis_i = \frac{Cov\left(R_m^3, R_i\right)}{\left[Var\left(R_m\right)\right]^2} \qquad (8)$$

To make our three measures of risk time-varying, we rely on the multivariate GARCH (MGARCH, Bollerslev, Engle and Woodridge, 1988). The simple system used to implement this procedure writes as follows:

$$f\left(y_t, \beta\right) = \varepsilon_t \qquad (9)$$

In Eq.(9), y_t is a vector of endogenous variables and ε_t is a vector of possibly serially correlated disturbances. Each equation of the system has its simplest expression: $y_{it} = \text{constant}_i + \varepsilon_{it}$. In our framework, the vector y_t takes the form: $y_t = \left[R_{it} \quad R_{mt} \quad R_{mt}^2 \quad R_{mt}^3\right]'$. The aim of this exercise is to find an estimate of the vector of parameters β 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 (h_{ij}) associated with the variables i and j may be written as follows (Mills, 1993):

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

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. The coefficient a_{ij} stands for the sensitivity of *cov* to the interaction between the innovations of the two variables—i and j—and b_{ij} is the autocorrelation coefficient. 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, Engle and Woodridge, 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), then modified by Beaudry, Caglayan and Schiantarelli (2001) and transposed to the financial sector by Baum, Caglayan and Ozkan (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:

$$y_t = \theta_0 + \mathbf{u}_t^{'}\boldsymbol{\theta}_1 + \hat{\boldsymbol{\sigma}}_t^{2'}\boldsymbol{\theta}_2 + \theta_3 y_{t-1} + \varepsilon_t \qquad (11)$$

In Eq. (11), y_t 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; $\hat{\boldsymbol{\sigma}}_t^2$ is the corresponding vector of their conditional covariances proxying for uncertainty and ε_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, Caglayan and Schiantarelli (2001) and Baum, Caglayan and Ozkan (2002, 2004, 2009) have computed the optimal share of a risky asset[7] $\left(w_{it}^{ra}\right)$ 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:

[7] There is only one risky asset in their model.

$$\forall i, \forall t \quad \operatorname{var}\left(w_{it}^{ra}\right) = \frac{\sigma_{\varepsilon t}^2 + \sigma_{vt}^2}{\varphi^2 \sigma_{vt}^4} \tag{12}$$

where φ is the degree of risk aversion of the representative investor.

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

$$\forall i, \forall t \quad \frac{\partial \operatorname{var}\left(w_{it}^{ra}\right)}{\partial \sigma_{vt}^2} = -\frac{1}{\varphi^2}\left(\frac{2\sigma_{\varepsilon t}^2}{\sigma_{vt}^6} + \frac{1}{\sigma_{vt}^4}\right) < 0 \tag{13}$$

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

As justified later, we borrow from the empirical APT model of Chen, Roll and Ross (1986) and from the market-timing factorial model of Gregoriou (2004) to specify our empirical model[8]. Its final expression is:

$$y_t = \lambda_0 + \lambda_1 gprod + \lambda_2 credit\_spread + \lambda_3 term\_spread + \lambda_4 VIX + \varsigma_t \quad (14)$$

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_ 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[9].

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 seek to 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 sales or on structured products (Agarwal, Ruenzi and Weigert, 2017b). In this respect, the presence of VIX in Eq. (14) is of a 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 like buying puts (Agarwal, Ruenzi and Weigert, 2017b). 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

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[8] i.e., the identification of the explanatory variables in Eq.(11). In this respect, according to Gregoriou (2004), the model we rely on is justified by the fact that hedge funds trade options (VIX) and have significant exposure to credit risk (credit_spread) and term risk (term_spread).

[9] Table 4 reports the list of the risk and uncertainty indicators experimented in this study and explains how they are built.

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[10]—i.e., through structured products like straight straddles or lookback straddles (Fung and Hsieh, 1997, 2001, 2002, 2004; Fieldhouse, 2013; Hespeler and Loiacono, 2015; Lambert and Plantania, 2016; Stafylas, Andersen and Uddin, 2017). 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 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[11], 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 might capture the return spread since the risk of such an operation is less than in recession. For instance, they could sell insurance by holding a short position in CDS (credit default swaps). In recession, they could decrease their exposure to credit risk by buying insurance—e.g., being long in CDS. This behavior is in line with Agarwal, Ruenzi and Weigert (2017b) who argue that many hedge fund strategies behave as short puts in expansion and as (long) puts in recession or crisis.

In other respects, an increase in the term spread usually signals a decrease in the likelihood of a recession (Estrella and Hardouvelis, 1991; Clinton, 1994-1995; Estrella and Mishkin, 1997, 1998, Gregoriou, 2004; Ang, Piazzesi and Wei, 2006; Wheelock and Wohar, 2009). Therefore, hedge funds should be induced to increase their risk, which suggests a positive sign for this variable in Eq. (14). However, the term spread may embed other dimensions of macroeconomic

[10] According to Asness, Krail and Liew (2001), hedge funds then load positively on the "long volatility" factor.

[11] 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.

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[12]. 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 sales, among others. However, in expansion, similarly to the credit spread, hedge funds may capture the term spread—i.e., increase their exposure to the term spread[13]. The sign of the term spread in equation (14) is thus an empirical matter.

In this article, we also focus particularly on three strategies involved in various degrees of short sales. By increasing order of the weight of short sales in their business lines, we select long-short, equity market neutral and short-sellers[14]. Having one of the highest positive betas in the hedge fund industry, the short sales 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 seeks 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 sales. Their market beta—which is always negative—may even exceed one in absolute value. Focusing on short sales thus allows us to see what impact the degree of short-selling may have on hedge fund risk along the business cycle. For instance, we expect that short-sellers should perform better during downturns[15] and thus offer good opportunities of portfolio diversification during bad times. Moreover, the portfolios of the equity market neutral and short-sellers strategies are more liquid than the one of the long-short strategy (Asness, Krail and Liew, 2001). This may give raise to different responses to shocks.

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[12] 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.

[13] See also Campbell, Lo and MacKinlay (1997) and Veronesi (2010) for other views on the predictive power of the term spread.

[14] Short-selling also represents an important share in the operations of the futures strategy.

[15] i.e., when the marginal utility of consumption is at its peak (Cochrane, 2005).

2.3 Nonlinear or asymmetric impulse response functions

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, Brown and Caglayan, 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 financial shocks in recessions or crises than in normal times (Lo, 2001; Chen and Liang, 2007; Racicot and Théoret, 2013; Bali, Brown and Caglayan, 2014).

In this paper, we rely on STVAR (smooth transition vector autoregressive model) to allow for different responses to shocks in recession and expansion (Auerbach and Gorodnichenko, 2012)[16]. 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[17]:

$$\mathbf{y_t} = f\left(z_t\right)\mathbf{B_R}\mathbf{(L)}\mathbf{y_{t-1}} + \left[1 - f\left(z_t\right)\right]\mathbf{B_E}\mathbf{(L)}\mathbf{y_{t-1}} + \boldsymbol{\xi}_\mathbf{t} \qquad (15)$$

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[16] 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.

[17] Bachmann and Sims (2012) adopt an alternative specification to this equation in which z_{t-j} and z_{t-j}^2 multiply y_{t-j} in their VAR system.

where $\mathbf{y_t}$ is the vector of endogenous variables; $\mathbf{B_R(L)}$ is the matrix of coefficients in recessions associated with lagged endogenous variables; $\mathbf{B_E(L)}$ is the matrix of coefficients in expansions associated with lagged endogenous variables. $f(z_t)$ is defined as follows:

$$f(z_t) = \frac{e^{-\gamma z_t}}{1+e^{-\gamma z_t}}, \quad \gamma > 0 \qquad (16)$$

i.e., a logistic function parameterized by γ.

In Eq. (16), 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.,

$$z_t = \frac{ma\_\mathrm{dln}(GDP) - \mu_{ma\_d\ln(GDP)}}{\sigma_{ma\_d\ln(GDP)}} \qquad (17)$$

where $ma\_\mathrm{dln}(GDP)$ is a moving average of GDP growth, $\mu_{ma\_d\ln(GDP)}$ is its mean, and $\sigma_{ma\_d\ln(GDP)}$ is its standard deviation. The length of the moving average and the value of γ are chosen to match the observed frequencies of U.S. recessions[18] (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_t is very positive—i.e., higher than 0.9—$\left[1 - f(z_t)\right]$ tends towards 1: the economy is then in a strong expansion. Finally, Auerbach and Gorodnichenko rely on the Monte Carlo Markov Chain method to estimate Eq. (15)[19].

Insert Table 1 here

2.4 Methodological issues

[18] 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 γ.

[19] See Auerbach and Gorodnichenko (2012) for a description of this econometric method. To identify the structural shocks in this setting, we rely on the generalized impulse response procedure (Pesaran and Shin, 1997, 1998). See the appendix for a description of this procedure.

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).

We know that many hedge fund strategies behave as short puts in normal times(Agarwal and Naik, 2004; Agarwal, Ruenzi and Weigert, 2017b). Indeed, the returns of these strategies are strongly correlated with the returns of short puts on major stock benchmarks like the S&P500 or the Russell 3000. However, short puts embed a lot of tail risk. Therefore, in times of crisis, these strategies must turn from short puts to puts to reduce their tail risk. According to Agarwal, Ruenzi and Weigert (2017b), portfolios managers may make this move simply by buying insurance against falling markets like puts or by moving to stocks which embed less tail risk. This is effectively what they observe in their experiments before the subprime crisis. Hedge fund portfolio managers seem to have anticipated the crisis and have reshuffled their portfolios in order to transform them in puts[20].

In this example, it is difficult to disentangle the impact of hedge fund asset holdings from the timing skills of the portfolio managers. To tackle this problem, we adopt a pragmatic approach. Since we are interested in the behavior of hedge fund risk in this paper and not by the portfolio managers' skills by themselves, we assume that these managers have timing skills if their exposures to risk decrease following adverse shocks. Moreover, we focus here 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[21]. 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

[20] However, it is not clear that hedge fund portfolios managers have anticipated the subprime crisis. Agarwal, Ruenzi and Weigert (2017b) locate the onset of this crisis in September 2008 which is associated with the failure of Lehman Brothers. However, this crisis has started one year before with the evaporation of the US secondary mortgage market in August 2007. Hence, to anticipate the crisis, portfolio managers should have adjusted their portfolios before this month. See Veronesi (2010), chap. 7.

[21] For other ways to compute indicators of macroeconomic uncertainty, see Chuliá et al. (2017).

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)[22] and EDHEC[23]. GAI manages one of the oldest hedge fund databases, containing more than 13500 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)[24]. 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,

[22] GAI's database website is: http://www.greenwichai.com.

[23] EDHEC's database website is: http://www.edhec-risk.com.

[24] The address of the EDHEC Risk Institute: Rue Louvrex 14, Bldg. N1, 4000 Liège, Belgium.

Ramadorai and Streatfield, 2015). This bias is accounted for in the GAI database as index returns for periods since 1994 include defunct funds[25]. Other biases which are tackled for in the GAI database are the self-selection bias and the early reporting bias[26] (Capocci and Hübner, 2004; Fung and Hsieh, 2004).

Insert Figure 1 here

3.2 Descriptive statistics

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. Not surprisingly, the futures (FUT, GAI) and Commodity Trading Advisor (CTA, EDHEC) returns are strongly correlated[27]. And even if the quants of macro strategies have a priori different expertise, this strategy delivers very similar returns in both databases.

Figure 1 also shows a big drop in the hedge fund general index return on September 2008, which is associated with the peak of the subprime crisis whereby Lehman Brothers, a big investment bank, defaulted. This decrease amounted to 40.80% on an annual basis for the GAI database and 70.80% for the EDHEC database. Since the long short strategy displays a higher beta than the general index, the drop of its return was even higher—i.e., 98.40% and 81.60% for the GAI and EDHEC databases, respectively. Surprisingly, the decrease in the return of the equity

[25] Source: Greenwich Alternative Investment website (2016).

[26] Other problems related to hedge fund returns are due to illiquidity and the practice of return smoothing (Pástor and Stambaugh, 2003; Getmansky, Lo and Makarov, 2004; Brown, Gregoriou and Pascalau, 2012). The problems may lead to an underestimation of risk in the hedge fund industry. See also Amihud (2002).

[27] Indeed, the CTA are also often associated with the managed futures strategy. Moreover, the returns of the CTA and futures strategies—i.e., trend follower strategies— tend to behave as long straddles (Huber and Kaiser, 2004; Stafylas, Andersen and Uddin, 2017).

market neutral strategy was substantial in spite of its low beta, being -40.80% and -70.80% in the GAI and EDHEC databases, respectively, which seems to contradict Duarte, Longstaff and Yu (2007) who argue that there is no evidence that this strategy expose investors to substantial downside risk. However, due to the importance of their short sales, the short-sellers and futures strategies delivered substantial positive returns on September 2008, i.e., 67.20% and 12.00%, respectively.

Insert Table 2 here

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[28], which is less the case for the stock market return (Figure 2)[29].

Insert Figure 2 here

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 sales—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[30]. Note that the hedge fund general index has clearly underperformed the stock market benchmark since the end of the subprime crisis. However, two strategies succeed in delivering positive returns in both samples during downturns: short-sellers and futures[31] (Figure 2). During economic expansions, short-sellers usually provide negative returns—which are related to their negative beta[32]—while futures continue to deliver positive returns, albe-

[28] The data used to construct this Figure come from the quarterly GAI database.

[29] Akay, Senyuz and Yoldas (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.

[30] This behavior may be due to the practice of return smoothing in the hedge fund industry (Getmansky, Lo and Makarov 2004; Brown, Gregoriou and Pascalau, 2012).

[31] i.e., the CTA strategy in the EDHEC database.

[32] Indeed, according to the CAPM, portfolios with negative betas command a negative risk premium because they act as buffers against bad events. The behavior of short-sellers is thus similar to the one of a put option. These options generate

it 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[33]. 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.

Insert Figure 3 here

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[34]. 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 strat-

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positive payoffs during downturns at the expense of a premium, which is paid in expansion for short-sellers. The payment of this premium leads to negative returns for short-sellers during normal times.

[33] Once more, this may be related to the return smoothing practice in the hedge fund industry.

[34] i.e., the same strategies having the highest skewness.

egies' 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):

$$kurtosis \geq 1 + skewness^2 \qquad (18)$$

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.(18) 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[35]. This relationship is consistent with the behavior of skewness and kurtosis in the hedge fund industry (Figure 3)[36].

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—another 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

[35] Note that hedge funds may temporarily loosen this relationship by getting involved in return smoothing, a current practice in the hedge fund industry (Getmansky, Lo and Makarov, 2004; Brown, Gregoriou and Pascalau, 2012; Bali, Brown and Caglayan, 2014).

[36] 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).

value, as if these higher moments could substitute for each other[37]. 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, Maillet and Merlin, 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 (Table 2). 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 short sales 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.

Insert Figure 4 here

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

To get a better grasp on the significance of the concepts of co-skewness and co-kurtosis,

[37] In this respect, MacGillivray and Balanda (1988) discuss the substitution between skewness and kurtosis.

Figure 4 relates hedge fund returns to the square (mkt^2) and the cube (mkt^3) of the stock market return[38]. During downturns, according to the Black (1976) leverage effect, 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 mkt^2 increases. For these strategies, co-skewness is positive during downturns, which contributes to reduce their risk during bad times (Jurczenko, Maillet and Merlin, 2006). This result is consistent with Asness, Krail and Liew (2001) who find that managed futures load positively on the long volatility factor—i.e., the squared market return—while the hedge fund general index and most other strategies load negatively on this factor. Our more recent sample which includes the subprime crisis supports this behavior.

As regards of the co-movements between hedge fund returns and mkt^3, note that mkt^3 tends to decrease and become negative during stock market downturns[39]. Figure 4 shows that when mkt^3 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^3 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,

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[38] 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.

[39] Indeed, mkt^3 is the product of mkt^2 and mkt. mkt^2 being always positive, the sign of mkt^3 depends on mkt. Since mkt tends to decrease and to become negative during stock market downturns, mkt^3 follows the same pattern.

which again contributes to reduce the risk of these strategies during bad times. In this respect, according to Jurczenko, Maillet and Merlin (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[40]. 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-kurtosisl, will then exhibit severe negative payoffs. Finally, we note in Figure 4 that mkt^2 and mkt^3 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^2 *and* mkt^3, on the other hand, during these periods.

Insert Figure 5 here

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[41].

We note the same pattern for the betas of the long-short and equity market neutral strat-

[40] According to Jurczenko, Maillet and Merlin (2006), these strategies embedded with such higher moments act as skewer enhancers and kurtosis reducers during market turmoil .

[41] Actually, if hedge funds behave optimally over the business cycle, they search a solution (or act as if they were searching a solution) to a stochastic Bellman equation which takes the form $J_t(.) = \max_{\{u\}}\{f_t(.) + \beta E[J_{t+1}(.)]\}$, where u is the vector of feedback control variables; β is a discount factor; $f_t(.)$ is the hedge fund objective function—i.e., profits, utility of profits, value added or any other criteria which they aim at maximizing—; $E(.)$ is the expected value operator, and $J_t(.)$ 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 $J_t(.)$ depends on $E[J_{t+1}(.)]$. For more details, see Sydsæter, Hammond, Seierstad and Strom (2005), chap. 12.

egies. 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—especially during the subprime crisis—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[42] (Jurczenko, Maillet and Merlin, 2006). During the crisis, in line with their beta, they seem to have *fine-tuned* their higher moment positions, reducing their co-skewness and increasing their co-kurtosis, which is consistent with the expectation of a reversal of financial markets[43]. 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 sales—obey to the same pattern[44].

Insert Table 3 here

[42] Remind that the co-kurtosis of short-sellers is negative.

[43] 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.

[44] The co-kurtosis of the futures strategy is also negative, which may be explained by its short-selling activities.

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. Some strategies have a low R^2. For instance, the fixed income and the market neutral strategies are less related to the stock market or neutralize its impact. Moreover, dynamic strategies—like futures and macro—have also a low R^2. It is thus more difficult to explain their behavior using the four-moment CAPM. In contrast, strategies as the long-short one have a R^2 which is more important. 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^3, is usually more important than co-skewness, as gauged by the standardized coefficient of mkt^2. 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[45], fixed income and distressed securities. However, in line with the stylized facts, two strategies benefit from stock market volatility: futures (GAI and EDHEC) and short-sellers (EDHEC)[46]. This benefit seems to be linked to the short sales of these strategies.

In other respects, we know that mkt^3 tends to decrease during downturns. A negative

[45] It is well-known that a volatile stock market is not favourable 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).

[46] The short-sellers strategy of the GAI database is insensitive to market volatility.

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^3. In contrast, the returns of the convertibles strategy drop significantly following a decrease in mkt^3. These results are globally consistent with those obtained by Davies, Kat and Lu (2009) in the framework of their model aiming at computing hedge fund optimal portfolios.

Insert Table 4 here

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[47]. 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)[48]; (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)[49]; (iii) the first principal component of our conditional variances uncertainty indicators listed in Table 4 (PC_CV).

[47] 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.

[48] 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.

[49] The website of this Group is : **http://www:policyuncertainty.com.** For details on the indicators produced by this Group, see: Baker, Bloom and Davis, 2015.

Insert Table 5 here

Among all the uncertainty indicators recorded, the VIX seems to be 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*).

Insert Figure 6 here

Figure 6 provides the plots of the VIX compared to other key uncertainty indicators. As 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[50] 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[51], we thus retain only one indicator of macroeconomic and financial uncertainty—i.e., the VIX—which appears to be very representative of the others.

Insert Table 6 here

[50] which are often associated with a rise in credit risk.

[51] Indeed, the estimation of a VAR model consumes many degrees of freedom. These degrees of freedom decrease quickly with the number of lagged variables.

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[52]. 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*[53] 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, El Bied and Martellini, 2003; Brealy and Kaplanis, 2010; Bali, Brown and Caglayan, 2014; Lambert and Platania, 2016). Furthermore, Agarwal, Arisoy and Naik (2017a) 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

[52] 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.

[53] 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.

rate in our model.

5.3. Estimation of the asymmetric VAR model

To implement the STVAR, we must compute the function $f(z_t)$ (Eq. (16) 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_t variable. To identify recessions, they use a smoothing parameter γ 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_t. After many experiments, we selected the same value for γ and we used a twenty-one-month moving average of the industrial production growth[54]. This calibration provides recession periods which best fitted our priors.

Insert Figure 7 here

Figure 7 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 $(f(z_t) \geq 0.8)$ —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 7). 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 necessarily coincide with the ranges es-

[54] Increasing the γ parameter reduces the smoothness of $f(z_t)$. For high values of γ, the probability function $f(z_t)$ becomes a step function, taking only two values—0 and 1—as in regime switching econometric models.

tablished 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 7 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.

Insert Figure 8 here

5.3.1 Hedge fund benchmarks

Figure 8 features the nonlinear 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[55].

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 *gprod* 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[56]. These results are consistent with the ones obtained by Agarwal, Ruenzi and Weigert (2017b) who find that many hedge fund strategies behave as short puts in expansion and long puts in recession. According to this framework, hedge funds increase their beta in expansion by

[55] Based on the usual information criteria—i.e., the AIC, AIC_c and SIC statistics—we retained three lagged values of the explanatory variables to compute the IRFs. Note that the AIC_c is a corrected version of the AIC criterion proposed by Hurvich and Tsay (1993) specially designed for VARs. See also Jordà (2005).

[56] In the absence of hedging operations, the hedge fund beta ought to increase in recession.

selling portfolio insurance and stabilize their beta in recession by buying insurance.

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). In other respects, a term spread shock and especially a credit spread shock lead to a significant decrease in the market beta in recession in both databases. 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). During expansion, the beta of a representative hedge fund increases significantly following a credit spread shock. Once more, this pattern may be cast in the Agarwal, Ruenzi and Weigert's (2017b) setting. Indeed, hedge funds behave as portfolio insurers by selling CDS in expansion, or any other credit derivative, but behave as long CDS in recession as they buy portfolio insurance. The reaction of the market beta to the last three shocks thus seems dominated by risk management policies taking place during economic downturns or financial crises (Jawadi and Khanniche, 2012).

The representative hedge fund's co-kurtosis is not significantly procyclical[57]. 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 and in line with the beta, 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 *gpayroll* shock (business cycle shock) impacts negatively and significantly co-skewness in the GAI database, suggesting that some strategies are

[57] 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.

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-skewness in expansion[58].

Insert Figure 9 here

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

Figure 9 reports the asymmetric impulse responses functions of strategies' betas to shocks. 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.

The reaction of the betas of our three strategies to a *gprod* shock involves three interesting issues (Figure 9). 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 *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[59] while the asymmetric pattern of the short-

[58] In expansion, the impact of a credit shock on co-skewness is quite weak.

[59] Note however that the beta of the equity market neutral strategy tends to increase significantly after a long delay following a VIX shock.

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.

Insert Figure 10 here

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 10). 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 sales thus seem to have difficulties in controlling their co-skewness risk in the presence of a VIX shock.

The responses of the strategies' betas to a term spread shock are much less asymmetric than their responses to an output shock. In recession, in contrast to the general index, the beta of the long short strategy is quite insensitive to this shock in both databases. This may be due to its return smoothing practice since a portion of the portfolio of this strategy is illiquid, including small firms' stocks (Asness, Krail and Liew, 2001)[60]. In expansion, the beta of the long short strategy responds positively and significantly to this shock in both databases, so we may conclude that this strategy "buys" the term spread (Lambert and Plantania, 2016). While the beta of the equity market neutral strategy is quite insensitive to a term spread shock in the GAI database, it responds positively and significantly to this shock in expansion and in recession in the EDHEC database. Hence, this strategy may have difficulties to hedge a liquidity shock in recession. Finally, a term spread shock does not impact significantly the beta of the short-sellers strategy in both

[60] According to Asness , Krail and Liew (2001), hedge fund portfolio managers may be more concerned with smoothing downside returns than upside ones.

databases, neither in expansion or recession. This may be due to the high degree of liquidity of the portfolios held by this strategy[61].

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).

Insert Figure 11 here

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 11)[62]. 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[63] 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.

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[61] A liquid portfolio may be viewed as a hedge or insurance against liquidity shocks. This must not be confused with return smoothing which may have the same effect but obviously hides risk (Getmansky, Lo and Makarov, 2004; Brown, Gregoriou and Pascalau, 2012).

[62] 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.

[63] Remind that short-sellers' co-kurtosis is expressed in absolute value.

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, Caglayan and Schiantarelli, 2001; Baum, Caglayan and Ozkan, 2002, 2004, 2009; Wagner, 2007, 2008, 2010; Shleifer and Vishny, 2010; Gennaioli, Shleifer and Vishny, 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.

Insert Figure 12 here

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 12). 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 during this crisis[64]. 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[65].

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[66] 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 Nonlinear impulse response functions of the cross-sectional dispersions

In this section, we apply our STVAR system (Eq. (15)) 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 13.

[64] 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.

[65] 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.

[66] i.e., credit default swaps.

Insert Figure 13 here

After a delay, a *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[67]. 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; Zhao et al., 2018). 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 *external* shocks are similar. In line with the beta, these cross-sectional dispersions increase with a *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[68]. In contrast to the beta cross-sectional 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.

[67] 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.

[68] Note that this impact is greater in 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, Brown and Caglayan, 2014; Lambert and Plantania, 2016; Namvar, Phillips, Pukthuangthong, Rau, 2016; Racicot and Théoret, 2016; Agarwal, Ruenzi and Weigert 2017b). Since hedge funds follow option-like strategies, their behavior is thus essentially dynamic (Fung and Hsieh, 1997, 2001, 2002, 2004; Stafylas, Andersen and Uddin, 2017). 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 a 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, Maillet and Merlin, 2006; Berg and van Rensburg, 2008; Davies, Kat and Lu, 2009; Xiong and Idzorek, 2011). In this paper, relying on nonlinear impulse response functions, our main contribution is to show that hedge funds also seem to trail their higher moment risk by timing 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, among return moments, the most asymmetric to the business cycle, hedge funds increasing their beta during periods of expansion and stabilizing it in recession. The two other higher moment risk measures—i.e., co-skewness and co-kurtosis—seem less sensitive to the business cycle. However, our results indicate that the three measures of hedge fund risk we examine are very responsive to VIX shocks—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 after a VIX shock, 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[69]—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. Overall, our results are consistent with Agarwal, Ruenzi and Weigert (2017b). Indeed, the representative hedge fund is an insurance seller in expansion but, in contrast, it becomes an insurance buyer or hedger in recession.

In this study, we also examine how the intensity of short sales can impact the behavior of hedge funds. Compared to the long-short strategy, strategies more involved in short sales—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 sales may thus be hampered by this kind of shocks (Lambert and Plantania, 2016). However, similarly to the futures strategy, short-sellers are well positioned to capture positive payoffs at the start of financial crises. They can thus stand as skewness enhancers and kurtosis reducers (Jurczenko, Maillet and Merlin, 2006). We also find that the equity market neutral strategy, which seeks to neutralize all systematic risk by derivatives or short sales in the long run, may be risky during crises. It is not so neutral, after all (Duarte, Longstaff and Yu, 2007; Patton, 2009). This finding is in line with Huang, Chen and Kato (2017) who assert that minimizing risk exposure by means of hedging does not always produce good results. It is also consistent with Agarwal and Naik (2004) who argue that the mean-variance approach may underestimate portfolio losses and that this underestimation may be substantial for portfolios with low volatility like the ones held by the equity market neutral strategy. Finally, we also rely on our nonlinear 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.

Overall, the strong linkages between hedge fund higher co-moments, on the one hand, and

[69] Which suggests a deliberate reduction of risk (Zhao et al., 2018).

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 job[70]. 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, Brown and Caglayan, 2012). Hence, insofar as hedge funds actually become insurance buyers in recession or crisis, there should be too much concern about tail risk in the hedge fund industry.

[70] 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).

Appendix

The generalized impulse response procedure

If the vector of shocks is not is not diagonal in a VAR, 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, Pesaran and Potter, 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):

$$IRF\left(t,h,\mathbf{d},\Omega_{t-1}\right)=E\left(\mathbf{Y_{t+h}}\,|\,\mathbf{d}=\varepsilon_t,\Omega_{t-1}\right)-E\left(\mathbf{Y_{t+h}}\,|\,\mathbf{d}=\mathbf{0},\Omega_{t-1}\right) \qquad (19)$$

where $\mathbf{d}$ is a vector containing the experimental shocks and Ω_{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 $\mathbf{d}'=(\varepsilon_{1t},\varepsilon_{2t},...,\varepsilon_{kt})'$ hitting the economy at time t is compared with a baseline profile at time $t+n$ whereby $\mathbf{d}=\mathbf{0}$. To implement the generalized impulse procedure, Eq. (19) is modified as follows:

$$IRF\left(t,h,d_j,\Omega_{t-1}\right)=E\left(\mathbf{Y_{t+h}}\,|\,d_j=\varepsilon_{jt},\Omega_{t-1}\right)-E\left(\mathbf{Y_{t+h}}\,|\,\mathbf{d}=\mathbf{0},\Omega_{t-1}\right) \qquad (20)$$

Therefore, rather than shocking all elements of the vector $\mathbf{d}$ as in Eq.(19), only one of its elements is shocked, say ε_{jt}. The other shocks are computed using the historical distribution of the errors. More precisely, Koop, Pesaran and Potter (1996) have shown that:

$$E\left(\varepsilon_t\,|\,d_j=\varepsilon_{jt}\right)=\left(\sigma_{1j},\sigma_{2j},...,\sigma_{kj}\right)'\sigma_{jj}^{-1}d_j \qquad (21)$$

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

$$IRF_{jh}=\sigma_{jj}^{-1/2}\mathbf{\Phi_h\Sigma_\varepsilon e_j} \qquad (22)$$

where $\mathbf{E}\left(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\right)=\mathbf{\Sigma_\varepsilon}$, and $\mathbf{e_j}$ is a $k\times1$ 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 $j=1$[71]. The generalized impulse responses are thus unique and take into account the historical pattern of correlations among shocks (Pesaran and Shin, 1997, 1998).

To understand Eq. (22), we must compare it to the method used to compute the coefficients of the IRFs issued from a standard linear VAR. The coefficients of the IRF functions over the horizon $\{1, 2, ..., h\}$ are then computed recursively, the recursive equation used to compute the IRF coefficients ($\boldsymbol{\theta}_{\mathbf{h}}$) being (Kilian and Kim, 2011):

$$\boldsymbol{\theta}_{\mathbf{h}} = \boldsymbol{\Phi}_{\mathbf{h}}\mathbf{P}^{\mathbf{-1}} = \sum_{\mathbf{s=1}}^{\mathbf{h}} \boldsymbol{\Phi}_{\mathbf{h-s}}\mathbf{B}_{\mathbf{s}}\mathbf{P}^{\mathbf{-1}} \qquad (23)$$

with $\boldsymbol{\Phi}_{\mathbf{0}} = \mathbf{I}_{\mathbf{k}}$. For instance, $\boldsymbol{\theta}_{\mathbf{1}} = \mathbf{B}_{\mathbf{1}}\mathbf{P}^{\mathbf{-1}}$, $\boldsymbol{\theta}_{\mathbf{2}} = \left(\mathbf{B}_{\mathbf{1}}^{2} + \mathbf{B}_{\mathbf{2}}\right)\mathbf{P}^{\mathbf{-1}}$, $\boldsymbol{\theta}_{\mathbf{3}} = \left(\mathbf{B}_{\mathbf{1}}^{3} + \mathbf{B}_{\mathbf{1}}\mathbf{B}_{\mathbf{2}} + \mathbf{B}_{\mathbf{2}}\mathbf{B}_{\mathbf{1}} + \mathbf{B}_{\mathbf{3}}\right)\mathbf{P}^{\mathbf{-1}}$, and so on. If the VAR includes only one lag for each endogenous variable—i.e., if p=1—we then have: $\boldsymbol{\theta}_{\mathbf{1}} = \mathbf{B}_{\mathbf{1}}\mathbf{P}^{\mathbf{-1}}$, $\boldsymbol{\theta}_{\mathbf{2}} = \left(\mathbf{B}_{\mathbf{1}}^{2}\right)\mathbf{P}^{\mathbf{-1}}$, $\boldsymbol{\theta}_{\mathbf{3}} = \left(\mathbf{B}_{\mathbf{1}}^{3}\right)\mathbf{P}^{\mathbf{-1}}$, and so on. In this case, the coefficients of the IRFs can be viewed as multipliers of the individual structural shocks (Judge, Carter Hill, Griffiths, Lütkepohl and Lee, 1988).

[71] i.e., for the first equation of the VAR whose innovation is shocked.

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Tables

Table 1 List of the hedge fund strategies

Strategy	Description
convertible (CV)	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.
Distressed securities (DS)	Managers buy equity and debt at deep discounts issued by firms facing bankruptcy.
Event driven (ED)	Managers follow a multistrategy event driven approach.
Equity market neutral (EMN)	Managers aim at obtaining returns with low or no correlation with equity and bond markets. They exploit pricing inefficiencies between related equity securities. Leverage is often used to increase returns.
Fixed income (FI)	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.
Fund of funds (FOF)	Managers invest in many strategies
Futures (FUT)	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.
Long-short (LS)	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.
Macro (MACRO)	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.
Mergers (MERGER)	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.
Short sellers (SS)	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.

Sources: Davies, Kat and Lu (2009); Greenwich Global Hedge Fund Index Construction Methodology, Greenwich Alternative Investment (2015); Saunders, Cornett and McGraw (2014).

Table 2 Descriptive statistics

	CV		DS		ED		EMN		FI		FUT		LS		MACRO		MERGER		SS		GI	FOF	MKT
Return	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**			
Mean	0.0063	0.0048	0.0069	0.0071	0.0071	0.0066	0.0054	0.0050	0.0060	0.0045	0.0061	0.0048	0.0073	0.0066	0.0046	0.0060	0.0054	0.0056	-0.0019	-0.0003	0.0065	0.0045	0.0072
Median	0.0081	0.0034	0.0100	0.0091	0.0090	0.0088	0.0047	0.0055	0.0070	0.0057	0.0040	0.0034	0.0100	0.0084	0.0040	0.0050	0.0060	0.0061	-0.0040	-0.0051	0.0070	0.0059	0.0129
Maximum	0.0704	0.0691	0.0570	0.0504	0.0890	0.0442	0.0670	0.0253	0.0347	0.0365	0.1080	0.0691	0.1180	0.0745	0.1050	0.0738	0.0276	0.0272	0.2490	0.2463	0.0900	0.0666	0.1135
Minimum	-0.1936	-0.0543	-0.0777	-0.0836	-0.0820	-0.0886	-0.0337	-0.0587	-0.0800	-0.0867	-0.0710	-0.0543	-0.0819	-0.0675	-0.0960	-0.0313	-0.0490	-0.0544	-0.2430	-0.1340	-0.0790	-0.0618	-0.1715
St.-Dev.	0.0213	0.0237	0.0176	0.0177	0.0207	0.0175	0.0111	0.0082	0.0114	0.0122	0.0274	0.0237	0.0270	0.0207	0.0209	0.0153	0.0098	0.0100	0.0511	0.0489	0.0202	0.0162	0.0460
Skewness	-4.7338	0.1793	-0.8471	-1.3076	-0.3611	-1.4087	1.1480	-2.2952	-3.5643	-3.8251	0.4366	0.1793	0.0389	-0.3794	0.6003	0.9231	-1.2727	-1.3783	0.2590	0.7332	0.0843	-0.3741	-0.6497
Kurtosis	44.0750	2.8388	5.8394	7.5981	5.6272	7.6811	9.5847	18.7185	26.3333	27.4243	3.8098	2.8388	5.0631	4.2569	9.6512	5.4055	7.9057	8.6633	7.5879	5.9687	6.1238	6.7085	3.8607
Bêta																							
mean	0.1542	0.1589	0.2562	0.2892	0.3705	0.3306	0.1236	0.0863	0.0822	0.0586	0.0372	0.0381	0.5125	0.3946	0.1930	0.1652	0.1314	0.1361	-0.9843	-0.8929	0.3477	0.2377	1.0000
St.-Dev.	0.1180	0.0662	0.1050	0.1252	0.0683	0.1461	0.0525	0.0444	0.0421	0.0497	0.1314	0.1106	0.0871	0.0822	0.1039	0.0736	0.0533	0.0476	0.2882	0.2064	0.0581	0.0606	
Co-skewness (cs)																							
mean	0.0206	-0.0288	-0.1788	-0.2210	-0.1616	-0.1943	0.0262	0.0310	-0.0481	-0.0819	0.3875	0.1813	-0.1817	-0.0650	0.0756	0.1643	-0.1070	-0.1078	0.5034	0.7748	-0.1210	-0.1213	-0.4689
St.-Dev.	0.1195	0.0404	0.1219	0.1528	0.1098	0.1358	0.0311	0.0395	0.0800	0.0584	0.3047	0.1306	0.1467	0.0531	0.1090	0.1089	0.0746	0.0764	0.3520	0.5407	0.1054	0.0997	0.4897
Co-kurtosis (ck)																							
mean	0.8035	0.8781	1.1933	1.7235	1.8854	1.8011	0.3971	0.2360	0.6545	0.5204	-1.2977	-0.8962	2.3778	1.8846	0.8282	0.9008	0.9207	0.9059	-4.8394	-5.9802	1.9719	1.4100	10.1655
St.-Dev.	0.6411	0.7008	0.9274	1.4499	1.5365	1.5242	0.2817	0.1668	0.8228	0.4054	1.0445	0.7592	1.7798	1.5575	0.6147	0.7481	0.7592	0.7664	3.3363	4.5902	1.5026	1.1451	8.2690
ρ(beta,ck)	0.14	0.71	0.93	0.95	0.62	0.97	0.52	0.35	0.36	0.22	-0.60	-0.52	0.58	0.88	-0.33	0.67	0.64	0.51	-0.19	0.09	0.16	0.45	
ρ(beta,cs)	-0.46	-0.45	-0.85	-0.95	-0.64	-0.97	-0.08	0.26	-0.59	-0.09	0.70	0.56	-0.57	-0.77	-0.14	0.67	-0.64	-0.52	0.28	-0.04	-0.14	-0.21	
ρ(ck,cs)	-0.15	-0.42	-0.90	-0.98	-0.98	-0.99	0.44	0.39	0.10	-0.90	-0.93	-0.90	-0.90	-0.86	0.48	0.99	-0.97	-0.99	-0.94	-0.98	-0.85	-0.81	-0.91

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. $\rho(x,y)$ designates the correlation between x and y.

Table 3 Estimation of the four-moment CAPM for hedge fund strategies' returns

Panel A

OLS coefficients

	c		mkt		mkt^2		mkt^3		ar(1)		R^2	
	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC
CV	0.0064	0.0066	0.05	0.04	-0.14	-0.38	14.05	10.19	0.54	0.53	0.52	0.48
	3.43	*5.00*	*1.63*	*2.76*	*-0.31*	*-1.48*	*2.19*	*4.84*	*13.23*	*6.47*		
DS	0.0072	0.0064	0.28	0.26	-1.24	-0.21	-22.88	-17.41	0.44	0.43	0.44	0.48
	2.95	*4.51*	*6.18*	*7.07*	*-2.69*	*-0.68*	*-2.06*	*-2.03*	*4.70*	*6.91*		
ED	0.0059	0.0065	0.38	0.29	-1.02	-1.16	-13.27	-4.35	0.25	0.36	0.49	0.55
	3.70	*3.59*	*6.65*	*10.07*	*-2.17*	*-2.11*	*-0.97*	*-0.47*	*3.77*	*6.44*		
EMN	0.0041	0.0040	0.15	0.10	0.05	0.05	-16.70	-3.93	0.29	0.33	0.18	0.26
	2.28	*5.20*	*7.71*	*6.89*	*0.14*	*0.28*	*-2.93*	*-2.43*	*3.91*	*5.18*		
FI	0.0078	0.0054	0.07	0.08	-0.87	-0.82	0.54	-6.25	0.42	0.48	0.28	0.29
	6.70	*3.84*	*2.11*	*2.15*	*-3.05*	*-2.68*	*0.07*	*-0.74*	*7.38*	*8.27*		
FUT	0.0004	0.0013	0.30	0.35	1.78	1.40	-98.98	-98.86	-0.02	-0.02	0.12	0.09
	0.17	*0.68*	*3.34*	*4.00*	*2.62*	*2.04*	*-5.05*	*-4.83*	*-0.29*	*-0.27*		
LS	0.0051	0.0051	0.56	0.41	-1.07	-0.88	-14.95	-7.01	0.26	0.21	0.61	0.62
	2.85	*2.86*	*8.64*	*11.04*	*-2.04*	*-1.97*	*-0.97*	*-0.78*	*3.90*	*2.87*		
MACRO	0.0020	0.0043	0.41	0.28	0.05	-0.08	-50.29	-31.10	0.06	0.09	0.18	0.21
	1.09	*3.56*	*3.18*	*8.02*	*0.11*	*-0.19*	*-2.02*	*-3.71*	*1.27*	*1.37*		
MERGER	0.0058	0.0063	0.10	0.12	-0.85	-0.92	5.48	2.04	0.26	0.32	0.30	0.38
	4.58	*5.10*	*2.46*	*4.05*	*-2.05*	*-2.38*	*0.53*	*0.25*	*3.63*	*4.73*		
SS	0.0022	0.0034	-0.96	-0.95	-0.04	1.93	31.76	3.91	0.05	0.20	0.53	0.61
	1.21	*1.09*	*-12.19*	*-8.33*	*-0.08*	*2.02*	*1.72*	*0.14*	*0.70*	*3.08*		
GI	0.0052	0.0042	0.39	0.29	-0.85	-0.95	-12.07	-17.95	0.29	0.34	0.54	0.44
	2.83	*2.65*	*8.39*	*9.10*	*-2.04*	*-2.18*	*-1.02*	*-2.15*	*3.87*	*3.94*		

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Panel B

Standardized coefficients

	mkt		mkt^2		mkt^3	
	GAI	**EDHEC**	**GAI**	**EDHEC**	**GAI**	**EDHEC**
CV	0.08	0.09	-0.01	-0.05	0.11	0.10
DS	0.62	0.58	-0.15	-0.03	-0.22	-0.17
ED	0.73	0.65	-0.11	-0.15	-0.11	-0.04
EMN	0.56	0.49	0.01	0.01	-0.26	-0.08
FI	0.24	0.25	-0.17	-0.15	0.01	-0.09
FUT	0.43	0.58	0.14	0.13	-0.62	-0.71
LS	0.83	0.79	-0.09	-0.09	-0.09	-0.06
MACRO	0.78	0.74	0.01	-0.01	-0.41	-0.35
MERGER	0.40	0.48	-0.19	-0.20	0.09	0.03
SS	-0.75	-0.78	0.00	0.09	0.11	0.01
GI	0.77	0.72	-0.09	-0.13	-0.10	-0.19

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 $\frac{\sigma_x}{\sigma_y}$ —i.e., the ratio of the standard deviation of the explanatory variable and the standard deviation of the dependent variable.

Table 4 Description of the model indicators of macroeconomic and financial risk and uncertainty

First moments		Second moments	
Variable	**Description and construction**	**Variable**	**Description and construction**
credit_spread	Spread between BBB and AAA corporate bond yields	**cv_creditspread**	The conditional variance of the credit spread. It is the conditional variance of the innovation of an AR(2) process —i.e., the mean equation—applied to the credit spread. This conditional variance is built with an EGARCH(1,1) process.
inf	The inflation rate. It is equal to log(CPI/CPI(-4))*100, CPI being the consumer price index.	**cv_inf**	The conditional variance of inflation. It is the conditional variance of the innovation of an AR(6) process—i.e. the mean equation—applied to inflation. This conditional variance is built using an EGARCH(1,1) process.
gpayroll	The non-farm payroll growth rate. It is equal to log(payroll/payroll(-4))*100.	**cv_gpayroll**	The conditional variance of the growth of non-farm payroll . It is the conditional variance of the innovation of an AR(2) process —i.e. the mean equation—applied to the payroll growth. The conditional variance is built using an EGARCH(1,1) process.
gprod	The industrial production growth rate. It is equal to log(prod/prod(-4))*100.	**cv_gprod**	The conditional variance of the industrial production growth. It is the conditional variance of an AR(6) process—i.e., the mean equation—applied to the industrial production growth. The conditional variance is built using andEGARCH(1,1) process.
mkt	The rate of return on the S&P500.	**cv_mkt**	The conditional variance of the return of the S&P500. It is the conditional variance of an AR(6) process—i.e., the mean equation—applied to the return on the S&P500. The conditional variance is built using an EGARCH(1,1) process.
output_gap	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.	**cv_outputgap**	The conditional variance of the output gap. It is the conditional variance of an AR(2) process—i.e., the mean equation—applied to the output gap. The conditional variance is built using an EGARCH(1,1) process.
term_spread	Spread between the ten-year interest rate and the 3-month Treasury bills.	**cv_termspread**	The conditional variance of the term spread. . It is the conditional variance of an AR(2) process—i.e., the mean equation—applied to the term spread. The conditional variance is built using an EGARCH(1,1) process.
unrate	Unemployment rate.	**cv_unrate**	The conditional variance of the unemployment rate. It is the conditional variance of an AR(6) process—i.e., the mean equation—applied to the unemployment rate. The conditional variance is built using an EGARCH(1,1) process.
		VIX	A measure of the volatility of the U.S. stock market. It represents an average of call and puts written on the S&P500.

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

Correlation Probability	VIX	FRED_UEQ	PC_FRED_NEWS	cv_credit	cv_inf	cv_mkt	cv_outputgap	cv_gpayroll	cv_gprod	cv_termspread	cv_unrate	PC_CV
VIX	1.00											

FRED_UEQ	0.64	1.00										
	0.00	-----										
PC_FRED_NEWS	0.60	0.69	1.00									
	0.00	0.00	-----									
cv_creditspread	0.63	0.18	0.46	1.00								
	0.00	0.01	0.00	-----								
cv_inf	0.22	-0.01	0.05	0.47	1.00							
	0.00	0.92	0.43	0.00	-----							
cv_mkt	0.80	0.58	0.52	0.60	0.28	1.00						
	0.00	0.00	0.00	0.00	0.00	-----						
cv_outputgap	0.37	0.18	0.22	0.41	0.37	0.22	1.00					
	0.00	0.01	0.00	0.00	0.00	0.00	-----					
cv_gpayroll	0.27	0.12	0.16	0.19	0.19	0.28	0.20	1.00				
	0.00	0.06	0.01	0.00	0.00	0.00	0.00	-----				
cv_gprod	0.60	0.20	0.34	0.82	0.54	0.54	0.66	0.22	1.00			
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-----			
cv_termspread	0.40	0.42	-0.01	-0.02	0.03	0.34	0.05	0.12	0.13	1.00		
	0.00	0.00	0.91	0.71	0.61	0.00	0.45	0.05	0.04	-----		
cv_unrate	0.47	0.22	0.45	0.64	0.33	0.44	0.29	0.11	0.68	0.13	1.00	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.04	-----	
PC_CV	0.76	0.36	0.48	0.86	0.61	0.76	0.59	0.36	0.91	0.22	0.71	1.00
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-----

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.

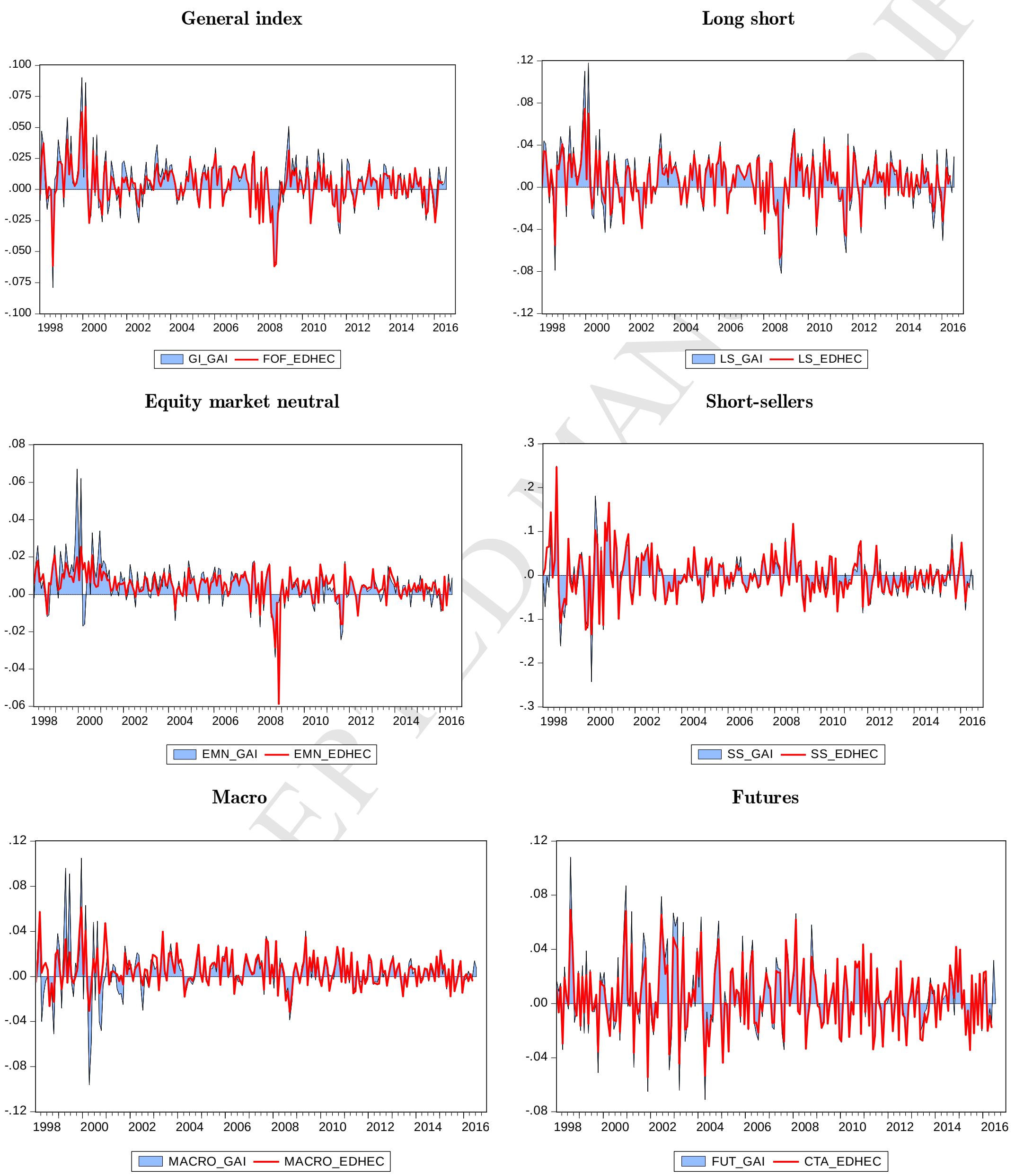
Table 6 Correlation between moments and macroeconomic (financial) indicators

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

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

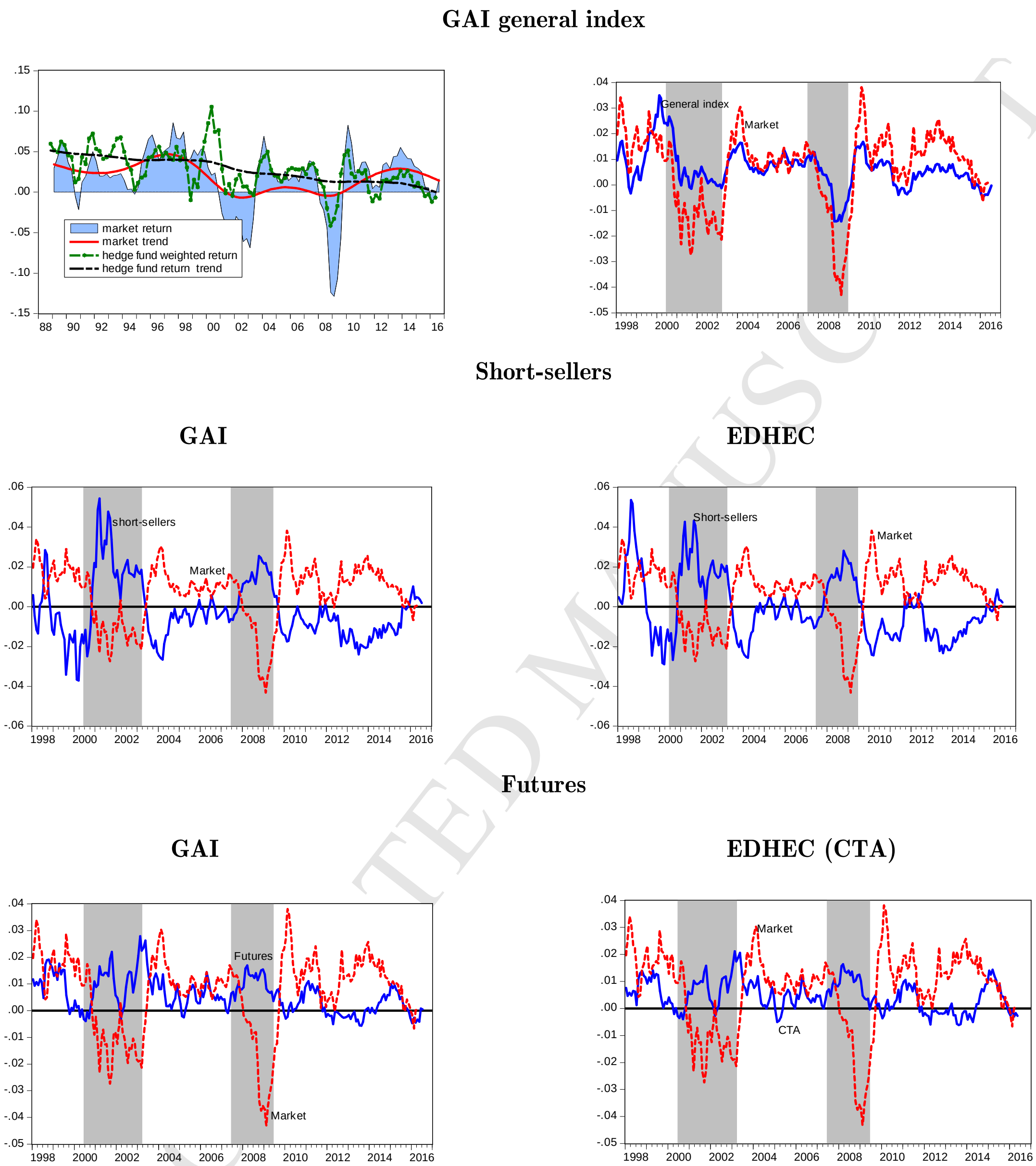
Figures

Figure 1 Comparison of GAI and EDHEC monthly returns



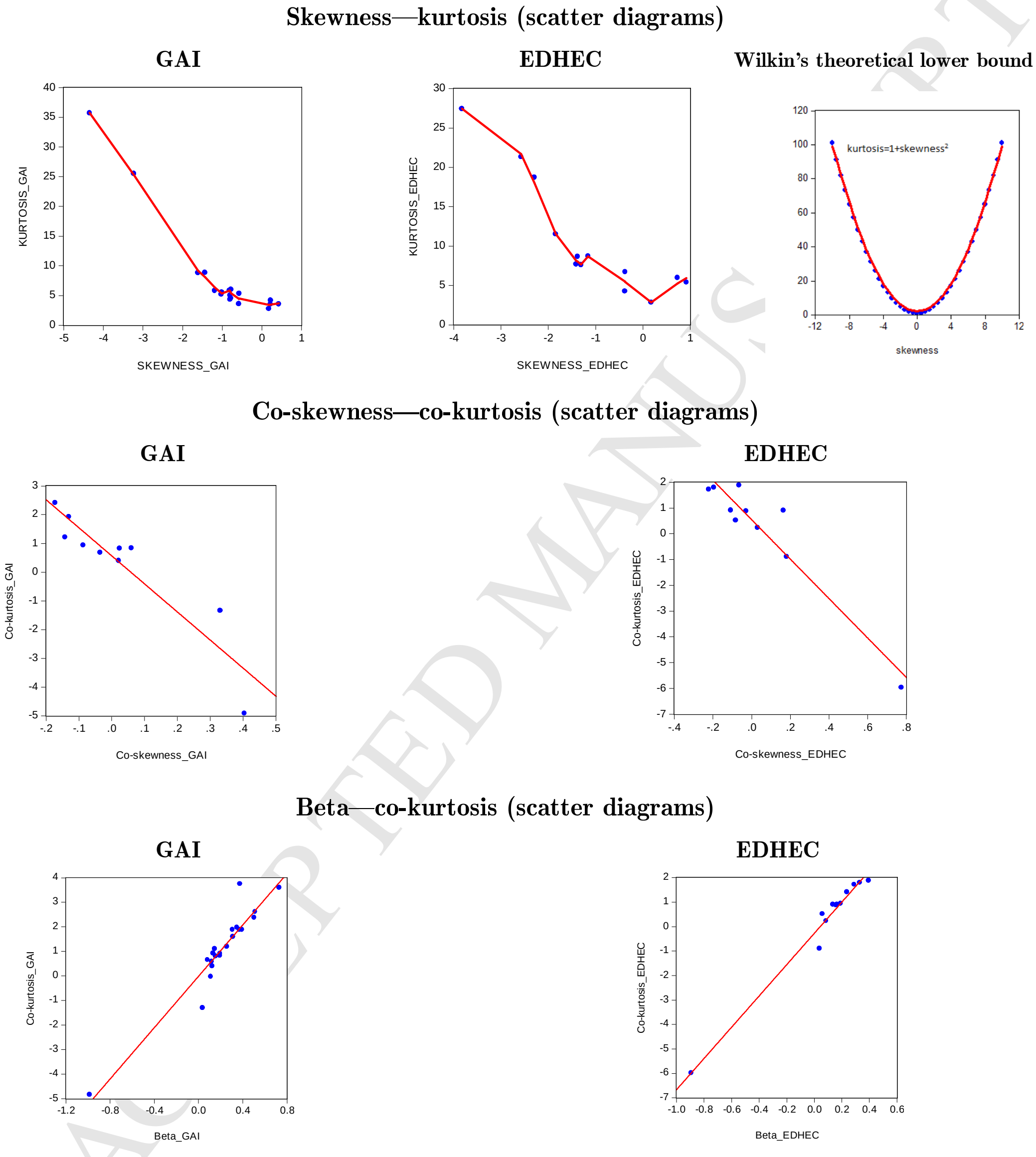
Notes: The acronyms of the strategies are reported in Table 1. *GI* stands for the GAI weighted composite index and FOF, for the EDHEC fund of funds index.

Figure 2 Hedge fund returns and the stock market return



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

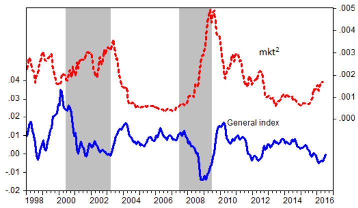


Notes: These Figures are scatter diagrams of moments of the strategies included in the GAI and EDHEC databases, respectively. The Wilkin's theoretical lower bound is explained in Section 3.2.

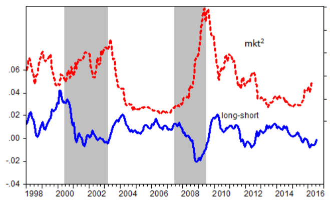
Figure 4 Cyclical co-movements between hedge fund returns and mkt^2, mkt^3

Hedge fund strategies' returns and mkt^2

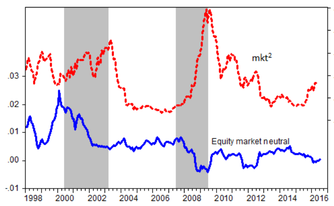
General index



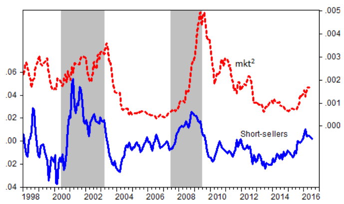
Long-short



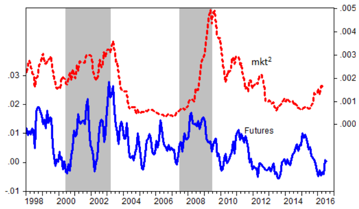
Equity market neutral



Short-sellers

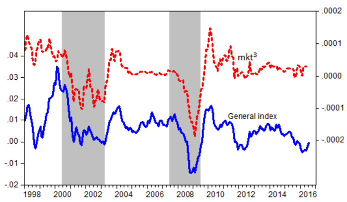


Futures

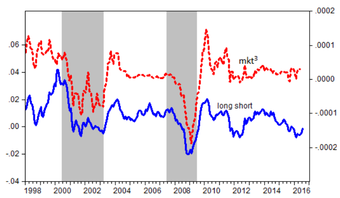


Hedge fund strategies' returns and mkt^3

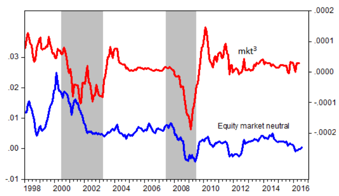
General index



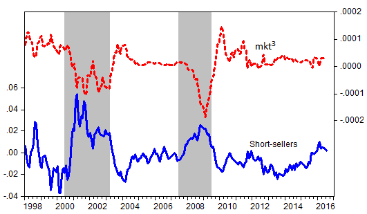
Long-short



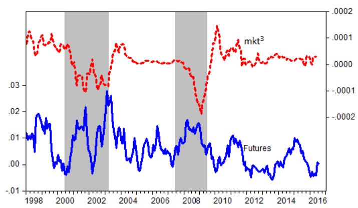
Equity market neutral



Short-sellers



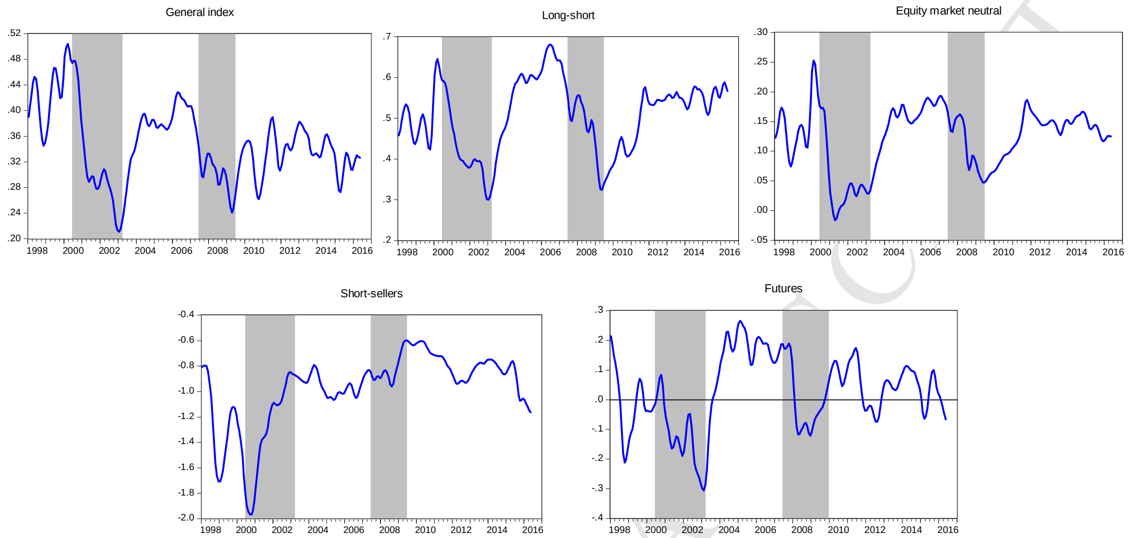
Futures



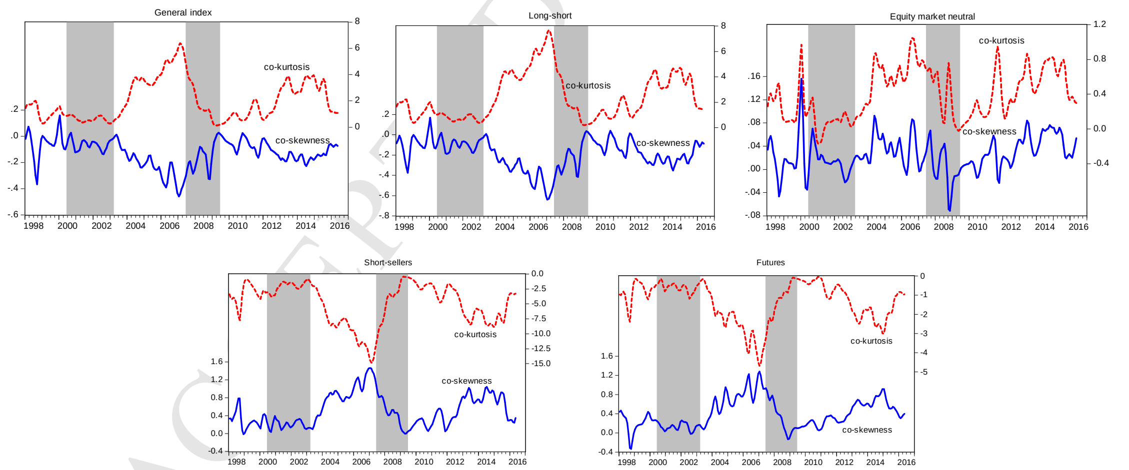
Notes: mkt is the return on the S&P500. Returns are expressed as a twelve-month moving average. Shaded areas represent recession episodes.

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

beta

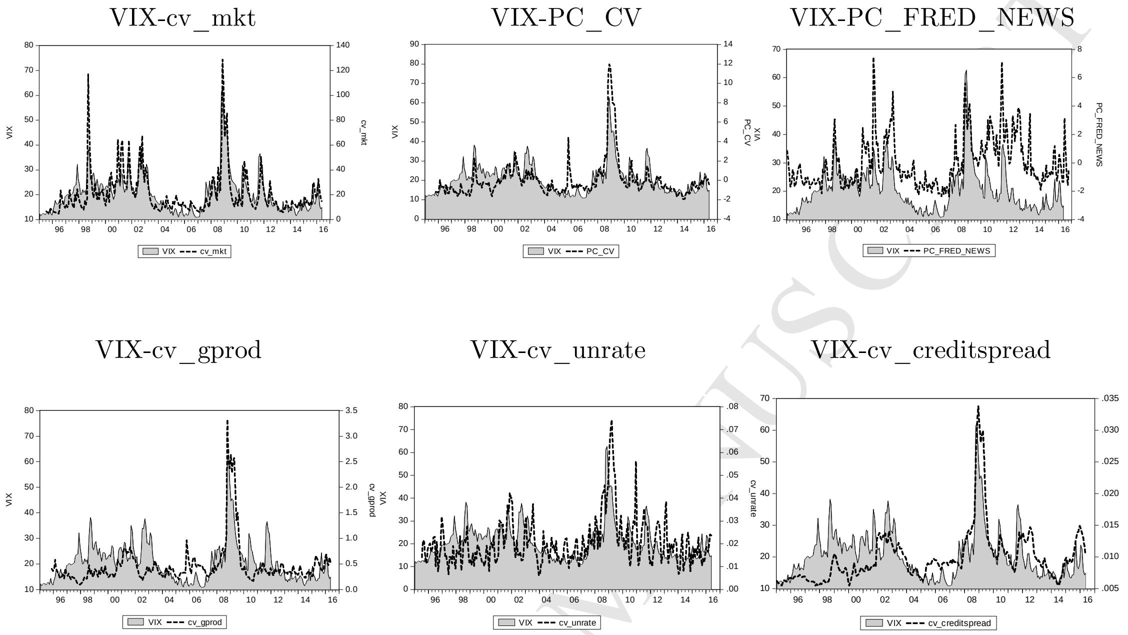


Co-skewness and co-kurtosis



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



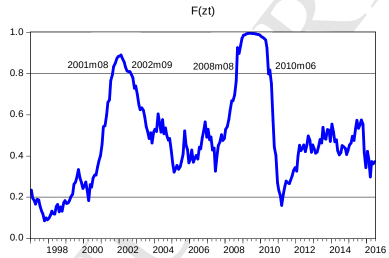
Notes: PC_FRED_NEWS: the first principal component of the two uncertainty indicators published by FRED and two other uncertainty indicators produced by the Economic Policy Uncertainty group; PC_CV: the first principal component of our conditional variances uncertainty indicators listed in Table 4. The acronyms of the other indicators are reported in Table 4.

Figure 7 Components of STVAR: z_t and $f(z_t)$

U.S. industrial production (monthly growth rate)

z_t

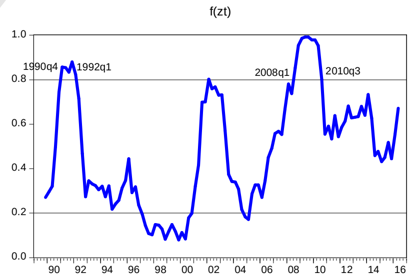
$f(z_t)$: smooth transition probability of being in recession



U.S. GDP (quarterly growth rate)

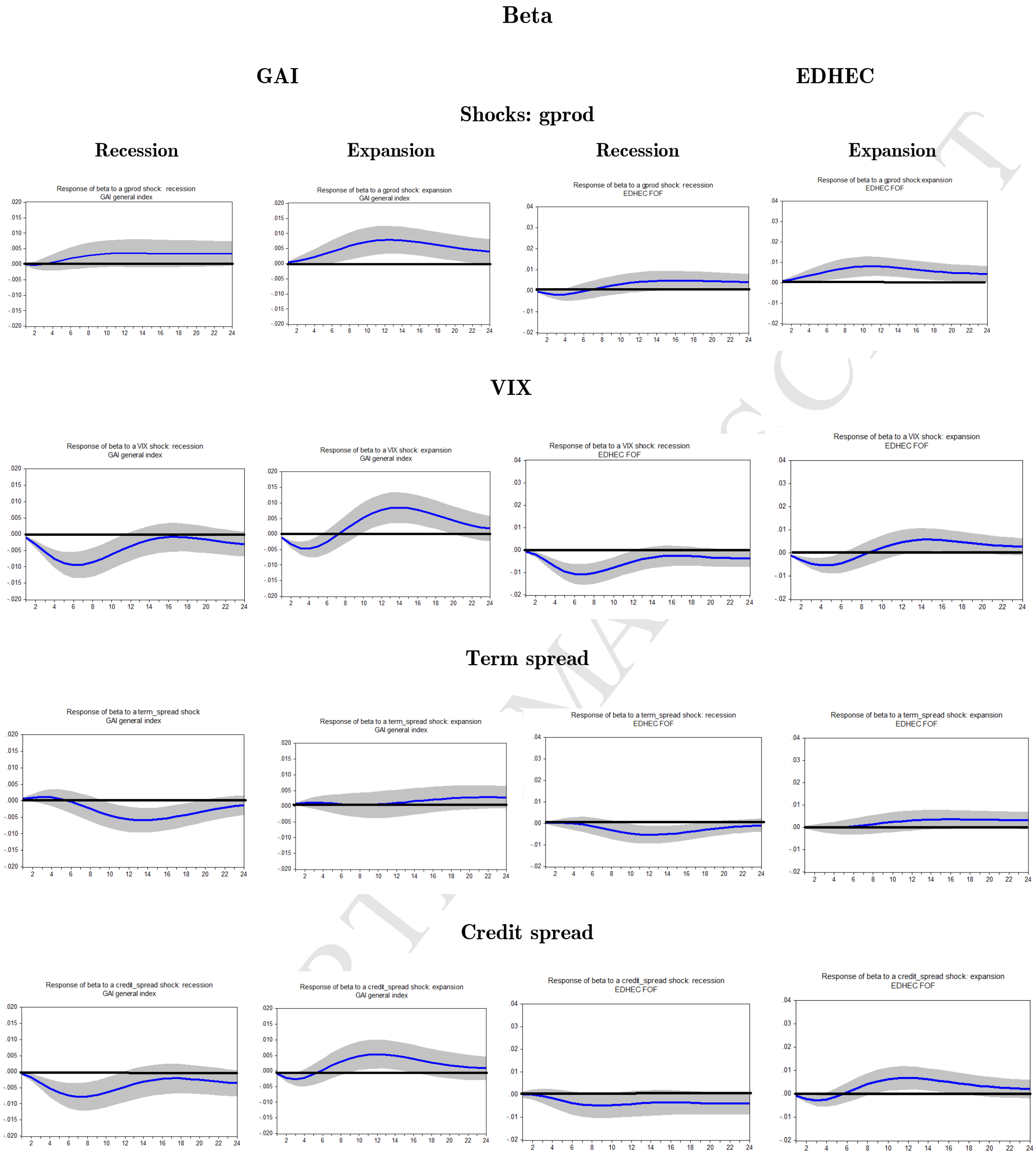
z_t

$f(z_t)$: smooth transition probability of being in recession



Notes: z_t and $f(z_t)$ are computed using Eq.(17) and Eq.(16), respectively. The selected cyclical indicator used to construct the scaled variable z_t is the U.S. industrial production growth for monthly data and the U.S. GDP growth for quarterly data.

Figure 8 Nonlinear impulse response functions: general index moments

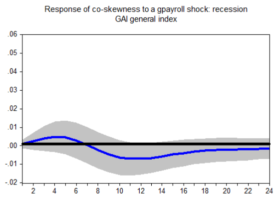


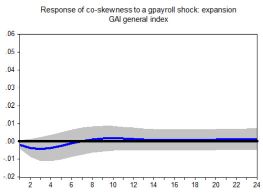
Co-skewness

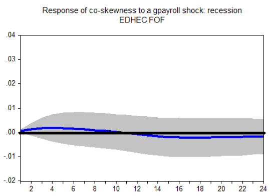
GAI **EDHEC**

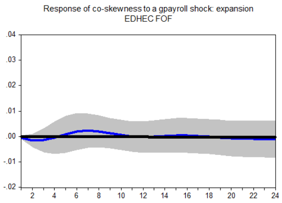
gprod

Recession **Expansion** **Recession** **Expansion**

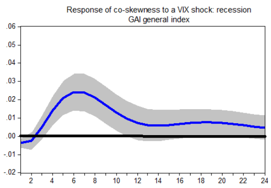


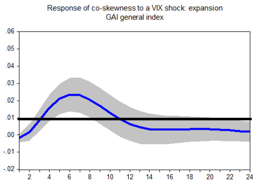


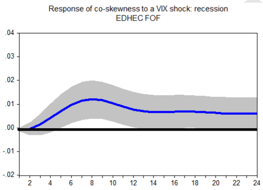


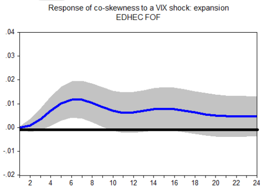


VIX

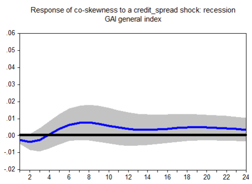


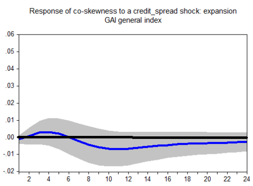


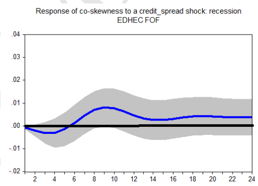


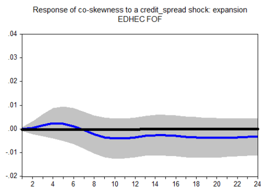


Credit spread







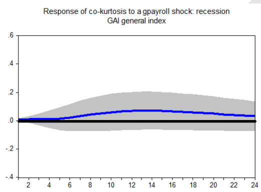


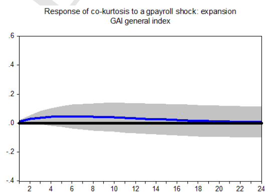
Co-kurtosis

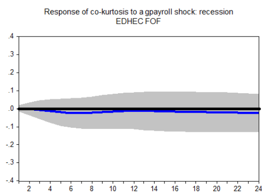
GAI **EDHEC**

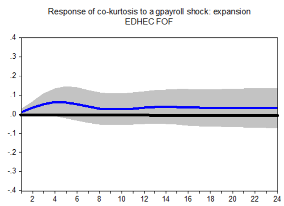
gprod

Recession **Expansion** **Recession** **Expansion**

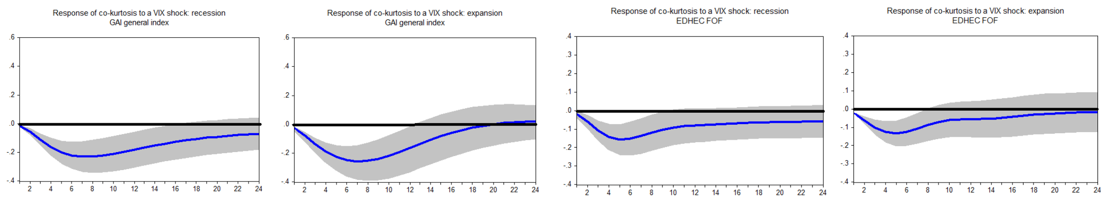




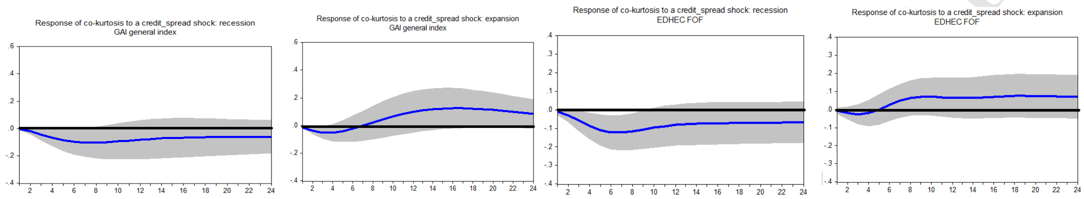




VIX

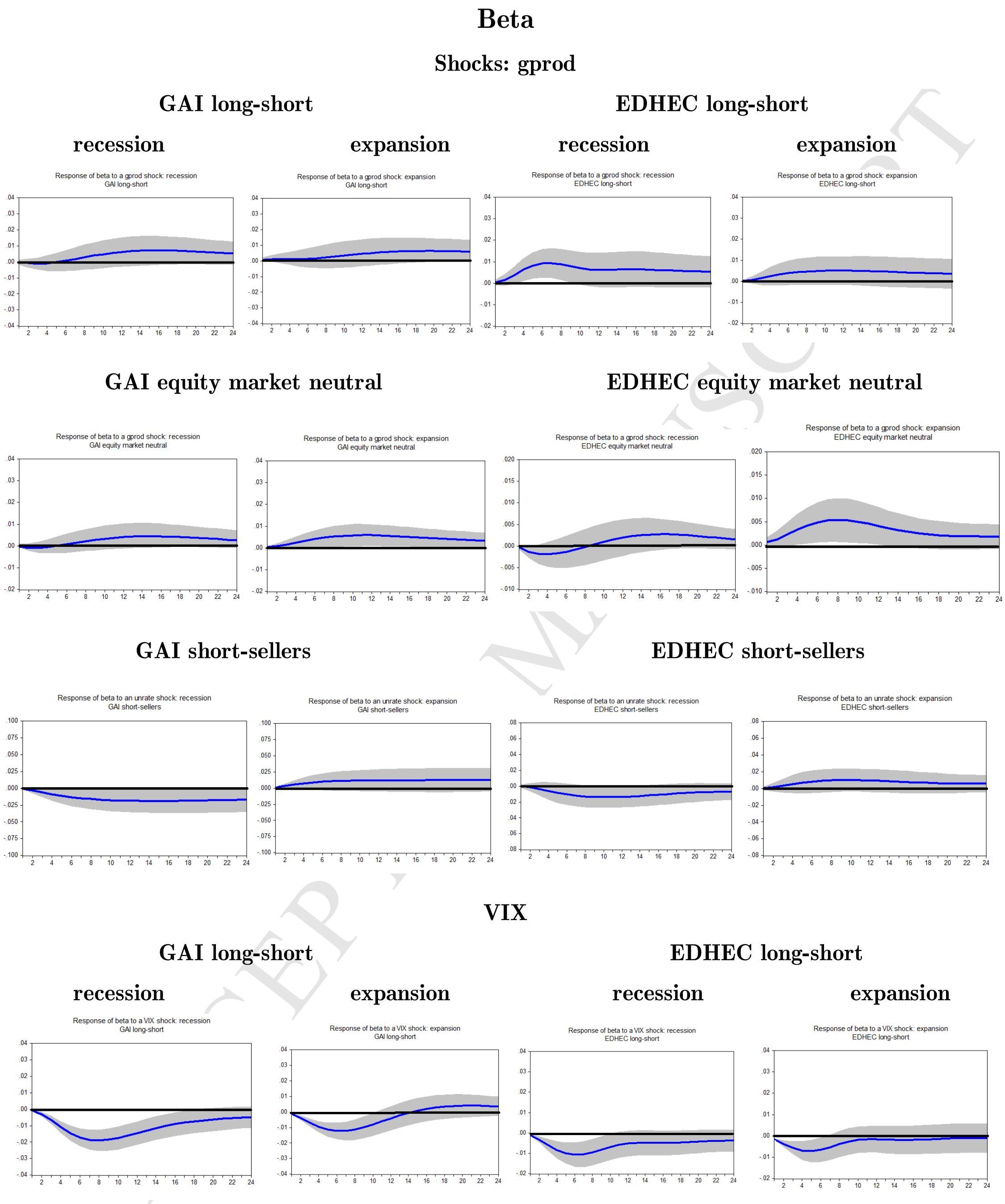


Credit spread



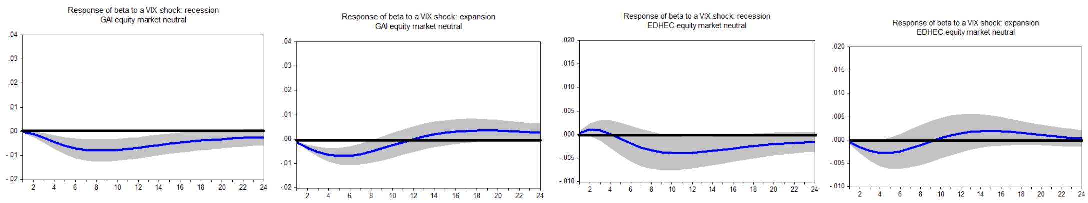
Notes: The IRFs are estimated with the STVAR—i.e., Eq. (15). $\mathbf{Y_t} = \left[beta_{ijt} \quad gprod_t \quad VIX_t \quad term\_spread_t \quad credit\_spread_t \right]'$ for the beta and $\mathbf{Y_t} = \left[moment_{ijt} \quad gprod_t \quad VIX_t \quad credit\_spread_t \right]'$ with $moment_{ijt}$ being equal to co-skewness or co-kurtosis. The shaded area encloses the 95% confidence interval.

Figure 9 Nonlinear impulse response functions of beta: three strategies involved in short sales at different degrees



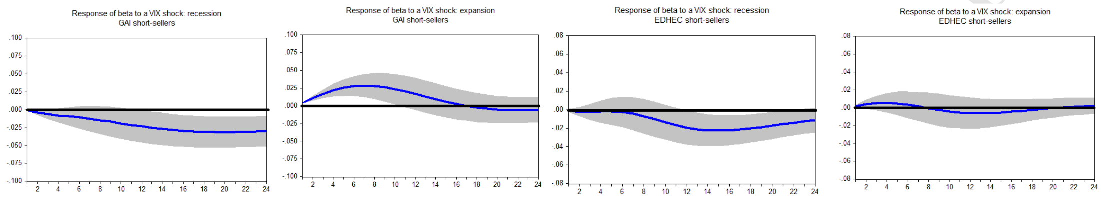
GAI equity market neutral

EDHEC equity market neutral



GAI short-sellers

EDHEC short-sellers



Term spread

GAI long-short

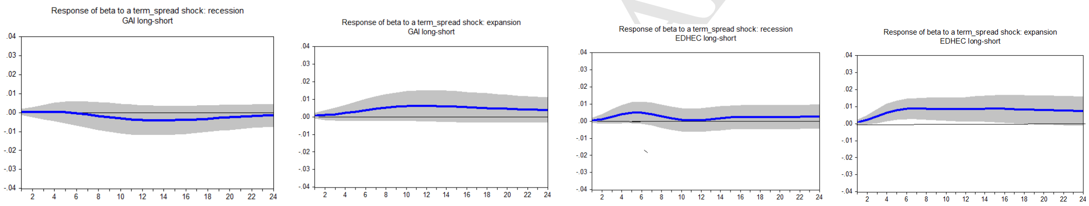
EDHEC long-short

recession

expansion

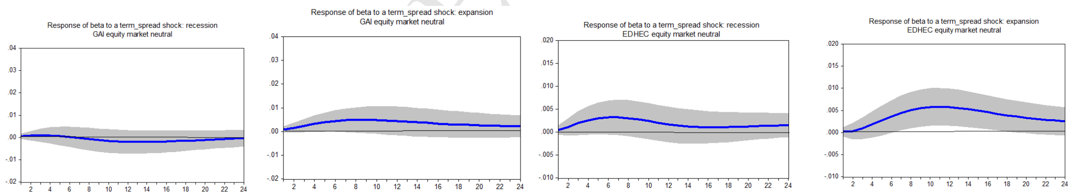
recession

expansion



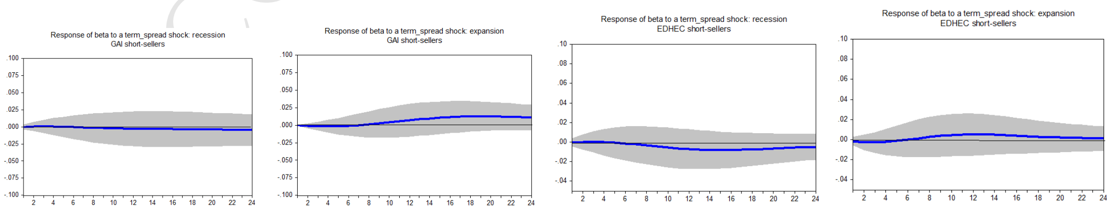
GAI equity market neutral

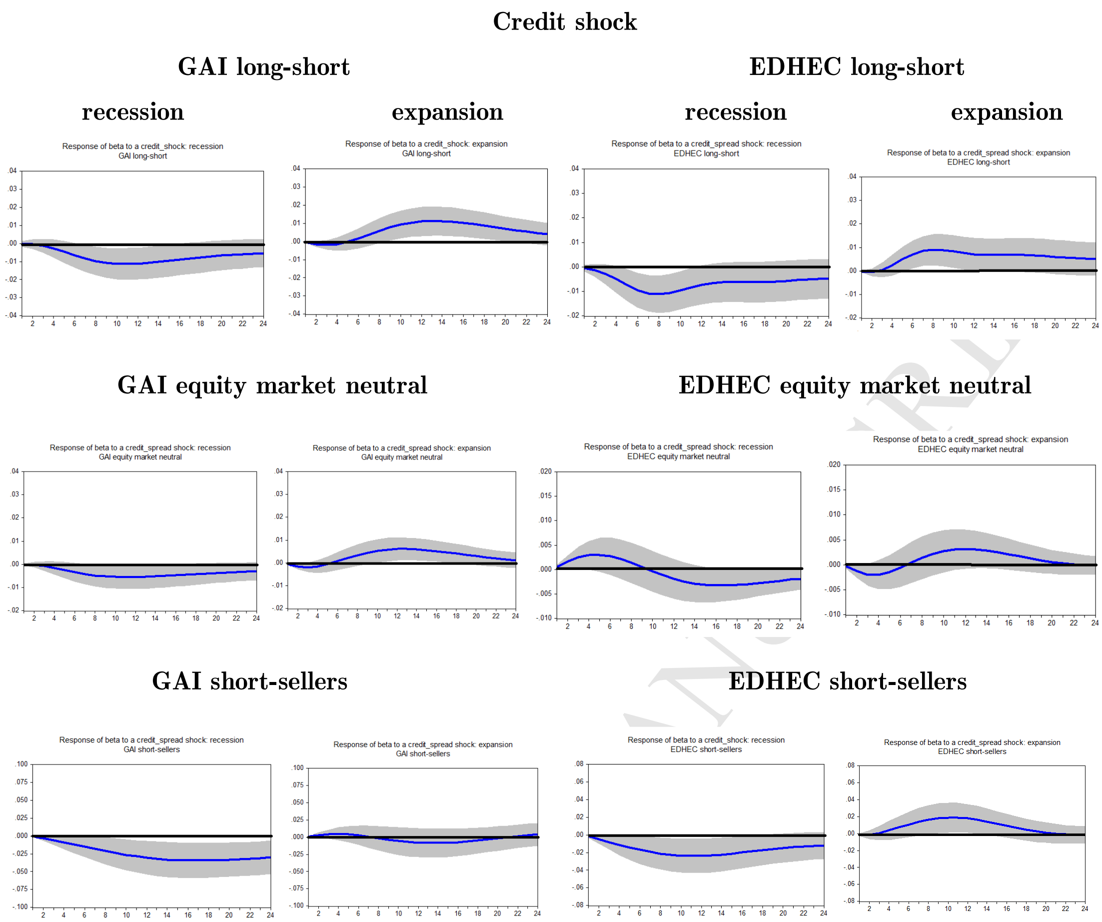
EDHEC equity market neutral



GAI short-sellers

EDHEC short-sellers





Notes: Notes: Notes: The IRFs are estimated with the STVAR—i.e., Eq. (15). $\mathbf{Y}_t = [beta_{it} \quad gprod_t \quad VIX_t \quad credit\_spread_t]'$. The shaded area encloses the 95% confidence interval.

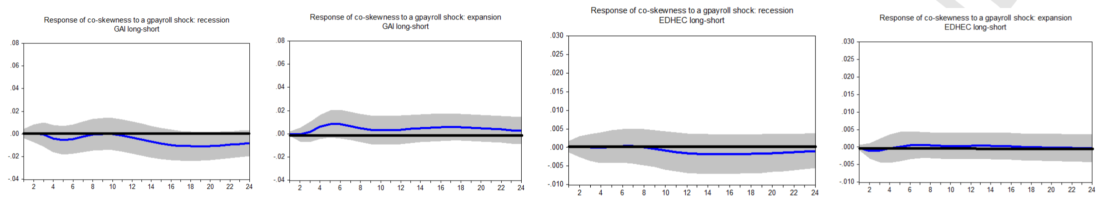
Figure 10 Nonlinear impulse response functions of co-skewness: three strategies involved in short sales at different degrees

Co-skewness

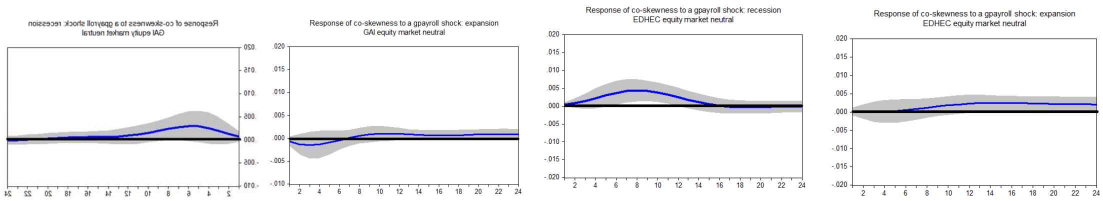
gprod

recession **expansion** **recession** **expansion**

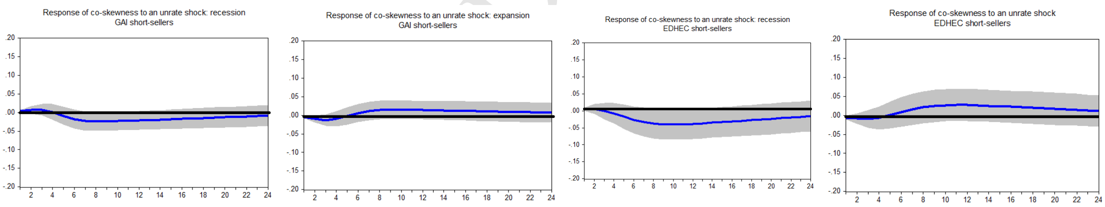
GAI long-short **EDHEC long-short**



GAI equity market neutral **EDHEC equity market neutral**



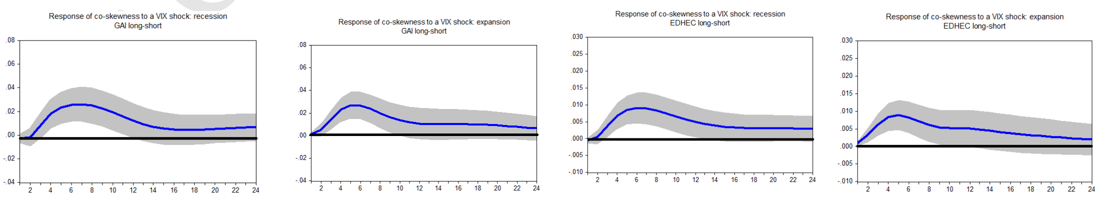
GAI short-sellers **EDHEC short-sellers**



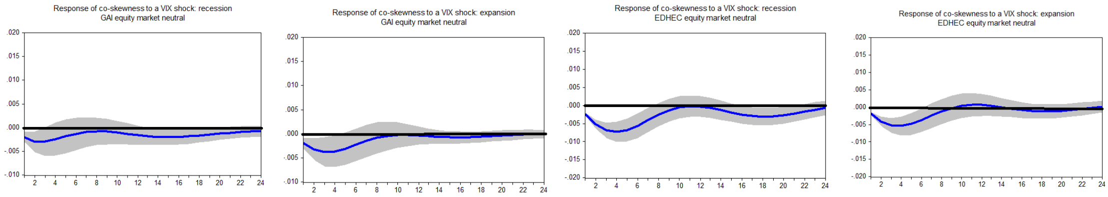
VIX

recession **expansion** **recession** **expansion**

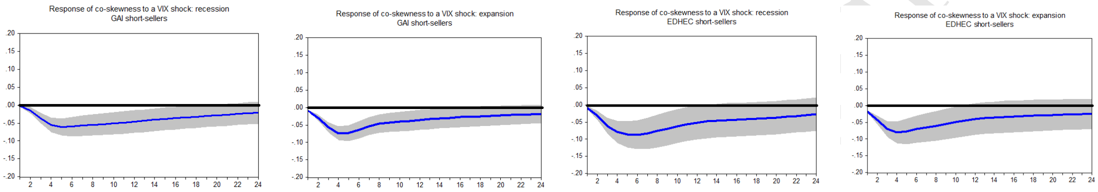
GAI long-short **EDHEC long-short**



GAI equity market neutral **EDHEC equity market neutral**



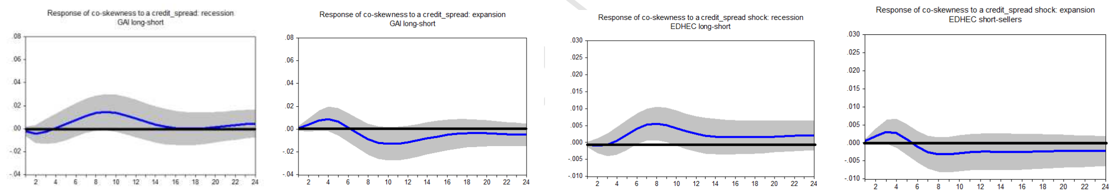
GAI short-sellers **EDHEC short-sellers**



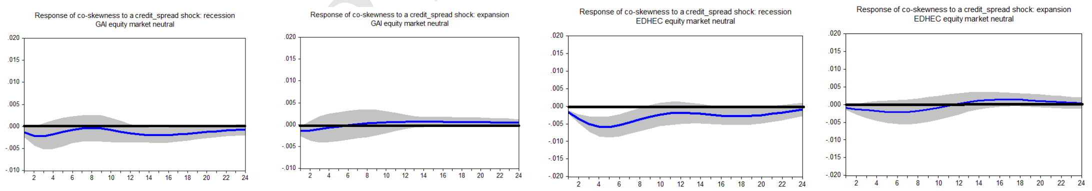
Credit shock

recession **expansion** **recession** **expansion**

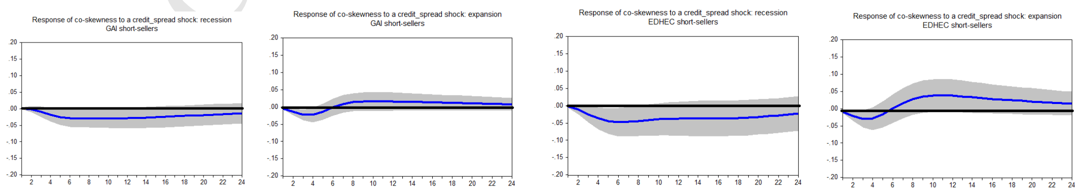
GAI long-short **EDHEC long-short**



GAI equity market neutral **EDHEC equity market neutral**

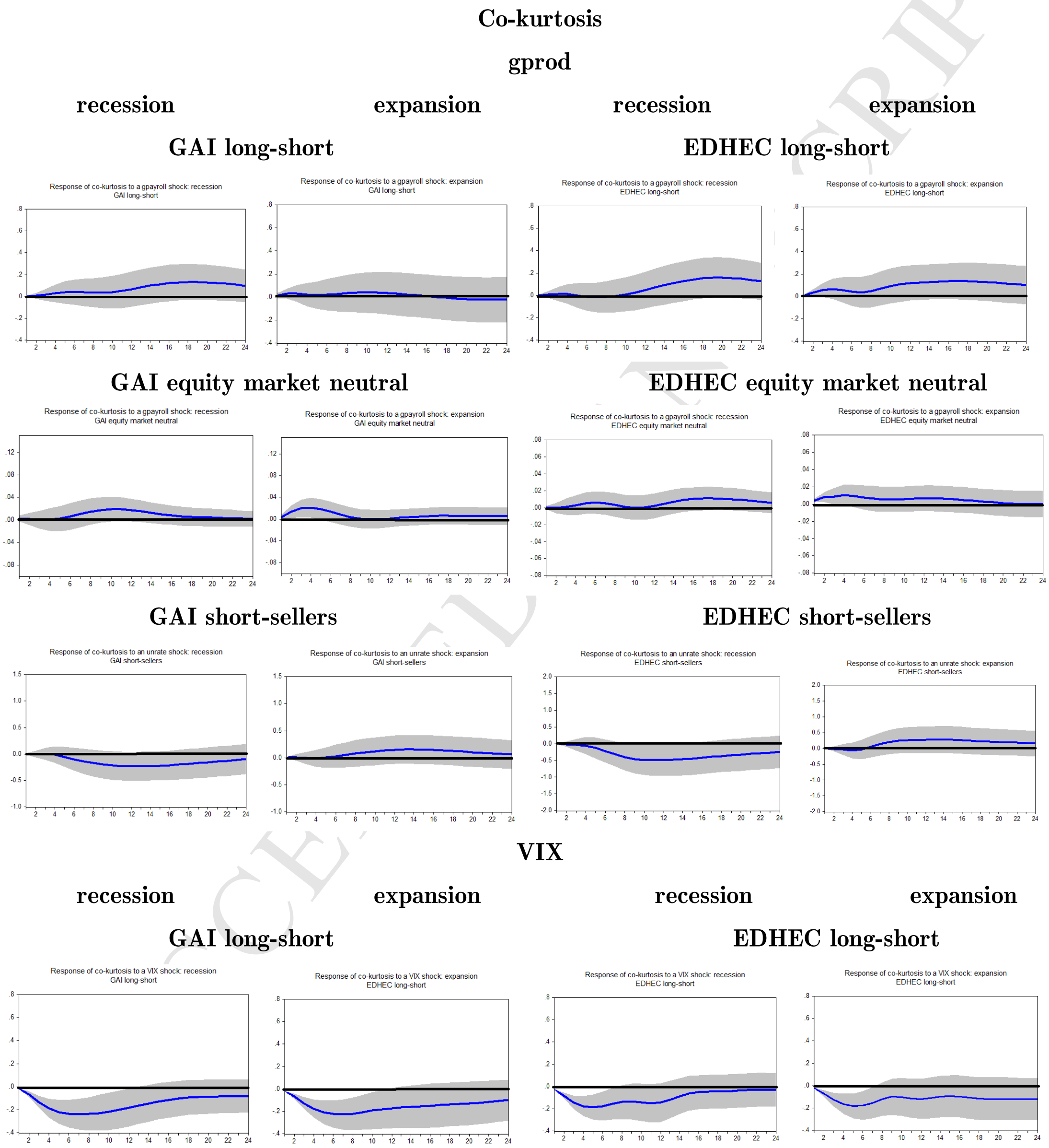


GAI short-sellers **EDHEC short-sellers**

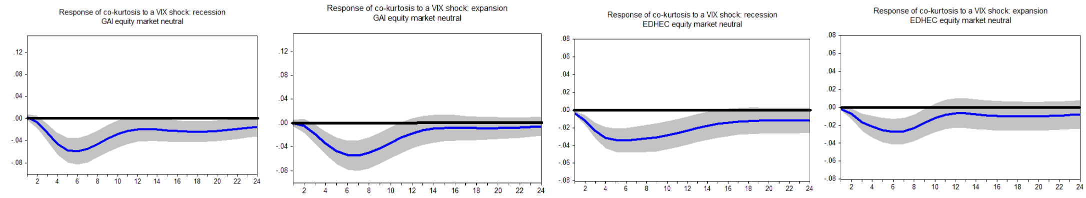


Notes: The IRFs are estimated with the STVAR—i.e., Eq. (15). $\mathbf{Y_t} = [co-skewness_{it} \quad gprod_t \quad VIX_t \quad credit\_spread_t]'$. The shaded area encloses the 95% confidence interval.

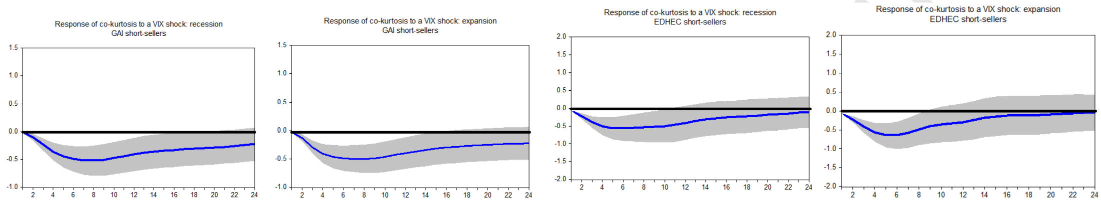
Figure 11 Nonlinear impulse response functions of co-kurtosis: three strategies involved in short sales at different degrees



GAI equity market neutral **EDHEC equity market neutral**



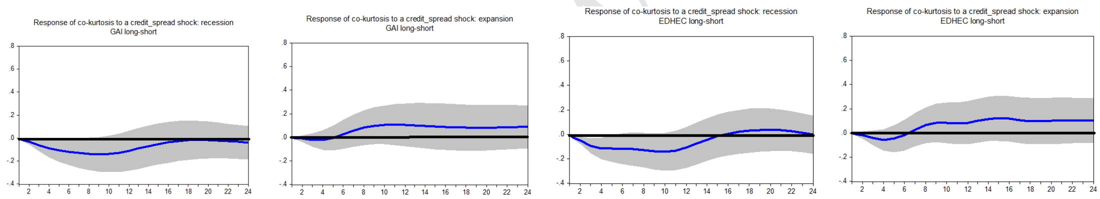
GAI short-sellers **EDHEC short-sellers**



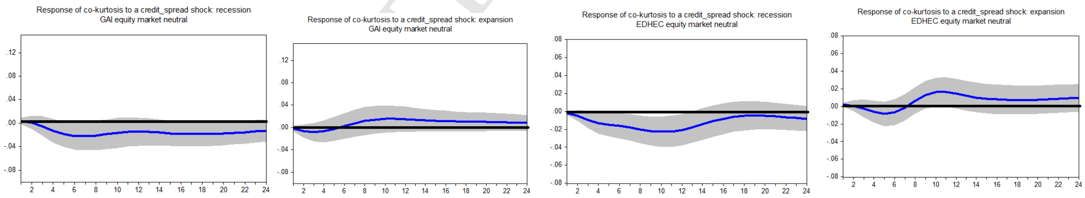
Credit shock

recession **expansion** **recession** **expansion**

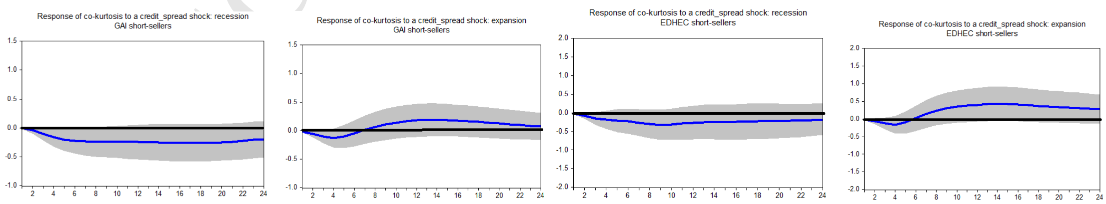
GAI long-short **EDHEC long-short**



GAI equity market neutral **EDHEC equity market neutral**



GAI short-sellers **EDHEC short-sellers**

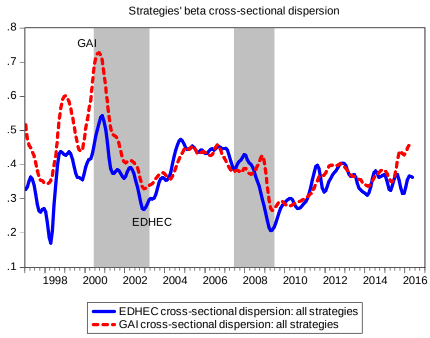


Notes: Notes: The IRFs are estimated with the STVAR—i.e., Eq. (15). $\mathbf{Y}_t = [co-kurtosis_{it} \quad gprod_t \quad VIX_t \quad credit\_spread_t]'$. The shaded area encloses the 95% confidence interval.

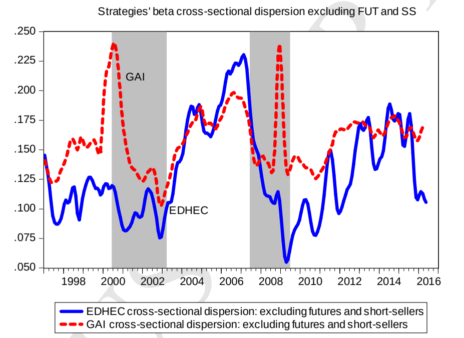
Figure 12 Cross-sectional dispersions of beta, co-skewness and co-kurtosis: EDHEC and GAI databases

Beta

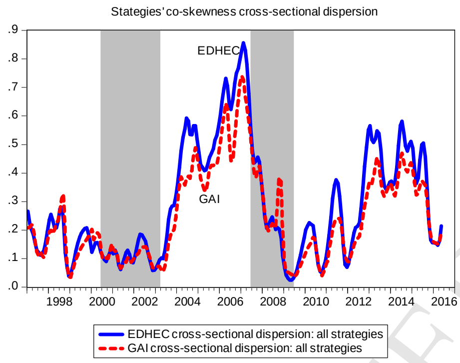
All strategies

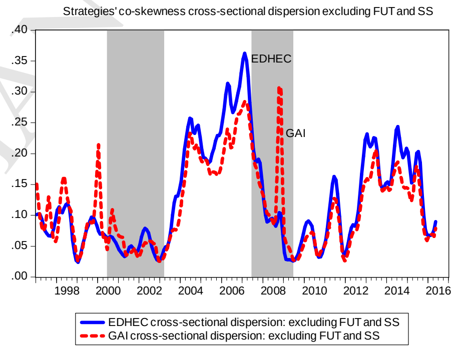


Excluding futures and short-sellers

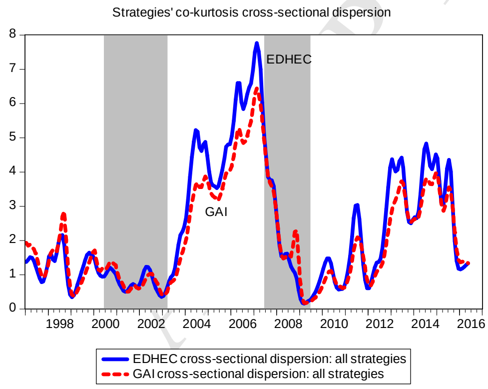


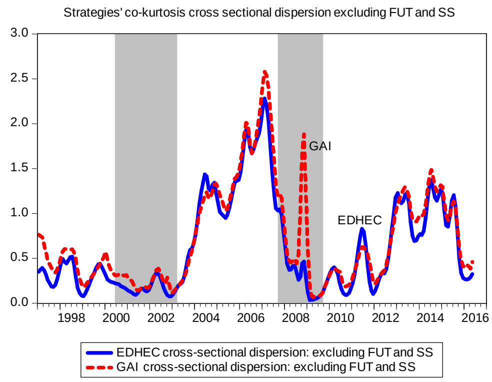
co-skewness





co-kurtosis





Notes: 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.

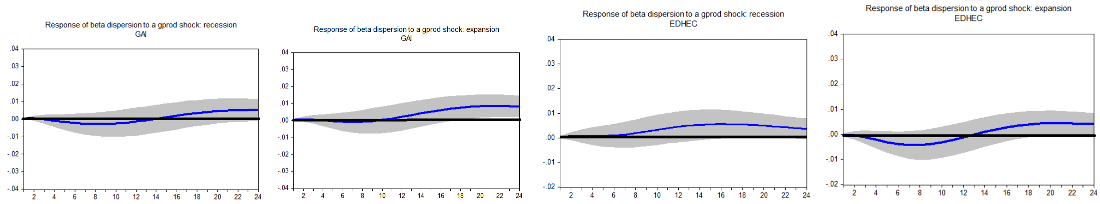
Figure 13 Nonlinear impulse response functions of beta, co-skewness and co-kurtosis cross-sectional dispersions: EDHEC and GAI databases

Beta

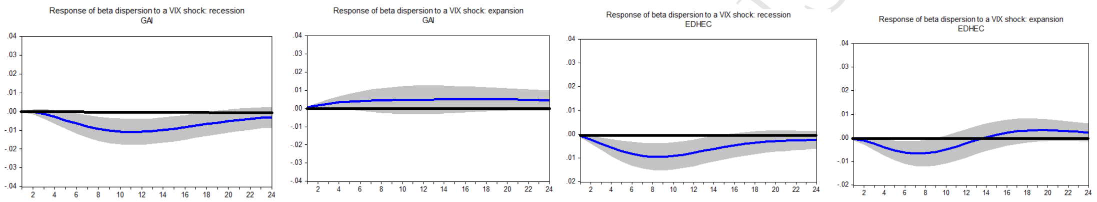
GAI **EDHEC**

Recession **expansion** **Recession** **expansion**

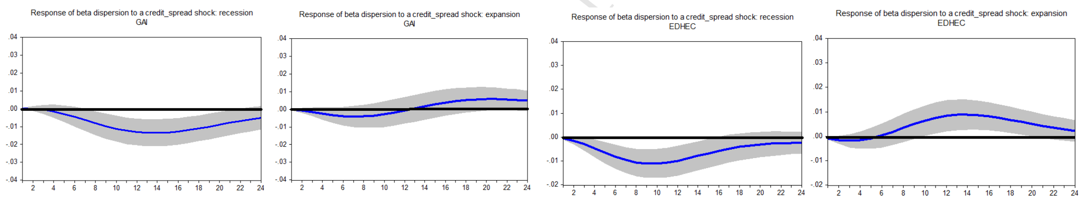
gprod



VIX



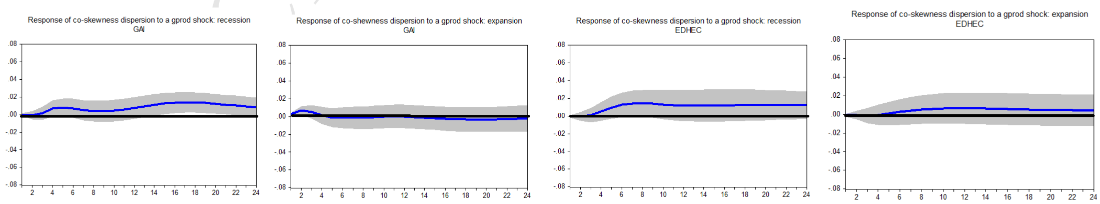
Credit shock



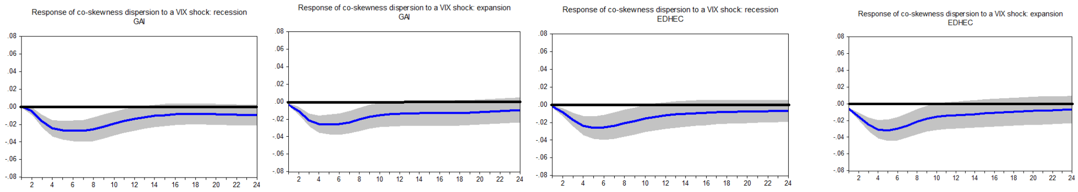
co-skewness

gprod

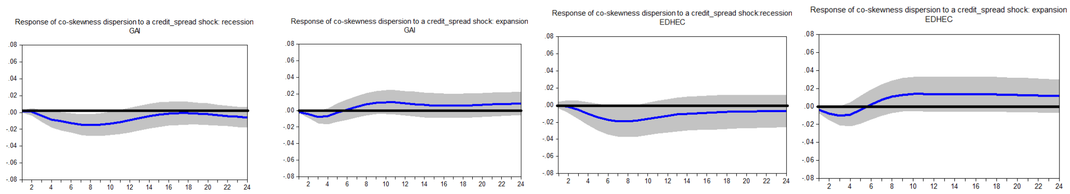
GAI **EDHEC**



VIX



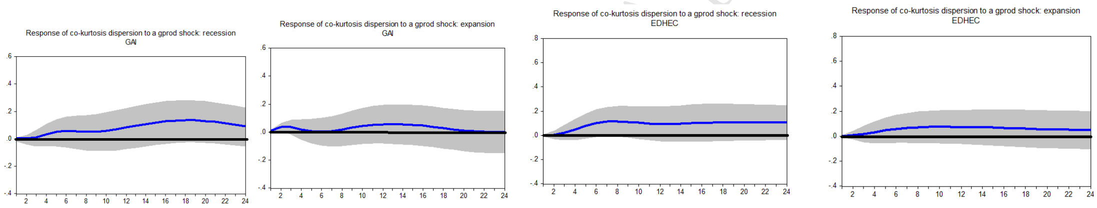
Credit shock



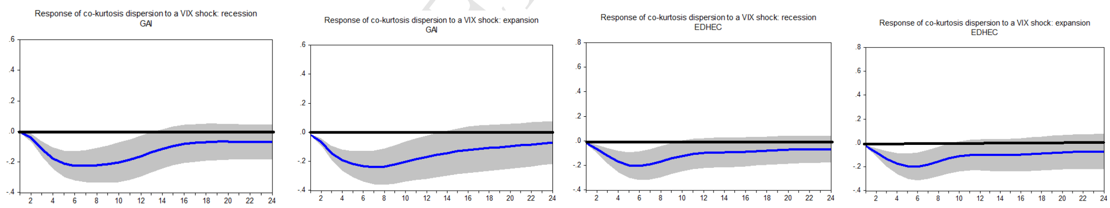
Co-kurtosis

GAI **EDHEC**

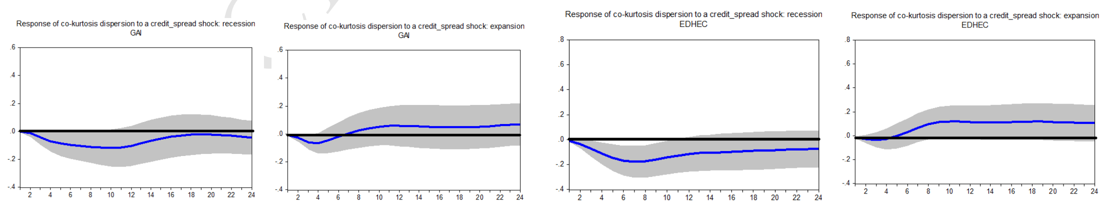
gprod



VIX



Credit shock



Notes: The IRFs are estimated with the STVAR—i.e., Eq. (15). $\mathbf{Y}_t = \left[cross\_sectional\_dispersion_{jt} \quad gprod_t \quad VIX_t \quad credit\_spread_t \right]'$, where j stands for the moment. The shaded area encloses the 95% confidence interval.

Table 1

Strategy	Description
convertible (CV)	Managers take a long position in convertibles and short simultaneously the stock of companies having issued these convertibles in order to hedge a p
Distressed securities (DS)	Managers buy equity and debt at deep discounts issued by firms facing bankruptcy.
Event driven (ED)	Managers follow a multistrategy event driven approach.
Equity market neutral (EMN)	Managers aim at obtaining returns with low or no correlation with equity and bond markets. They exploit pricing inefficiencies between related equi Leverage is often used to increase returns.
Fixed income (FI)	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.
Fund of funds (FOF)	Managers invest in many strategies
Futures (FUT)	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.
Long-short (LS)	Managers invest simultaneously on both the long and short sides of the equity market. Unlike the equity market neutral strategy, they maintain a lo Their beta can thus exceed substantially the one of the hedge fund weighted composite indices.
Macro (MACRO)	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.
Mergers (MERGER)	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 spre between the current price of the acquired company and its final price.
Short sellers (SS)	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- Managers' positions may be highly leveraged.

Table 2

	CV		DS		ED		EMN		FI	
Return	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**
Mean	0.0063	0.0048	0.0069	0.0071	0.0071	0.0066	0.0054	0.0050	0.0060	0.0045
Median	0.0081	0.0034	0.0100	0.0091	0.0090	0.0088	0.0047	0.0055	0.0070	0.0057
Maximum	0.0704	0.0691	0.0570	0.0504	0.0890	0.0442	0.0670	0.0253	0.0347	0.0365
Minimum	-0.1936	-0.0543	-0.0777	-0.0836	-0.0820	-0.0886	-0.0337	-0.0587	-0.0800	-0.0867
St.-Dev.	0.0213	0.0237	0.0176	0.0177	0.0207	0.0175	0.0111	0.0082	0.0114	0.0122
Skewness	-4.7338	0.1793	-0.8471	-1.3076	-0.3611	-1.4087	1.1480	-2.2952	-3.5643	-3.8251
Kurtosis	44.0750	2.8388	5.8394	7.5981	5.6272	7.6811	9.5847	18.7185	26.3333	27.4243
Bêta										
mean	0.1542	0.1589	0.2562	0.2892	0.3705	0.3306	0.1236	0.0863	0.0822	0.0586
St.-Dev.	0.1180	0.0662	0.1050	0.1252	0.0683	0.1461	0.0525	0.0444	0.0421	0.0497
Co-skewness (cs)										
mean	0.0206	-0.0288	-0.1788	-0.2210	-0.1616	-0.1943	0.0262	0.0310	-0.0481	-0.0819
St.-Dev.	0.1195	0.0404	0.1219	0.1528	0.1098	0.1358	0.0311	0.0395	0.0800	0.0584
Co-kurtosis (ck)										
mean	0.8035	0.8781	1.1933	1.7235	1.8854	1.8011	0.3971	0.2360	0.6545	0.5204
St.-Dev.	0.6411	0.7008	0.9274	1.4499	1.5365	1.5242	0.2817	0.1668	0.8228	0.4054
ρ(beta,ck)	0.14	0.71	0.93	0.95	0.62	0.97	0.52	0.35	0.36	0.22
ρ(beta,cs)	-0.46	-0.45	-0.85	-0.95	-0.64	-0.97	-0.08	0.26	-0.59	-0.09
ρ(ck,cs)	-0.15	-0.42	-0.90	-0.98	-0.98	-0.99	0.44	0.39	0.10	-0.90

	FUT		LS		MACRO		MERGER		SS		GI	FOF	MKT
Return	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**	**Gai**	**EDHEC**			
Mean	0.0061	0.0048	0.0073	0.0066	0.0046	0.0060	0.0054	0.0056	-0.0019	-0.0003	0.0065	0.0045	0.0072
Median	0.0040	0.0034	0.0100	0.0084	0.0040	0.0050	0.0060	0.0061	-0.0040	-0.0051	0.0070	0.0059	0.0129
Maximum	0.1080	0.0691	0.1180	0.0745	0.1050	0.0738	0.0276	0.0272	0.2490	0.2463	0.0900	0.0666	0.1135
Minimum	-0.0710	-0.0543	-0.0819	-0.0675	-0.0960	-0.0313	-0.0490	-0.0544	-0.2430	-0.1340	-0.0790	-0.0618	-0.1715
St.-Dev.	0.0274	0.0237	0.0270	0.0207	0.0209	0.0153	0.0098	0.0100	0.0511	0.0489	0.0202	0.0162	0.0460
Skewness	0.4366	0.1793	0.0389	-0.3794	0.6003	0.9231	-1.2727	-1.3783	0.2590	0.7332	0.0843	-0.3741	-0.6497
Kurtosis	3.8098	2.8388	5.0631	4.2569	9.6512	5.4055	7.9057	8.6633	7.5879	5.9687	6.1238	6.7085	3.8607
Bêta													
mean	0.0372	0.0381	0.5125	0.3946	0.1930	0.1652	0.1314	0.1361	-0.9843	-0.8929	0.3477	0.2377	1.0000
St.-Dev.	0.1314	0.1106	0.0871	0.0822	0.1039	0.0736	0.0533	0.0476	0.2882	0.2064	0.0581	0.0606	
Co-skewness (cs)													
mean	0.3875	0.1813	-0.1817	-0.0650	0.0756	0.1643	-0.1070	-0.1078	0.5034	0.7748	-0.1210	-0.1213	-0.4689
St.-Dev.	0.3047	0.1306	0.1467	0.0531	0.1090	0.1089	0.0746	0.0764	0.3520	0.5407	0.1054	0.0997	0.4897
Co-kurtosis (ck)													
mean	-1.2977	-0.8962	2.3778	1.8846	0.8282	0.9008	0.9207	0.9059	-4.8394	-5.9802	1.9719	1.4100	10.1655
St.-Dev.	1.0445	0.7592	1.7798	1.5575	0.6147	0.7481	0.7592	0.7664	3.3363	4.5902	1.5026	1.1451	8.2690
ρ(beta,ck)	-0.60	-0.52	0.58	0.88	-0.33	0.67	0.64	0.51	-0.19	0.09	0.16	0.45	
ρ(beta,cs)	0.70	0.56	-0.57	-0.77	-0.14	0.67	-0.64	-0.52	0.28	-0.04	-0.14	-0.21	
ρ(ck,cs)	-0.93	-0.90	-0.90	-0.86	0.48	0.99	-0.97	-0.99	-0.94	-0.98	-0.85	-0.81	-0.91

Table 3

Panel B below

Panel A

	c		mkt		mkt^2		mkt^3		ar(1)		R^2	
	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC	GAI	EDHEC
CV	0.0064	0.0066	0.05	0.04	-0.14	-0.38	14.05	10.19	0.54	0.53	0.52	0.48
	3.43	*5.00*	*1.63*	*2.76*	*-0.31*	*-1.48*	*2.19*	*4.84*	*13.23*	*6.47*		
DS	0.0072	0.0064	0.28	0.26	-1.24	-0.21	-22.88	-17.41	0.44	0.43	0.44	0.48
	2.95	*4.51*	*6.18*	*7.07*	*-2.69*	*-0.68*	*-2.06*	*-2.03*	*4.70*	*6.91*		
ED	0.0059	0.0065	0.38	0.29	-1.02	-1.16	-13.27	-4.35	0.25	0.36	0.49	0.55
	3.70	*3.59*	*6.65*	*10.07*	*-2.17*	*-2.11*	*-0.97*	*-0.47*	*3.77*	*6.44*		
EMN	0.0041	0.0040	0.15	0.10	0.05	0.05	-16.70	-3.93	0.29	0.33	0.18	0.26
	2.28	*5.20*	*7.71*	*6.89*	*0.14*	*0.28*	*-2.93*	*-2.43*	*3.91*	*5.18*		
FI	0.0078	0.0054	0.07	0.08	-0.87	-0.82	0.54	-6.25	0.42	0.48	0.28	0.29
	6.70	*3.84*	*2.11*	*2.15*	*-3.05*	*-2.68*	*0.07*	*-0.74*	*7.38*	*8.27*		
FUT	0.0004	0.0013	0.30	0.35	1.78	1.40	-98.98	-98.86	-0.02	-0.02	0.12	0.09
	0.17	*0.68*	*3.34*	*4.00*	*2.62*	*2.04*	*-5.05*	*-4.83*	*-0.29*	*-0.27*		
LS	0.0051	0.0051	0.56	0.41	-1.07	-0.88	-14.95	-7.01	0.26	0.21	0.61	0.62
	2.85	*2.86*	*8.64*	*11.04*	*-2.04*	*-1.97*	*-0.97*	*-0.78*	*3.90*	*2.87*		
MACRO	0.0020	0.0043	0.41	0.28	0.05	-0.08	-50.29	-31.10	0.06	0.09	0.18	0.21
	1.09	*3.56*	*3.18*	*8.02*	*0.11*	*-0.19*	*-2.02*	*-3.71*	*1.27*	*1.37*		
MERGER	0.0058	0.0063	0.10	0.12	-0.85	-0.92	5.48	2.04	0.26	0.32	0.30	0.38
	4.58	*5.10*	*2.46*	*4.05*	*-2.05*	*-2.38*	*0.53*	*0.25*	*3.63*	*4.73*		
SS	0.0022	0.0034	-0.96	-0.95	-0.04	1.93	31.76	3.91	0.05	0.20	0.53	0.61
	1.21	*1.09*	*-12.19*	*-8.33*	*-0.08*	*2.02*	*1.72*	*0.14*	*0.70*	*3.08*		
GI	0.0052	0.0042	0.39	0.29	-0.85	-0.95	-12.07	-17.95	0.29	0.34	0.54	0.44
	2.83	*2.65*	*8.39*	*9.10*	*-2.04*	*-2.18*	*-1.02*	*-2.15*	*3.87*	*3.94*		

Panel B

	mkt		mkt^2		mkt^3	
	GAI	**EDHEC**	**GAI**	**EDHEC**	**GAI**	**EDHEC**
CV	**0.08**	**0.09**	-0.01	-0.05	**0.11**	**0.10**
DS	**0.62**	**0.58**	**-0.15**	-0.03	**-0.22**	**-0.17**
ED	**0.73**	**0.65**	**-0.11**	**-0.15**	-0.11	-0.04
EMN	**0.56**	**0.49**	0.01	0.01	**-0.26**	**-0.08**
FI	**0.24**	**0.25**	**-0.17**	**-0.15**	0.01	-0.09
FUT	**0.43**	**0.58**	**0.14**	**0.13**	**-0.62**	**-0.71**
LS	**0.83**	**0.79**	**-0.09**	**-0.09**	-0.09	-0.06
MACRO	**0.78**	**0.74**	0.01	-0.01	**-0.41**	**-0.35**
MERGER	**0.40**	**0.48**	**-0.19**	**-0.20**	0.09	0.03
SS	**-0.75**	**-0.78**	0.00	**0.09**	**0.11**	0.01
GI	**0.77**	**0.72**	**-0.09**	**-0.13**	-0.10	**-0.19**

First moments		Second moments	
Variable	**Description and construction**	**Variable**	**Description and construction**
credit_spread	Spread between BBB and AAA corporate bond yields.	**cv_creditspread**	The conditional variance of the credit spread. It is the conditional variance of the innovation of an AR(2) process. —i.e., the mean equation—applied to the credit spread. This conditional variance is built with an EGARCH(1,1) process.
inf	The inflation rate. It is equal to log(CPI/CPI(-4))*100, CPI being the consumer price index.	**cv_inf**	The conditional variance of inflation. It is the conditional variance of the innovation of an AR(6) process–i.e. the mean equation— applied to inflation. This conditional variance is built using an EGARCH(1,1) process.
gpayroll	The non-farm payroll growth rate. It is equal to log(payroll/payroll(-4))*100.	**cv_gpayroll**	The conditional variance of the growth of non-farm payroll . It is the conditional variance of the innovation of an AR(2) process —i.e. the mean equation—applied to the payroll growth. The conditional variance is built using an EGARCH(1,1) process.
gprod	The industrial production growth rate. It is equal to log(prod/prod(-4))*100.	**cv_gprod**	The conditional variance of the industrial production growth. It is the conditional variance of an AR(6) process—i.e., the mean equation— applied to the industrial production growth. The conditional variance is built using andEGARCH(1,1) process.
mkt	The rate of return on the S&P500.	**cv_mkt**	The conditional variance of the return of the S&P500. It is the conditional variance of an AR(6) process—i.e., the mean equation— applied to the return on the S&P500. The conditional variance is built using an EGARCH(1,1) process.
output_gap	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.	**cv_outputgap**	The conditional variance of the output gap. It is the conditional variance of an AR(2) process—i.e., the mean equation— applied to the output gap. The conditional variance is built using an EGARCH(1,1) process.
term_spread	Spread between the ten-year interest rate and the 3-month Treasury bills.	**cv_termspread**	The conditional variance of the term spread. . It is the conditional variance of an AR(2) process—i.e., the mean equation— applied to the term spread. The conditional variance is built using an EGARCH(1,1) process.
unrate	Unemployment rate.	**cv_unrate**	The conditional variance of the unemployment rate. It is the conditional variance of an AR(6) process—i.e., the mean equation— applied to the unemployment rate. The conditional variance is built using an EGARCH(1,1) process.
		VIX	A measure of the volatility of the U.S. stock market. It represents an average of call and puts written on the S&P500.

Table 5

Correlation
Probability

	VIX	FRED_UEQ	PC_FRED_NEWS	cv_creditspread	cv_inf	cv_mkt	cv_outputgap	cv_gpayroll	cv_gprod	cv_termspread	cv_unrate	PC_CV
VIX	1.00											

FRED_UEQ	0.64	1.00										
	0.00	-----										
PC_FRED_NEWS	0.60	0.69	1.00									
	0.00	0.00	-----									
cv_creditspread	0.63	0.18	0.46	1.00								
	0.00	0.01	0.00	-----								
cv_inf	0.22	-0.01	0.05	0.47	1.00							
	0.00	0.92	0.43	0.00	-----							
cv_mkt	0.80	0.58	0.52	0.60	0.28	1.00						
	0.00	0.00	0.00	0.00	0.00	-----						
cv_outputgap	0.37	0.18	0.22	0.41	0.37	0.22	1.00					
	0.00	0.01	0.00	0.00	0.00	0.00	-----					
cv_gpayroll	0.27	0.12	0.16	0.19	0.19	0.28	0.20	1.00				
	0.00	0.06	0.01	0.00	0.00	0.00	0.00	-----				
cv_gprod	0.60	0.20	0.34	0.82	0.54	0.54	0.66	0.22	1.00			
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-----			
cv_termspread	0.40	0.42	-0.01	-0.02	0.03	0.34	0.05	0.12	0.13	1.00		
	0.00	0.00	0.91	0.71	0.61	0.00	0.45	0.05	0.04	-----		
cv_unrate	0.47	0.22	0.45	0.64	0.33	0.44	0.29	0.11	0.68	0.13	1.00	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.04	-----	
PC_CV	0.76	0.36	0.48	0.86	0.61	0.76	0.59	0.36	0.91	0.22	0.71	1.00
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-----

Table 6

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

Highlights

- This article aims at studying the response of hedge fund portfolio managers to macroeconomic and financial risk and uncertainty.
- We rely on nonlinear impulse response functions to track the asymmetries in the exposures of strategies' return higher moments to risk factors.
- The impulse response functions show that a deleveraging process takes place during crises for most strategies.
- Investing in short-selling strategies may be beneficial in terms of portfolio diversification during crises.