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

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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 behaviour of the cross-sectional dispersions of hedge fund strategies' returns, 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 economic slowdowns, which makes their strategies more homogeneous and thus contributes to increase systemic risk in the financial system. However, the cyclical behaviour of the cross-sectional dispersions of strategies' returns and strategies' alphas is not in line with Beaudry et al.'s conjecture. These dispersions increase during times of rising macroeconomic uncertainty, which suggests the prevalence of the Black's (1976) leverage effect during times of financial turmoil and the fact that the exposure of hedge fund strategies to risk factors is quite different. Finally, although remaining important, procyclicality seems to recede in the hedge fund industry, which suggests that a learning process is at play.

Keywords: Hedge fund; Shadow banks; Systemic risk; Macroeconomic shocks; Forward-looking dynamics; EGARCH; GMM.
JEL classification: C13; C58; G11; G23.

Chocs macroéconomiques, dynamique prospective, & comportement des fonds de couverture

Résumé

Nous analysons de quelle façon les stratégies des fonds de couverture réagissent en groupe au risque macroéconomique et à l'incertitude. En recourant à la méthodologie de Beaudry et al. (2001), nous monitorons le comportement des dispersions en coupe transversale des rendements des stratégies des hedge funds, de leur beta ainsi que de leur alpha au cours du cycle économique. La configuration des betas des stratéies appuie la conjecture de Beaudry et al., à savoir que les hedge funds réduisent leur exposition au risque (betas) durant les récessions, ce qui rend les stratégies plus homogènes et ce qui contribue donc à augmenter le risque systémique dans le système financier. Toutefois, le comportement cyclique des dispersions en coupe transversale des rendements et des alphas des stratégies n'est pas au diapason de la conjoncture de Beaudry et al. Ces dispersions s'accroissent en période d'incertitude macroéconomique, ce qui donne à penser que l'effet de levier de Black (1976) domine en période de crise économique et que l'exposition des stratégies des hedge funds aux facteurs de risque diffère grandement. Finalement, même si elle demeure importante, la procyclicité semble régresser dans l'indstrie des hedge funds, ce qui laisse croire qu'un processus d'apprentissage est en cours.

Mots-clefs : Fonds de couverture; Système bancaire parallèle; Risque systémique; Chocs macroéconomiques; Dynamique prospective; EGARCH; GMM.
Classification JEL : C13; C58; G11; G23.

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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. During these periods, the behaviour 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 behaviour, 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), 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

[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.

strategies' returns, betas and alphas. Indeed, in the current context of depressed interest rates and relatively low market risk premia on stocks, 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.

The behaviour of the cross-sectional dispersion of hedge fund strategies' 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 the rise in macroeconomic uncertainty. This behaviour may be explained by the increased volatility of financial markets when business conditions worsen—i.e., the Black's (1976) leverage effect. Finally, the behaviour 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 organised as follows. Section 2 presents the benchmark model we use to analyze the links between macroeconomic risk and uncertainty and our cross-sectional dispersion measures—defined in terms of strategies' returns, alphas and betas. This section is also concerned with the estimation methods used in this paper, namely the Generalized method of moments (GMM) which deals with the endogeneity of our measures of macroeconomic uncertainty (Racicot and Théoret, 2014). 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 The benchmark model

Macroeconomic shocks can distort the behaviour of hedge funds. In this study, we follow the methodology of Beaudry et al. (2001), Baum *et al.* (2002, 2004, 2009), Quagliariello (2007, 2008, 2009) and Yu and Sharaiha (2007). In order to test the herd-like behaviour in the hedge fund industry, we consider the following reduced-form equation model:

$$disp(.)_t = \beta_0 + \beta_1 \mu_{mv,t} + \beta_2 \sigma^2_{c,mv,t} + \beta_3 disp(.)_{t-1} + \xi_t \qquad (1)$$

where $disp(.)_t$ is the cross-sectional dispersion of strategies' returns, strategies' betas and strategies' alphas, denoted by *disp(ret)*, *disp(beta)* and *disp(alpha)* respectively; $\mu_{mv,t}$ 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.

For a given month, *disp(ret)* is the variance of the 15 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 beta (Racicot and Théoret, 2013)[2]. Then, for each month, we compute the standard deviation[3] over the 15 strategies' alphas and betas.

Turning to the explanatory variables of Eq.(1), the first moment of a macroeconomic variable may be the industrial production growth and its corresponding second moment the conditional variance of industrial production growth. The model may include a lagged dependent variable to control for residuals autocorrelation and account for the adjustment delay of the observed $disp(.)_t$ 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 macroeconomic uncertainty fosters more herding in the hedge fund industry than macroeconomic risk *per se* which can be hedged more easily.

A second, more technical motivation for including both the first and second moments in Eq.(1) 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 lead 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.

[2] For more details on the computation of these state variables, see Appendix A1.
[3] For computational convenience, we rely on the standard deviation rather than on the variance to compute the cross-sectional dispersions of strategies' alphas and betas.

For example, for the dispersion of strategies' betas in terms of industrial production growth uncertainty, our model can be expressed as follows:

$$disp\left(beta\right)_t = \delta_0 + \delta_1 gprod_t + \delta_2 cv\_gprod + \delta_3 disp\left(beta\right)_{t-1} + \varepsilon_t \qquad (2)$$

where *disp(beta)* is the cross-sectional dispersion of strategies' betas; *gprod* is the industrial production growth rate and *cv_gprod* is the conditional variance 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 beta, which increases the correlation between hedge funds' strategies and therefore rises systemic risk in the financial sector[4]. However, Beaudry et al's model, which is inspired from Lucas' signalling model (1973)—i.e., a model which highlights signal extraction problems—does not provide any indication about the sign of the coefficient of the first moment in Eq.(2). In line with the impact of macroeconomic uncertainty, we expect that a decrease in industrial production growth rate decreases *disp(beta)*. When business conditions worsen, hedge funds should thus take less risk by reducing their 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, like betas, easily manageable. It is thus difficult *a priori* to assess the signs of β_1 and β_2 in Eq.(1) for *disp(ret)* and *disp(alpha)*. This issue is a matter of empirical analysis.

2.2 *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 used 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:

$$b\left(\ell\right) y_t = \gamma + c\left(\ell\right)\varepsilon_t \qquad (3)$$

[4] 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., 2013).

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.,

$$\sigma_t^2=\phi_0+\phi_1\varepsilon_{t-1}^2+\phi_2\sigma_{t-1}^2 \tag{4}$$

or an EGARCH(1,1) (Nelson, 1991)—i.e.,

$$\ln(\sigma_t^2)=\eta_1+\eta_2\frac{\varepsilon_{t-1}}{\sigma_{t-1}}+\eta_3\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|+\eta_4\ln(\sigma_{t-1}^2)-\sqrt{\frac{2}{\pi}} \tag{5}$$

According to Eq.(4), 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.(5) 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 $(\eta_3+\eta_2)\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|$, while if $\varepsilon_{t-1}<0$, it can be measured by $(\eta_3-\eta_2)\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|$. 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 the returns on a stock 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.

2.3 Estimation of the cross-sectional dispersion models

To estimate Eq.(1), 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[5] (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

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

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, 2014)[6].

Insert Table 1 here

3. Data sources and stylized facts

3.1 Data

The data are taken from the database managed by Greenwich Alternative Investment (GAI). The dataset runs from January 1995 to September 2012, for a total of 213 observations. In addition to the weighted composite index, the database includes 12 indices of well-known hedge fund strategies reported in Table 1. We also report the indices of GAI strategy groups whose sample starts in January 1995. We transform the indices into monthly returns using the following formula: $\ln\left(\frac{P_t}{P_{t-1}}\right)=\ln\left(1+r_t\right)\cong r_t$, where P_t is the monthly stock index at time t and r_t is the monthly return. 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.

Table 1 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 the short sellers[7] to 1.07% for the value index, whereas the return standard deviation ranges from 1.29% for the market neutral group to 5.83% for the short sellers. An hedge fund's beta is generally low, the average beta computed over all strategies being equal to 0.22. Two strategies display a negative beta: the short sellers (-0.91) and the futures strategy (-0.08)[8]. 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).

We can classify hedge fund strategies in three main categories according to the value of their beta[9]. Some strategies are directional in the sense that they are more exposed to the

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

[7] Note that the negative return delivered by short-sellers should not be viewed as abnormal or excessively low. For example, in the real or physical universe—as opposed to the risk neutral or forward risk neutral universe—if the real world expected required return is 16%, the expected required return of a long put is close to -50% as opposed to 40% for a long call in an Hull's (2012) example.

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

[9] Connor and Lasarte (2005) distinguish two broad categories of hedge fund strategies: the market neutral and directional ones.

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 the 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[10]. 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. Another usual category is the event driven one. Strategies like the event-driven, distressed securities, diversified event-driven, and opportunistic enter in this category. Their beta is usually moderate. Note that these 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.

Insert Figure 1 here

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 1). In fact, the standard deviation of the return of the weighted composite index seems to decline through time, which is not the case for the S&P500 return (Figure 1). More importantly, the standard deviation of the weighted return increased less during the subprime crisis than during the bubble tech 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 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). Furthermore, the hedge fund weighted return co-moves less (negatively) with the *VIX*, a measure of volatility on financial markets (Figure 1).

Insert Figure 2 here

Not surprisingly, the strategies' standard deviations are positively correlated with their betas (Figure 2). Note that short sellers are outside the regression line relating standard deviation to 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

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

return also co-moves positively with the beta (Figure 3). 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.

Insert Figure 3 here

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%).

Insert Figure 4 here

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 market portfolio return which is negatively skewed. Note that our results are more or less in line with Chan *et al.* (2007) 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 (Figure 4). 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.

Insert Figure 5 here

3.2 Stylized facts about cross-sectional dispersions

In this article, we analyze three cross-sectional dispersions related to the hedge fund behaviour: the cross-sectional variance of GAI hedge fund strategies' returns, and the cross-sectional standard deviation of these strategies' alphas and betas. Figure 5 plots a moving average of *disp(ret)* series and of 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 bubble-tech crises than during the subprime crisis. Further, in times of expansions, *disp(ret)* is quite low. Panel B of Figure 5 provides further information on the behaviour of *disp(ret)*. It plots the Quandt-Andrews breakpoint test performed on this time series (Quandt, 1960; Andrews, 1993, 2003; Stock and Watson, 2003). 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 bubble tech, 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.

Insert Figure 6 here

In contrast to strategies' returns, *disp(beta)* tends to decrease in times of economic slowdown (Figure 6). This suggests that hedge fund strategies become more homogeneous in terms of betas when business conditions worsen. In other words, hedge fund managers "herd" by taking less risk or by decreasing their beta. This behaviour supports Beaudry et al.'s (2001) conjecture—i.e., that investors take less risk in times of macroeconomic uncertainty[11]. 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 behaviour 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 (Figure 6). Hence, hedge funds anticipate an economic downturn and decrease

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

their beta before the occurrence of this downturn[12]. 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 bubble tech episode but later, its behaviour 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, the cross-sectional dispersion has progressively returned toward its pre-crisis level, which suggests higher diversification benefits for hedge fund investors. Panel B of Figure 6 provides the Quandt-Andrews breakpoint test applied to *disp(beta)* (Quandt, 1960; Andrews, 1993, 2003: Stock and Watson, 2003). According to the test, the breakpoints in the series occurred during times of financial crisis. For the first breakpoint, observed during the bubble tech, 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.

Insert Figure 7 here

Turning to *disp(alpha)*, first note it tends to decrease over this period, suggesting a more homogeneous pattern for strategies' alphas (Figure 7). Similarly to the betas, this pattern is mainly due to the late 1990s and to the early 2000s when the dispersion of alphas was particularly high. Second, in contrast to *disp(beta)*, *disp(alpha)* tends to be countercyclical[13]: it decreases in expansions and increases in recessions. The increase in the dispersion was especially high during the subprime crisis, suggesting that funds delivered a wide range of alphas. 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 2013). Finally, Panel B of Figure 7 provides the Quandt-Andrews breakpoint test performed on *disp(alpha)* (Quandt, 1960; Andrews, 1993, 2003; Stock amd Watson, 2003). 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 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.

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

[13] And not procyclical like the beta cross-sectional dispersion.

Summarizing, albeit procyclicality remains important in the hedge fund sector, it seems to recede 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 bubble tech one. The Quandt-Andrews breakpoint tests performed on *disp(ret)* and *disp(beta)* also suggest that the changes in regime observed for these series were much more significant during the bubble tech crisis than during the subprime one. 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 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.(1): the growth of industrial production (*gprod*); the detrended[14] ten-year interest rate (*r10*); the rate of inflation (*inf*); the return on the S&P500 (*rSP500*); the growth of consumer credit (*gcredit*)[15]; 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 of financial uncertainty (second moments)—i.e., the conditional variances of these variables.

Insert Table 2 here

As specified before, the mean equation of a macroeconomic or financial variable is estimated by Eq.(3) and its corresponding conditional variance by Eq.(4) or (5) 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 2 provides the estimations of the mean and variance equations of our macroeconomic and financial variables.

Insert Figure 8 here

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

[14] According to the Dickey-Fuller test, the ten-year interest rate is trend-stationary.
[15] 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.

negative for these variables, which suggests that they are more volatile in times of economic slowdown. Figure 8, which plots the conditional variances of the variables appearing in Table 2, clearly shows that these variables are much more volatile in bad times (shaded areas in the plots)[16]. 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.

Insert Tables 3 and 4 here

4.2 The cross-sectional dispersion of strategies' returns (disp(ret))[17]

Table 3 provides OLS estimations of nine specifications of Eq.(1) for *disp(ret)* while Table 4 delivers the corresponding GMM estimations. 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.

Insert Figures 9 and 10 here

According to Table 3, *disp(ret)* reacts positively most of the time to macroeconomic uncertainty[18]. For instance, the conditional variances of the growth of industrial production, of the 10-year rate, of the return of the S&P500, and of the term spread impact positively the cross-sectional dispersion. In many specifications of Eq.(1), we 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 (Figure 9) and the conditional variance of the stock market return (Figure 10). 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 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

[16] This asymmetry is often observed for the volatility of macroeconomic variables.
[17] 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 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.
[18] 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.

adding *VIX* in specification (5), 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) found 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.

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 significantly *disp(ret)*. 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.

Insert Figure 11 here

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 Figure 11, 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 (ξ) of Y with respect to X is equal to: $\xi = \frac{\Delta Y}{Y} \Big/ \frac{\Delta X}{X} = \frac{\Delta Y}{\Delta X} \times \frac{X}{Y}$. The econometric counterpart of this formula is: $\xi = coef \times \frac{\bar{X}}{\bar{Y}}$, where *coef* is the estimated coefficient of *X*—i.e., the slope $\frac{\Delta Y}{\Delta X}$—and $\bar{X}$ and $\bar{Y}$ are, respectively, the average of X_t and Y_t computed over the sample period[19]. 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 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[20]. 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 4, 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 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.

Insert Table 5 here

Our expectations are not deceived. According to Table 5 that reports the OLS estimations of Eq.(1) 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 betas closer. Diversification in the hedge fund industry thus decreases in terms of systematic risk when

[19] For more detail on this formula, see Pindyck and Rubinfeld, 1998, p. 99.
[20] Remind that the correlation between the *VIX* and the conditional variance of the term spread is high.

uncertainty increases. Similarly to banks, hedge funds deleverage when macroeconomic uncertainty increases, or in other words, hedge fund managers tend to decrease concomitantly their betas. Actually, there is a close link between financial leverage—as measured by the ratio of assets to equity—and beta, a decrease in leverage leading to a lower beta (Modigliani and Miller, 1958; Miller and Modigliani, 1961; McGuire and Tsatsaronis, 2008). Figure 12 illustrates this behavior for some strategies. As mentioned before, this figure clearly illustrates that the behaviour of hedge funds' betas follow a forward-looking dynamics in the sense that hedge funds have decreased their beta before the occurrence of the subprime crisis[21]. 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. The close connection between banks and hedge funds contributes to magnify this risk.

Insert Figure 12 here

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 betas. In the same vein, an increase in the 10-year interest rate may signal rising inflation, which inhibits risk-taking.

Insert Table 6 here

Table 6 is an estimation of Table 5 specifications using GMM to deal with the endogeneity problem related to the presence of generated variables in the Eq.(1) specifications. Once more, the OLS results are robust to this change in the 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 over time. However, one should expect some correspondence between *disp(ret)* and *disp(alpha)*, the alphas being components of returns.

Insert Table 7 here

This expected link tends to hold between *disp(alpha)* and our measures of uncertainty (Table 7). Following an increase in the *VIX*, in the conditional variance of the industrial

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

production growth, in the conditional variance of the 10-year rate or in the conditional variance of the stock market return, *disp(alpha)* increases. 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—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 behaviour of hedge funds' strategies over the business cycle are sparse. Yet, this behaviour is related to systemic risk in the hedge fund industry. Indeed, a decrease in the cross-sectional dispersions of hedge fund strategies' returns, alphas and 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. Sharp moves in hedge fund strategies' behaviour are observed during these periods. Macroeconomic and financial uncertainty impacts negatively the cross-sectional dispersion of strategies' betas regardless of the uncertainty measure used. 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 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 easily manageable. Hence, not surprisingly, the cross-sectional dispersions of hedge fund strategies' alphas and returns do not support Beaudry et al.'s conjecture. The cross-sectional dispersions of strategies' alphas and returns 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 betas increase, which offers different opportunities to investors. In recession, even if hedge funds decrease their beta, the cross-sectional dispersions of returns and alphas increase, which suggests that some strategies—like the distressed securities and futures' strategies—benefit from the turmoil, another good opportunity for investors in times of average negative returns.

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 the hedge fund betas, may be substantial according to our computations and may thus amplify 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 receded in the hedge fund sector over the last decade in the sense that the return and 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.

Appendix A1

Computation of the time-varying alpha and beta for each hedge fund strategy

To compute the time-varying alpha and beta of each strategy, we rely on the Kalman filter. The Kalman filter comprises a signal equation and state space equations. In our case, the signal equation is a return model. This equation reads:

$$\forall i, \forall t \quad R_{it} - r_{ft} = \alpha_{it} + \beta_{it}\left(R_{mt} - r_{ft}\right) + \gamma_1 SMB_t + \gamma_2 Spread_t + \varepsilon_{it} \qquad (6)$$

where r_{ft} is the risk-free return; α_{it} is the time-varying alpha; β_{it} is the time-varying 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; $Spread_t$ is the term structure spread, that is the spread between the Federal Reserve ten-year constant maturity yield and the 3-month Treasury bills yield.

In Eq.(6), $\left(R_{mt} - r_{ft}\right)$ 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. To these two factors, we add the term spread ($Spread_t$), a variable which has gained strength in explaining returns in line with the development of shadow banking. This variable may be considered as a portfolio which is long in the long-term (10-year) interest rate and short in the short-term interest rate. An increase in the spread usually signals an increase in the risk premia on bonds and possibly on stocks, which tends to give raise to an increase in expected returns on these securities since returns usually follow a mean-reverting or Ornstein-Uhlenbeck process. Moreover, an increase in the spread also forecasts an economic recovery, which is associated with higher expected returns (Ang et al., 2004). Note also that a positive relationship seems to link the long-term interest rate and stock risk premia at the statistical level[22]. Indeed, one of the main drivers of the structural decrease in stock risk premia would be the structural drop in long-term interest rates. According to this argumentation, which is quite unexplored in the hedge fund industry, the sign of the coefficient (γ_2) of the term spread should be positive in Eq.(6). These arguments which favor a positive sign for γ_2 are akin to a "price of risk" approach to the term spread.

[22] This relationship is in line with the well-known theory of asset substitution.

This approach is based on the following equation—borrowed from Veronesi (2010)—of the current long term $r(0,T)$ rate observed at time 0 and having a maturity equal to T:

$$r(0,T) = E(r) + \frac{\lambda_t}{T} - \frac{(T-1)^2}{2T}\sigma_t^2 \qquad (7)$$

where $E(r)$ is the expected future yield; λ_t is the price of risk, here market risk—i.e., risk related to the bond duration—since there is no default-risk on government bonds, and σ_t^2 is the variance of the interest rate. The last term of Eq. (7) represents an adjustment term which accounts for the convexity linking the price of a bond to its yield. According to Eq. (7), an increase in λ_t leads to an increase in the long term yield but is not associated with an increase in future spot rates as in the expectation theory. According to Veronesi (2010), it is rather associated with an increase in future bond prices or capital gains on bond holdings. Another argument which favors a positive sign for γ_2 is that hedge funds are big investors in mortgage-backed securities (MBS). Yet, an increase in the term spread is associated with an increase in the yield of MBS, which entails an increase in expected returns for hedge funds holding MBS.

However, according to the "expectations approach" to the term spread—which is associated with the first term of Eq. (7)—the sign of γ_2 would be negative. Indeed, the term spread has become an important indicator of monetary policy but is also a proxy for the phases of the business cycle. According to Adrian and Shin (2010), the fact that short-term interest rates are close to zero has induced central banks to change the way they manage monetary policy. The credit channel[23] is now partly implemented through this spread. An increase in the spread is associated with a tightening of monetary policy. Moreover, the term structure spread is also an important indicator of monetary policy in the literature focusing on a new channel of the transmission of monetary policy, namely the risk-taking channel[24] (e.g., Disyatat, 2010; Gambacorta and Marques-Ibanez, 2011). Finally, the term-structure spread is a proxy for the phases of the business cycle, an increase in the spread being associated with an economic contraction. It is thus a countercyclical indicator of business conditions. The expectations approach to the term spread thus states that $\gamma_2 < 0$. The sign of the term spread in Eq.(6) is thus an empirical issue[25].

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[23] The broad credit channel regroups the traditional lending channel and the balance-sheet channel (Bernanke and Gertler, 1995).
[24] According to the risk-taking channel, monetary policy impacts business conditions by changing the perception of risk in the financial system. It focuses on financial frictions in the lending sector.
[25] Veronesi (2010) casts Eq. (7) in a macroeconomic model where the price of risk depends of the business cycle.

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

$$\forall i, \forall t \quad \alpha_{it} = \alpha_{i,t-1} + \theta_{1i} r_{ft} + \theta_{2i} \left(R_{mt} - r_{ft} \right) + \xi_t \qquad (8)$$

We thus postulate that the alpha follows an autoregressive process augmented with conditioning market information. Eq.(8) may be written in first-differences, such as:

$$\forall i, \forall t \quad \alpha_{it} - \alpha_{i,t-1} = \theta_{1i} r_{ft} + \theta_{2i} \left(R_{mt} - r_{ft} \right) + \xi_t \qquad (9)$$

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[26]. 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 the beta is:

$$\forall i, \forall t \quad \beta_{it} = \beta_{i,t-1} + \delta_{1i} r_{ft} + \delta_{2i} \left(R_{mt} - r_{ft} \right) + \delta_{3i} pc\_lookback_t + \varsigma_t \qquad (10)$$

In addition to the two conditioning variables included in the state space equation of the alpha, the state space equation of the beta includes the $pc\_lookback$ variable. This variable is the first principal component of the Fung and Hsieh's option risk factors which are lookback straddles[27] on stocks, bonds, short interest, commodities and foreign currencies. Fung and Hsieh (1997, 2001, 2004) rely on lookback straddles to study the behaviour of trend followers[28] in the hedge fund industry. However, according to these authors, there are substantial differences in trading strategies among trend follower funds, so it may not be possible to pin down a single benchmark that can be used to monitor the performance of trend followers (Fung and Hsieh, 2001). We thus combine the five ABS trend-following factors into one principal component.

Let us conjecture the expected signs of the variables included in Eq.(9) and (10). First, an increase in the interest rate might signal a deterioration of business conditions. It thus leads

[26] Compared to Cai and Liang (2012), we introduce directly the selected macroeconomic and financial variables in the state space equations of alpha and 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.
[27] 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, 2001).
[28] Mainly managed futures or CTA funds.

to a decrease in the alpha (θ_{1i}<0) and to a decrease in the beta (δ_{1i}<0), hedge funds reducing their exposure to market risk in times of economic slowdown. Second, an increase in the market risk premium $\left(R_{mt}-r_{ft}\right)$ is viewed as a strengthening of the stock market. This may induce hedge funds to position themselves for an increase in their alpha, this behaviour 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 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 δ_{2i} >0.

Insert Figure 13 here

Finally, we expect a negative sign for the coefficient associated with the *pc_lookback* variable. We thus expect that hedge funds reduce their 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 (Figure 13). Note that this covariance—which is computed with a multivariate GARCH (MGARCH) using a BEKK procedure (Bollerslev et al., 1988; Engel 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 one. More precisely, this factor may be viewed as an insurance factor in our return model (Agarwal and Naik, 2004). Figure 14 shows that the MGARCH conditional covariance between the *pc_lookback* and the GAI weighted composite index 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.

Insert Figure 14 here

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. However, in our study, the lookback factor is the first principal component of the lookback returns on five assets and it is a factor in the beta's state equation. In Fung and Hsieh (2001), the lookback factors are not combined and constitute individual risk factors in the return equations.

Insert Figure 15 here

Another interpretation of the link between the *pc_lookback* factor and a strategy's beta hinges on the following argument. Recall that the *pc_lookback* factor is built with lookback straddles that provide greater payoffs when the financial markets are volatile. Figure 15 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. Figure 15 shows that the MGARCH conditional covariance between the *VIX* and the GAI 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, Figure 16 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, Figure 17 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 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.

Insert Figures 16 and 17 here

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

$$pc\_lookback_t = \alpha + \beta_{t,pc\_look}\left(R_{mt} - r_{ft}\right) + \varsigma_t \qquad (11)$$

Figure 18, which plots the estimated 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.(11) into Eq.(10) and then Eq.(10) into Eq.(6) leads to the appearance of the following term in a strategy return equation: $\beta_{i,t}\delta_{3i}\beta_{t,pc\_look}\left(R_{mt} - r_{ft}\right)^2$. Given our previous results, the coefficient of $\left(R_{mt} - r_{ft}\right)^2$ is positive. The strategies which have a significant δ_{3i} in Eq.(10)—especially the futures, opportunistic, value index, and diversified event driven—thus benefit when the volatility of the stock market (as measured by $\left(R_{mt} - r_{ft}\right)^2$) increases. 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).

Appendix A2
The GMM procedure used in this paper

In this article, we rely on the asymptotic properties of the Generalizes 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):

$$\arg\min_{\hat{\beta}} \left\{ n^{-1} \left[\mathbf{Z}^{\mathbf{T}} \left(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}} \right) \right]^{T} \mathbf{W}\, n^{-1} \left[\mathbf{Z}^{\mathbf{T}} \left(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}} \right) \right] \right\} \qquad (12)$$

In Eq.(12), **Z** is the matrix of instrumental variables; **y** is the dependent variable; **X** is the matrix of the explanatory variables, and **W** is a weighting matrix. To implement the GMM, we rely on an innovative set of instruments defined as:

$$d_{it} = x_{it} - \hat{x}_{it} \qquad (13)$$

with $\hat{x}_{it}$ 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 resort to 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 (13), we perform the following regression using the *z* (cumulant) instruments:

$$x_{it} = \hat{\gamma}_0 + \mathbf{z}\hat{\phi} + \varsigma_t = \hat{x}_{it} + \varsigma_t \qquad (14)$$

The computation of the **z** instruments is based on our previous works (cf. Racicot and Théoret, 2014). They are based on the cumulants of the explanatory variables **X**. More specifically, the **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:

$$\arg\min_{\hat{\beta}} \left\{ n^{-1} \left[\mathbf{d}^{\mathbf{T}} \left(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}} \right) \right]^{T} \mathbf{W} \, n^{-1} \left[\mathbf{d}^{\mathbf{T}} \left(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}} \right) \right] \right\} \qquad (15)$$

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Table 1 Descriptive Statistics, Greenwich Alternative Investment hedge fund indices, 1995-2012

	Mean	Median	Max	Min	sd	Skew	Kurtosis	Sharpe index	CAPM-beta
Equity Market Neutral	0.77%	0.60%	8.10%	-2.53%	1.39%	1.21	8.77	0.55	0.08
Event driven	0.93%	1.15%	10.70%	-6.90%	2.03%	-0.17	6.98	0.46	0.28
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	0.81%	0.86%	14.08%	-9.46%	3.03%	0.25	6.53	0.29	0.22
Directional Trading Grou	0.81%	0.64%	7.50%	-6.20%	2.41%	0.33	3.03	0.34	0.07
Market neutral group	0.78%	0.90%	5.10%	-5.40%	1.29%	-0.94	7.66	0.60	0.17
Speciality Strategies Grou	0.81%	0.94%	7.90%	-12.50%	2.26%	-1.11	8.73	0.36	0.32
Weighted-Composite Inde	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 index 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 excess return. The beta is the slope of this regression. The directional trading group includes the futures and macro strategies. The market neutral group includes the equity market neutral, event-driven and market neutral arbitrage strategies. The specialty strategies group includes the long-short credit strategy and the multi-strategy.
Source: Greenwich Alternative Investment.

Table 2 Estimation of the conditional variances of the macroeconomic and financial variables used in this study

	mean equation				conditional variance						
	c	AR(1)	AR(2)	MA(1)	η_2	η_3	η_4	$\phi 1$	$\phi 2$	R^2	DW
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. (5) whilst the ϕ coefficients are those of Eq. (4).

Table 3 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. (1)). 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 *t* statistics are in parentheses. n is the number of observations

Table 4 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. (1)). 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 *t* statistics are in parentheses. n is the number of observations.

Table 5 OLS estimations of models of the cross-sectional dispersion of strategies' 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 *t* statistics are in parentheses. n is the number of observations

Table 6 GMM estimations of models of the cross-sectional dispersion of strategies' 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 *t* statistics are in parentheses. n is the number of observations

Table 7 OLS estimations of models of the cross-sectional dispersion of strategies' alphas, 1997-2012

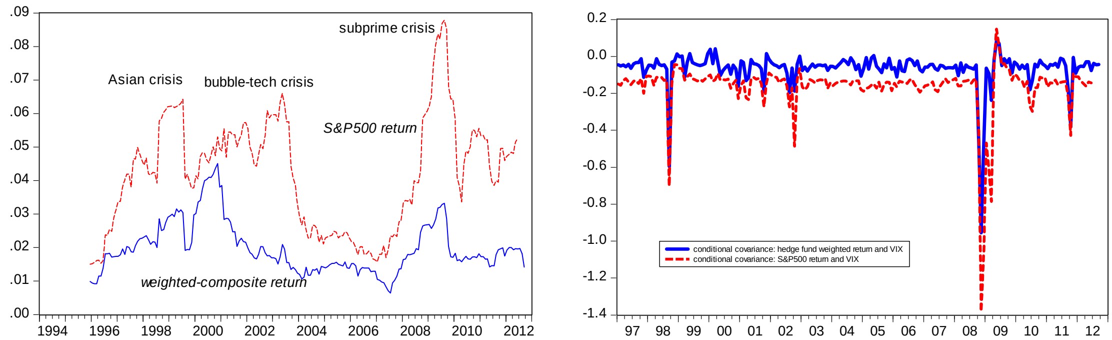
Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
c	0.008	0.0018	-0.006	7.51E-05	-0.008	0.005	0.005	0.016	0.0003
	(1.48)	(0.33)	(-0.82)	(0.008)	(-0.81)	(0.88)	(1.12)	(1.55)	(0.05)
gprod	-0.00015	-3.43E-05							
	(-1.12)	(-0.20)							
cv_ gprod	6.50E-05	3.43E-05							
	(2.47)	(1.20)							
r10			0.005						
			(1.08)						
cv_ r10			0.002						
			(1.87)						
VIX		0.0003	0.0007		0.001		-0.0003	0.0009	0.0004
		(2.34)	(4.87)		(4.08)		(-2.76)	(4.62)	(2.32)
inf				0.002	0.002				
				(1.60)	(2.31)				
cv_ inf				4.52E-05	7.98E-06				
				(0.32)	(0.06)				
rSP500						-0.0001	-0.00014		
						(-6.31)	(-6.15)		
cv_ rSP500						2.97	3.05		
						(4.77)	(5.66)		
gcredit								0.0004	
								(0.87)	
cv_ gcredit								-7.20E-05	
								(-2.80)	
spread									-0.0009
									(-1.02)
cv_ spread									0.14
									(1.87)
Descriptive statistics									
R^2	0.95	0.95	0.95	0.94	0.95	0.96	0.96	0.96	0.95
DW	1.93	1.96	1.93	1.91	1.90	2.32	2.35	1.90	1.93
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 *t* statistics are in parentheses. n is the number of observations

Figure 1 Rolling standard deviations and conditional covariances with the *VIX*: GAI weighted composite return and S&P 500 return

Panel A
Rolling standard deviations of indices

Panel B
Conditional covariances of indices with the *VIX*



Notes. The standard deviations are computed on a rolling window of twelve months. The conditional covariances are computed with a MGARCH based on the BEKK procedure (Bollerslev et al., 1988; Engle and Kroner, 1995).

Figure 2 Strategies' beta and return volatility

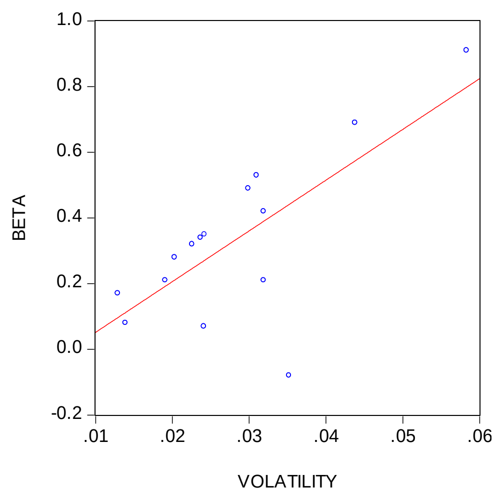


Figure 3 Strategies' mean return and beta

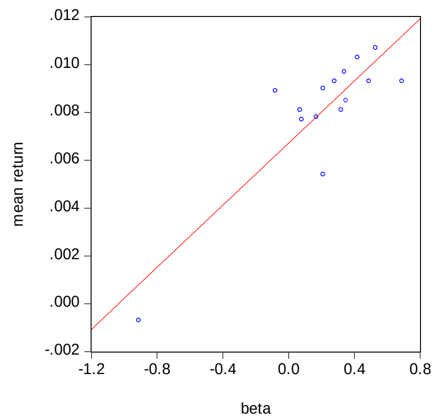


Figure 4 Strategies' kurtosis and return standard deviation

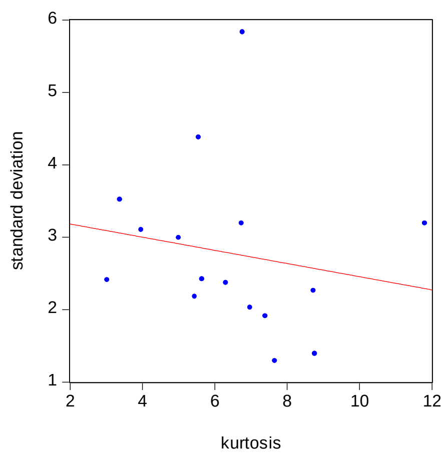
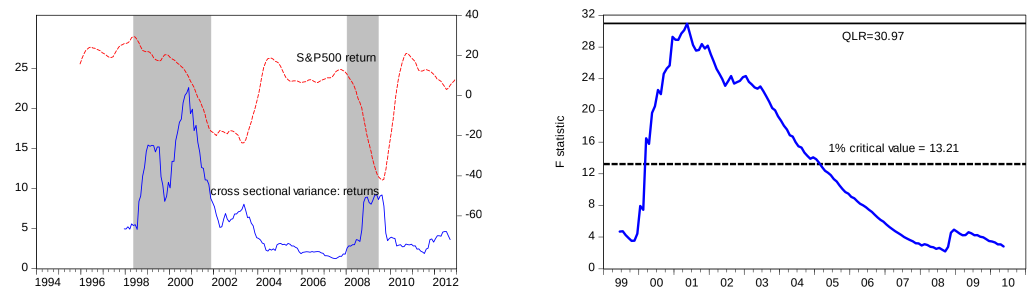


Figure 5 Moving averages: cross-sectional variance of hedge funds returns (*disp(ret)*) and S&P500 return. Quandt-Andrews breakpoint test on *disp(ret)*.

Panel A
Moving averages

Panel B
Quandt-Andrews breakpoint test on *disp(ret)*

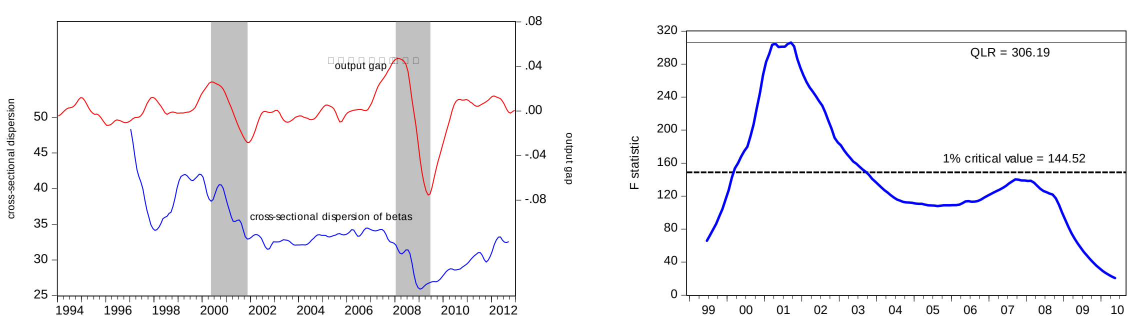


Notes : Shaded areas are associated with periods of economic slowdown. QLR is the abbreviation of "Quandt likelihood ratio". See Quandt, (1960), Andrews (1993, 2003), Stock and Watson (2003).

Figure 6 Cross-sectional dispersion of strategies' betas (*disp(beta)*). Quandt-Andrews breakpoint test on *disp(beta)*.

Panel A
disp(beta)

Panel B
Quandt-Andrews breakpoint test on *disp(beta)*

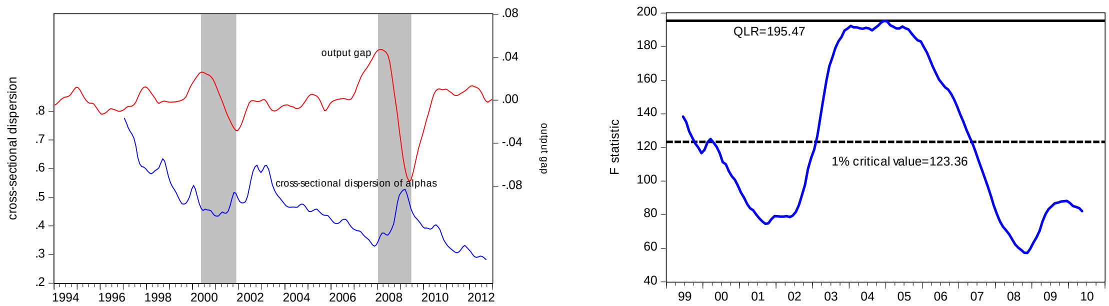


Notes : Shaded areas are associated with periods of economic slowdown. To compute the monthly output gap, we first take the log of the industrial production. We then detrend this transformed series with the Hodrick-Prescott filter using a smoothing coefficient (λ) equal to 14400—the trend of the series 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).

Figure 7 Cross-sectional dispersion of strategies' alphas (*disp(alpha)*). Quandt-Andrews breakpoint test on *disp(alpha)*.

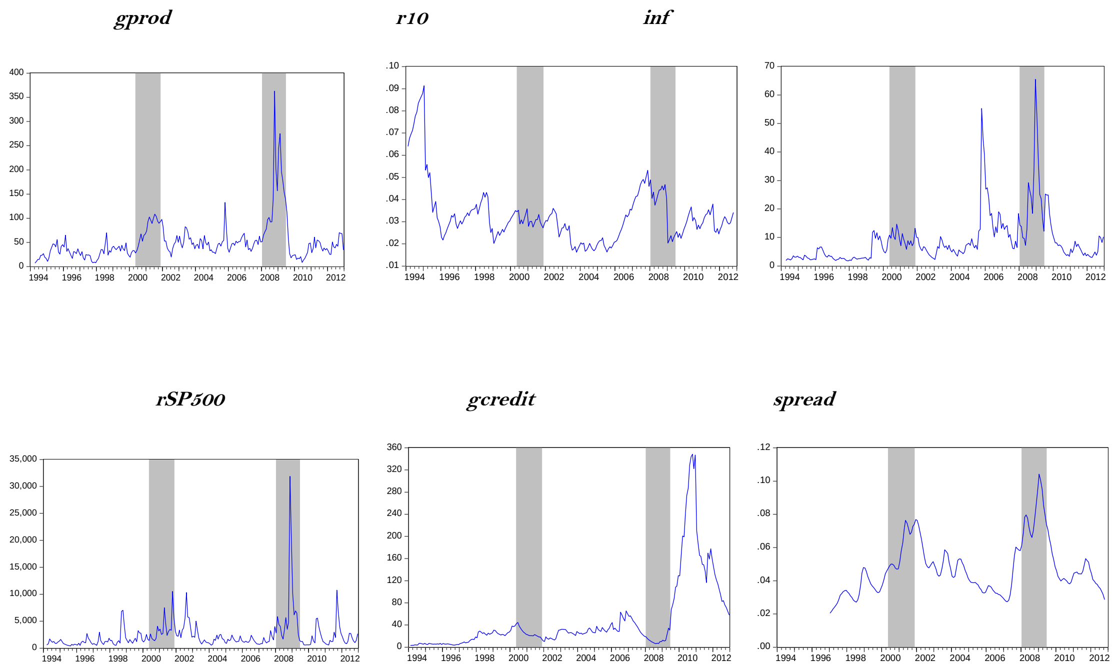
Panel A *disp(alpha)*

Panel B Quandt-Andrews breakpoint test on *disp(alpha)*



Note : 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).

Figure 8 Conditional variances of some macroeconomic and financial variables



Note : Shaded areas are associated with periods of economic slowdown. The construction of these series is explained in section 4.1.

Figure 9 *VIX* and term spread conditional variance

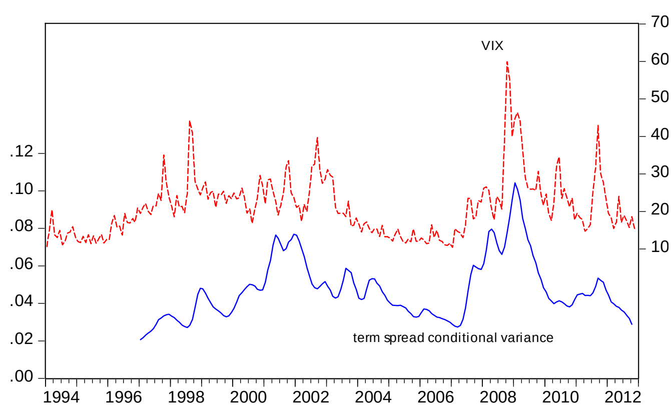


Figure 10 *VIX* and S&P500 conditional variance

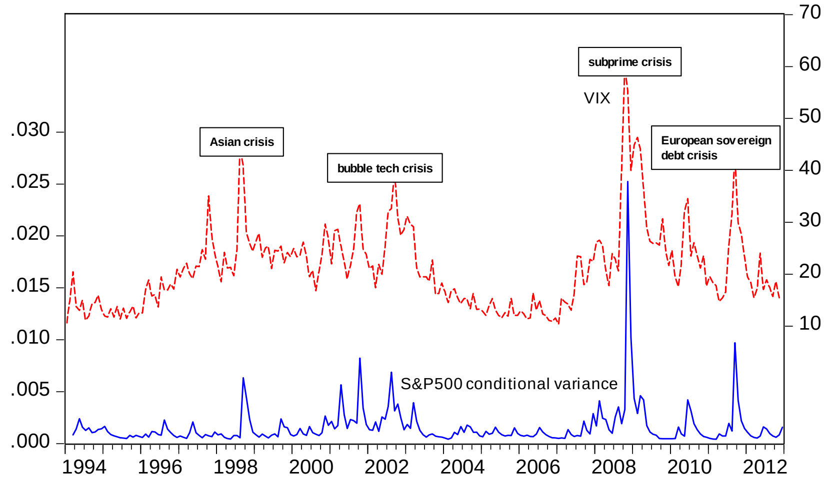
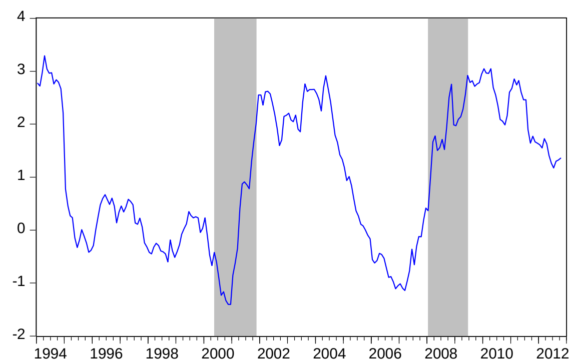
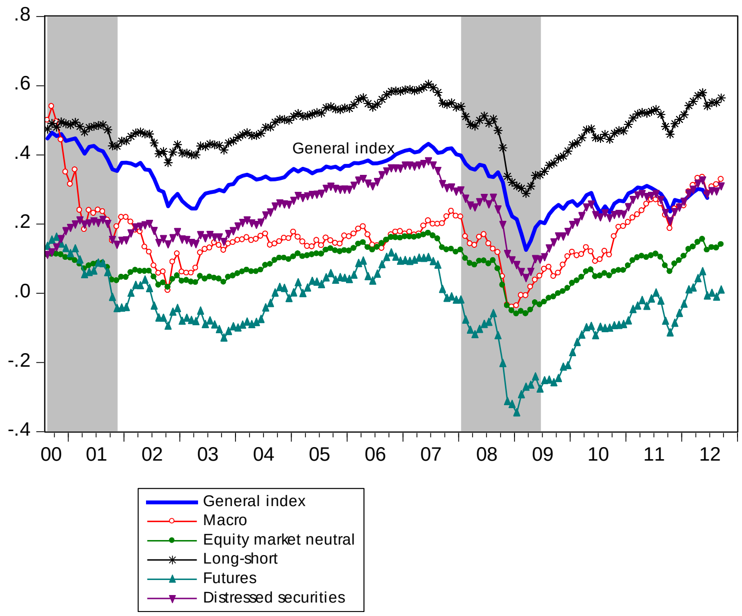


Figure 11 Term spread



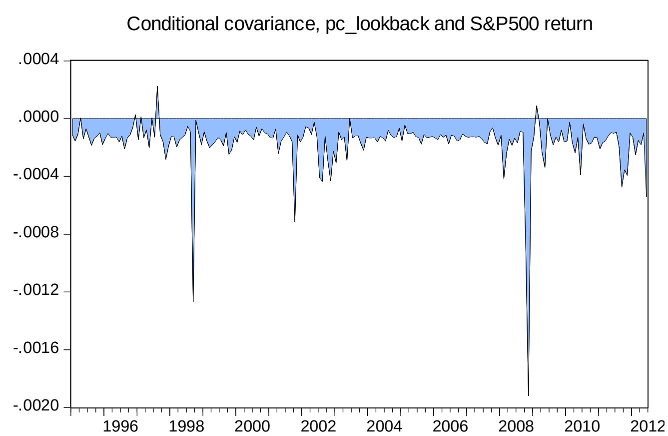
Note : Shaded areas are associated with periods of economic slowdown.

Figure 12 Time-varying betas of several hedge fund strategies



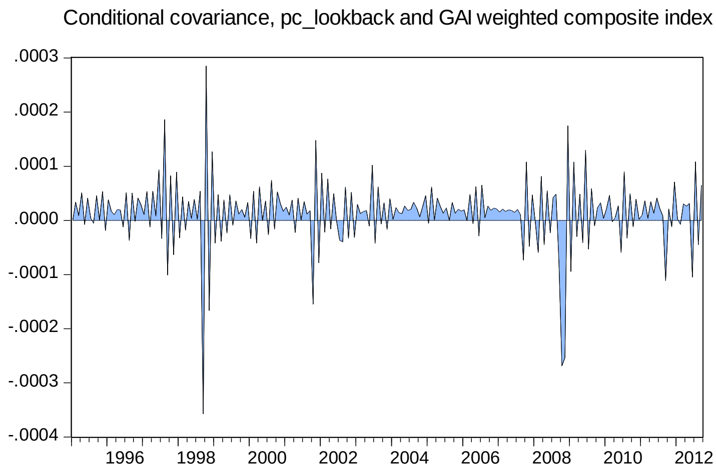
Notes: The time-varying betas are computed using the Kalman Filter (Racicot and Théoret, 2013). Shaded areas are associated with periods of economic slowdown.

Figure 13 Conditional covariance between the *pc_lookback* and S&P return



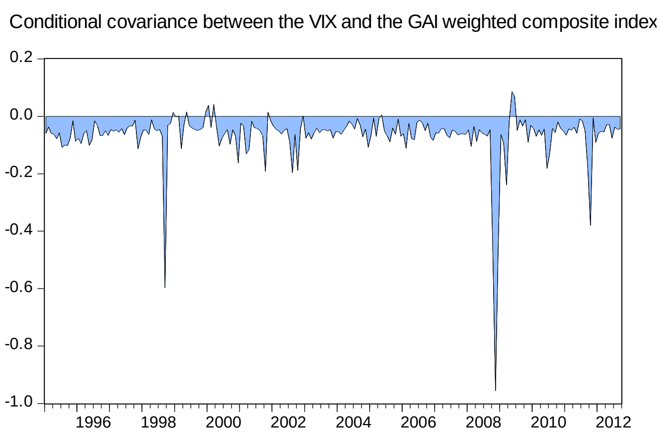
Note. The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al.*, 1988; Engle and Kroner, 1995).

Figure 14 Conditional covariance between the *pc_lookback* and GAI weighted composite index



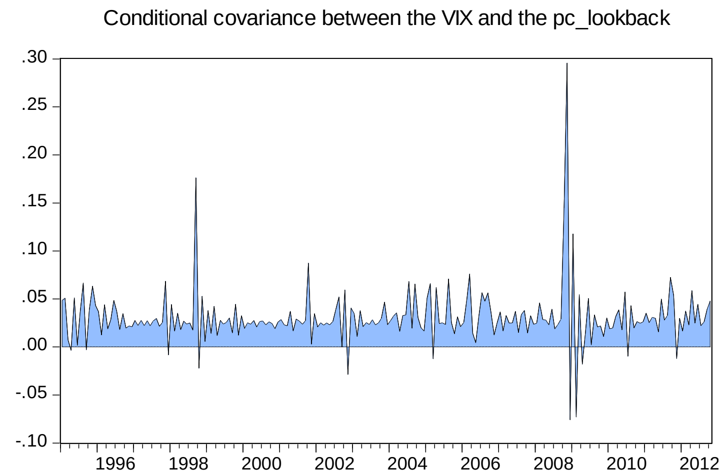
Note. The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al.*, 1988; Engle and Kroner, 1995).

Figure 15 Conditional covariance between the *VIX* and the GAI weighted composite index



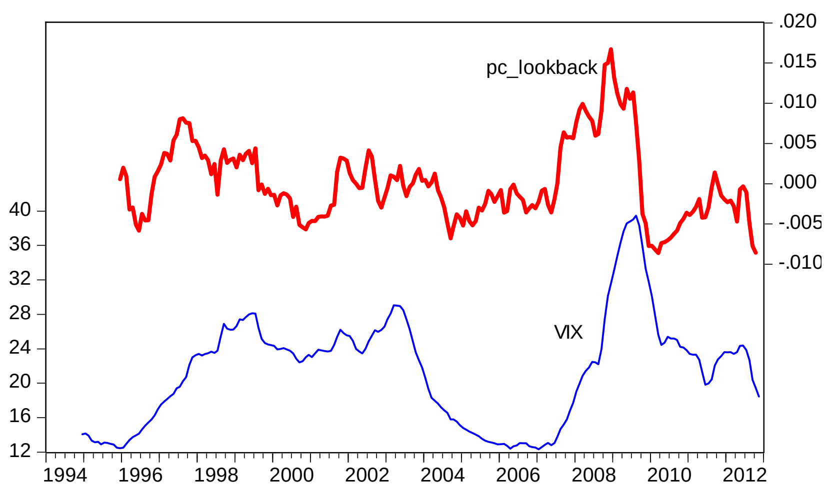
Note. The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al.*, 1988; Engle and Kroner, 1995).

Figure 16 Conditional covariance between the *VIX* and the *pc_lookback*



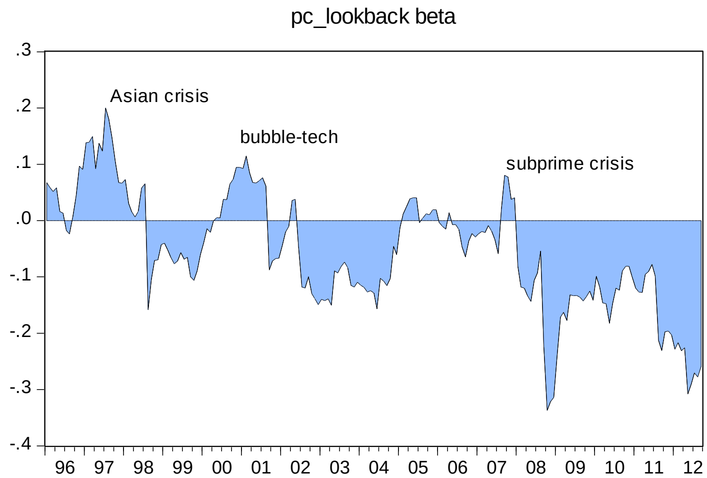
Note. The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al.*, 1988; Engle and Kroner, 1995).

Figure 17 Moving average, *pc_lookback* and *VIX*



Note. The moving average is computed on a rolling window of twelve months.

Figure 18 Beta of the *pc_lookback*



Note. The time-varying beta is computed with the Kalman filter applied to the simple market model.