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Macroeconomic shocks, forward-looking dynamics, and the behavior of hedge funds

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

[a] Telfer School of Management, University of Ottawa, 55 Laurier Avenue East, Ottawa, Ontario, Canada
[b] Chaire d'information financière et organisationnelle, ESG-UQAM, Canada
[c] CGA-Canada Accounting and Governance Research Center (CGA-AGRC), Canada
[d] Université du Québec (Montréal), École des sciences de la gestion, 315 est Ste-Catherine, R-3555 Montréal, Québec, Canada
[e] Université du Québec (Outaouais), Canada

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ABSTRACT

We investigate how hedge funds' strategies react, as a group, to macroeconomic risk and uncertainty. Adopting the methodology of Beaudry et al. (2001), we track the behavior of the cross-sectional dispersions of hedge fund strategies' returns, market betas and alphas over the business cycle. The pattern of strategies' betas supports Beaudry et al.'s conjecture: hedge funds reduce their risk-taking (betas) during times of macroeconomic uncertainty, which makes their strategies more homogeneous and thus contributes to increased systemic risk in the financial system. However, the cyclical behavior of the cross-sectional dispersions of strategies' returns and strategies' alphas is not in line with Beaudry et al.'s conjecture. These dispersions tend to increase during episodes of rising macroeconomic uncertainty, which suggests the prevalence of the Black's (1976) leverage effect during financial turmoil and the fact that the exposure of hedge fund strategies to risk factors is quite different from each other. Finally, although remaining important, procyclicality seems to have declined through time in the hedge fund industry, which suggests that a learning process is at play.

1. Introduction

Co-movements between macroeconomic variables and financial institutions' performance may be an important source of systemic risk[1] (Fama and French, 1989; Chen, 1991; Beaudry et al., 2001; Boyson et al., 2010; Veronesi, 2010; Cochrane, 2011). In this respect, informational problems and agency costs are generally more severe during slow growth episodes and especially during financial crises, when financial institutions are most exposed to moral hazard and adverse selection (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Vennet et al., 2004). During these periods, the behavior of financial institutions tends to become more homogeneous, which magnifies the amplitude of the crisis. Indeed, to restore the health of their balance sheet, financial institutions get involved in a deleveraging process which leads to fire sales of assets (Acharya, 2009; Shleifer and Vishny, 2010). These forced sales give rise to negative externalities across the financial system, an obvious source of systemic risk. Moreover, diversification in the financial sector also induces intermediaries to adopt a more homogeneous behavior, especially in crisis (Wagner, 2007, 2008, 2010). These more homogeneous patterns, which are driven by co-movements between macroeconomic variables and financial institutions' performance, threaten the resiliency of the financial system.

In this paper, using a framework developed by Beaudry et al. (2001) and Baum et al. (2002, 2004, 2009), we study the co-movements between macroeconomic risk and uncertainty, on the one hand, and three measures of cross-sectional dispersion in the hedge fund industry: the cross-sectional dispersions of strategies'

* Corresponding author at: Telfer School of Management, University of Ottawa, 55 Laurier Avenue East, Ottawa, Ontario, Canada. Tel: +1 613 562 5800 (4757).

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

[1] For instance, the covariance between GDP growth and expected returns is negative—i.e., expected returns increase when GDP growth decreases, because risk aversion increases when business conditions worsen (Veronesi, 2010).

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returns, market betas[2] and alphas. Indeed, in the current context of depressed interest rates and relatively lower real returns on stocks,[3] portfolio diversification relying on hedge fund strategies may be a way opened to financial investors to enhance their return. Low interest rates are particularly problematic for pension funds whose liabilities are bloated by depressed long-term interest rates.

In this study, our main finding is that the behavior of the cross-sectional dispersion of hedge fund strategies' market betas is in line with Beaudry et al.'s conjecture. This dispersion is procyclical and tends to decrease with the rise in macroeconomic uncertainty. Indeed, hedge fund managers reduce their risk-taking when macroeconomic uncertainty increases, which leads to a decrease in the cross-sectional dispersion of their betas.

However, in contrast to the results obtained on investment project data or banking data (Beaudry et al., 2001; Baum et al., 2002, 2004, 2009; Quagliariello, 2007, 2008, 2009; Calmès and Théoret, 2014), the cross-sectional dispersion of hedge fund strategies' returns increases with a rise in macroeconomic uncertainty. This behavior may be explained by the increased volatility of financial markets when business conditions worsen—i.e., the Black's (1976) leverage effect. Finally, the behavior of the cross-sectional dispersion of strategies' alphas is more akin to the pattern of their cross-sectional dispersion of returns. Interestingly, the cross-sectional dispersion of alphas tends to increase with macroeconomic uncertainty, suggesting that some strategies benefit from financial turmoil.

This paper is organized as follows. Section 2 presents the literature review and the benchmark model used to analyze the links between macroeconomic risk and uncertainty and our cross-sectional dispersion measures—defined in terms of strategies' returns, alphas and market betas. This section is also concerned with the estimation methods used in this paper, namely the Kalman filter—used to build the cross-sectional dispersions of alphas and betas—and the generalized method of moments (GMM) which deals with the endogeneity embedded in our measures of macroeconomic uncertainty (Racicot and Théoret, 2014b). Section 3 discusses the data and some key stylized facts related to our cross-sectional dispersion measures. In Section 4, we report our main results before concluding in Section 5.

2. Methodology

2.1. Literature review

To analyse hedge fund systemic risk, we rely on a theoretical underpinning based on a signal extraction problem à la Lucas (1973). This framework was refined by Beaudry et al. (2001) who also found an empirical counterpart to this model. Baum et al. (2002, 2004, 2009) contributed to the transposition of this setting to financial institutions.

Assume that the portfolio of an investor designated by i—i.e., hedge fund strategies in our setting—is composed of two categories of assets—a security (risk-free) asset and a risky asset (ra). The returns on the two categories of assets which are included in the representative investor's portfolio are given by the following equations:

$$\forall i, \quad \forall t, \quad r_{i,t}^{S} = r_f \tag{1}$$

$$\forall i, \quad \forall t, \quad r_{i,t}^{ra} = r_f + \rho + \varepsilon_{i,t} \tag{2}$$

where $r_{i,t}^{S}$ is the return on the security for investor i at time t; r_f is the return on a risk-free asset and $r_{i,t}^{ra}$ is the return on the risky asset. The expected return on the risky asset is equal to $r_f + \rho$, where ρ is the expected risk premium assumed to be fixed. The idiosyncratic risk is represented by the random variable $\varepsilon_{i,t}\tilde{N}(0, \sigma_{\varepsilon,t}^2)$.

At time t, when an investor determines the optimal allocation of his portfolio between the risk-free and risky assets, he is confronted to uncertainty, $\varepsilon_{i,t}$ (Eq. (2)). Assume that at time t each investor observes an imperfect signal $S_{i,t}$ which enables him to formulate a forecast of the value of $\varepsilon_{i,t}$: $S_{i,t} = \varepsilon_{i,t} + \upsilon_t$, with $\upsilon_t \sim N(0, \sigma_{\upsilon,t}^2)$ and $E(\varepsilon_{it}, \upsilon_t) = 0$. Assume that $\sigma_{\upsilon,t}^2$ is driven by macroeconomic uncertainty so that when uncertainty rises, the noise incorporated in the signal rises concomitantly with $\sigma_{\upsilon,t}^2$ and it becomes increasingly difficult to determine the true value of $\varepsilon_{i,t}$ and the optimal return on the risky asset. The best way to predict the return on the risky asset is then to estimate $E[\varepsilon_{i,t}|S_{i,t}]$, the expected value of the idiosyncratic noise conditional on the signal. Baum et al. (2002, 2004, 2009) assume that the conditional expectation of $\varepsilon_{i,t}$ is equal to a proportion λ_t of the signal:

$$\forall i, \quad \forall t, \quad E[\varepsilon_{i,t}|S_{i,t}] = \lambda_t[\varepsilon_{i,t} + \upsilon_t] \tag{3}$$

with

$$\forall t, \quad \lambda_t = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\upsilon,t}^2} \tag{4}$$

Baum et al. (2002,2004, 2009) then compute w_{it}^{ra}, the optimal share of the risky asset in the bank portfolio using a model which maximizes the expected utility of a representative investor subject to portfolio risk. They obtain the following expression for w_{it}^{ra}:

$$\forall i, \quad \forall t, \quad w_{it}^{ra} = \frac{\rho + \lambda_t S_{i,t}}{\varphi \lambda_t \sigma_{\upsilon,t}^2} \tag{5}$$

where φ measures the representative investor's degree of risk aversion. They then compute the variance of w_{it}^{ra}—i.e., the cross-sectional dispersion of the shares of risky assets in the investors' portfolios:

$$\forall i, \quad \forall t, \quad Var(w_{it}^{ra}) = \frac{\sigma_{\varepsilon,t}^2 + \sigma_{\upsilon,t}^2}{\varphi^2 \sigma_{\upsilon,t}^4} \tag{6}$$

Its derivative with respect to macroeconomic uncertainty $\sigma_{\upsilon,t}^2$ is thus:

$$\forall i, \quad \forall t, \quad \frac{\partial Var(w_{it}^{ra})}{\partial \sigma_{\upsilon,t}^2} = -\frac{1}{\varphi^2}\left[\frac{2\sigma_{\varepsilon,t}^2}{\sigma_{\upsilon,t}^6} + \frac{1}{\sigma_{\upsilon,t}^4}\right] < 0 \tag{7}$$

Beaudry et al. (2001), who are concerned with the distribution of firms' investment rates of return, also obtain a theoretical negative relationship between their source of macroeconomic uncertainty—i.e., monetary instability—and the cross-sectional dispersion of returns.

Eq. (7) is the assumption we examine in this study. It asserts that the behavior of investors become more homogenous in times of rising macroeconomic uncertainty—i.e., the more macroeconomic uncertainty increases, the more financial institutions' portfolios become similar in terms of asset allocation. Regarding hedge funds, we may thus postulate that the cross-sectional dispersions of strategies' financial leverages and market betas are reduced with an increase in macroeconomic uncertainty. Indeed, an increase in uncertainty leads to closer shares of risky assets held by various strategies: strategies' leverages and market betas thus also get closer. Macroeconomic shocks can thus distort the behavior of hedge funds.

In this study, we follow the empirical methodology of Beaudry et al. (2001), Baum et al. (2002, 2004, 2009), Quagliariello (2007,

[2] When we talk about the beta of a strategy, we refer to the beta computed from the excess market return—i.e., the spread between the S&P500 return and the risk-free rate.

[3] See IMF, 2014, chapter 3.

2008, 2009), Yu and Sharaiha (2007), and Calmès and Théoret (2014) to find an empirical counterpart to Eq. (7) which fits our objective. These authors rely on an equation taking the following form:

$$disp(.)_t = \varphi_0 + \varphi_1 \mu_{mv,t} + \varphi_2 \sigma^2_{c,mv,t} + \varphi_3 disp(.)_{t-1} + \xi_t \tag{8}$$

where $disp(.)_t$ is the cross-sectional dispersion of the variable under study computed using the standard deviation of this variable at a given point in time; $\mu_{mv,t}$ is the first moment of a macroeconomic variable proxying for risk; $\sigma^2_{c,mv,t}$ is the corresponding conditional variance of the macroeconomic variable—i.e., the second moment measuring macroeconomic uncertainty—and ξ_t is the innovation. Researchers analyze the impact of *alternative* sources of economic uncertainty on the cross-sectional dispersion of risk borne by investors instead of only one like in Eq. (7). They thus investigate the impact of one macroeconomic or financial factor at a time, a procedure we follow in this paper.

This kind of approach has been successfully applied in several studies including analyses of the cross-sectional dispersion of firm investment, corporate liquidity, financial markets and bank portfolios (Beaudry et al., 2001; Baum et al., 2002, 2004, 2009; Baum et al., 2006; Hwang and Salmon, 2004; Quagliariello, 2007; Vives, 2010; Calmès and Théoret, 2014). In the banking literature, authors have shown that an increase in macroeconomic uncertainty reduces the cross-sectional dispersion of loans-to-assets ratios (Baum et al., 2002, 2004, 2009; Quagliariello, 2007), and the cross-sectional dispersion in the shares of non-interest income in net operating income—i.e., a measure of bank involvement in risky non-traditional business lines (Calmès and Théoret, 2014).

2.2. The empirical framework

2.2.1. Kalman filter and time-varying alpha and beta

In order to test the herd-like behavior in the hedge fund industry, we will run Eq. (8) on our sample of hedge fund strategies. In this equation, $disp(.)_t$ stands successively for the cross-sectional dispersion of strategies' returns, strategies' market betas and strategies' alphas, denoted by *disp*(*ret*), *disp*(*beta*) and *disp*(*alpha*), respectively. To the best of our knowledge, we are the first to apply this kind of methodology to the analysis of hedge fund risk taking and return.

For a given month, *disp*(*ret*) is the variance of the hedge fund strategies' returns observed during this month. To compute *disp* (*alpha*) and *disp*(*beta*), we proceed as follows. First, using the Kalman filter—a forward-looking procedure—we simulate for each strategy a monthly time series for their alpha and market beta (Racicot and Théoret, 2014a). Then, for each month, we compute the standard deviation[4] over the strategies' alphas and market betas.

Let us detail the procedure we follow to obtain the strategies' time series of alphas and market betas. The Kalman filter comprises a signal equation and state space equations[5]. In our case, the signal equation is a return model. This model is an augmented version of the Fama and French (1993) three-factor model which incorporates the Fung and Hsieh factors (1997, 2001, 2004). This equation reads:

$$\begin{aligned}\forall i,\ \forall t \quad R_{it} - r_{ft} = {} & \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + \gamma_{1i} SMB_t + \gamma_{2i} HML_t \\ & + \gamma_{3i} bond\_look_t + \gamma_{4i} stock\_look_t + \cdots \\ & + \gamma_{5i} shortint\_look_t + \gamma_{6i} currency\_look_t \\ & + \gamma_{7i} commod\_look_t + \gamma_{8i} d(r10) \\ & + \gamma_{9i} d(credit\_spread) + \varepsilon_{it}\end{aligned} \tag{9}$$

where r_{ft} is the risk-free return; α_{it} is the time-varying alpha; β_{it} is the time-varying market beta; R_{mt} is the market portfolio return; SMB_t is the return of a mimicking portfolio which is long in small firm stocks and short in big firm stocks—size being measured by stock market capitalization; HML_t is the return on a mimicking portfolio which is long in firm stocks with a high book-to-market value (value stocks) and short in firm stocks with a low book-to-market value (growth stocks). The five following variables are the Fung and Hsieh (1997, 2001, 2004) lookback straddles[6] on bonds (*bond_look*), stocks (*stock_look*), short-term interest rate (*shortint_look*), foreign currencies (*currency_look*) and commodities (*commod_look*). Fung and Hsieh (1997, 2001, 2004) rely on lookback straddles to study the behavior of trend followers[7] in the hedge fund industry. Finally, *d*(*r10*) is the change in the rate of the 10-year U.S. federal government bond and *d*(*credit_spread*) stands for the change in the credit spread—i.e., the spread between the BBB and AAA U.S. corporate bond yields.

In Eq. (9), $(R_{mt} - r_{ft})$ and SMB_t are two important risk factors found in most hedge fund return models. Fung and Hsieh (2004) call them the equity ABS (asset-based-style) factors, which stand for the main drivers of the long/short hedge fund strategy—i.e., the conventional hedge fund strategy. The *HML* factor aims at measuring the relative preference of hedge funds between value stocks and growth stocks. In other respects, the lookback straddle[8] factors are proxies for the volatility of the respective underlying asset and γ_{3i} to γ_{7i} are gauges of the respective exposures of strategy *i* to these volatility variables. According to Fung and Hsieh (2004), trend-followers are betting on big moves of financial markets and lookback straddles are good proxies for such moves.[9] Finally, $[\gamma_{8i}$ measures a strategy's exposure to interest rate risk, while γ_{9i} measures its exposure to credit risk.

We relate the state space equations of the alpha and market beta to macroeconomic and financial variables, given the importance of the timing of the alpha and beta on this kind of variables in the hedge fund literature (Chen and Liang, 2007; Avramov et al., 2011; Cai and Liang, 2012; Cao et al., 2013). The state space equation for the alpha may be written as follows:

$$\forall i, \forall t \quad \alpha_{it} = \alpha_{i,t-1} + \theta_{1i} r_{ft} + \theta_{2i}(R_{mt} - r_{ft}) + \xi_t \tag{10}$$

We thus postulate that the alpha follows an autoregressive process augmented with conditioning market information. Eq. (10) may be written in first-differences, such as:

$$\forall i, \forall t \quad \alpha_{it} - \alpha_{i,t-1} = \theta_{1i} r_{ft} + \theta_{2i}(R_{mt} - r_{ft}) + \xi_t \tag{11}$$

[4] For computational convenience, we rely on the standard deviation rather than on the variance to compute the cross-sectional dispersions of strategies' alphas and market betas.

[5] For a classical book on the Kalman filter, see Harvey (1989) and for applications to hedge funds, see Racicot and Théoret (2010, 2014a). Note that in the Kalman filter procedure, the signal equation and the state space equations—here Eqs. (9), (10) and (12)—are estimated simultaneously using an optimization recursive procedure.

[6] A lookback call option gives the right to buy the underlying asset at its lowest price observed over the life of the option. Similarly, a lookback put option allows the owner to sell the underlying asset at the highest price observed over the life of the option. The combination of these two options is the lookback straddle (Fung and Hsieh, 2004). As reported later, the time series of the straddles appear on the Hsieh's website.

[7] Mainly managed futures or CTA funds.

[8] Remind that a strategy involving straddles is a bet on the volatility (upward or downward) of their underlying assets.

[9] The estimated coefficients of lookback straddles should thus be positive for trend-followers.

The updating of the alpha from one period to the next is thus a function of three elements: the interest rate, the market risk premium and an innovation.[10] The coefficients θ_{1i}, θ_{2i} and the variance of the innovation result from the search procedure inherent to the Kalman filter.

Similarly, the state space equation for a strategy's market beta is:

$$\forall i,\ \forall t \quad \beta_{it} = \beta_{i,t-1} + \delta_{1i} r_{ft} + \delta_{2i}(R_{mt} - r_{ft}) + \delta_{3i} pc\_lookback_t + \varsigma_t \tag{12}$$

In addition to the two conditioning variables included in the state space equation of the alpha, the state space equation of the market beta includes the *pc_lookback* variable. The *pc_lookback* variable is the first principal component of the Fung and Hsieh five lookback straddles presented previously. It stands for a *global* indicator of volatility on financial, commodity and currency markets.[11]

Let us conjecture the expected signs of the variables included in Eqs. (10) and (12). First, an increase in the interest rate might signal a deterioration of business conditions. It thus leads to a decrease in the alpha ($\theta_{1i} < 0$) and to a decrease in the market beta ($\delta_{1i} < 0$), hedge funds reducing their exposure to market risk in times of economic slowdown. Second, an increase in the market risk premium ($R_{mt} - r_{ft}$) is viewed as a strengthening of the stock market. This may induce hedge funds to position themselves for an increase in their alpha, this behavior being related to the portfolio manager's skills. In this case, the sign of θ_{2i} is positive. However, if the alpha is not manageable, this coefficient should be close to zero. This should not be the case for the time-varying market beta, which is considered as a control or decision variable. As a signal of market strengthening, an increase in the market risk premium should induce hedge funds to take more risk, and therefore to increase their beta. We thus expect $\delta_{2i} > 0$.

Finally, we expect a negative sign for the coefficient associated with the *pc_lookback* variable in Eq. (12). We thus expect that hedge funds reduce their market beta when the stock market declines or shows unusual volatility. In this respect, there is a negative conditional covariance between the *pc_lookback* and the stock market return as measured by the S&P500 (Fig. 1). Note that this covariance—which is computed with a multivariate GARCH (MGARCH) using a BEKK procedure (Bollerslev et al., 1988; Engle and Kroner, 1995)—is particularly high in times of crisis, especially during the subprime crisis. The behavior of the *pc_lookback* may therefore be assimilated to a long put. More precisely, this variable may be viewed as an insurance factor in our return model (Agarwal and Naik, 2004). Fig. 2 shows that the MGARCH conditional covariance between the *pc_lookback* and our hedge fund weighted composite index[12] is generally positive. This suggests that the *pc_lookback* may act as a backstop for hedge funds against the fluctuations of the stock market. Note that the covariance between the *pc_lookback* and the weighted composite index may become negative in times of market turmoil—suggesting that the *pc_lookback* does not provide a perfect hedge—but this covariance is much less in absolute value than the one linking the *pc_lookback* and the S&P500 return. Consistent with our interpretation, Fung and Hsieh (2001) argue that a portfolio of lookback straddles on currencies, bonds, and commodities can reduce the volatility of a typical stock and bond portfolio during extreme market downturns.

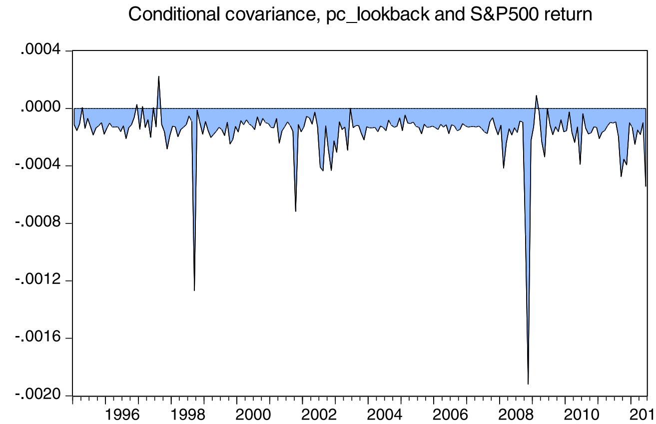

Fig. 1. Conditional covariance between the *pc_lookback* and S&P500 return. *Notes*: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev et al., 1988; Engle and Kroner, 1995). The *pc_lookback* variable is the first principal component of the Fung and Hsieh (2001) five lookback straddles.

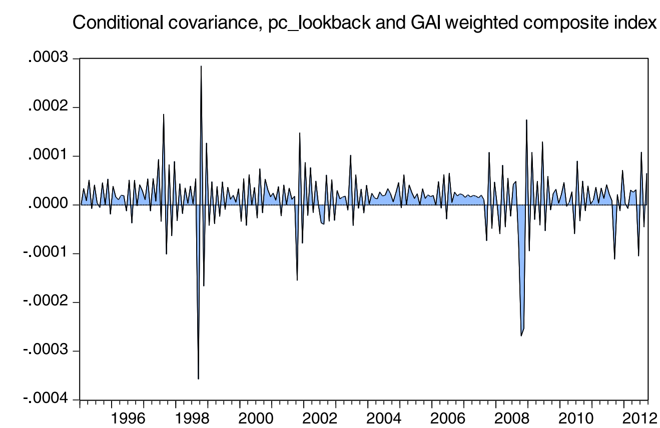

Fig. 2. Conditional covariance between the *pc_lookback* and GAI weighted composite return. *Notes*: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev et al., 1988; Engle and Kroner, 1995). The *pc_lookback* variable is the first principal component of the Fung and Hsieh (2001) five lookback straddles.

Another interpretation of the link between the *pc_lookback* factor and a strategy's market beta hinges on the following argument. Recall that the *pc_lookback* factor is built with lookback straddles that provide greater payoffs when financial markets are volatile. Fig. 3 plots the conditional covariance between the *VIX*—a well-known indicator of the implicit volatility of stock returns—and the S&P500 returns. This covariance—which is also computed with a MGARCH—is usually negative, which supports the Black (1976) leverage effect, and it peaks when the market is dropping, its largest drop being observed during the subprime crisis. Fig. 3 also shows that the MGARCH conditional covariance between the *VIX* and our hedge fund weighted composite index shares a similar profile. However, this covariance is lower in absolute value than the one linking the *VIX* to the S&P500. This may be explained by the influence of the *pc_lookback*. In this respect, Fig. 4 shows that the MGARCH conditional covariance between the *pc_lookback* and the *VIX* is positive. As expected, it peaks when the market trends downward. Moreover, Fig. 5 plots the behavior of the *pc_lookback* and the *VIX*. Note that the *pc_lookback* seems to be a leading indicator with respect to the *VIX*—especially during the

[10] Compared to Cai and Liang (2012), we introduce directly the selected macroeconomic and financial variables in the state space equations of alpha and market beta. Cai and Liang (2012) assume that alpha and beta follow a strict random walk process in a first step and correlate their filtered alpha and beta with macroeconomic variables in a second step. Our multivariate procedure for analyzing the timing of alpha and beta is thus more efficient than the Cai and Liang's (2012) one.

[11] Introducing this principal component rather than the five Fung and Hsieh's straddles seems more relevant since state space equations must rely on parsimonious formulations in the Kalman filter procedure. Indeed, this procedure becomes unstable when too many variables are added in state space equations.

[12] i.e., the Greenwich Alternative Investment (GAI) composite index.

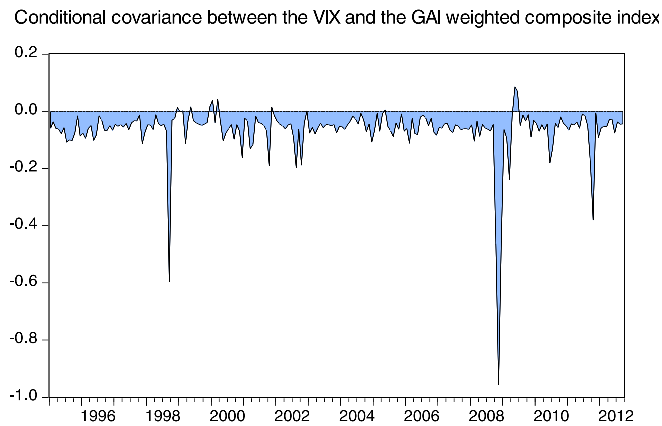

Fig. 3. Conditional covariance between the *VIX* and the GAI weighted composite return. *Note*: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev et al., 1988; Engle and Kroner, 1995). The *VIX* is drawn from the FRED database, which is managed by the Federal Reserve Bank of St-Louis.

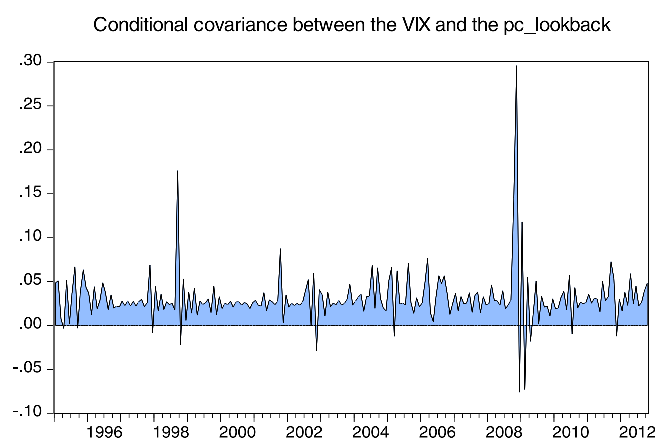

Fig. 4. Conditional covariance between the *VIX* and the *pc_lookback*. *Notes*: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev et al., 1988; Engle and Kroner, 1995). The *pc_lookback* variable is the first principal component of the Fung and Hsieh (2001) five lookback straddles. The *VIX* is drawn from the FRED database, which is managed by the Federal Reserve Bank of St-Louis.

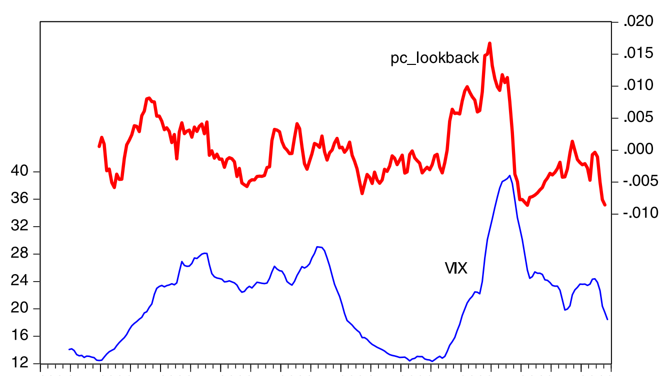

Fig. 5. Moving averages, *pc_lookback* and *VIX*. *Notes*: The moving average is computed on a rolling window of twelve months. The *pc_lookback* variable is the first principal component of the Fung and Hsieh (2001) five lookback straddles. The *VIX* is drawn from the FRED database, which is managed by the Federal Reserve Bank of St-Louis.

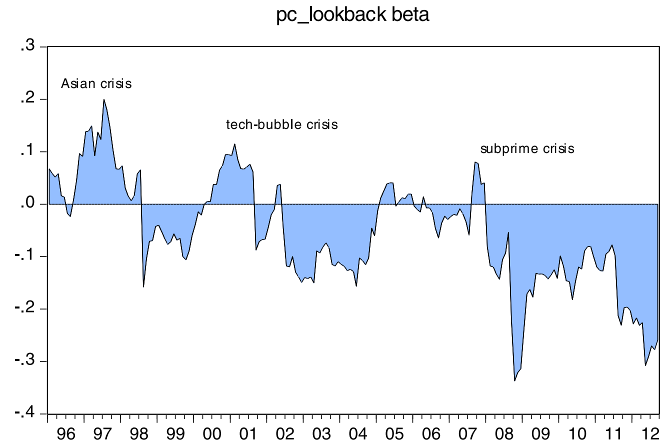

Fig. 6. Market beta of the *pc_lookback*. *Note*: The *pc_lookback* variable is the first principal component of the Fung and Hsieh (2001) five lookback straddles. The time-varying market beta is computed with the Kalman filter run on the simple market model.

subprime crisis. It does signal a market downturn before the *VIX*. Consistent with our results, hedge funds are induced to take less systematic risk during these episodes.

To gain a better understanding of the link between the *pc_lookback* factor and strategies' returns, we can compute the time-varying market beta of this factor, relying on the following simple market model estimated with the Kalman filter:

$$pc\_lookback_t = \alpha + \beta_{t,pc\_look}(R_{mt} - r_{ft}) + \varepsilon_t \quad (13)$$

Fig. 6, which plots the estimated market beta of the *pc_lookback*, shows that it is usually negative but that it increases in absolute value during a crisis, which suggests that the *pc_lookback* behaves as a backstop against the decrease in portfolio returns. Substituting Eq. (13) into Eq. (12) and then Eq. (12) into Eq. (9) leads to the following term in a strategy return equation: $\beta_{i,t}\delta_{3i}\beta_{t,pc\_look}(R_{mt} - r_{ft})^2$. Given our previous results, the coefficient of $(R_{mt} - r_{ft})^2$ is positive. The strategies which have a significant δ_{3i} in Eq. (12)—especially the futures, opportunistic, value index, and diversified event driven—thus benefit when the volatility of the stock market (as measured by $(R_{mt} - r_{ft})^2$) increases (Racicot and Théoret, 2014a). These strategies thus share the nature of the Fung and Hsieh's (2001, 2004) trend followers. Note that this result is in line with the papers of Treynor and Mazuy (1966) and Henriksson and Merton (1981) on market-timing where non-linear functions of the market risk premium are relied on to deal with option-like return features (Fung and Hsieh, 2001).

2.2.2. The benchmark equation

Turning to the explanatory variables of Eq. (8), the first moment[13] of a macroeconomic variable may be the industrial production growth and its corresponding second moment[14] the conditional variance of industrial production growth.[15] The model may include a lagged dependent variable to control for residuals autocorrelation and account for the adjustment delay of the observed $disp(\cdot)_t$ toward its target level.

Importantly, note that our model makes an explicit distinction between macroeconomic risk and uncertainty—macroeconomic risk relating to the phase of the business cycle and macroeconomic uncertainty to its volatility. Indeed, we conjecture that macroeco-

[13] i.e., a measure of risk.
[14] i.e., a measure of uncertainty.
[15] See Appendix A1 for the construction of the conditional variance variables.

nomic uncertainty fosters more herding in the hedge fund industry than macroeconomic risk *per se* which can be hedged more easily.

A second and more technical motivation for including both the first and second moments in Eq. (8) is that, from an econometric perspective, the first moment of a variable used to define macroeconomic uncertainty must also be included in the regression for the sake of robustness (Huizinga, 1993; Quagliariello, 2007, 2009). Indeed, excluding the first moment might wrongfully leads the researcher to attribute to the second moment an impact which is actually explained by the first one.

In line with previous studies, we analyze the impact of one macroeconomic factor at a time. For example, for the dispersion of strategies' market betas in terms of industrial production growth uncertainty, our model can be expressed as follows:

$$disp(beta)_t = \delta_0 + \delta_1 gprod_t + \delta_2 cv\_gprod + \delta_3 disp(beta)_{t-1} + \varepsilon_t \quad (14)$$

where *disp*(*beta*) is the cross-sectional dispersion of strategies' betas; *gprod* is the industrial production growth rate (first moment) and *cv_gprod* is the conditional variance (second moment) of *gprod*. The other sources of macroeconomic risk and uncertainty studied in this article will be detailed later. According to Beaudry et al.'s (2001) conjecture, we expect $\delta_2 < 0$. Indeed, when macroeconomic uncertainty increases, hedge funds' strategies should become more homogeneous. More precisely, hedge funds should then take less risk by reducing their market beta, which increases the correlation between hedge funds' strategies and therefore rises systemic risk in the financial sector.[16] However, Beaudry et al.'s model does not provide any indication about the sign of the coefficient of the first moment in Eq. (14). In line with the impact of macroeconomic uncertainty, we expect that a decrease in the industrial production growth rate leads to a decrease in *disp* (*beta*). When business conditions worsen, hedge funds should thus take less risk by reducing their market betas. *disp*(*beta*) should thus decrease, strategies becoming more similar. We thus expect that $\delta_1 > 0$.

Unlike the returns on the risky assets analyzed in the studies of Beaudry et al. (2001), Baum et al. (2002, 2004, 2009), Quagliariello (2007, 2008, 2009) and Calmès and Théoret (2014), market returns and alphas are not directly under the control of portfolio managers. Indeed, strategy returns and alphas—a measure of a strategy's absolute return—are more difficult to monitor than the market beta. The relationship of these variables with macroeconomic and financial uncertainty is thus an empirical issue.

2.3. Estimation of the cross-sectional dispersion model

To estimate Eq. (8), we first rely on ordinary least squares (OLS). However, we must also resort to instrumental estimation procedures since the variables which measure macroeconomic uncertainty are generated variables—i.e., potentially noisy proxies for their associated unobservable regressors (Pagan, 1984, 1986). Indeed, even if relying on OLS or simple maximum likelihood estimation in the presence of generated variables does not lead to inconsistency at the level of the coefficients, the *t* tests associated with the estimated coefficients are invalid[17] (Pagan 1984, 1986). This issue is mentioned in previous studies on cross-sectional dispersions (e.g., Beaudry et al., 2001; Baum et al., 2002, 2004, 2009; Quagliariello, 2007, 2008, 2009; Calmès and Théoret, 2014). To deal with this endogeneity issue, we rely on the generalized method of moments (GMM). To implement the GMM, we resort to robust instruments, which, in addition to the standard predetermined variables, include the higher moments or cumulants of the model's explanatory variables (Fuller, 1987; Lewbel, 1997; Racicot and Théoret, 2014b).[18]

3. Data sources and stylized facts

3.1. Data

Data on hedge fund returns are taken from the database managed by Greenwich Alternative Investment (GAI). GAI manages one of the oldest hedge fund databases, containing more than 13,500 records of hedge funds as of March 2010. Returns provided by the database are net of fees. Our dataset runs from January 1995 to September 2012, for a total of 213 observations. In addition to the weighted composite index, our database includes all strategies which have reported data since at least January 1995—i.e., 11 strategies. We also include the indices of GAI strategy groups whose sample starts in January 1995—i.e., 4 strategy groups. We consider them like so many diversified portfolios. These strategy groups may also be viewed as funds of hedge funds which fill the gaps in the continuum of returns offered by hedge funds.[19] The description of our set of strategies appears in Table 1. Data for U.S. macroeconomic and financial variables are drawn from the FRED database, which is managed by the Federal Reserve Bank of St-Louis. Finally, the Fama and French factors are drawn from French's database[20] and the Fung and Hsieh lookback straddles come from Hsieh's database.[21]

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). This bias is accounted for in the GAI database as index returns for periods since 1994 include the defunct funds.[22] Other biases which are tackled for in the GAI database are the self-selection bias and the early reporting bias[23] (Cappoci and Hübner, 2004; Fung and Hsieh, 2004).

Table 2 reports the descriptive statistics of our hedge fund database. There is some heterogeneity in the historical returns and risk characteristics of hedge fund strategies. For instance, the monthly mean returns range from −0.07% for short sellers to 1.07% for value index, whereas the return standard deviation ranges from 1.29% for market neutral group to 5.83% for short sellers. A hedge fund's market beta is generally low, the average market beta computed over all strategies being equal to 0.22. Two strategies display a negative beta: short sellers (−0.91) and futures strategies (−0.08).[24] The strategy with the highest positive beta is the growth one (0.69) while the strategy with the lowest positive beta is, as expected, the equity market neutral one (0.08).

[16] Note that systemic risk is concerned with the *co-dependence* of financial institutions' risks and not with the individual risk of these institutions (Anginer et al., 2014).

[17] However, the *F* tests or Wald tests on groups of coefficients remain valid.

[18] For a summary of our approach to the GMM computation used in this paper—especially on the kind of instruments used—see Appendix A2.

[19] For the sake of simplicity, we consider from now on that our sample is composed of 15 strategies.

[20] The address of French's website is: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[21] The address of Hsieh's database is: https://faculty.fuqua.duke.edu/~dah7/HFData.htm.

[22] Source: Greenwich Global Hedge Fund Index Construction Methodology, Greenwich Alternative Investments (2015).

[23] Other problems related to hedge fund returns are due to illiquidity and the practice of return smoothing (Pástor and Stambaugh, 2003; Getmansky et al., 2004). The problems may lead to an underestimation of risk in the hedge fund industry.

[24] Selling short may thus be a dominant strategy for futures hedge funds.

Table 1
Description of hedge fund strategies.

Strategy	Description
Equity market neutral (arbitrage)	The managers aim at obtaining returns with low or no correlation with equity and bond markets. They exploit pricing inefficiencies between related equity securities
Distressed securities (event-driven)	The managers buy equity and debt at deep discounts issued by firms facing bankruptcy
Diversified event driven (event-driven)	The managers follow a multistrategy event driven approach
Long–short (directional)	This is the strategy which characterized hedge funds at their beginnings. Managers hold long positions in some securities and short positions in others
Growth (directional)	The managers invest in companies experiencing strong growth in earnings per share
Opportunistic (directional)	The managers' investment approach changes over time to better take advantage of current market conditions and investment opportunities
Short sellers (directional)	Managers take advantage of declining stocks
Value index (arbitrage)	Managers invest in securities which are perceived undervalued with respect to their "fundamentals"
Futures (arbitrage and directional)	The manager utilizes futures contracts to implement directional positions in global equity, interest rate, currency and commodity markets
Macro (directional)	These funds have a particular interest for macroeconomic variables. They take positions according to their forecasts of these variables
Multi-strategy index (directional)	The manager utilizes investment strategies from more than one of the four broad strategy group indices
Directional trading group (directional)	This group is composed of the strategies displaying the highest market betas
Event driven group (event driven)	The managers invest in event-driven situations—i.e., mergers, takeovers, reorganizations, leveraged buyouts, spin-offs and share buybacks
Market neutral group (arbitrage)	This group is composed of the strategies having a relatively low market beta
Speciality strategies group (directional)	This group is composed of the long–short credit strategy and multi-strategy

Sources: Greenwich Global Hedge Fund Index Construction Methodology, Greenwich Alternative Investments (2015); Saunders et al. (2014), chap. 5. The category in which a strategy is classified appears in parentheses.

Table 2
Descriptive Statistics, Greenwich Alternative Investment hedge fund strategy returns, 1995–2012.

	Mean (%)	Median (%)	Max (%)	Min (%)	sd (%0	Skew	Kurtosis	Sharpe ratio	CAPM-beta
Equity market neutral	0.77	0.60	8.10	−2.53	1.39	1.21	8.77	0.55	0.08
Distressed securities	0.90	1.16	9.30	−7.44	1.91	−0.27	7.40	0.47	0.21
Diversified event driven	0.97	1.10	11.70	−8.00	2.37	−0.02	6.31	0.41	0.34
Long–short	0.93	1.20	13.20	−9.24	2.99	0.03	5.01	0.31	0.49
Growth	0.93	1.04	20.10	−12.99	4.38	0.40	5.56	0.21	0.69
Opportunistic	1.03	1.14	21.20	−8.51	3.19	1.27	11.81	0.32	0.42
Short sellers	−0.07	−0.36	29.10	−21.30	5.83	0.37	6.77	−0.01	−0.91
Value index	1.07	1.40	9.90	−9.65	3.10	−0.37	3.97	0.34	0.53
Futures	0.89	0.45	11.90	−7.40	3.52	0.43	3.38	0.25	−0.08
Macro	0.54	0.60	15.00	−9.90	3.19	0.29	6.74	0.17	0.21
Multi-strategy index	0.85	0.86	8.80	−9.60	2.42	−0.12	5.65	0.35	0.35
Mean	0.80	0.83	14.39	−9.69	3.12	0.29	6.49	0.29	0.21
Directional trading group	0.81	0.64	7.50	−6.20	2.41	0.33	3.03	0.34	0.07
Event driven group	0.93	1.15	10.70	−6.90	2.03	−0.17	6.98	0.46	0.28
Market neutral group	0.78	0.90	5.10	−5.40	1.29	−0.94	7.66	0.60	0.17
Speciality strategies group	0.81	0.94	7.90	−12.50	2.26	−1.11	8.73	0.36	0.32
Weighted-composite index	0.90	1.09	10.10	−6.10	2.18	0.20	5.45	0.41	0.33
S&P500	0.78	1.29	10.93	−16.80	4.59	−0.67	3.84	0.17	1.00

Notes: sd is the standard deviation computed over the January 1995 to September 2012 period. The Sharpe ratio is the ratio of the index average excess return and the standard deviation of the index computed over the sample period. The CAPM beta is computed by regressing an index excess return on the market (S&P500) excess return. The beta is the slope of this regression. Table 1 provides the description of the strategies reported in Table 2.
Source: Greenwich Alternative Investment.

We can classify hedge fund strategies in three main categories according to the value of their market beta. Some strategies are directional in the sense that they are more exposed to the fluctuations of the overall stock market. They thus tend to have a higher beta than the strategies' average one. In this group, we may include growth (0.69), long–short (0.49), macro (0.21), futures (−0.08) and short-sellers' (−0.91) strategies. Note that the futures strategy displays a low beta but is usually considered as directional.[25] The value strategy could also be a candidate for this category since its beta is relatively high (0.53), but actually it is usually classified in the arbitrage category (Connor and Lasarte, 2005). The strategies with the highest beta are usually the ones which display the highest adjusted R^2 in standard multifactor return models such as the Fama and French model. Conversely, the strategies with the lowest beta—equity market neutral (0.08), and market neutral group (0.17)—are often involved in arbitrage activities—i.e., activities associated with the inefficiencies or mispricings observed on financial markets. A third usual category is the event driven one. Strategies like distressed securities, diversified event-driven, and opportunistic enter in this category. Their beta is usually moderate. Note that these three categories are not exclusive as a strategy may belong to two categories, such as the distressed one which may also be considered as an arbitrage strategy. Summarizing, hedge fund strategies may be classified into three categories: directional (higher market beta), arbitrage (lower market beta) and event-driven (moderate market beta).

The standard deviation of the GAI weighted return is less than the S&P500 return one over our sample period, the respective levels being 2.18% and 4.59% (Table 2). In fact, the rolling standard deviation of the return of the weighted composite index seems to

[25] See: Greenwich Alternative Investment, Greenwich Global Hedge Fund Index Construction Methodology.

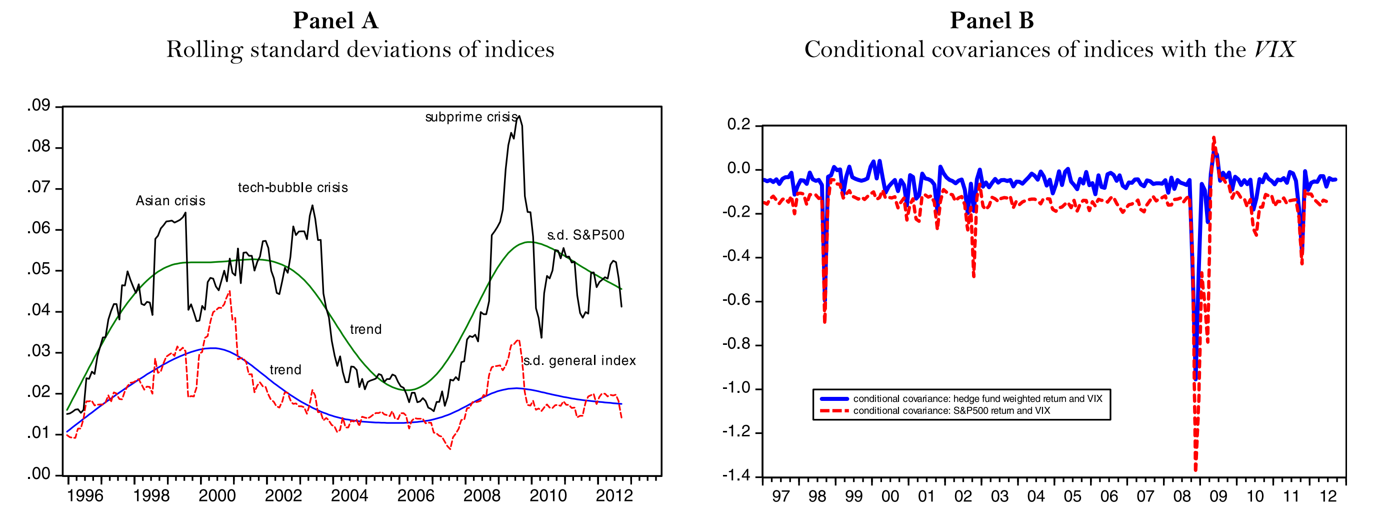

Fig. 7. Rolling standard deviations and conditional covariances with the *VIX*: GAI weighted composite return and S&P 500 return. *Notes*: The standard deviations are computed on a rolling window of twelve months. The trends of the standard deviations are built using the Hodrick–Prescott filter with a smoothing coefficient equal to 14400. The conditional covariances are computed with a MGARCH based on the BEKK procedure (Bollerslev et al., 1988; Engle and Kroner, 1995). The *VIX* is drawn from the FRED database, which is managed by the Federal Reserve Bank of St-Louis.

decline since 2000, which is not the case for the S&P500 return (Fig. 7). More importantly, the standard deviation of the weighted return increased less during the subprime crisis than during the tech-bubble one, while the standard deviation of the S&P500 return increased much more during the subprime crisis. This is first evidence of a decline of procyclicality in the hedge fund sector, which is further supported by our Quandt–Andrews breakpoint tests[26] on the cross-sectional dispersions reported below and our analysis of the co-movements of the strategies in Section 4 (Quandt, 1960; Andrews, 1993, 2003; Stock and Watson, 2003, 2011). Furthermore, the hedge fund weighted return co-moves less (negatively) with the *VIX*, a measure of volatility on financial markets (Fig. 7).

Not surprisingly, the strategies' standard deviations are positively correlated with their market betas (Fig. 8). Note that short sellers are outside the regression line relating standard deviation to market beta but actually, their beta—when measured in absolute value—is relatively high, consistent with the standard deviation of the returns of this strategy. The hedge fund mean return also co-moves positively with the beta (Fig. 9). According to the CAPM, the slope of this regression multiplied by the beta is equal to the risk premium of the strategy. However, there are two outliers: the macro and short sellers' strategies. Other risk factors must thus be relied on to explain their returns.

The strategies displaying the highest mean return are not necessarily those embedded with the highest Sharpe ratio—a risk-adjusted measure of returns. For instance, the value and opportunistic strategies have the highest mean return but their respective Sharpe ratio is close to the strategies' average. Conversely, the market neutral group has the highest Sharpe ratio (0.60) while its mean return is close to the corresponding strategies' average (0.81%).

Many strategy returns display negative skewness: event driven, distressed securities, diversified event driven, value index, specialty and the multi-strategy index. Returns of directional strategies tend to display a positive skewness. This contrasts with the

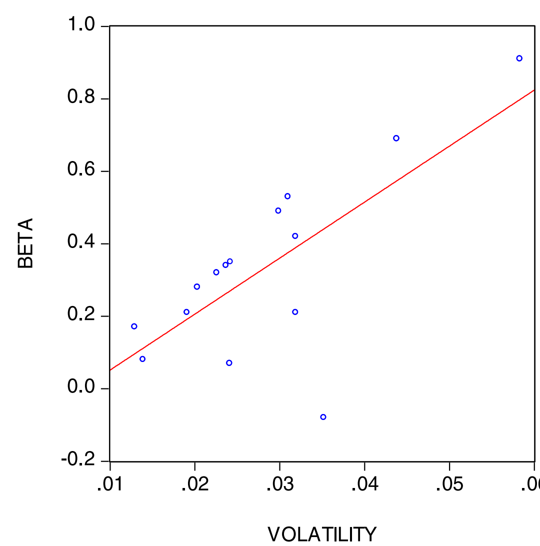

Fig. 8. Strategies' market beta and return volatility. *Notes*: See Table 2 for the statistics used in this table.

market portfolio return (S&P500) which is negatively skewed. Note that our results are more or less in line with Chan et al. (2005) and Heuson and Hutchinson (2011) who find that most hedge fund strategies display negative skewness, what they consider as an indication of tail risk. However, a more straightforward measure of tail risk is kurtosis. Most hedge funds present excess kurtosis. For our hedge fund strategies, kurtosis ranges from 3.38 (futures) to 11.81 (opportunistic index). Note also that there is a negative correlation between strategy kurtosis and standard deviation (Fig. 10). Since kurtosis is a direct measure of fat tail risk—i.e., risk associated with rare events—a strategy return volatility does not necessarily measure its whole market risk. In this sense, a more reliable risk measure would be the fourth cumulant, which combines standard deviation and kurtosis.

3.2. Stylized facts about cross-sectional dispersions

In this article, we analyze three cross-sectional dispersions related to hedge fund behavior: the cross-sectional variance of

[26] According to Stock and Watson (2011, p. 560), the *QLR* (Quandt likelihood ratio) statistic is given by: $QLR = MAX[F(\tau_0), F(\tau_0+1), \ldots, F(\tau_1)]$ $\tau_0 \leqslant \tau \leqslant \tau_1$ where $F(\cdot)$ refers to the standard *F* statistic evaluated at time τ. In other words, the *QLR* statistic is the maximum *F* statistic computed over a possible set of breakpoints stretched over the sample used. It is thus a generalization of the basic Chow test.

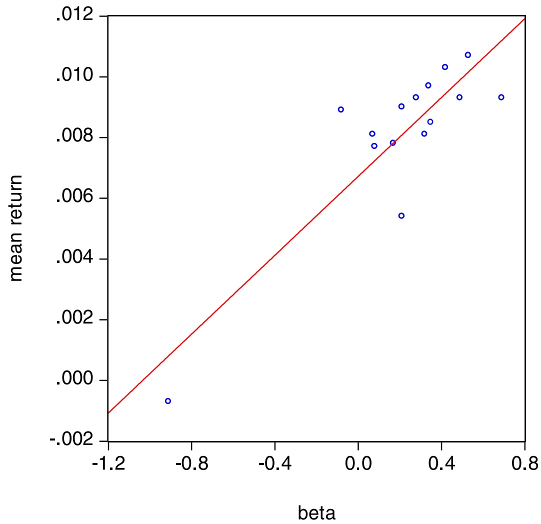

Fig. 9. Strategies' mean return and market beta. *Notes*: See Table 2 for the statistics used in this table.

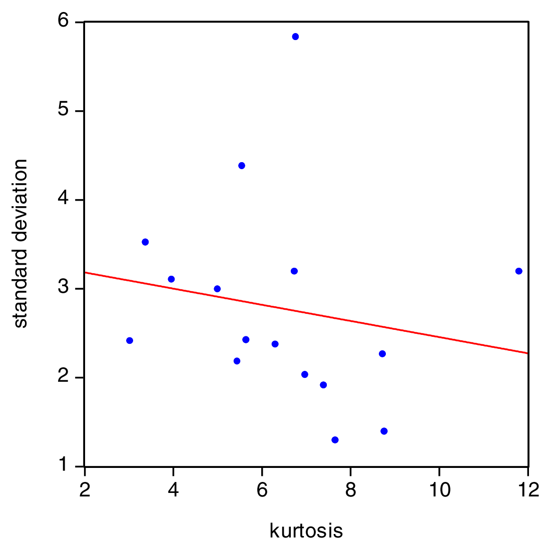

Fig. 10. Strategies' kurtosis and return standard deviation. *Notes*: See Table 2 for the statistics used in this table.

GAI hedge fund strategies' returns, and the cross-sectional standard deviation of these strategies' alphas and market betas. Fig. 11 plots our *disp*(*ret*) series and a moving average of the S&P500 return over the period 1995–2012. We note that *disp*(*ret*) tends to increase in periods of market slowdowns, which suggests that hedge fund strategies display a more heterogeneous pattern of returns in bad times. This pattern is consistent with the Black's (1976) leverage effect, whereby stock returns display more volatility when the market trends downwards. However, this pattern is not in line with the conjecture of Beaudry et al. (2001) who find that the cross-sectional dispersion of firm investment returns decreases when macroeconomic uncertainty increases. Note also that *disp*(*ret*) increased much more during the Asian and tech-bubble crises than during the subprime crisis. Further, in times of expansion, *disp*(*ret*) is quite low. Panel B of Fig. 11 provides further information on the behavior of *disp*(*ret*). It plots the Quandt–Andrews breakpoint test performed on this time series (Quandt, 1960; Andrews, 1993, 2003; Stock and Watson, 2003, 2011). This test is a dynamic Chow test which aims at identifying all breakpoints or regime changes in a time series. To run the test, we simply regress our cross-sectional time series on a constant. The test aims at pinning down changes in structure in the residuals, which are the deviations of a series from its sample mean. Panel B plots (i) the *F* statistic on which the test is based, (ii) its supremum—i.e., the Quandt likelihood ratio (*QLR*) or sup-Wald statistic—and (iii) the 1% critical *F* value of the test. The test clearly confirms the presence of a breakpoint during the tech-bubble, the *QLR*, at 30.97, being well above the test critical value (13.21). The test also suggests that no significant breakpoint occurred during the subprime crisis.

In contrast to strategies' returns, *disp*(*beta*) tends to decrease in times of economic slowdown (Fig. 12). This suggests that hedge fund strategies become more homogeneous in terms of market betas when business conditions worsen. In other words, hedge fund managers "herd" by taking less risk or by decreasing their market beta. This behavior supports Beaudry et al.'s (2001) conjecture—i.e., that investors take less risk in times of rising macroeconomic uncertainty.[27] This observation is also in line with the works of Baum et al. (2002, 2004, 2009), Quagliariello (2007, 2008, 2009), and Calmès and Théoret (2014) who find that banks adopt a more prudent behavior in times of macroeconomic uncertainty: they decrease the weight of their risky assets in their balance sheets and hoard liquidities. Moreover, *disp*(*beta*) is *forward-looking* with respect to the output gap (Fig. 12). Hence, hedge funds anticipate an economic downturn and decrease their market beta before the occurrence of this downturn.[28] The link between *disp*(*beta*) and macroeconomic uncertainty will be tested in the empirical section. Note that *disp*(*beta*) seems to decrease from the late 1990s to the early 2000s. Indeed, it was especially high during the Asian crisis and at the start of the tech-bubble episode but later, its behavior seems to evolve according to a mean-reverting process. Note that the decrease in *disp*(*beta*) was severe during the subprime crisis. But since the end of 2008, this cross-sectional dispersion has progressively returned toward its pre-crisis level, which suggests higher diversification benefits for hedge fund investors. Panel B of Fig. 12 provides the Quandt–Andrews breakpoint test applied to *disp*(*beta*) (Quandt, 1960; Andrews, 1993, 2003; Stock and Watson, 2003, 2011). According to the test, the breakpoints in the series occurred during times of financial crisis. For the first breakpoint, observed during the tech-bubble, the *QLR* (306.19) is well above the 1% critical value (144.52). Furthermore, during the subprime crisis, the *F* statistic peaks at a level just below the 1% critical value, which may be considered as another breakpoint in the *disp*(*beta*) series.

Turning to *disp*(*alpha*), first note that it tends to decrease over our sample period, suggesting a more homogeneous pattern for strategies' alphas (Fig. 13). Similarly to market betas, this pattern is mainly due to the late 1990s and the early 2000s when the dispersion of alphas was particularly high. Second, in contrast to *disp* (*beta*), *disp*(*alpha*) has increased during the subprime crisis, suggesting that funds delivered a wide range of alphas during this episode. More precisely, some strategies—as distressed securities, event driven, market neutral and futures—benefited from the crisis, which contributed to increase the dispersion of strategies' alphas (Racicot and Théoret 2014a). Finally, Panel B of Fig. 13 provides the Quandt–Andrews breakpoint test performed on *disp*(*alpha*) (Quandt, 1960; Andrews, 1993, 2003; Stock and Watson, 2003, 2011). The result of the test is quite different from the ones obtained for *disp*(*ret*) and *disp*(*beta*). Indeed, the test does not highlight the crises but rather the drop in the *disp*(*alpha*) series observed over the 2003–2005 period. There is also a less significant

[27] This asymmetry in the behavior of hedge funds with respect to macroeconomic variables was observed by many researchers (e.g., Lo, 2001; Cai and Liang, 2012).

[28] For the time-varying aspects of risk, see the: Royal Swedish Academy of Sciences, 2013, Understanding Asset Prices.

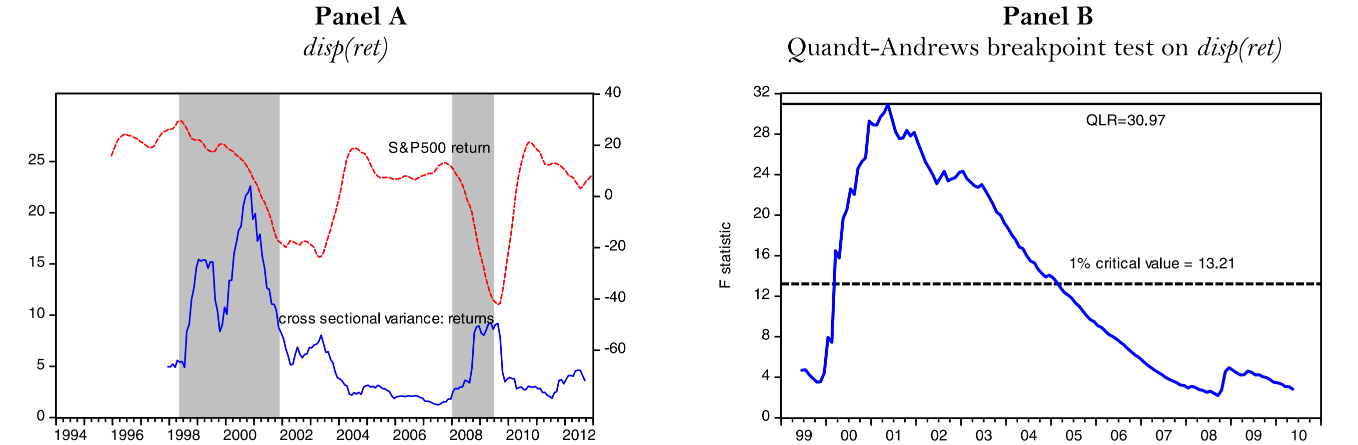

Fig. 11. Cross-sectional variance of hedge funds returns (*disp*(*ret*)) and moving average (12 months) of the S&P500 return. Quandt–Andrews breakpoint test on *disp*(*ret*). *Notes*: Shaded areas are associated with periods of economic slowdown. *QLR* is the abbreviation of "Quandt likelihood ratio". See Quandt (1960), Andrews (1993, 2003), Stock and Watson (2003, 2011).

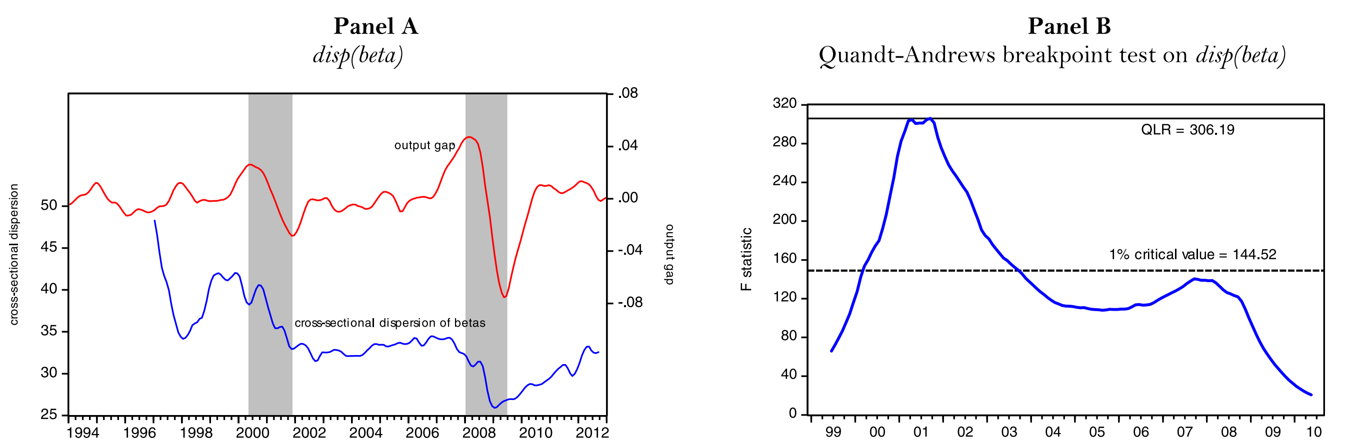

Fig. 12. Cross-sectional dispersion of strategies' market betas (*disp*(*beta*)). Quandt–Andrews breakpoint test on *disp*(*beta*). *Notes*: Shaded areas are associated with periods of economic slowdown. To compute the monthly output gap, we first take the log of the industrial production. We then detrend this transformed series with the Hodrick–Prescott filter using a smoothing coefficient (λ) equal to 14400—the trend of the series being a measure of potential output. The resulting residuals are the output gap measure. *QLR* is the abbreviation of "Quandt likelihood ratio". See Quandt (1960), Andrews (1993, 2003), Stock and Watson (2003, 2011).

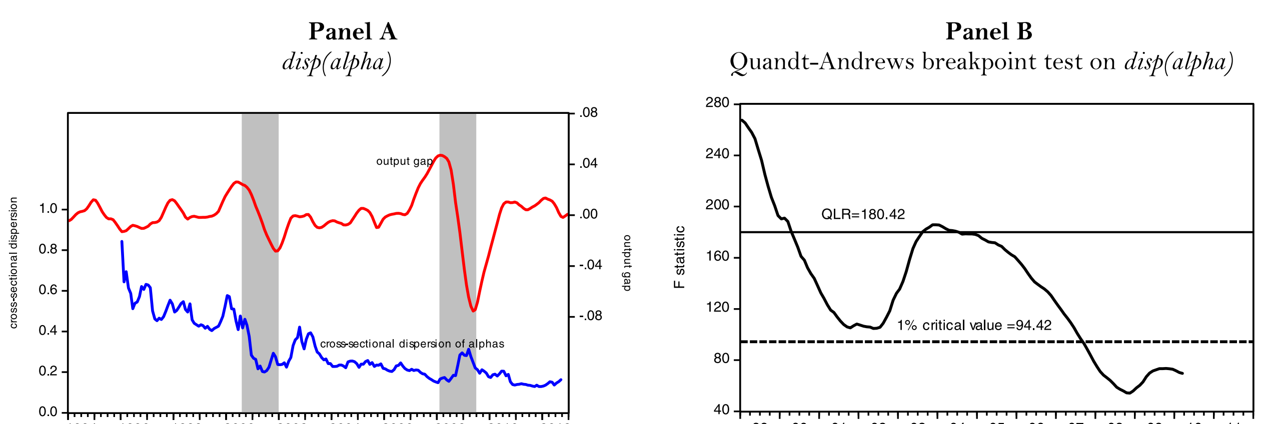

Fig. 13. Cross-sectional dispersion of strategies' alphas (*disp*(*alpha*)). Quandt–Andrews breakpoint test on *disp*(*alpha*). *Notes*: Shaded areas are associated with periods of economic slowdown. To compute the monthly output gap, we first take the log of the industrial production. We then detrend this transformed series with the Hodrick–Prescott filter using a smoothing coefficient (λ) equal to 14400—the trend of the series being a measure of potential output. The resulting residuals are the output gap measure. *QLR* is the abbreviation of "Quandt likelihood ratio". See Quandt (1960), Andrews (1993, 2003), and Stock and Watson (2003, 2011).

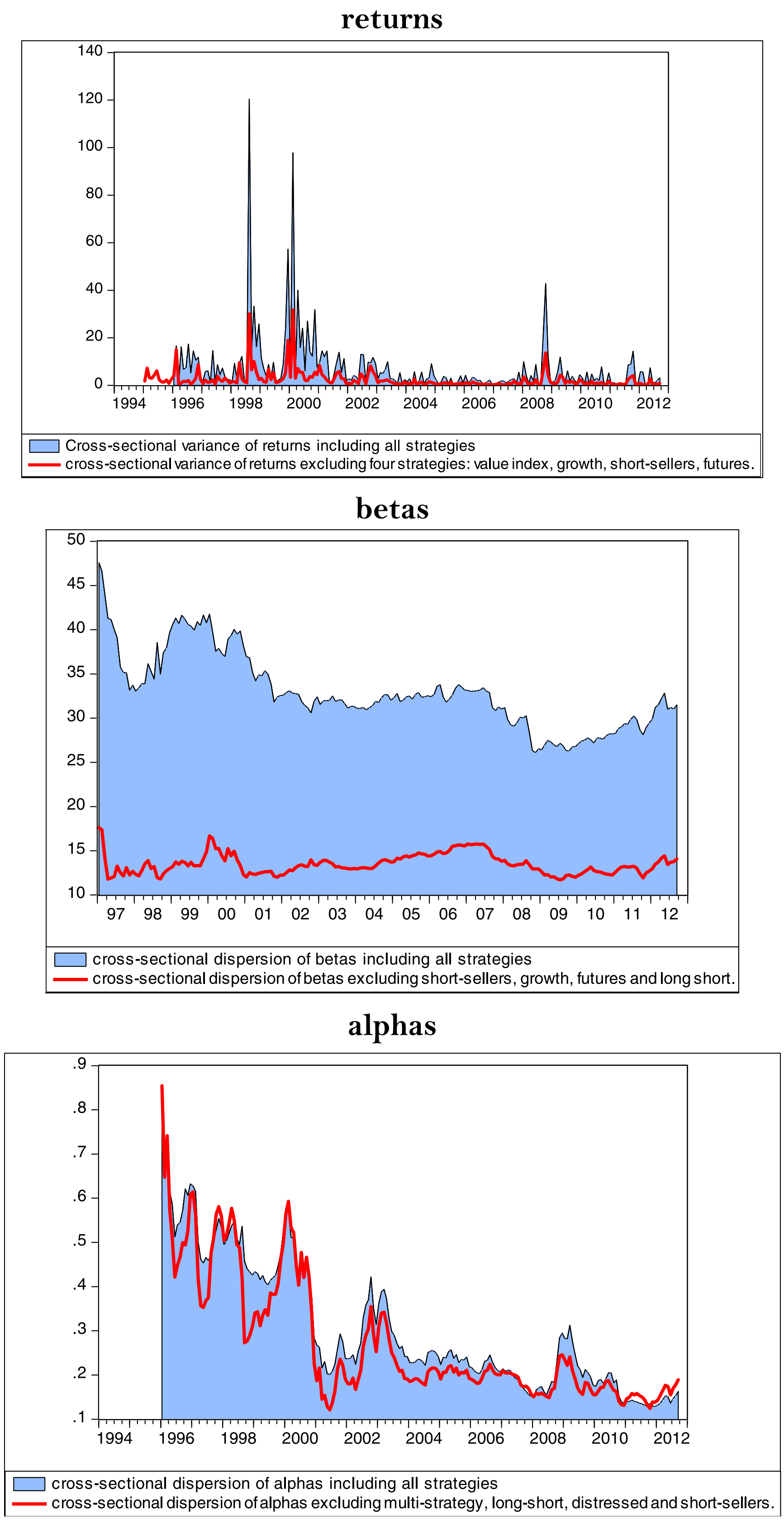

Fig. 14. Analysis of the composition of hedge fund cross-sectional dispersions.

Table 3
Estimation of the conditional variances of macroeconomic and financial variables.

	Mean equation				Conditional variance					R^2	DW
	c	AR(1)	AR(2)	MA(1)	η_2	η_3	η_4	$\varphi1$	$\varphi2$		
gprod	2.35	0.53	0.26	−0.52	−0.30	−0.04	0.85			0.19	1.97
	(2.05)	(4.45)	(3.42)	(−4.56)	(−5.85)	(−0.64)	(16.30)				
r10	0.05	0.78		0.33	0.07	−0.09	0.95			0.77	1.93
	(0.75)	(21.02)		(5.06)	(3.27)	(−3.17)	(85.36)				
inf	2.61	0.36	−0.16		0.09	0.40	0.93			0.18	1.72
	(14.61)	(4.73)	(−2.69)		(2.02)	(5.31)	(34.81)				
rSP500	5.30	0.80		−0.63	−0.42	0.15	0.81			0.04	1.84
	(0.83)	(7.00)		(−4.56)	(−4.71)	(1.25)	(10.66)				
gcredit	1.14	0.91			−0.18	0.11	0.98			0.81	1.92
	(0.39)	(68.51)			(−5.54)	(4.18)	(114.62)				
spread	1.25	0.68		0.46				−0.35	0.89	0.93	0.65
	(10.57)	(11.17)		(2.35)				(−7.33)	(11.45)		

Notes: The dependent variables are the following: *gprod*: monthly rate of growth of the industrial production; *r10*: ten-year interest rate; *inf*: monthly inflation; *rSP500*: S&P500 monthly return; *gcredit*: monthly growth of a global measure of consumer credit; *spread*: term spread. The estimated η correspond to the coefficients of Eq. (17) whilst the ϕ coefficients are those of Eq. (16). See Appendix A1 for more details.

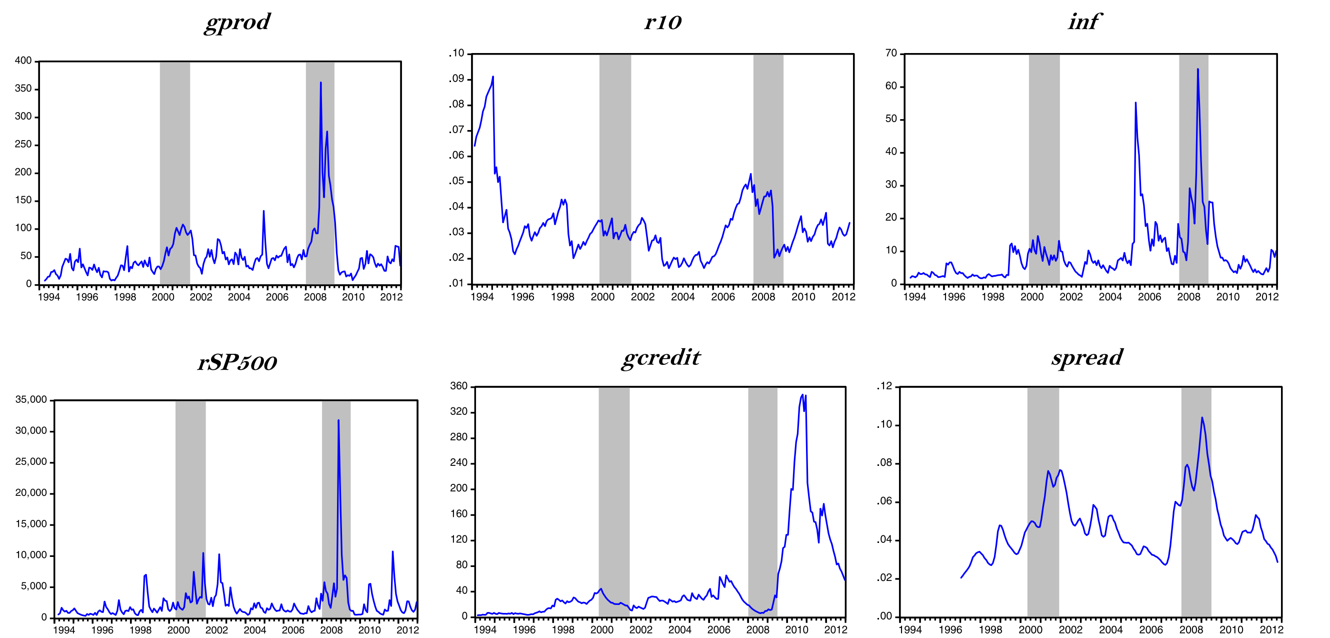

Fig. 15. Conditional variances of some macroeconomic and financial variables. *Notes*: Shaded areas are associated with periods of economic slowdown. The construction of these series is explained in Section 4.1 and Appendix A1. The definition of the variables is the following: *gprod*: industrial production growth; *r10*: ten-year interest rate on U. S. Government bonds; *inf*: inflation rate; *rSP500*; monthly return on the S&P500 index; *gcredit*: credit growth; *spread*: term spread.

breakpoint observed at the beginning of the series, while it was also on a downward trend. However, we do not have enough observations at our disposal to conclude that these regime changes associated with decreases in *disp*(*alpha*) are structural.

It is interesting to identify the strategies which contribute the most to the cross-sectional dispersions.[29] Fig. 14 provides the cross-sectionals dispersions of returns, betas and alphas with and without strategies which contribute the most to these cross-sectional dispersions. Strategies which contribute the most to the cross-sectional dispersion of returns are, in order of importance: value index, growth, short sellers and futures. The cross-sectional dispersion of returns excluding these strategies has a lower amplitude, especially during crises, but its general profile remain unchanged compared to the dispersion including all strategies.[30] The same comments apply for the cross-sectional dispersion of betas. However, the strategies contributing the most to this cross-sectional dispersion are somewhat different. These are, in order of importance: short-sellers, growth, futures and long–short.[31] Finally, strategies contributing the most to the cross-sectional dispersion of alphas are: multi-strategy, long–short, distressed, short-sellers. However, the cross-sectional dispersion of alphas is not reduced substantially following the removal of these strategies.

Summarizing, albeit procyclicality remains important in the hedge fund sector, it seems to decrease through time in our sample. Indeed, in contrast to the return on the S&P500, the standard deviation of hedge fund weighted return was lower during the subprime crisis than during the tech-bubble one. The Quandt–Andrews breakpoint tests performed on *disp*(*ret*) and *disp*(*beta*)

[29] To identify strategies which contribute the most to our three categories of cross-sectional dispersions—returns, betas and alphas—we relied on two procedures. First, we selected strategies with the highest standard deviations of returns, betas and alphas, respectively. Second, we regressed the cross-sectional dispersions of returns, betas and alphas on the squares of strategies' returns, betas, and alphas, respectively. Strategies with the highest positive coefficients contribute the most to the respective cross-sectional dispersion. Note that the two methods used to identify strategies which contribute the most to the cross-sectional dispersions give quite similar results.

[30] The long–short and equity market neutral strategies contribute to reduce significantly the cross-sectional dispersion of returns.

[31] The distressed securities strategy contributes to reduce the cross-sectional dispersion of betas.

Table 4
OLS estimations of models of the cross-sectional variance of strategies' returns, 1997–2012.

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
c	−1.01	−4.61	0.98	−5.87	2.12	−3.23	−5.73	−3.03	−3.88
	(−0.55)	(−2.07)	(0.47)	(−1.83)	(2.63)	(−1.98)	(−2.82)	(−1.42)	(−1.33)
gprod	0.18	0.18						0.18	
	(2.50)	(2.64)						(2.73)	
cv_gprod	0.04	0.03						0.03	
	(2.61)	(1.75)						(1.65)	
r10	−3.21	−1.25	−4.12	−1.33	−2.53	0.47			
	(−1.95)	(−0.71)	(−2.22)	(−0.63)	(−3.85)	(0.37)			
cv_r10	1.54	1.28	1.64	0.94	0.36	−0.08			
	(2.65)	(2.22)	(2.37)	(1.62)	(1.13)	(−0.23)			
VIX		0.21		0.32		0.28	0.38	0.31	0.32
		(2.76)		(3.82)		(3.32)	(4.29)	(4.20)	(4.49)
inf			0.38	1.12					0.64
			(1.13)	(2.53)					(1.28)
cv_inf			−0.10	−0.11					−0.16
			(−2.57)	(−2.56)					(−3.29)
rSP500					−0.01	−0.01			
					(−1.78)	(−3.88)			
cv_rSP500					259.44	1409.66			
					(5.37)	(3.11)			
gcredit							0.43		
							(3.94)		
cv_gcredit							−0.01		
							(−1.96)		
spread								−1.97	−1.91
								(−0.28)	(−4.10)
cv_spread								41.24	75.12
								(0.74)	(2.11)
Dum_bub	84.29	83.15	85.48	84.34	66.78	113.06	83.48	81.71	82.98
	(19.20)	(19.20)	(5.85)	(5.52)	(12.88)	(26.91)	(5.49)	(19.89)	(5.46)
Descriptive statistics									
R^2	0.69	0.70	0.68	0.71	0.61	0.57	0.70	0.73	0.73
DW	1.45	1.55	1.53	1.71	1.40	1.77	1.71	1.70	1.84
n	189	189	189	189	189	189	189	189	189

Notes: The columns correspond to various specifications of our benchmark model (Eq. (8)). The explanatory variables are the following: *gprod*: monthly growth of industrial production; *cv_gprod*: conditional variance of *gprod*; *r10*: ten-year interest rate; *cv_r10*: conditional variance of *r10*; *VIX*: implicit volatility of options on S&P500; inf: monthly inflation; *cv_inf*: conditional variance of *inf*; *rSP500*: S&P500 monthly return; *cv_SP500*: conditional variance of *rSP500*; *gcredit*: monthly growth of a global measure of consumer credit; *cv_gcredit*: conditional variance of *gcredit*; *spread*: term spread; *cv_spread*: conditional variance of *spread*; *Dum_bub*: dummy variable taking the value of 1 on August 1998, December 1999 and February 2000, three outliers in the hedge fund return time series. The Newey-West *t* statistics are displayed in parentheses. *n* is the number of observations

also suggest that the changes in regime observed for these series were much more significant during the tech-bubble crisis than during the subprime crisis. Hence, we conjecture that a learning process is at play in the hedge fund sector whereby hedge fund managers are becoming, with the help of the development of structured products, more experimented in managing risk.

4. Empirical results

4.1. The construction of the measures of macroeconomic uncertainty

We rely on six macroeconomic and financial variables to measure $\mu_{mv,t}$ in Eq. (8): the growth of industrial production (*gprod*); the detrended[32] ten-year interest rate (*r10*); the rate of inflation (*inf*); the return on the S&P500 (*rSP500*); the growth of consumer credit (*gcredit*)[33]; the term spread—i.e., the spread between the 10-year interest rate and the 3-month interest rate (*spread*). These variables are alternative measures of macroeconomic and financial risk (first moments) in our models. For each of these variables, we compute the corresponding measure of macroeconomic and financial uncertainty (second moments)—i.e., the conditional variances of these variables.

As specified in Appendix A1, the mean equation of a macroeconomic or financial variable is estimated using an ARMA (*p*,*q*) model and its corresponding conditional variance using a GARCH or an EGARCH procedure depending on the nature of conditional heteroskedasticity. In the framework of our study, the conditional variance of a macroeconomic or financial variable gauges the uncertainty stemming from this variable. Table 3 provides the estimations of the mean and variance equations of our macroeconomic and financial variables.

The estimated coefficients of AR(1) indicate that many of these variables are quite persistent, these coefficients being over 0.75 for three of them: *gcredit* (0.91), *rSP500* (0.80) and *r10* (0.78). More importantly, among our measures of uncertainty, three display the Black's leverage effect—i.e., *gprod*, *rSP500* and *gcredit*. Indeed, the coefficient of asymmetry (η_2) is negative for these variables, which suggests that they are more volatile in times of economic slowdown. Fig. 15, which plots the conditional variances of the variables appearing in Table 3, clearly shows that these variables are much more volatile in bad times (shaded areas in the plots).[34] The conditional variance of the term spread appears also to be more volatile during recessions, even if this volatility was estimated using a GARCH(1,1) procedure. In contrast, the coefficient of asymmetry is positive for *r10* and *inf*, which supports the view that these variables tend to be more volatile in good times.

[32] According to the Dickey–Fuller test, the ten-year interest rate is trend-stationary.

[33] Consumption is a crucial determinant of economic activity and a key variable in asset pricing models. So we add the growth of consumer credit in our set of macroeconomic time series as an indicator of the state of credit in the economy.

[34] This asymmetry is often observed for the volatility of macroeconomic variables.

Table 5
GMM estimations of models of the cross-sectional variance of strategies' returns, 1997–2012.

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
c	−0.98	−3.03	1.06	−9.84	2.40	−2.49	−2.96	−3.78	−6.53
	(−1.20)	(−2.95)	(0.51)	(−2.57)	(1.37)	(−1.03)	(−2.19)	(−10.65)	(−1.16)
gprod	0.09	−0.001						0.18	
	(2.26)	(−0.04)						0.18	
cv_gprod	0.03	0.02						0.02	
	(3.16)	(2.15)						(9.26)	
r10	−3.52	−2.44	−4.15	0.31	−3.11	−1.12			
	(−2.74)	(−2.16)	(−2.23)	(−0.13)	(−1.90)	(−0.64)			
cv_r10	1.50	0.60	1.64	0.00	1.07	0.94			
	(4.17)	(1.94)	(2.51)	(0.00)	(1.84)	(1.65)			
VIX		0.21		0.60		0.27	0.30	0.39	0.53
		(5.04)		(3.44)		(2.90)	(4.23)	(24.20)	(2.21)
inf			0.38	1.44					1.09
			(1.13)	(3.01)					(1.25)
cv_inf			−0.11	−0.15					−0.15
			(−2.50)	(−2.61)					(−2.51)
rSP500					−0.03	−0.03			
					(−2.70)	(−2.50)			
cv_rSP500					146.53	−376.71			
					(0.56)	(−1.20)			
gcredit							0.40		
							(2.95)		
cv_gcredit							−0.01		
							(−2.92)		
spread								−2.00	−1.79
								(−31.00)	(−3.44)
cv_spread								25.38	21.09
								(2.63)	(0.36)
Dum_bub	82.67	104.51	85.46	80.32	85.38	83.84	84.46	81.30	82.15
	(12.84)	(21.47)	(5.83)	(6.03)	(19.63)	(19.51)	(5.45)	(135.20)	(5.40)
Descriptive statistics									
R^2	0.69	0.66	0.68	0.72	0.69	0.70	0.71	0.73	0.72
DW	1.44	1.63	1.53	1.70	1.57	1.63	1.71	1.73	1.88
n	189	189	189	189	189	189	189	189	189

Notes: The columns correspond to various specifications of our benchmark model (Eq. (8)). The explanatory variables are the following: *gprod*: monthly growth of industrial production; *cv_gprod*: conditional variance of *gprod*; *r10*: ten-year interest rate; *cv_r10*: conditional variance of *r10*; *VIX*: implicit volatility of options on S&P500; inf: monthly inflation; *cv_inf*: conditional variance of *inf*; *rSP500*: S&P500 monthly return; *cv_SP500*: conditional variance of *rSP500*; *gcredit*: monthly growth of a global measure of consumer credit; *cv_gcredit*: conditional variance of *gcredit*; *spread*: term spread; *cv_spread*: conditional variance of *spread*; *Dum_bub*: dummy variable taking the value of 1 on August 1998, December 1999 and February 2000, three outliers in the hedge fund return time series. The Newey-West *t* statistics are displayed in parentheses. *n* is the number of observations. Our GMM procedure is explained in Appendix A2.

4.2. The cross-sectional dispersion of strategies' returns (disp(ret))[35]

Table 4 provides OLS estimations of nine specifications of Eq. (8) for *disp*(*ret*) while Table 5 delivers the corresponding GMM estimations.[36] The results support the view found in the literature (Adrian, 2007; Sabbaghi, 2012) that the cross-sectional dispersion of stock returns has a tendency to increase in periods of financial crisis. Our contribution here is to explain the cross-sectional dispersion using a rigorous model which gauges the impact of macroeconomic risk and uncertainty on the cross-sectional dispersion of returns.

According to Table 4, *disp*(*ret*) reacts positively most of the time to macroeconomic uncertainty.[37] For instance, the conditional variances of the growth of industrial production, of the 10-year rate, of the return on the S&P500, and of the term spread impact positively the cross-sectional dispersion. In many specifications of Eq. (8), we

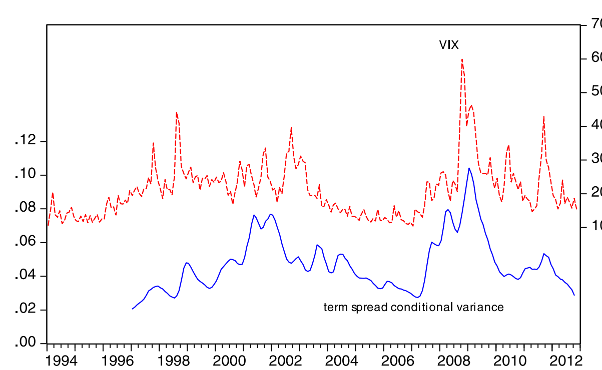

Fig. 16. *VIX* and term spread conditional variance. *Note*: The *VIX* is drawn from the FRED database, which is managed by the Federal Reserve Bank of St-Louis.

have first excluded the *VIX*—an indicator of the implicit volatility of stock returns (S&P500)—and then included it to assess its differential impact. In all cases, *VIX* impacts quite positively and significantly *disp*(*ret*). In this respect, the *VIX* shares many similarities with other measures of financial volatility—as the conditional variance of the term spread (Fig. 16) and the conditional variance of the stock market return (Fig. 17). The co-variation between the *VIX* and the conditional variance of the term spread has been particularly high since 2000, regardless of the phase of the business cycle. In comparison, similarly to the *VIX*, the conditional variance of the stock market

[35] Note that we performed Dickey–Fuller (DF) tests to pin down unit roots in our cross-sectional dispersion series. Regarding the cross-sectional dispersions of returns and market betas, the DF test rejects the presence of a unit root at the 5% threshold. For the cross-sectional dispersion of alphas, the rejection threshold is 10% but we have not differentiated this series due to the lack of power of the DF test.

[36] Note that we removed the first two years of the simulated strategies' alphas and betas computed with the Kalman filter because, as usual, the results of the filter are unstable at the start of the computation. Therefore, twenty-four observations are lost. It thus remains 189 observations to run the estimations from Tables 4–8.

[37] Even if our methodology aims at analyzing only one source of macroeconomic risk and uncertainty at a time, we have retained the 10-year rate in some specifications because its contribution was significant.

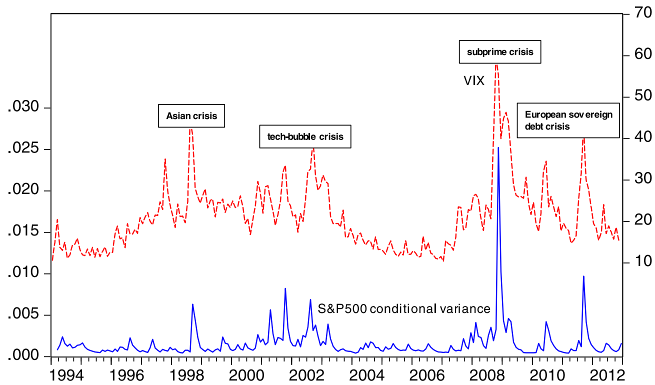

Fig. 17. *VIX* and S&P500 conditional variance. *Note*: The *VIX* is drawn from the FRED database, which is managed by the Federal Reserve Bank of St-Louis.

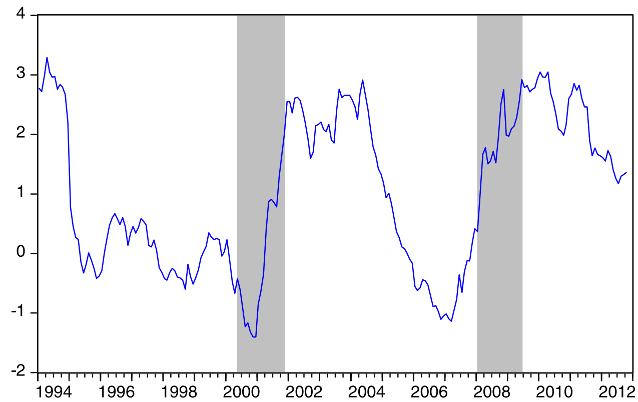

Fig. 18. Term spread. *Note*: Shaded areas are associated with periods of economic slowdown. The term spread is the spread between the 10-year interest rate on the U.S. Government bonds and three-month T-bills.

return tracks quite well the periods of financial crises—registering jumps during these episodes—but, in contrast to the *VIX*, this conditional variance is quite stable in good times. Surprisingly, when adding *VIX* in specification (5) to obtain specification (6), the effect of the conditional variance of the stock market return is strengthened.

The impact of the conditional variances of inflation and credit growth on *disp*(*ret*) differs from the other measures of macroeconomic uncertainty, in the sense that they influence negatively the cross-sectional dispersion. In this respect, Beaudry et al. (2001) find that inflation uncertainty decreases the cross-sectional dispersion of returns on firm investment projects because it adds noise to the signals delivered by market prices. *Mutatis mutandis*, inflation blurs the signals issued by the stock market and this might explain why *disp*(*ret*) decreases when inflation uncertainty increases. In other respects, credit growth is a lagged indicator of economic activity. The negative impact of this factor may indicate that *disp*(*ret*) mean-reverts after having absorbed other shocks which are more contemporaneous with the cross-sectional dispersion.

Table 6
OLS estimations of models of the cross-sectional dispersion of strategies' market betas, 1997–2012.

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
c	32.98	33.58	2.52	1.95	2.84	2.10	2.60	2.71	3.03
	(27.48)	(26.42)	(4.42)	(2.98)	(3.93)	(4.17)	(5.17)	(3.36)	(3.44)
gprod	0.01	0.01							
	(2.33)	(2.02)							
cv_gprod	−0.01	−0.01							
	(−4.40)	(−3.29)							
r10			−0.50						
			(−2.38)						
cv_r10			−0.01						
			(−0.24)						
VIX		−0.06	−0.03		−0.02		−0.01	−0.02	−0.02
		(−7.08)	(−3.73)		(−3.21)		(−1.66)	(−3.17)	(−2.44)
inf				−0.02	−0.09				
				(−0.40)	(−1.90)				
cv_inf				−0.01	−0.01				
				(−2.08)	(−1.20)				
rSP500						0.01	0.01		
						(3.76)	(5.40)		
cv_rSP500						−80.21	−49.68		
						(−2.87)	(−2.18)		
gcredit								0.05	
								(1.91)	
cv_gcredit								−0.01	
								(−2.92)	
spread									0.00
									(0.01)
cv_spread									−8.50
									(−2.74)
Descriptive statistics									
R^2	0.95	0.96	0.95	0.95	0.96	0.96	0.95	0.96	0.96
DW	1.91	2.01	1.99	1.96	1.97	2.11	2.04	1.97	1.94
n	189	189	189	189	189	189	189	189	189

Notes: The columns correspond to various specifications of our benchmark model. The explanatory variables are the following: *gprod*: annual growth of industrial production; *cv_gprod*: conditional variance of gprod; *r10*: ten-year interest rate; *cv_r10*: conditional variance of *r10*; *VIX*: implicit volatility of options on S&P500; *inf*: monthly inflation; *cv_inf:* conditional variance of *inf*; *rSP500*: S&P500 monthly return; *cv_SP500*: conditional variance of *rSP500*; *gcredit*: monthly growth of a global measure of consumer credit; *cv_gcredit*: conditional variance of *gcredit*; *spread*: term spread; *cv_spread*: conditional variance of *spread*. The Newey-West *t* statistics are displayed in parentheses. *n* is the number of observations.

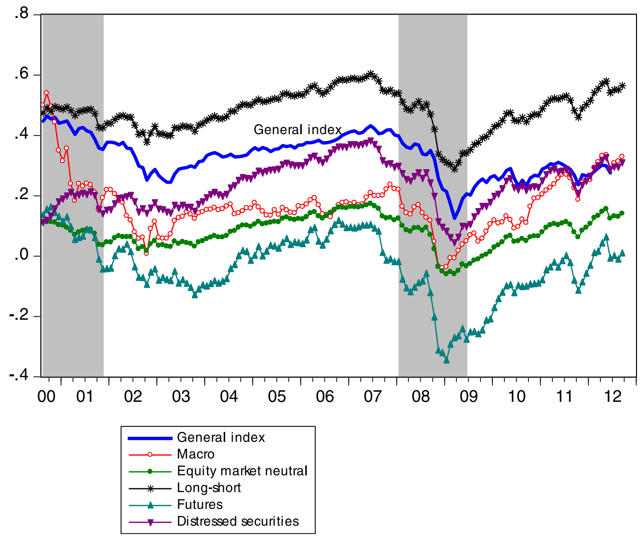

Fig. 19. Time-varying market betas of several hedge fund strategies. *Notes*: The time-varying market betas are computed using the Kalman Filter (Harvey, 1989; Racicot and Théoret, 2010 2014a). Shaded areas are associated with periods of economic slowdown.

Turning to the influence of the first moments of economic and financial variables—which, in our framework, measure macroeconomic and financial risk—we note that, except for the return indicators, an increase in the first moments tends to increase *disp* (*ret*) significantly. For instance, an increase in the rates of growth of industrial production and credit leads to more heterogeneous strategies' returns, strategies reacting differently to these factors. Inflation also impacts positively *disp*(*ret*), some strategies benefiting from inflation while others are impacted negatively by this factor.

In contrast, an increase in the 10-year rate, in the stock market return and in the term spread—i.e., three financial return variables—leads to a decrease in *disp*(*ret*). These increases contribute to raise the hedge fund margin—i.e., the spread between the hedge fund gross return and their cost of funding—and thus tend to make strategies more homogeneous in terms of returns. The case of the term spread is particularly interesting. As evidenced by Fig. 18, the term spread is a countercyclical indicator, decreasing when business conditions improve and increasing when business conditions worsen. The negative sign attached to the coefficient of the term spread in the cross-sectional dispersion model is thus consistent with the estimated positive co-movement between *disp*(*ret*) and the industrial production growth.

Similarly to Baum et al. (2002, 2004, 2009) and Calmès and Théoret (2014), it is interesting to report the elasticities of several macroeconomic and financial variables analyzed to gauge the relative importance of their impact on *disp*(*ret*). The elasticity (ζ) of Y with respect to X is equal to: $\zeta = \frac{\Delta Y}{Y} / \frac{\Delta X}{X} = \frac{\Delta Y}{\Delta X} \times \frac{X}{Y}$. The econometric counterpart of this formula is: $\zeta = coef \times \frac{\bar{X}}{\bar{Y}}$, where *coef* is the estimated coefficient of X—i.e., the slope $\frac{\Delta Y}{\Delta X}$—and $\bar{X}$ and $\bar{Y}$ are, respec-

Table 7
GMM estimations of models of the cross-sectional dispersion of strategies' market betas, 1997–2012.

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
c	32.59	34.33	2.43	1.45	2.29	1.70	3.28	4.55	3.43
	(24.65)	(25.57)	(3.98)	(2.30)	(1.36)	(3.41)	(1.60)	(4.42)	(1.68)
gprod	0.02	0.02							
	(2.25)	(2.72)							
cv_gprod	−0.01	−0.01							
	(−1.78)	(−2.40)							
r10			−0.44						
			(−1.94)						
cv_r10			−0.08						
			(−1.22)						
VIX		−0.08	−0.03		−0.04		0.00	−0.04	−0.05
		(−4.23)	(−2.07)		(−2.25)		(0.51)	(−3.36)	(−1.95)
inf				−0.01	−0.16				
				(−0.15)	(−2.18)				
cv_inf				−0.01	0.00				
				(−2.93)	(0.00)				
rSP500						0.01	0.01		
						(3.26)	(3.65)		
cv_rSP500						−82.71	−112.56		
						(−3.14)	(−2.52)		
gcredit								0.05	
								(1.95)	
cv_gcredit								−0.02	
								(−2.02)	
spread									−0.08
									(−0.77)
cv_spread									9.90
									(1.06)
Descriptive statistics									
R^2	0.95	0.96	0.96	0.95	0.95	0.96	0.95	0.95	0.95
DW	1.93	1.98	2.01	1.97	1.92	2.12	1.95	1.76	1.70
n	189	189	189	189	189	189	189	189	189

Notes: The columns correspond to various specifications of our benchmark model. The explanatory variables are the following: *gprod*: annual growth of industrial production; *cv_gprod*: conditional variance of gprod; *r10*: ten-year interest rate; *cv_r10*: conditional variance of *r10*; *VIX*: implicit volatility of options on S&P500; *inf*: monthly inflation; *cv_inf*: conditional variance of *inf*; *rSP500*: S&P500 monthly return; *cv_SP500*: conditional variance of *rSP500*; *gcredit*: monthly growth of a global measure of consumer credit; *cv_gcredit*: conditional variance of *gcredit*; *spread*: term spread; *cv_spread*: conditional variance of *spread*. The Newey-West *t* statistics are displayed in parentheses. *n* is the number of observations Our GMM procedure is explained in Appendix A2.

Table 8
OLS estimations of models of the cross-sectional dispersion of strategies' alphas, 1997–2012.

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
c	0.001	0.002	−0.010	0.008	−0.003	0.002	0.003	0.005	0.0008
	(0.37)	(−0.43)	(−1.20)	(3.64)	(−0.81)	(0.61)	(0.78)	(1.27)	(1.23)
gprod	9.11E−05	0.001							
	(0.65)	(−1.46)							
cv_gprod	5.38E−05	1.20E−05							
	(2.81)	(0.42)							
r10			0.016						
			(2.53)						
cv_r10			0.001						
			(0.68)						
VIX		0.0002	0.0009		0.0002		−0.0001	0.0002	0.0004
		(1.60)	(3.03)		(2.12)		(−0.68)	(1.65)	(2.06)
inf				−0.002	0.001				
				(−2.98)	(1.16)				
cv_inf				−2.54E−05	4.35E−07				
				(−0.21)	(0.01)				
rSP500						−0.0001	−0.0001		
						(−4.38)	(−4.30)		
cv_rSP500						1.28	1.65		
						(3.20)	(3.14)		
gcredit								−0.0001	
								(−0.04)	
cv_gcredit								−3.26E−05	
								(−2.32)	
spread									−0.0005
									(−0.35)
cv_spread									−0.146
									(−1.15)
Descriptive statistics									
R^2	0.95	0.95	0.96	0.95	0.95	0.95	0.96	0.95	0.96
DW	1.72	1.73	1.76	1.72	1.74	1.76	1.76	1.75	1.66
n	189	189	189	189	189	189	189	189	189

Notes: The columns correspond to various specifications of our benchmark model. The explanatory variables are the following: *gprod*: annual growth of industrial production; *cv_gprod*: conditional variance of gprod; *r10*: ten-year interest rate; *cv_r10*: conditional variance of *r10*; *VIX*: implicit volatility of options on S&P500; *inf*: monthly inflation; *cv_inf*: conditional variance of *inf*; *rSP500*: S&P500 monthly return; *cv_SP500*: conditional variance of *rSP500*; *gcredit*: monthly growth of a global measure of consumer credit; *cv_gcredit*: conditional variance of *gcredit*; *spread*: term spread; cv_*spread*: conditional variance of *spread*. The Newey-West *t* statistics are displayed in parentheses. *n* is the number of observations.

tively, the average of X_t and Y_t computed over the sample period.[38] The elasticity is estimated at the point of the mean of both variables and may thus be called "elasticity at means".

According to our computations, the elasticity of *disp*(*ret*) with respect to *VIX* ranges in an interval comprised between 0.70 and 1.00 depending on model specifications, which are relatively high monthly elasticities according to previous studies (Baum et al., 2002, 2004, 2009; Calmès and Théoret, 2014). Moreover, the monthly elasticity of *disp*(*ret*) with respect to the conditional variance of the industrial production growth is around 0.30[39] while the elasticity with respect to the conditional variance of the term spread is 0.80 when excluding the *VIX* from the regression and 0.30 when including it.[40] Once again, these elasticities are substantial. Regarding the first moments, the inflation rate displays an elasticity of 0.38 while the other elasticities are lower.

In Table 5, we report the estimation of our benchmark model with GMM. In this estimation run, the conditional variances of the macroeconomic and financial variables and the *VIX* are viewed as generated variables—i.e., endogenous variables. Our OLS results are robust to this change in the estimation method.

4.3. The cross-sectional dispersion of strategies' betas (disp(beta))

Similarly to the investment projects in Beaudry et al. (2001), to banks' loans in Baum et al. (2002, 2004, 2009) and Quagliariello (2007, 2008, 2009) and to banks' loans and fee-generating assets in Calmès and Théoret (2014), the market beta is more under the control of the fund manager than market returns *per se*. In line with these authors, we could thus conjecture that there is a negative co-movement between *disp*(*beta*), on the one hand, and the various indicators of macroeconomic and financial uncertainty, on the other hand.

Our expectations are not deceived. According to Table 6 that reports the OLS estimations of Eq. (8) transposed to *disp*(*beta*), macroeconomic and financial uncertainty impacts negatively *disp* (*beta*) regardless of the uncertainty measure used. The impact of the conditional variances of the industrial production growth and the *VIX* is particularly significant. When uncertainty increases, hedge fund managers thus take less risk, which moves their market betas closer. Diversification in the hedge fund industry thus decreases in terms of systematic risk when uncertainty increases. Similarly to banks, hedge funds deleverage when macroeconomic uncertainty increases, or in other words, hedge fund managers tend to decrease concomitantly their market betas. Actually, there is a close link between financial leverage—as measured by the ratio of assets to equity—and market beta, a decrease in leverage leading to a lower beta (Modigliani and Miller, 1958; Miller and Modigliani, 1961; McGuire and Tsatsaronis, 2008). Fig. 19 illustrates this behavior for some strategies. As mentioned before, this Figure clearly illustrates that the behavior of hedge funds' market betas follow a forward-looking dynamics in the sense that hedge

[38] For more detail on this formula, see Pindyck and Rubinfeld, 1998, p. 99.

[39] i.e., if the conditional variance of industrial production growth increases by 1%, the dispersion of returns increases by 0.3% on a monthly basis. During a crisis, it is not unusual that uncertainty as measured by the industrial production increases by 100%. According to our results, the cross-sectional dispersion of returns then increases by 30%, compared to its mean increase of 100% in times of crises. Thus the impact of the conditional variance of industrial production on the cross-sectional dispersion of returns is far from being negligible.

[40] Remind that the correlation between the *VIX* and the conditional variance of the term spread is high.

funds had decreased their beta before the occurrence of the subprime crisis.[41] It is precisely this deleveraging process being observed during bad times which leads to a rise in systemic risk in the financial system (Shleifer and Vishny, 2010; Gennaioli et al, 2011). Like banks, hedge funds are thus a source of systemic risk when macroeconomic uncertainty trends upward (Chan et al., 2005; Saunders et al., 2014; Bussière et al., 2015).[42] The close connection between banks and hedge funds contributes to magnify this risk.

Turning to the impact of the first moments, we note that *disp* (*beta*) increases in good times, as measured by the industrial production growth, the stock market return or the credit growth. When optimistic, hedge fund managers tend to rely on more heterogeneous strategies. *disp*(*beta*) thus tends to be procyclical. In contrast, an increase in inflation or in the 10-year interest rate tends to reduce *disp*(*beta*), leading to more homogeneous strategies. Consistent with Beaudry et al. (2001), an increase in inflation incentivizes agents to take less risk, here to reduce their market betas. In the same vein, an increase in the 10-year interest rate may signal rising inflation, which inhibits risk-taking.

Table 7 is an estimation of Table 6 specifications using GMM to deal with the endogeneity issue related to the presence of generated variables in Eq. (8) specifications. Once more, the OLS results are robust to this change in estimation method.

4.4. The cross-sectional dispersion of strategies' alphas (disp(alpha))

It is more difficult to estimate our model with *disp*(*alpha*), since this series evolves very slowly through time. However, one should expect some correspondence between *disp*(*ret*) and *disp*(*alpha*), the alphas being components of returns.

This expected link tends to hold between *disp*(*alpha*) and our measures of uncertainty (Table 8). Following an increase in the *VIX*, in the conditional variance of the industrial production growth and in the conditional variance of the stock market return, *disp* (*alpha*) increases significantly. Strategies thus become more heterogeneous in terms of alphas when uncertainty increases. As argued previously, some strategies can benefit from uncertainty in terms of alphas—especially those that are more involved in short selling or arbitrage business lines—which is not the case for others. The impact of the first moments of the macroeconomic and financial variables analyzed is less significant. However, similarly to *disp* (*ret*), we note that an increase in the stock market return tends to depress *disp*(*alpha*).

5. Conclusion and public policy issues

Studies about the joint behavior of hedge funds' strategies over the business cycle are sparse. Yet, this behavior is related to systemic risk in the hedge fund industry (Chan et al., 2005; Saunders et al., 2014; Bussière et al., 2015). Indeed, a decrease in the cross-sectional dispersions of hedge fund strategies' returns, alphas and market betas is associated with a decrease in the diversification benefits provided by hedge funds' strategies. Such moves also increase systemic risk in the financial sector.

In this paper, we find that informational problems and agency costs are more severe during slow growth episodes in the hedge fund industry (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Vennet et al., 2004). Sharp moves in hedge fund strategies' behavior are observed during these periods. Macroeconomic and financial uncertainty impacts negatively the cross-sectional dispersion of strategies' market betas regardless of the uncertainty measure considered. The impact of the conditional variance of industrial production growth and of the *VIX* is particularly significant. Conversely, when optimistic, hedge fund managers tend to rely on more heterogeneous strategies, which decreases systemic risk.

In contrast to returns on the risky assets analyzed in the studies of Beaudry et al. (2001), Baum et al. (2002, 2004, 2009), Quagliariello (2007, 2008, 2009) and Calmès and Théoret (2014), market returns and alphas are not easily manageable. Hence, not surprisingly, the cross-sectional dispersions of hedge fund strategies' alphas and returns do not support Beaudry et al.'s conjecture. These cross-sectional dispersions tend to increase in times of macroeconomic uncertainty, in line with Black's (1976) leverage effect.

In other respects, we find that the *VIX* embeds many properties of the other macroeconomic uncertainty measures used in this article. In this sense, it stands as a good substitute for these other measures. However, it tends to decrease in economic expansion, while systemic risk evolves upwards. This is an obvious shortcoming of the *VIX*. Hence, the *VIX* ought to be balanced with other macroeconomic uncertainty measures like those developed in this article.

Finally, our results have important implications in terms of investment and public policies. For investors, our findings show that hedge fund strategies remain an interesting avenue to diversify portfolios. In expansion, the cross-sectional dispersion of hedge fund market betas increase, which offers different opportunities to investors. In recession, even if hedge funds decrease their market beta, the cross-sectional dispersions of returns and alphas increase, which suggests that some strategies—like the distressed securities, short-sellers and futures' strategies—benefit from the turmoil, another good opportunity for investors in times of average negative returns (Racicot and Théoret, 2014a).

Regarding public policy, macro-prudential policies should track the deleveraging process which takes place in the hedge fund industry when economic conditions worsen. This deleveraging, which is associated with a general drop in hedge fund market betas, may be substantial according to our computations and may thus magnify procyclicality in the financial sector (Shleifer and Vishny, 2010; Gennaioli et al., 2011). This monitoring is all the more important than the link between banks and shadow banks—which include the hedge fund sector—clearly trends upward. Fortunately, procyclicality—an obvious source of instability—seems to have declined in the hedge fund sector over the last decade in the sense that the return and market beta cross-sectional dispersions are more immune to macroeconomic shocks. Thanks to a learning process at play in the hedge fund industry, hedge fund managers seem to rely on structural products with more circumspection for managing their idiosyncratic and systematic sources of risk.

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[41] In macroeconomics, the present is a function of the future in the theory of endogenous business cycles. See Grandmont (1985, 1998) and Guesnerie (1992).

[42] According to these authors, hedge funds tend to follow similar procedures and to rely on similar asset pricing models. Moreover, hedge funds interact more and more with the banking system. Hedge funds thus may cause systemic risk. In this respect, the problems of LTCM in September 1998—a hedge fund with an exposure of $1.25 trillion in derivatives and other securities—greatly disrupted the world financial markets (Saunders et al., 2014). We study another source of systemic risk in this study which originates from hedge funds—i.e., their herd-like behavior when economic or financial uncertainty increases.

Appendix A1

Estimation of the conditional variances of macroeconomic and financial variables

To estimate the conditional variances of our macroeconomic and financial variables, we rely on a GARCH (1,1) and more frequently on an EGARCH (1,1).

The equation structure of these procedures is the following:

(i) A mean equation, which is an ARMA (p,q) specification of the (stationary) macroeconomic times series used to measure macroeconomic uncertainty. It thus takes the following form:

$$b(\ell)y_t = \gamma + c(\ell)\varepsilon_t \tag{15}$$

where the lag operators $b(\ell)$ and $c(\ell)$ are equal to: $b(\ell) = \sum_{i=0}^{p} b_i \ell^i$, $b_0 = 1$, $b_{i,i\neq 0} = -\beta_i$, and $c(\ell) = \sum_{j=0}^{q} c_j \ell^j$.

(ii) A variance equation, which may be a GARCH (1,1) (Bollerslev, 1986)—i.e.,

$$\sigma_t^2 = \phi_0 + \phi_1 \varepsilon_{t-1}^2 + \phi_2 \sigma_{t-1}^2 \tag{16}$$

or an EGARCH(1,1) (Nelson, 1991; Franses and van Dijk, 2000)—i.e.,

$$\ln(\sigma_t^2) = \eta_1 + \eta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \eta_3 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \eta_4 \ln(\sigma_{t-1}^2) \tag{17}$$

According to Eq. (16), the conditional variance of the innovation is related to the lagged squared innovation and the lagged conditional variance. The sum of the coefficients ϕ_1 and ϕ_2 is a measure of persistence. Eq. (17) adds an asymmetrical effect in the conditional variance model. This effect depends on the sign of ε_{t-1}. If $\varepsilon_{t-1} > 0$, the total effect of ε_{t-1} on the log of the conditional variance can be measured by $(\eta_3 + \eta_2)|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}|$, while if $\varepsilon_{t-1} < 0$, it can be measured by $(\eta_3 - \eta_2)|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}|$. Thus, the asymmetric leverage effect can be tested with the coefficient η_2. If $\eta_2 < 0$, the asymmetrical effect is higher when $\varepsilon_{t-1} < 0$. This is the Black's (1976) leverage effect, whereby the volatility of a stock return is higher when the price of this stock trends downward. In contrast, if $\eta_2 > 0$, the asymmetrical effect is higher when $\varepsilon_{t-1} > 0$. Further, volatility persistence increases with η_4 in the EGARCH model.

Appendix A2

GMM procedure

In this article, we rely on the asymptotic properties of the generalized method of moments estimator (GMM) with respect to the correction of heteroskedasticity and autocorrelation to weight the instruments obtained with the generalized least squares estimation method (GLS). Note that when using GMM, we give up some efficiency gain in order to avoid the complete specification of the nature of the autocorrelation or heteroskedasticity of the innovation and the data generating process (DGP) of the measurements errors (Hansen, 1982). This is also a great advantage over GLS.

The GMM estimator may be written as follows (Racicot and Théoret, 2001):

$$\arg\min_{\hat{\beta}} \left\{ n^{-1} \left[\mathbf{Z}^{\mathbf{T}}(\mathbf{y} - \mathbf{X}\hat{\beta}) \right]^T \mathbf{W}\, n^{-1} \left[\mathbf{Z}^{\mathbf{T}}(\mathbf{y} - \mathbf{X}\hat{\beta}) \right] \right\} \tag{18}$$

In Eq. (18), $\mathbf{Z}$ is the matrix of instrumental variables; $\mathbf{y}$ is the dependent variable; $\mathbf{X}$ is the matrix of the explanatory variables, and $\mathbf{W}$ is a weighting matrix. To implement GMM, we rely on an innovative set of instruments defined as:

$$d_{it} = x_{it} - \hat{x}_{it} \tag{19}$$

where $\hat{x}_{it}$ is the predicted value of x_{it}.

These instruments—called the d instruments or distance instruments—may be considered as filtered versions of the endogenous variables. We thus rely on a distance metrics to compute our instruments. The d_{it} series removes some of the nonlinearities embedded in the x_{it}. It is thus a smoothed version of the x_{it} which might be regarded as a proxy for its long-term expected value—the relevant variables in the asset pricing models being theoretically defined on the explanatory variables expected values. To compute the $\hat{x}_{it}$ in (19), we perform the following regression using the z (cumulant) instruments:

$$x_{it} = \hat{\gamma}_0 + \mathbf{z}\hat{\phi} + \varsigma_t = \hat{x}_{it} + \varsigma_t \tag{20}$$

The computation of the $\mathbf{z}$ instruments is based on our previous works (cf. Racicot and Théoret, 2014b). They are based on the cumulants of the explanatory variables $\mathbf{X}$. More specifically, the $\mathbf{z}$ instruments are a weighting of Durbin and Pal's estimators defined for models embedding errors in variables. Finally, our new version of GMM defined on d instruments—named GMM-d—obtains:

$$\arg\min_{\hat{\beta}} \left\{ n^{-1} \left[\mathbf{d}^{\mathbf{T}}(\mathbf{y} - \mathbf{X}\hat{\beta}) \right]^T \mathbf{W}\, n^{-1} \left[\mathbf{d}^{\mathbf{T}}(\mathbf{y} - \mathbf{X}\hat{\beta}) \right] \right\} \tag{21}$$

Appendix A3

Recent behavior of procyclicality[43]

At the time of the writing of this article, we have three crises at our disposal to conduct our study: the Asian-Russian-LTCM crisis, the tech-bubble crisis and the subprime crisis. The periods of expansion outside these crises were sufficiently long in our sample to observe the procyclical behavior of hedge fund returns. Given the asymmetric behavior of hedge funds, procyclicality is observed especially in crisis (or recession). This is during these periods that hedge funds reduce drastically their risk exposure. Their behavior is much smoother in normal times[44] (Racicot and Théoret, 2013).

As shown in Fig. 20 which is an update of our sample till March 2015, there has been no increase in the volatility of the hedge fund general index return since the end of 2012.[45] Moreover, the time-varying beta computed using the general index has increased progressively since 2012, which suggests that procyclicality evolves normally. However, hedge funds remain prudent since the beta related to the general index is quite below its level observed before the tech-bubble crisis when a structural break in our hedge fund time series was found. The rolling standard deviation of the general index return has continued to decrease and evolves quite below the standard deviation of the S&P500 return.[46] Procyclicality thus remains on its decreasing track, which suggests that the learning process in the hedge fund industry reported in our article seems to go its way.

[43] We thank an anonymous referee for having suggested this addendum.

[44] We also depicted this kind behavior using another hedge fund database—i.e., the Eureka database (Racicot et al., 2014).

[45] Uncertainty has thus remained at a very low level since the end of 2012 in the hedge fund industry according to this measure.

[46] Note in Fig. 20 that the increase in standard deviation observed during the recent sovereign debt turmoil in Europe is much lower for the hedge fund general index return than for the S&P500 return.

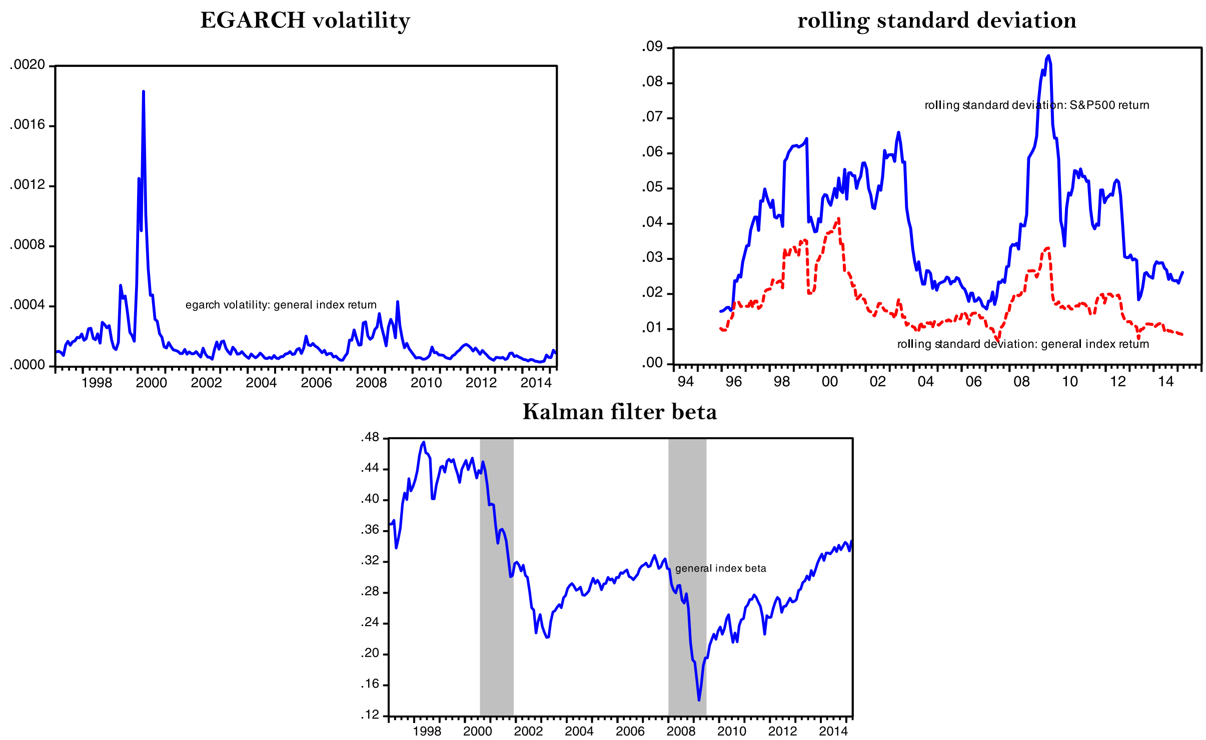

Fig. 20. EGARCH volatility, standard deviation and beta of the general index return after 2012. *Notes*: The sample used to build these figures ends in March 2015. The conditional volatility of the general index return is computed by estimating Eq. (9) with the EGARCH procedure. The volatility is the conditional variance of the equation innovation. The standard deviations are computed on a rolling window of twelve months. The general index beta is computed by estimating Eqs. (9), (10) and (12) with the Kalman filter procedure.

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