CHAIRE d'information financière et organisationnelle
ESG UQÀM

Cahier de recherche 2013-10

Procyclicality and diversification in the hedge fund industry†

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

[a] *Telfer School of Management, Member of the CGA-Canada Accounting and Governance Research Center (CGA-AGRC), University of Ottawa, 55 Laurier Avenue East, Ottawa, Ontario; Chaire d'information financière et organisationnelle, ESG UQAM;*

[b] *Université du Québec (Montréal), École des sciences de la gestion, 315 est Ste-Catherine, R-3555, Montréal, Québec; Université du Québec (Outaouais); Chaire d'information financière et organisationnelle, ESG UQAM.*

(This version December 10th 2013)

† **Aknowledgements**. We would like to thank Ying L. Becker and seminar participants at the Southern Finance Association Annual Meeting held in Key West, Florida in November 2011 for their helpful suggestions. We also thank Bhaswar Gupta for his enlightening comments. We finally thank the seminar participants at the Southern Finance Association Annual Meeting held in Charleston, South Carolina, in November 2012.

---

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

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

Procyclicality and diversification in the hedge fund industry

Abstract: The apparent structural decrease in interest rates and market risk premia induces investors to search for alternative sources of investments. This new regime is particularly problematic for pension funds that are pre-committed to actuarial cash-outflows growing faster than their inflows. In this paper, we show that hedge funds continue to provide good prospects for investors in terms of risk-adjusted returns. Actually, the procyclicality of hedge fund strategies' returns seems to decrease through time. Moreover, the strategies' behaviour in terms of alpha and beta tends to become more heterogeneous in times of crisis. The strategy exposure to adverse shocks seems to recede even after accounting for the subprime crisis. Finally, many hedge fund strategies benefit from an increase in the volatility of stock market returns. Hedge fund strategies may thus constitute a way to offset the lower expected returns observed in the conventional financial markets and may contribute to portfolio diversification.

Keywords: Kalman filter; Hedge funds; Shadow banks; Diversification; Procyclicality; Cross-sectional dispersion measures; MGARCH.

JEL classification: C13; C58; G11; G23.

Procyclicalité et diversification dans l'industrie des hedge funds

Résumé : La diminution structurelle apparente des taux d'intérêt et des primes de risques encourage les investisseurs à rechercher des véhicules d'investissement de rechange. Ce nouveau régime est particulièrement problématique pour les fonds de pension qui sont liés à des engagements actuariels qui croissent plus rapidement que leurs sources de fonds. Dans cet article, nous montrons que les fonds de couverture continuent à offrir des opportunités intéressantes en termes de rendement ajusté pour le risque. En fait, la procyclicalité des rendements dégagés par les stratégies suivies par les hedge funds semble diminuer à travers le temps. De plus, le comportement des stratégies en termes des alphas et des betas tend à devenir plus hétérogène en temps de crise. L'exposition des stratégies aux chocs négatifs tend à se résorber à travers le temps, même après prise en compte de la crise des *subprimes*. Finalement, plusieurs stratégies bénéficient d'une hausse de la volatilité des marchés financiers. Les placements dans les stratégies des hedge funds peuvent donc être un moyen de compenser la baisse des rendements espérés sur les marchés financiers et même contribuer à la diversification des portefeuilles.

Mots-clefs : Filtre de Kalman; Hedge funds; Banques parallèles; Diversification; Procyclicalité; mesures de dispersion en coupe instantanée; MGARCH.

1. Introduction

The structural decrease in interest rates and market risk premia induces investors to search for alternative sources of investments. This new regime is particularly problematic for pension funds that are pre-committed to actuarial cash-outflows growing faster than their cash-inflows. Short-term interest rates being close to zero and showing no sign of increase, the bond markets deliver very low yields. Given the positive link between long-term interest rates and stock returns, the expected returns on stocks are much lower than in the past. Banks and investment bankers tried to get out of this conundrum by taking more risk and more leveraged positions (Borio and Zhu, 2008; Adrian and Shin, 2010; Disyatat, 2010; Gambacorta and

Marques-Ibanez, 2011). Actually, this herding behaviour of financial institutions with respect to risk—may it be rational or not—led to an increase in *systemic* risk in the financial system resulting from the rising interconnectedness between these institutions, an obvious source of externalities (Schoenmaker, 2013). A major crisis followed.

Alternative investments—such as those provided by hedge fund strategies—may be a way to improve a portfolio manager's risk-return trade-off in a financial landscape characterized by depressed expected returns. Hedge funds deliver absolute returns which seem partly immune to financial crises. Some strategies—such as the distressed, futures, short sellers and event-driven ones—even benefit from economic downturns or financial crises. Others—e.g., the trend followers—benefit from the stock market volatility which is often associated with a downward trend in stock market returns (Black, 1976; Fung and Hsieh, 1997, 2001, 2004)[1]. More precisely, there seems to be a persistent alpha puzzle in the hedge fund industry. According to this puzzle, hedge funds would deliver absolute positive returns after taking into account the risk embedded in this sector (Racicot and Théoret, 2009, 2012).

In this study, we focus on the time-varying aspects of investment in hedge fund strategies. Indeed, return procyclicality is a subject quite neglected in the academic studies on hedge funds. To shed light on this dimension, we feature a parsimonious return model based on the Kalman filter in order to pin down the dynamics of hedge fund strategies. In this model, the alpha and beta are time-varying and depend on conditioning market information. More precisely, the beta of a strategy is related to the payoffs of a lookback straddle defined as the first principal component of the Hsieh's lookback risk factors (Fung and Hsieh, 2001, 2004). This feature of our model allows us to analyze how hedge funds behave when the volatility of financial markets increases (Treynor and Mazuy, 1961; Henriksson and Merton, 1981; Fung and Hsieh, 2001). The co-movements of hedge fund strategies' returns, betas and alphas have also not been studied yet using a comprehensive approach accounting for the impact of business cycles[2]. We adopt this perspective to better document the diversifying virtues of hedge fund strategies.

Our analysis shows that the alphas related to hedge fund strategies tend to decrease through time. However, they remain positive, suggesting that hedge funds continue to deliver positive absolute returns. Surprisingly, for many strategies, the alpha increased during the

---

[1] Indeed, there is an asymmetry in the volatility of stock returns that is related to the nature of economic and financial news. In this respect, the relative volatility of returns depends on the sign of the innovation in return models. When the sign of the innovation is negative—i.e., in times of bad news—return volatility is higher than when the sign of the innovation is positive—i.e., in times of good news. For further detail on this asymmetry, see Nelson (1991).

[2] Sabbaghi (2012) analyses the co-movement of the Credit Suisse hedge fund index returns by using the indicators proposed by Adrian (2007). In this study, we also transpose these indicators to the study of the co-movements of strategy alphas and betas.

subprime crisis, suggesting that hedge fund strategies may display a good performance even in times of turmoil. In other respects, the beta of hedge funds is quite procyclical but the strategies' betas behave more heterogeneously during crises, suggesting again diversification opportunities. Strategies' returns also tended to move less homogenously during the subprime crisis than during the two preceding ones—i.e., the Asian and bubble tech crises—another indication of increasing diversification benefits in the hedge fund sector. However, our analysis shows that the indicators used to monitor the cross-sectional co-movements of time series may deliver divergent signals and thus ought to be interpreted with caution, an issue which is overlooked in many previous studies.

This article is organized as follows. Section 2 presents our empirical return model. Section 3 reports our database and the stylized facts associated with the hedge fund strategies' returns. Section 4 analyses the empirical results while section 5 concludes.

2. The empirical return model

Our model aims at studying the procylicality of the hedge fund strategies over the period spanning January 1995 to September 2012. To do so, we rely on a hedge fund return model estimated with the Kalman filter. In such a model, the structure of the signal and state equations ought to be parsimonious so we only introduce key risk-based factors in the signal equation. We therefore do not resort to more elaborated hedge fund return models such as the Fung and Hsieh's (2004) seven risk-based factor model.

The signal or observation equation, which relates the return of strategy i (R_{it}) to its risk factors, is formulated as follows:

$$\forall i, \forall t \quad R_{it} - r_{ft} = \alpha_{it} + \beta_{it}\left(R_{mt} - r_{ft}\right) + \gamma_1 SMB_t + \gamma_2 Spread_t + \varepsilon_{it} \quad (1)$$

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 equation (1), $\left(R_{mt} - r_{ft}\right)$ 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[3]. 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 equation (1). These arguments which favor a positive sign for γ_2 are akin to a "price of risk" approach to the term spread.

This argument 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:

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

where $E\left(r\right)$ 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. (2) represents an adjustment term which accounts for the convexity linking the price of a bond to its yield. According Eq. (2), 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.

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

However, according to the "expectations approach" to the term spread—which is associated with the first term of Eq. (2)—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[4] 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[5] (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 equation (1) is thus an empirical issue[6].

The state space equation for the alpha may be written as follows:

$$\forall i, \forall t \quad \alpha_{it} = \alpha_{i,t-1} + \theta_{1i} r_{ft} + \theta_{2i}\left(R_{mt} - r_{ft}\right) + \xi_t \qquad (3)$$

We thus postulate that the alpha follows an autoregressive process augmented with conditioning market information. Equation (3) may be written in first-differences, such as:

$$\forall i, \forall t \quad \alpha_{it} - \alpha_{i,t-1} = \theta_{1i} r_{ft} + \theta_{2i}\left(R_{mt} - r_{ft}\right) + \xi_t \qquad (4)$$

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. 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:

$$\forall i, \forall t \quad \beta_{it} = \beta_{i,t-1} + \delta_{1i} r_{ft} + \delta_{2i}\left(R_{mt} - r_{ft}\right) + \delta_{3i}\, pc\_lookback_t + \varsigma_t \qquad (5)$$

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

[4] The broad credit channel regroups the traditional lending channel and the balance-sheet channel.

[5] 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.

[6] Veronesi (2010) casts Eq. (2) in a macroeconomic model where the price of risk depends of the business cycle.

principal component of the Fung and Hsieh's option risk factors which are lookback straddles[7] 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[8] 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.

We can conjecture the expected signs of the variables included in equations (3) and (5). 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 a decrease in the 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 $\left(R_{mt}-r_{ft}\right)$ 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 $\delta_{2i}>0$. The sign of the coefficient of the *pc_lookback* factor in equation (5) will be discussed later.

3. Data sources and stylized facts

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: $\ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t is the monthly index at time *t*. The market risk premium

[7] 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).

[8] Mainly managed futures or CTA funds.

and the risk factor *SMB* are drawn from French's website[9]. The lookback-straddle option factors come from the Hsieh's database[10].

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 Group	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 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 index is the ratio of the average index excess return on 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.

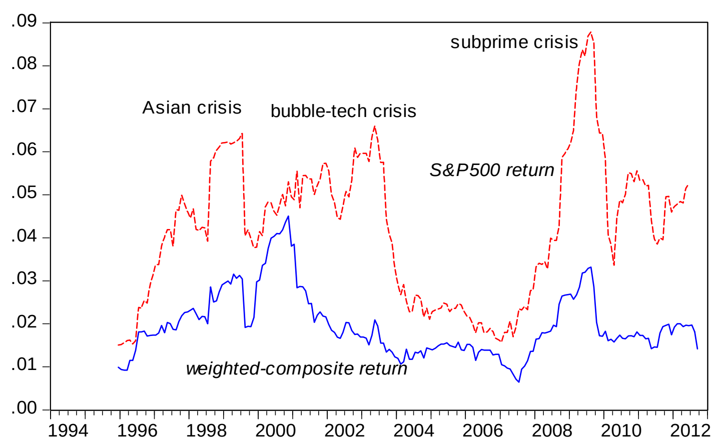
Table 1 reports the descriptive statistics of our hedge fund database. There is some heterogeneity in the historical returns and risk characteristics of hedge fund strategies. For instance, the monthly mean returns range from -0.07% for the short sellers[11] to 1.07% for the value index, and the standard deviation ranges from 1.29% for the market neutral group to 5.83% for the short sellers. The hedge funds' betas are 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)[12]. The strategy with the highest positive beta is the

[9] Kenneth French's website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[10] Hsieh' s database website is https://faculty.fuqua.duke.edu/~dah7/HFData.htm.
[11] Note that the negative return of 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—the expected return of a long put is close to -50% as opposed to 40% for a long call in an Hull's (2012) example.
[12] Selling short may thus be a dominant strategy of futures hedge funds.

growth one (0.69) while the strategy with the lowest positive beta is the equity market neutral one (0.08).

We can classify the hedge fund strategies in three main categories according to the value of their beta[13]. Some strategies are directional in the sense that they have a greater exposure 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 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[14]. The value strategy might also be a candidate for this category since its beta is quite 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.

Figure 1 Rolling standard deviations: GAI weighted composite return and S&P 500 return



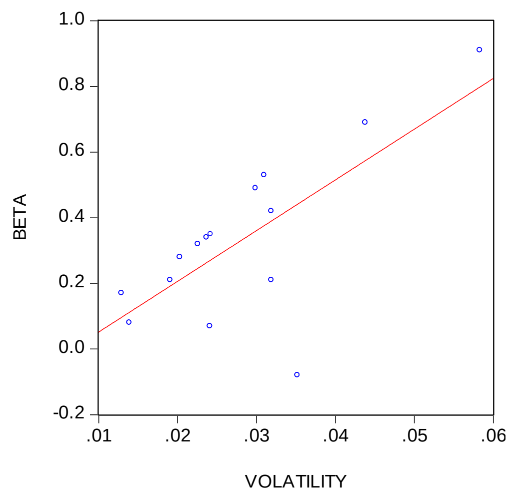
Note. The standard deviation is computed on a rolling window of twelve months.

The standard deviation of the GAI weighted composite index is less than the S&P500 one over our sample period, the respective levels being 2.18% and 4.59% (Table 1). In fact, the

[13] Connor and Lasarte (2005) distinguish two broad categories of hedge fund strategies : the market neutral and directional ones.
[14] See: Greenwich Alternative Investments, Greenwich Global Hedge Fund Index Construction Methodology.

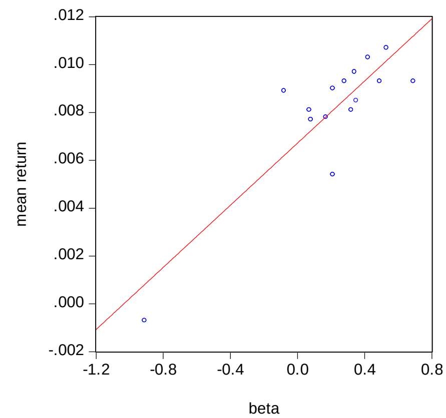
standard deviation of the return of the weighted composite index seems to decline through time, which is not the case for the S&P500 return (Figure 1). More importantly, the standard deviation of the weighted-composite index increased less during the subprime crisis than during the bubble tech one, while the standard deviation of the S&P500 return increased much more during the subprime crisis. This is a first evidence of a decline of procyclicality in the hedge fund sector, which is supported by our analysis of the cross-sectional co-movements of the strategies in section 4.

Figure 2 Strategies' beta and return volatility



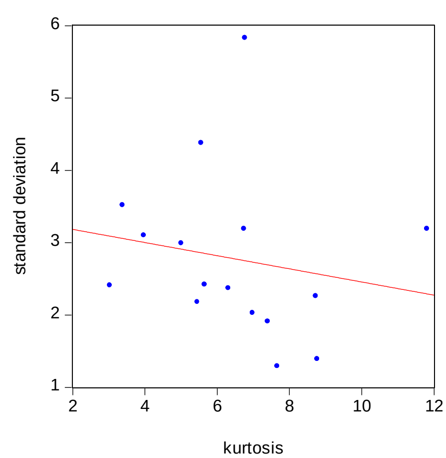
Not surprisingly, the strategies' standard deviations are correlated positively to their betas (Figure 2). Note that short sellers are outside the regression line relating standard deviation to beta but actually, their beta—when measured in absolute value—is relatively high, consistent with the standard deviation of the returns for this strategy. The hedge fund mean 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 be relied on to explain their returns.

Figure 3 Strategies' mean return and beta



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 strategies' corresponding average (0.81%).

Figure 4 Strategies' kurtosis and return standard deviation



Many strategy returns display negative skewness: event driven, distress securities, diversified event driven, value index, speciality and the multi-strategy index. Returns of directional strategies tend to display a positive skewness. This contrasts with the market portfolio which displays a negative skewness. 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.

4. Empirical results

4.1 Estimation of the benchmark model

Table 2 State space regressions of strategy index returns using the Kalman filter, January 1995 – September 2012

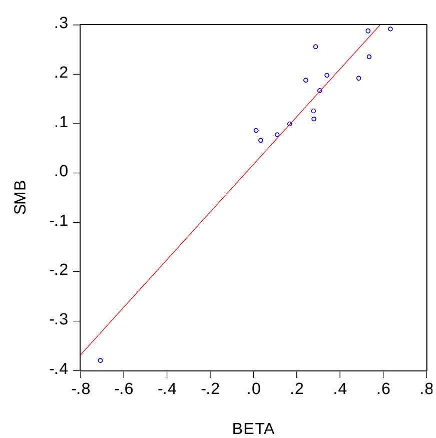
	time-varying alpha			time-varying beta									
	sv1	*rf*	*(Rm-Rf)*	*sv2*	*rf*	*(Rm-Rf)*	*pc_lookback*	*SMB*	*Spread*	*dummy_up*	*dummy_down*	*L*	*AIC*
Equity Market Neutral	0.0020	-0.1531	0.0019	0.1129	-13.33	0.067	-0.7631	0.0764	0.6144	0.0657	-0.0119	123.4	-6.01
	2.85	*-3.82*	*0.58*	*7.42*	*-0.20*	*1.12*	*-2.42*	*3.59*	*2.11*	*11.25*	*-1.74*		
Event driven	0.0050	-0.0688	-0.0045	0.309	-0.014	0.0602	-1.1818	0.1659	-0.2783	0.0777	-0.0398	596.3	-5.74
	6.19	*-1.90*	*-1.42*	*17.76*	*-0.02*	*0.69*	*-3.50*	*7.40*	*-0.79*	*21.25*	*-4.90*		
Distressed Securities	0.0036	-0.0258	-0.0095	0.282	1.6034	0.1321	-0.8958	0.1085	0.0884	0.0427	-0.0406	556.6	-5.35
	3.69	*-0.56*	*-2.21*	*13.31*	*1.60*	*1.21*	*-2.04*	*3.72*	*0.20*	*8.25*	*-4.07*		
Diversified Event Driven	0.0051	-0.0878	-0.0032	0.3421	0.1112	0.0383	-0.9415	0.1969	-0.3231	0.0938	0.0386	569	-5.48
	5.50	*-2.13*	*-0.89*	*17.42*	*0.12*	*0.37*	*-2.60*	*7.62*	*-0.78*	*20.97*	*4.64*		
Long-Short	0.0014	-0.1556	0.0057	0.5375	-0.414	0.1689	-0.9137	0.2346	0.7583	0.1173	-0.0215	572.6	-5.51
	2.07	*-3.18*	*1.48*	*27.48*	*-0.36*	*1.68*	*-2.09*	*8.16*	*1.65*	*28.91*	*-2.53*		
Growth	-0.0068	-0.0911	0.0037	0.636	0.1479	0.0798	-0.1245	0.2905	2.7218	0.1931	0.0249	484.1	-4.64
	-4.76	*-1.15*	*0.62*	*20.98*	*0.10*	*0.60*	*-0.17*	*6.65*	*3.69*	*35.01*	*-1.56*		
Opportunistic	0.0007	-0.1456	0.0014	0.4892	-0.687	0.2074	-1.2879	0.1907	1.0128	0.1746	-0.0301	528.9	-5.08
	0.60	*-2.66*	*0.33*	*20.14*	*-0.52*	*1.63*	*-2.37*	*5.67*	*1.97*	*36.51*	*-2.65*		
Short sellers	0.0062	-0.1702	-0.0002	0.7057	6.2219	0.054	1.0839	-0.381	-0.4949	-0.2919	0.0431	395.5	-3.77
	2.80	*-1.00*	*-0.03*	*-15.00*	*2.33*	*0.26*	*0.99*	*-4.65*	*-0.36*	*-0.22*	*2.62*		
Value Index	0.0047	-0.1969	0.0068	0.5322	-1.584	0.0755	-1.2803	0.287	0.0849	0.0889	-0.0237	564.3	-5.43
	4.91	*-3.92*	*1.69*	*26.10*	*-1.48*	*0.85*	*-2.70*	*11.19*	*0.19*	*23.77*	*-1.94*		
Futures	0.0074	-0.0097	-0.1177	0.036	-2.358	-0.0667	-2.4833	0.065	-1.442	0.0024	0.0477	378.4	-3.61
	3.09	*-0.08*	*-1.01*	*0.70*	*-1.07*	*-0.23*	*-1.76*	*0.79*	*-1.31*	*0.04*	*3.05*		
Macro	0.002	0.0266	0.3007	0.2899	-6.476	0.4231	-0.5451	0.2548	0.3995	0.0894	0.019	122.6	-4.04
	1.04	*0.23*	*0.11*	*7.05*	*-3.05*	*2.18*	*-0.66*	*3.82*	*0.41*	*1.61*	*1.53*		
Multi-Strategy Index	0.0012	-0.0736	0.009	0.2804	-1.172	-0.1303	-0.8577	0.1249	1.6586	0.0571	-0.0224	538.2	-5.17
	1.13	*-1.68*	*2.00*	*12.09*	*-1.62*	*-1.27*	*-1.81*	*4.11*	*3.96*	*4.91*	*-2.63*		
Mean	0.0027	-0.0960	0.0162	0.3794	-1.4959	0.0924	-0.8492	0.1345	0.4000	0.0592	-0.0014	452.49	-4.99
	3.22	*-1.86*	*1.03*	*15.45*	*-1.04*	*1.01*	*-1.93*	*5.61*	*1.45*	*16.06*	*-2.82*		
Directional Trading Group	0.0042	-0.0302	-0.0013	0.0142	-3.581	0.0728	-1.5416	0.0851	0.0215	0.0501	0.0358	462.3	-4.43
	2.69	*-0.39*	*-0.18*	*4.20*	*-2.46*	*0.42*	*-1.61*	*1.63*	*0.03*	*0.96*	*3.77*		
Market neutral group	0.0023	-0.0833	-0.0031	0.1704	0.1207	0.0688	-0.4647	0.0986	0.4294	0.0407	-0.0347	692.2	-6.68
	4.60	*-3.51*	*-1.35*	*15.74*	*0.23*	*1.40*	*-2.35*	*7.19*	*2.03*	*14.82*	*-9.51*		
Speciality Strategies Grou	0.006	0.0039	0.0047	0.2441	-3.407	0.0372	-0.7605	0.1872	0.454	0.0543	-0.052	560.3	-5.39
	6.15	*0.08*	*1.21*	*11.73*	*-3.22*	*0.33*	*-1.71*	*6.44*	*0.964*	*6.94*	*-4.16*		
Weighted-Composite Inde	0.0021	-0.1070	0.0021	0.3411	-1.1326	0.0770	-0.8560	0.1736	0.7194	0.0906	-0.0228	621.4	-6.00
	2.94	*-2.97*	*0.07*	*2.19*	*-1.31*	*0.95*	*-2.49*	*7.84*	*2.12*	*28.43*	*-3.75*		

Notes : The coefficients are obtained using the model given by equation (1). Variables are defined as follows: r_f: the risk-free return given by the U.S. Treasury bills 3-month rate; R_m - R_f: the excess market return; *SMB*: a mimicking portfolio accounting for the firm small size anomaly; *Spread*: the term spread defined as the difference between the ten-year yield and the three-month yield on the U.S. Federal Government securities; *pc_lookback*: the first principal component obtained with the Fung and Hsieh's U.S. lookback returns on stocks, bonds, currencies, commodities and short-interest; Dummy_up: a binary variable taking the value of 1 on February 2000—an upside outlier related to the bubble-tech—and 0 otherwise; Dummy_down: a binary variable taking the value of 1 in September and October 2008—two outliers related to the subprime crisis—and 0 otherwise; *sv1* is a state coefficient related to the alpha; *sv2* is a state coefficient related to the beta; *L* is the likelihood ratio and *AIC* is the Akaike statistics.

Table 2 provides the results of the estimation of our benchmark model given by equation (1). As indicated by the likelihood ratio (*L*), the fit of the model is quite good for most of the strategies. However, four strategies display a low likelihood ratio: macro, equity market neutral, futures and short sellers. These results suggest that other specific risk factors are at play to explain the returns of these strategies.

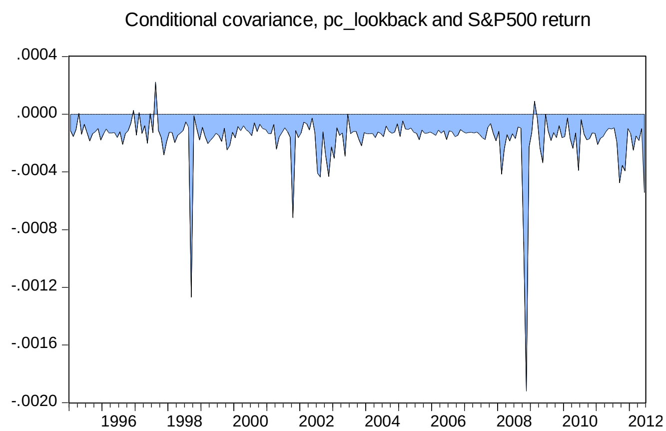
In our model, the coefficient of the market risk premium is time-varying. Its state space value, which may be associated with its mean value or long-term value, is given by *sv2* in Table 2. As expected, the market risk premium is the factor which impacts the most hedge fund returns. The betas of the strategies are very close to the ones estimated with the standard market model (Table 1). The other factor which stands as an important driver of hedge fund returns is *SMB*. Actually, hedge funds have a preference for the stocks of small firms over the stocks of big ones. In other words, hedge funds have a greater exposure to smaller capitalization stocks. Researchers find the same kind of preferences in the mutual fund industry (Haiss 2005). According to McGuire *et al.* (2005), this result is consistent with hedge fund investment in technology stocks and startup companies during the dotcom boom. In other respects, Figure 5 shows that the sensitivity of hedge fund strategies to *SMB* is quite correlated to their market beta.

Figure 5 Strategies' SMB and beta



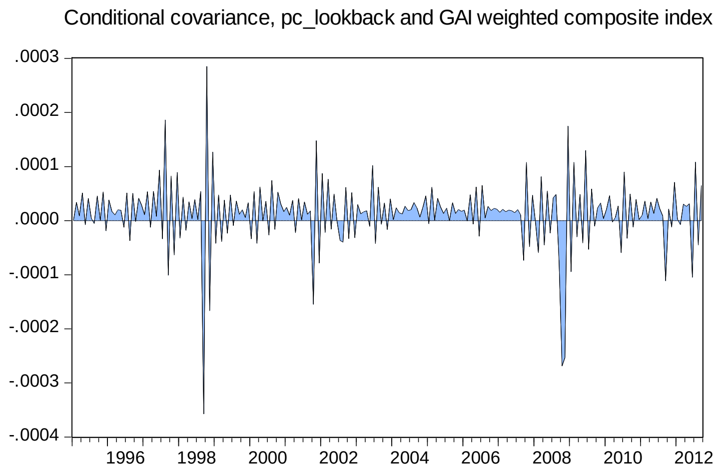
The term spread—which may be viewed as a portfolio long in the 10-year bond yield and short in the three-month Treasury bills yield—impacts positively and significantly many hedge fund strategies' returns. The "price of risk" approach to the term spread thus dominates in this case. For instance, the estimated coefficient of the term spread is equal to 0.7194 in the weighted composite index equation, significant at the 5% level. The strategies which are the most exposed to the term spread are the growth (2.7218), multi-strategy (1.6586), opportunistic (1.0128), long-short (0.7583), and equity market neutral (0.6144). As stated previously, the impact of the spread variable as a driver of performance is quite unexplored in the hedge fund literature but our experiments show that it might be important to explain hedge fund returns—especially in times of low interest rates.

Figure 6 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 7 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).

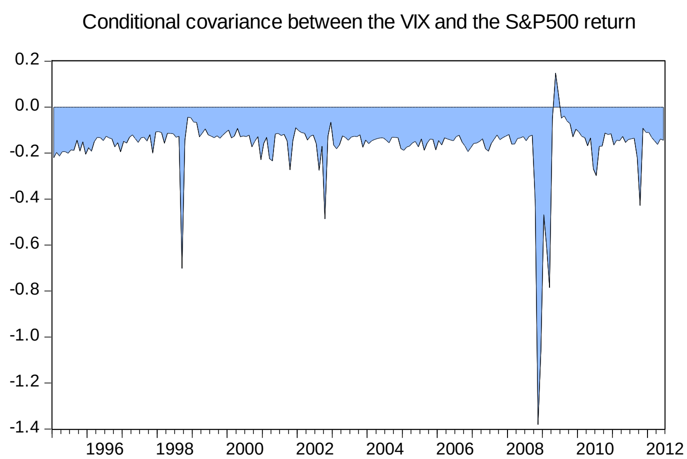
Turning to the factors which explain the time-variability of the beta, Table 2 shows that *pc_lookback* contributes the most to this time variability. With the exception of short sellers, its impact is negative and significant for most of the funds. For instance, in the model of the weighted composite index, its estimated coefficient is equal to -0.8560, significant at the 5% level. The strategies which are the most exposed to this factor are: futures (-2.4833), opportunistic (-1.2879), value index (-1.2803) and diversified event driven (-0.9415). Hedge funds thus reduce their market beta (systematic risk) when the yield on the *pc_lookback* increases. In other words, this factor may be associated with the hedging operations of hedge funds 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 6). Note that this covariance—which is computed with a multivariate GARCH[15] (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). In line with this interpretation, Figure 7 shows that the MGARCH conditional covariance between the *pc_lookback* and the GAI weighted composite index is generally positive. This suggests that

[15] See the appendix for the presentation of the multivariate GARCH procedure.

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.

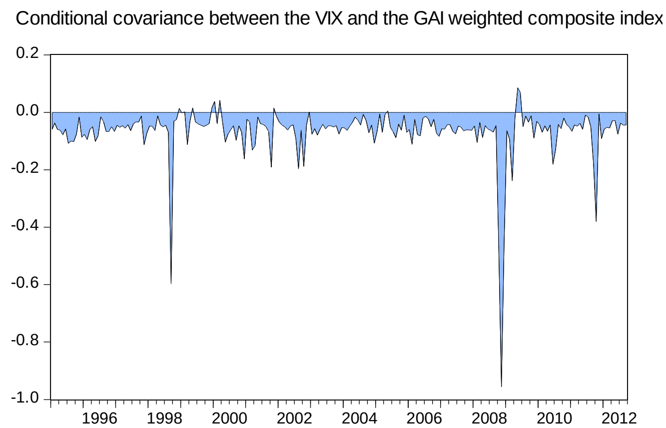
Consistent with our interpretation, Fung and Hsieh (2001) argue that a portfolio of lookback straddles on currencies, bonds, and commodities can reduce the volatility of a typical stock and bond portfolio during extreme market downturns. However, in our study, the lookback factor is the first principal 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.

Figure 8 Conditional covariance between the *VIX* 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).

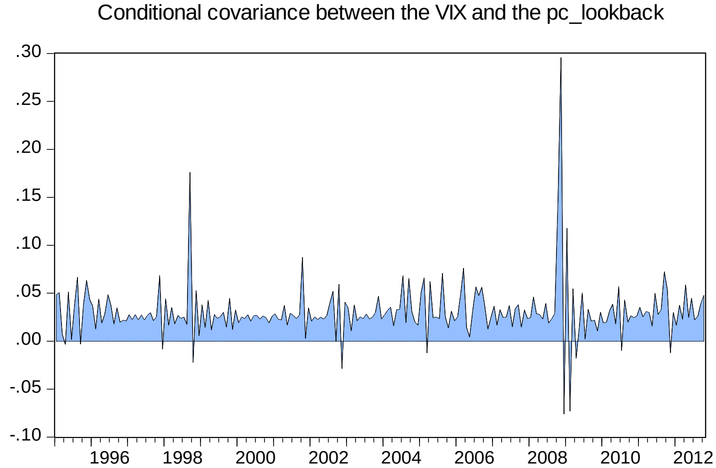
Figure 9 Conditional covariance between the *VIX* and the GAI weighted composite index



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

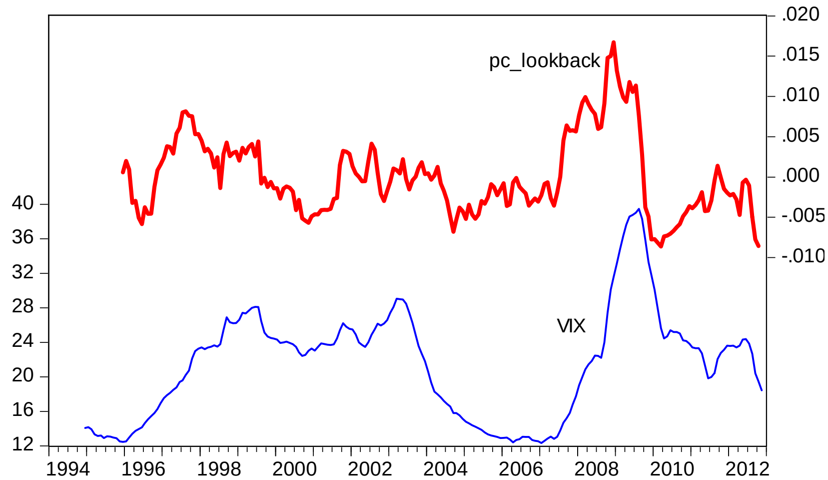
Another interpretation of the link between the *pc_lookback* factor and a strategy's beta hinges on the following argument. Recall that the *pc_lookback* factor is built with lookback straddles that provide greater payoffs when the financial markets are volatile. Figure 8 plots the conditional covariance 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 9 shows that the MGARCH conditional covariance between the *VIX* and the GAI weighted composite index shares a similar profile. However, this covariance is less 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 10 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 11 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.

Figure 10 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 11 Moving average, *pc_lookback* and *VIX*



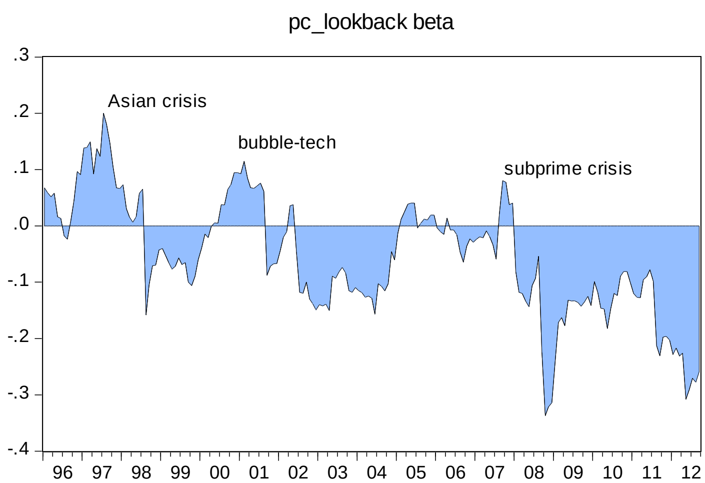
Note. The moving average is computed on a rolling window of twelve months.

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 simple market model estimated with the Kalman filter:

$$pc\_lookback_t = \alpha + \beta_{t,pc\_look}\left(R_{mt} - r_{ft}\right) + \varsigma_t \quad (6)$$

Figure 12, 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 equation (6) into equation (5) and then equation (5) into equation (1) 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 equation (5)—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).

Figure 12 Beta of the *pc_lookback*



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

The level of the interest rate (r_f) also impacts negatively and significantly the beta of some strategies. These strategies (or group of strategies) are: macro (-6.4763), directional trading group (-3.5814) and speciality strategies group (-3.4073). When the interest rate increases, these strategies thus reduce their beta since an increase in interest rate may signal a coming decline of the stock market. Since central banks control short-term interest rates, they can thus rely on the interest rate channel to impact the risk taking behavior of hedge funds. It is interesting to observe that the beta of the macro strategy is the most responsive to the interest rate, this strategy relying on models based on macroeconomic factors. It is thus quite sensitive to monetary policy. Note that short sellers seem to adopt a contrarian position when the interest rate increases, its impact on their beta being estimated at 6.2219, significant at the 5% level. Short-sellers thus decrease their risk when the interest rate increases. Actually, they follow the same behaviour as the other strategies since the short sellers' beta is usually negative.

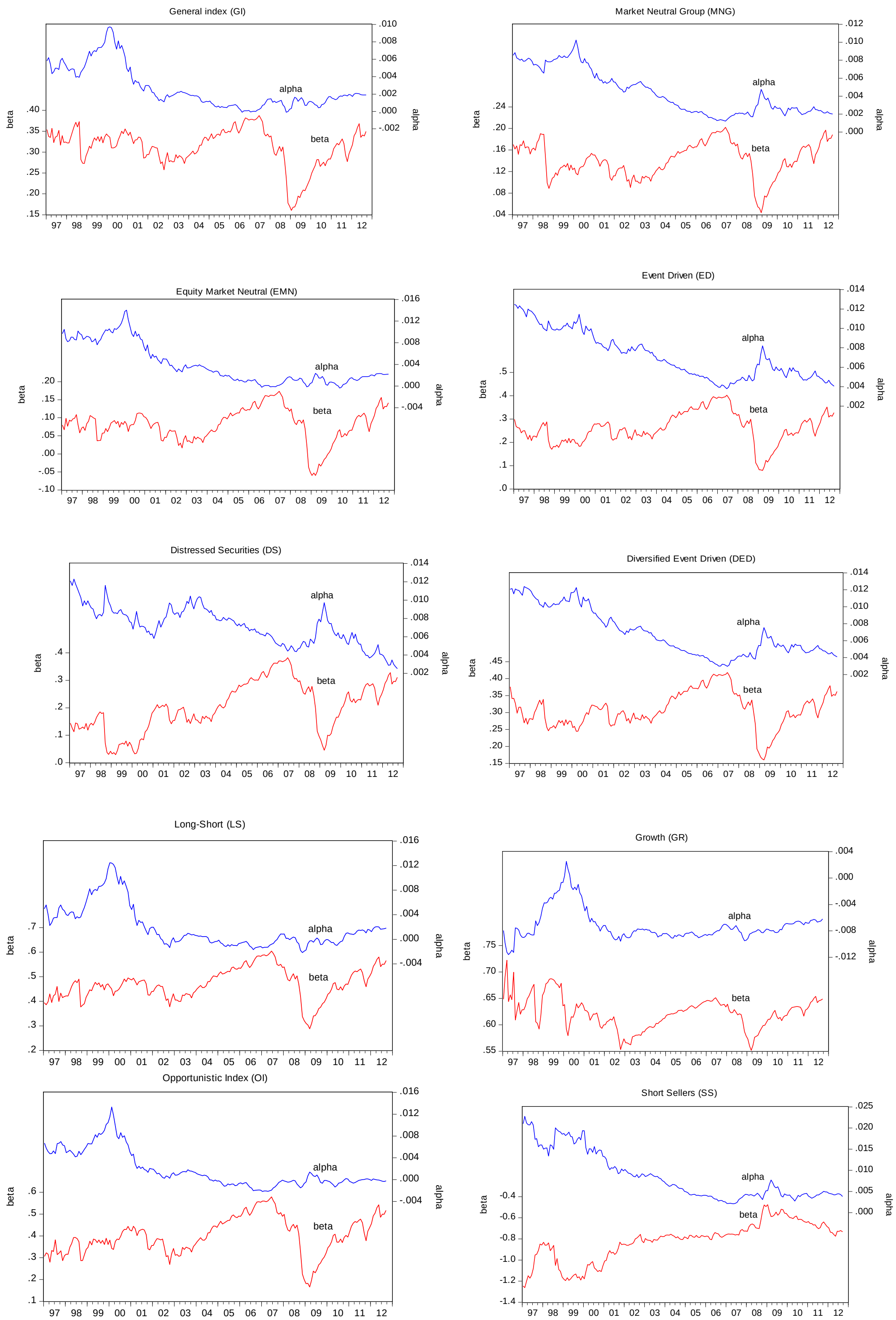
As indicated in Table 2, only few strategies' betas respond significantly to the market risk premium, which stands for the market trend. For one of them—the macro strategy—the estimated coefficient of R_m-R_f is positive and significant at the 5% level. This strategy seems to track closely the market trend. The long-short and opportunistic strategies also display a positive coefficient for R_m-R_f, these coefficients being significant at the 10% level.

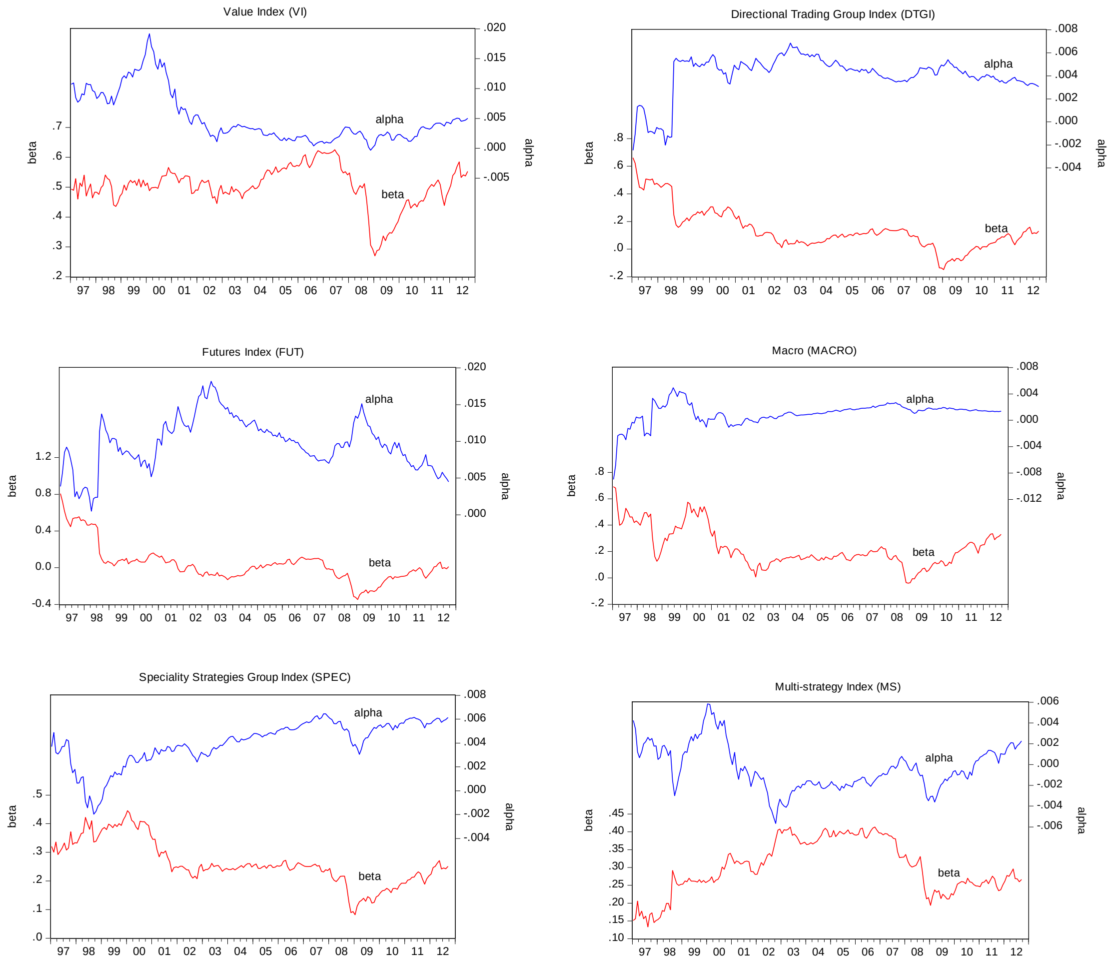
Even if our sample includes the subprime crisis, Table 2 shows that the alpha puzzle seems unsolved over our estimation period. Most of the strategies display significant alphas as measured by their estimated coefficients. Indeed, the average alpha (*sv1*) computed over the 12 strategies is equal to 0.27% on a monthly basis. The futures strategy displays the highest alpha (0.74%) while the growth strategy displays the lowest one (-0.68%). This is the only strategy endowed with a negative alpha. Note that the rank of a strategy in terms of the level of its mean return (Table 1) does not usually correspond to its rank in terms of the level of its alpha (Table 2).

Strategies' alphas seem quite sensitive to the level of the interest rate. For instance, the estimated coefficient of r_f in the weighted index state equation of sv_1 is equal to -0.1070, significant at the 1% level. In the same vein, the alphas of many strategies respond negatively and significantly to interest rates: value index (-0.1969), long-short (-0.1556), equity market neutral (-0.1531), opportunistic (-0.1456), diversified event driven (-0.0878), market neutral group (-0.0833), and multi-strategy index (-0.0736). Therefore, an increase in the interest rate tends to depress a strategy's alpha. This may be related to business conditions, an increase in the interest rate signaling a recession or an acceleration of inflation, with a corresponding tightening of monetary policy. These events tend to depress the alpha.

Like in the case of the beta analysis, few strategies display a link between their alpha and the market risk premium. For the distressed strategy, the coefficient of the market risk premium is equal to -0.0095, significant at the 5% level. This link can be easily explained since a deterioration in business conditions leads to an increase in business failures, a situation which benefits to the distressed securities' strategy. By contrast, an increase in the market trend benefits to the multi-strategy index (0.0090) and the value index (0.0068).

Figure 13 Strategies' time-varying alpha and beta





Note : The time-varying alpha and beta are computed by applying the Kalman filter to the model given by equations (1) to (5).

4.2. Kalman filtered time-varying alpha and beta

Figure 13 plots the Kalman-filtered time-varying alphas and betas[16] for the weighted-index and the strategies over the period 1997-2012. For most strategies, the beta follows a mean-reverting or Ornstein-Uhlenbeck process. Also for most of them, the beta trended upward during the economic expansion which preceded the subprime crisis. Hedge funds thus take more risk when business conditions are improving. However, the beta of these strategies decreased substantially during the subprime crisis, which suggests that hedge funds greatly reduced their market exposure during this period. Thereafter, there was a recovery of their beta which moved back near its pre-crisis level at the end of 2012.

[16] Or state alphas and betas.

However, it is interesting to note that some strategies' betas do not follow a mean-reverting process. In this respect, the short sellers' beta, usually negative, tends to move on an upward trend during the sample period. We note that the subprime crisis impacted less the short sellers' beta than the ones of the majority of the other strategies. In other respects, the beta of the directional trading group displays a low volatility and remains close to zero most of the time. In line with its group, the beta of the futures strategy tends also to remains close to zero. However, in contrast with the other strategies, its beta increased in absolute value during the subprime crisis, suggesting that it was more involved in "shorting" activities.

Turning to the time-variability of the alpha, we first note that some strategies succeed in maintaining a high alpha through time. This is the case of the following strategies (or group of strategies): growth, specialty strategy group, directional trading group, futures and short sellers. Second, for most of the strategies, the alpha has trended downward since 1999. The alpha puzzle thus tends to recede through time, at least over our sample period. However, the alpha remains positive for most strategies and it has recovered since the subprime crisis. In this respect, we find that the subprime crisis had little impact on the strategies' alphas. On the contrary, the alpha of some strategies increased during the crisis. In this respect, the following strategies benefited from the crisis in terms of their alpha: distressed securities, event driven, diversified event driven, market neutral group and futures. These strategies are very specialized and based on arbitrage, which may lead to positive payoffs during crises. Interestingly, the alpha of the futures strategy jumps at each crisis which occurred during our sample period— i.e., the Asian, bubble-tech and subprime crises. It is thus quite immune to crises. Finally, since the strategies' alphas are not mean-reverting like most of their betas, we can induce than the alpha is less manageable than the beta. It is more related to the particular situation of the hedge fund industry, like the low regulation in this sector.

4.3. The return co-movement of hedge fund strategies

The co-movement between security returns in a portfolio is an important indicator of its risk. Indeed, when the co-movement is high, this suggests that the potential for portfolio diversification is quite limited. It is thus interesting to examine the opportunities for diversification in a portfolio built with hedge fund strategies.

We rely on three indicators to track the co-movement of strategies' returns. The first—which corresponds to the cross-sectional standard deviation—is used by Beaudry *et al.* (2001) to study the co-movement of firm returns on investment[17]. Solnik and Roulet (2000) also rely on the cross-sectional dispersion to estimate the co-movement of stock market returns. Sabbaghi (2012) transposed this indicator to the study of the co-movements of the returns on hedge fund indexes. The cross-sectional standard deviation—also named cross-sectional dispersion—is defined as:

$$\forall t, \quad cs\_sd_t = \sqrt{\frac{1}{N}\mathbf{R}_{\mathbf{it}}^{'}\mathbf{R}_{\mathbf{it}}} \qquad (7)$$

Where N is the number of strategies, and $\mathbf{R}_{it}$ is the cross-sectional vector of the strategy returns observed at time t. The cross-sectional standard deviation of returns is thus the square-root of their cross-sectional realized variance. When the cross-sectional standard deviation of returns increases, the dispersion of returns increases. There is thus a rise in the heterogeneity of the hedge fund strategies in this case. This is good news in regard to portfolio diversification. And when the cross-sectional standard deviation decreases, there is an increase in the homogeneity of the strategies. This is bad news with respect to portfolio diversification because strategies' returns move closer in this case.

A more straightforward indicator of return co-movement is their cross-sectional covariance defined as:

$$\forall t, \quad cs\_cov_t = \frac{1}{N^2 - N}\mathbf{R}_{\mathbf{it}}^{'}\left[\mathbf{ii}'\text{-}\mathbf{I}\right]\mathbf{R}_{\mathbf{it}} \qquad (8)$$

where N is the number of strategies, $\mathbf{R}_{it}$ is the cross-sectional vector of the strategies' returns observed at time t, $\mathbf{i}$ is the unitary vector, and $\mathbf{I}$ is the identity matrix. The cross-sectional covariance is thus defined as the average of the cross-sectional second co-moments (Adrian, 2007). An increase in the cross-sectional covariance of the strategies' returns signals a higher co-movement between these returns, so the degree of homogeneity of the strategies increases. Conversely, a decrease in the cross-sectional covariance signals a decrease in return co-movement, so the degree of heterogeneity of the strategies increases.

It would be desirable that these two indicators of co-movement move in an opposite direction. That is, when *cs_sd* decreases, *cs_cov* should increase. This is then an unambiguous signal of an increase in the co-movement of the strategies' returns, hence an increase in homogeneity. But, as shown later, this is not necessarily the case at the empirical level.

---

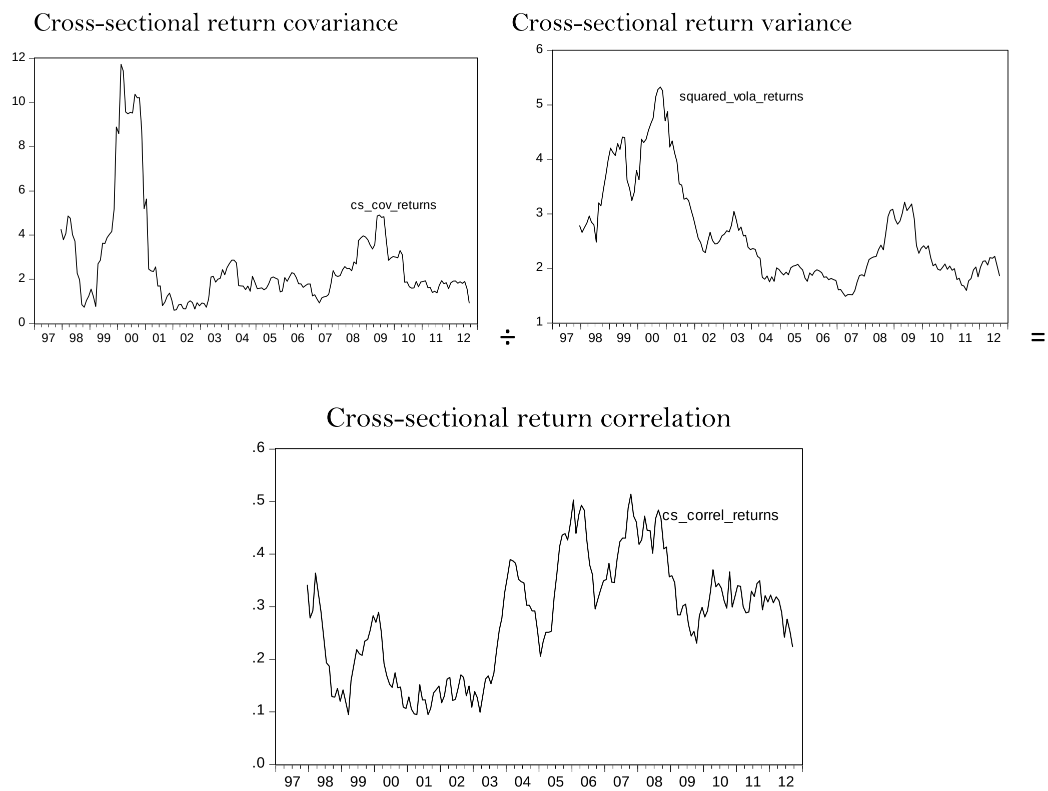
[17] Baum *et al.* (2004, 2009) rely on the cross-sectional standard deviation of the loans-to-assets ratio to study the herding behaviour in the banking sector.

The third indicator of return co-movement is the cross-sectional correlation of returns. It is defined as the ratio of equations (8) and (7) squared:

$$\forall t, \quad cs\_corr = \frac{cs\_cov_t}{cs\_var_t} \qquad (9)$$

where *cs_var* is the cross-sectional variance. When *cs_cov* increases and *cs_var* decreases simultaneously, *cs_corr* increases: the co-movement between strategies' returns increases unambiguously. Conversely, when *cs_cov* decreases and *cs_var* increases simultaneously, *cs_corr* decreases: the co-movement between returns decreases unambiguously. In the other cases, the signal given by *cs_corr* is somewhat ambiguous because *cs_var* and *cs_cov* do not indicate the same direction regarding the co-movement between strategies' returns.

Figure 14 Cross-sectional correlation (*cs_corr*) of the strategies' returns and its components



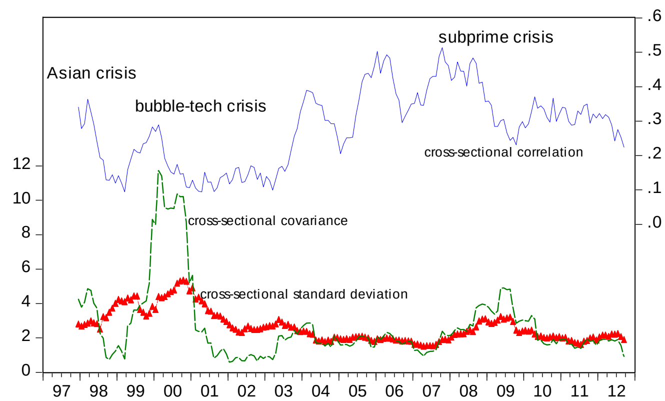
Note: The cross-sectional time series are computed using a moving average of twelve months.

Sabagghi (2012) rely on the three indicators of co-movement given by equations (7) to (9) in order to study the return co-movement of the strategy indices provided by Credit Suisse[18].

[18] Formerly known as the Credit Suisse/Tremont Hedge Fund Indexes.

We reproduce this exercise for the GAI strategies. Figure 14 plots our three indicators of strategies' return co-movement from 1997 to 2012. The cross-sectional covariance registered a big jump during the bubble-tech crisis and a small jump during the subprime crisis. According to this indicator, the strategies' return co-movement over the crises shows a tendency to decrease through time, a good news in regard to portfolio diversification. Outside the crises, the co-movement between the strategies' returns—as measured by the cross-sectional covariance—is low, which suggests that the risk associated with the hedge fund strategies is quite diversifiable.

Figure 15 Financial crises and co-movements between strategies' returns



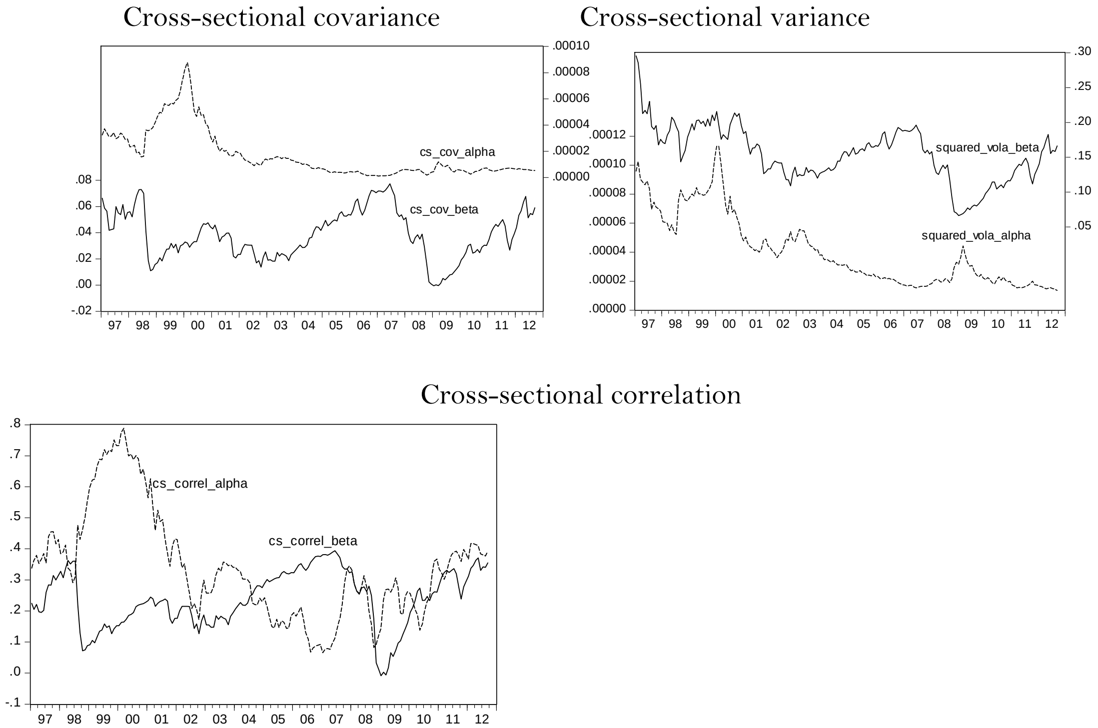
Note: The cross-sectional time series are computed using a moving average of twelve months.

The signal sent by the cross-sectional deviation in regard to the co-movement of the strategies' returns differs. First, the time-profile of the two co-movement series—i.e., *cs_var* and *cs_cov*—seems to diverge. The cross-sectional covariance jumps in time of crises and is low and stable otherwise. For its part, the cross-sectional deviation jumped during the bubble-tech crisis and declined progressively thereafter. However, similarly to the cross-sectional covariance, it jumped during the subprime crisis with a lower amplitude than the one observed during the bubble-tech crisis. Contrary to the cross-sectional covariance, the cross-sectional deviation indicates that the behavior of the strategies is more heterogeneous in times of crises and more homogeneous in times of economic expansion. Since the cross-sectional deviation trends downward, it signals that that the behaviour of the strategies tends to become more homogeneous through time.

A closer look at the two series shows that they are strongly correlated since 2003 (Figure 15). They thus send a different signal in terms of the pattern of diversification in the hedge fund industry. The cross-sectional correlation is the ratio of these two diverging signals sent by its components (Figure 14). First, it tends to increase through time, signaling that the behavior of the strategies becomes more homogeneous, a profile borrowed from the cross-sectional deviation. Second, the cross-sectional correlation increases during crises, suggesting a more homogenous return pattern during these periods (Figure 15). Thus, the impact of the cross-sectional covariance dominates the cross-sectional correlation one during these periods. Contrary to the profile of the cross-sectional covariance, we also note that the cross-sectional correlation was higher during the subprime crisis than during the bubble-tech one, which reflects the lower level of the cross-sectional dispersion during the subprime crisis. Fortunately, the cross-sectional correlation decreased significantly after the crisis, indicating less co-movement between the strategies' returns.

A regression of *cs_sd* on twelve Almon lags of *cs_cov* shows that the sum of the lags is equal to 0.36, significant at the 1% level. An increase in covariance was an early indicator of the high volatility that took place during the bubble-tech crisis but to a less extent during the subprime crisis (Adrian, 2007). In summary, according to *cs_cov*, the co-movement between the strategies' returns has decreased since 1997. Moreover, *cs_cov* increased less during the subprime crisis than during the bubble-tech one. Hence, the potential for diversification seems to have increased in the hedge fund industry. However, *cs_sd* shows a tendency to decrease over the sample period, which pushes *cs_corr* upward. In order to measure the co-movement of returns, it seems therefore more advisable to rely on *cs_cov*, a quite straightforward indicator of co-movement.

Figure 16 Cross-sectional correlation of the strategies' alphas and betas



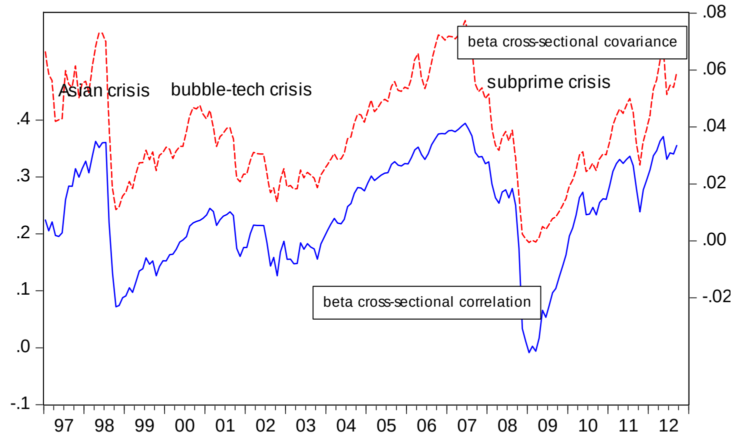
4.4 The alpha and beta co-movements of the of hedge fund strategies

We also computed the same statistics for the strategies' betas and alphas (Figure 16)[19]. In times of economic expansion, the cross-sectional covariance of the strategies' betas shows a tendency to increase. The strategies' behavior thus becomes more homogenous in terms of beta. This is the pattern we observed in the previous section in economic expansion. However, in times of crisis, the cross-sectional covariance of the beta decreases. This indicates that the risk-taking behavior of the strategies is more heterogeneous in periods of turmoil, which suggests a potential for portfolio diversification. Turning to the cross-sectional standard deviation of the betas, we note that its reaction to the bubble-tech crisis was very low but that it decreased substantially during the subprime crisis, which contradicts the signal sent by the cross-sectional covariance. Linking together the movements of the cross-sectional covariance and cross-sectional standard deviation, the cross-sectional correlation of the strategies' betas increases during economic expansions, which suggests that the risk-taking behaviour of the strategies is more homogenous during good times. However, the cross-sectional correlation of the betas decreased sharply during the subprime crisis, some strategies taking higher risk while others doing the opposite. A closer look at the link between the beta's *cs_cov* and *cs_corr* shows that

[19] Yu and Sharaiha (2007) rely on the cross-sectional dispersion to study investment opportunities in terms of alpha.

they are strongly and positively correlated (Figure 17). In other words, the *cs_sd* does not disturb the positive link between *cs_cov* and *cs_corr* for the betas as it was the case for returns.

Figure 17 Financial crises and beta's cross-sectional covariance and correlation



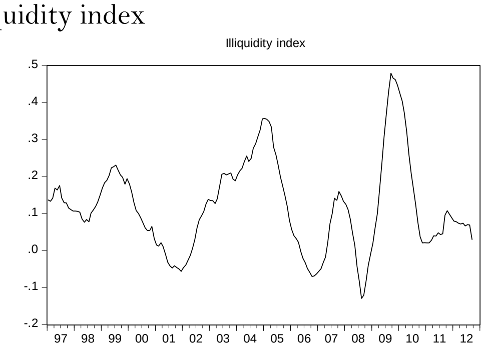
Regarding the alpha, the behavior of the cross-sectional indicators was quite different during the bubble-tech and subprime crises. The cross-sectional covariance jumped during the bubble-tech crisis, which suggests more homogeneity about the profiles of the strategies' alphas. The increase observed during the subprime crisis was not significant. After the bubble-tech crisis, the cross-sectional covariance of the alphas was stable and low, which indicates an increase in the alpha heterogeneity among strategies. The signal sent by the cross-sectional deviation of the alphas differs again. This indicator jumps during the two crises, which suggests less homogeneity in the behavior of the strategies' alphas. It tends to decrease during the sample period, suggesting more homogeneity.

The cross-sectional correlation of the alphas increased substantially during the bubble-tech crisis but it receded thereafter, which suggests that the behavior of the strategies' alphas is less homogenous. However, it resumed its increase after the subprime crisis. In summary, in view of the apparent maturation process for the strategies' alphas observed in the previous section—i.e., a downward trend for most alphas—there seems to be more heterogeneity at the alpha level than in the past. This pattern is shared by the strategies' betas, which indicates that the potential for diversification in the hedge fund industry tends to increase, especially in times of crisis.

4.5. Hedge fund illiquidity index

In the previous section, we noted that the cross-sectional covariance and cross-sectional correlation of strategies' returns show a tendency to increase during crises. This "herding" in the behavior of hedge fund strategies may be amplified by an increase in illiquidity, an obvious source of systemic risk. It is thus also interesting to analyze the cyclical behavior of liquidity in the hedge fund sector. Chan *et al.* (2007) propose an indicator of illiquidity for the hedge fund industry. It is equal to the first-order autocorrelation for the returns of an hedge fund index computed on a rolling window. An increase in this ratio indicates that the behavior of returns becomes more persistent, which suggests a decrease in liquidity for this index or strategy. According to Chan *et al.* (2007), the illiquidity index of the S&P500—as measured by its rolling autocorrelation ratio—is usually low even in times of crises, which signals that the stock market as a whole tends to remain liquid even in times of turmoil. This is not necessarily the case in the hedge fund industry. In time of crisis, liquidity can become very scarce in this industry as experienced during the subprime crisis. Indeed, hedge funds are big players in the field of structured products and liquidity may become quite scarce in this field when an adverse shock hits it. Moreover, the frequency of the transactions in the hedge fund industry may be low over quite long periods, which fosters illiquidity. Hedge fund managers may also get involved in profit smoothing due to the low frequency of their transactions, a practice that obviously exacerbates return autocorrelation.

Figure 18 Hedge fund illiquidity index



Note: The illiquidity index is computed using a twelve-month moving average of the autocorrelation coefficient of the first-order computed on the hedge-fund weighted composite index.

Figure 18 plots the illiquidity index for the GAI weighted composite index. It is equal to the first-order autocorrelation of the return of this index computed on a rolling-window of twelve months. This illiquidity index is very sensitive to adverse shocks such as recessions or financial crises. In this respect, it peaked during the subprime crisis, which suggests that liquidity was scarce during this episode. It thus stands as a reliable indicator of stress or rising systemic risk in the hedge fund industry.

Given our previous results, the cyclical behaviour of liquidity in the hedge fund sector should be an important indicator for supervisors and regulators. Indeed, our findings show that procyclicality tends to decline in the hedge fund sector and that the diversification benefits provided by hedge fund strategies seem also to increase in times of crisis. In this context, hedge funds, which may be viewed as shadow banks, are more and more candidates to compete with conventional commercial banks in the production of liquid financial claims or quasi-monies (DeAngelo and Stulz, 2013; Gennaioli *et al.*, 2013). However, if liquidity decreases in the hedge fund sector in times of crisis, the financial claims it has created will then become information sensitive, which will increase systemic risk and thus decrease financial stability (Diamond and Dybvig, 1983; Gorton and Pennachi, 1990; Gorton, 2010). This situation is all the more problematic than Basel III, by tightening bank capital rules, will increase the competitive disadvantage of banks vis-à-vis shadow banks in the production of financial claims. The production of financial claims will then progressively migrate from banks to shadow banks and increase systemic risk, what Basel III was fighting in the first place by imposing tighter capital rules to banks (DeAngelo and Stulz, 2013).

5. Conclusion

While the returns' behaviour of standard financial instruments over the business cycle is well-known, this is less the case for alternative investments like hedge funds. Yet, contrary to many other financial institutions for which short-selling is restricted by the law, hedge funds may adopt investment strategies that allow them to deliver positive payoffs during crises. Some strategies—as the distressed and short sellers' ones—even benefit from a decline in stock markets. It is thus important to model the behaviour of hedge fund strategies over the business cycle in order to pin down the dynamics of their risk-return trade-off.

The results of our study indicate that hedge fund strategies continue to provide good diversification benefits over the business cycle. First, the volatility of their returns seems to decrease through time, which suggests a better management of structured products. Second, in spite of the subprime crisis, the alpha of most strategies remains positive. Some strategies benefited from this crisis, which suggests good opportunities for hedge fund investors even in bad times. Third, our results are consistent with the fact that hedge funds' portfolio managers modify their betas in line with the volatility of financial markets—as measured in our return model by a principal component of returns computed with lookback straddles. They can thus benefit from an increase in the volatility of financial markets, which is often associated with a downward trend of the stock indices (Black, 1976). Fourth, the strategies' alphas and betas have co-moved less strongly during the subprime crisis—a major financial crisis—than during the preceding ones, which is in line with a learning-by-doing or a maturation process in the hedge fund sector. This development may suggest a decrease in systemic risk in the hedge fund industry which is often due to contagion or herding—i.e., a greater homogeneity in the behaviour of market participants (Wagner, 2010).

Procyclicality thus seems to decrease in the hedge fund industry, a good news for investors in search for higher yields like pension funds. One promising avenue for further research is to model the co-movements of the returns, alphas and betas of the strategies. Indeed, how macroeconomic shocks or uncertainty do impact these co-movements[20]? This is an important question which must be addressed to gain a better understanding of the hedge fund time-varying risk-return trade-off.

Appendix

The multivariate GARCH

We rely on a multivariate GARCH process (MGARCH) to compute the conditional covariances and correlations of key variables. The original autoregressive conditional heteroskedasticity model (ARCH(q)) due to Engle (1982) may be written as:

$$\sigma_t^2 = h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

where h_t is the conditional variance and ε_t, the innovation of the regression. Bollerslev (1986) generalizes Engle's model by allowing the conditional variance to follow an ARMA (p,q) process. The GARCH(p,q) model obtains:

$$\sigma_t^2 = h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}$$

[20] In Beaudry *et al.* (2001), the cross-sectional standard deviation of returns on investment is negatively related to macroeconomic uncertainty—as measured, for instance, by the conditional volatility of GDP growth. Baum *et al.* (2004, 2009) use a similar approach to study the bank herding behaviour in the market for loanable funds.

One problem with these formulations is that they neglect the conditional covariances between the innovations. The mGARCH model palliates this limitation. In this framework, assuming a GARCH(1,1) process, each element of the conditional variance-covariance matrix may be written as:

$$h_{ijt} = c_{ij} + a_{ij}\varepsilon_{it-1}\varepsilon_{jt-1} + b_{ij}h_{ijt-1}$$

Generalizing to a GARCH (p,q) process, we obtain the Bollerslev *et al.* (1988) vectorized (VEC) model:

$$vec(\mathbf{H_t}) = vec(\mathbf{C}) + \mathbf{A}vec\left(e_t e_{t-1}^{'}\right) + \mathbf{B}vec\left(\mathbf{H_{t-1}}\right)$$

where **C** is an $N \times N$ matrix and **A** and **B** are $N^2 \times N^2$ matrices.

The VEC MGARCH model thus requires the estimation of a number of coefficients which may be quite large. Hence we adopt the BEKK (Engle and Kroner 1995) procedure, a more parsimonious approach in terms of the number of parameters to estimate. It reads:

$$\mathbf{H_t} = \mathbf{C} + \mathbf{A}\left(\varepsilon_t \varepsilon_{t-1}^{'}\right)\mathbf{A'} + \mathbf{B}\mathbf{H_{t-1}}\mathbf{B'}$$

where **C**, **A**, and **B** are $N \times N$ matrices.

References

Adrian, T., 2007. Measuring risk in the hedge fund sector. Current issues in economics and finance. Federal Reserve Bank of New York 13, 1-7.

Adrian, T., Shin, H.S., 2010. Financial intermediaries and monetary economics. Staff Report, Federal Reserve Bank of New York.

Agarwal, V., Naik, N.Y., 2004. Risk and portfolio decisions involving hedge funds. Review of Financial Studies 17, 63-98.

Ang, A., Piazzesi, M., Wei, M., 2004. What does the yield curve tell us about GDP growth? Working paper, NBER, 10672.

Baum, C. F., Caglayan, M., Ozkan, N., 2004. The second moment matters: the response of bank lending behavior to macroeconomic uncertainty. Working Paper, Boston College.

Baum, C. F., Caglayan, M., Ozkan, N., 2009. The second moment matters: the impact of macroeconomic uncertainty on the allocation of loanable funds. Economics Letters 102, 87-89.

Beaudry, P., Caglayan, M., Schiantarelli, F., 2001. Monetary instability, the predictability of prices, and the allocation of investment: An empirical investigation using panel data. American Economic Review 91, 648-662.

Black, F., 1976. Studies of stock price volatility of changes. American Statistical Association Journal, 177-181.

Bollerslev, T., 1986. Generalized Autoregressive Conditional Hetetoskedasticity. Journal of Econometrics 31, 307-327.

Bollerslev, T., Engle, R.F., Woodridge, J.M., 1988. A capital asset pricing model with time-varying covariances. Journal of Political Economy 96, 116-131.

Borio, C., Zhu, H., 2008. Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism? Working paper, BIS.

Chan, N., Getmansky, M., Haas, S.M., Lo, A.W., 2007. Systemic risk and hedge funds. Working Paper, NBER.

Connor, G., Lasarte, T., 2005. A introduction to hedge fund strategies. Working Paper, Financial Markets Group, London School of Economics.

DeAngelo, H., Stulz, R.M., 2013. Why high leverage is optimal for banks? Working paper 19139, NBER.

Diamond, D., Dybvig, P., 1983. Bank runs, deposit insurance, and liquidity. Journal of Political Economy 99, 689-721.

Disyatat, P., 2010. The bank lending channel revisited. Working paper, Bank for International Settlements.

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimate of the variance of U.K. inflation. Econometrica 50, 987-1007.

Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous GARCH. Econometric Theory 11, 122-150.

Fung, W., Hsieh, D.A., 1997. Empirical characteristics of dynamic trading strategies: The case of hedge funds. Review of financial studies 10, 275-302.

Fung, W., Hsieh, D.A., 2001. The risk in hedge fund strategies: Theory and evidence from trend followers, Review of Financial Studies 14, 313-341.

Fung, W., Hsieh, D.A., 2004. Hedge fund benchmarks: A risk based approach. Financial Analysts Journal 60, 65-80.

Gambacorta, L., Marques-Ibanez, D., 2011. The bank lending channel: Lessons from the crisis, Working paper, Bank for International Settlements.

Gennaioli, N., Shleifer, A., Vishny, R., 2013. A model of shadow banking. Journal of Finance, forthcoming.

Gorton, G., 2010. Slapped by the invisible hand: The panic of 2007. Oxford University Press, Oxford.

Gorton, G., Pennachi, G., 1990. Financial intermediaries and liquidity creation. Journal of Finance 45, 49-72.
Haiss, P. R., 2005. Banks, herding and regulation: A review and synthesis, Working paper, Europe Institute.
Henriksson, R., Merton, R.C., 1981. On market timing and investment performance II: Statistical procedures for evaluating forecasting skills. Journal of Business 41, 867-887.
Heuson, A.J., Hutchinson, M.C., 2011. Which hedge fund managers deliver alpha? Assessing performance when returns are skewed. Working Paper, University of Miami.
Hull, J.C., 2012. Options, futures and other derivatives. 8th edition. Pearson.
McGuire, P., Remolona, E., Tsatsaronis, K., 2005. Time-varying exposures and leverage in hedge funds. BIS Quarterly Review, March.
Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347-370.
Racicot, F.E., Théoret., R., 2009. Integrating volatility factors in the analysis of the hedge fund alpha puzzle. Journal of Asset Management 10, 37-62
Racicot, F.E., Théoret, R., 2012. Optimally weighting higher moment instruments to deal with measurement errors in financial return models. Applied Financial Economics 22, 1135-1146.
Sabbaghi, O., 2012. Hedge fund return volatility and comovement: recent evidence. Managerial Finance 38, 101-119.
Schoenmaker, D., 2013. Governance of international banking: The financial trilemma, Oxford University Press, Oxford.
Solnik, B., Roulet, J., (2000). Dispersion as cross-sectional correlation. Financial Analysts Journal 56, 54-61.
Veronesi, P., 2010. Fixed income securities: Valuation, risk, and risk management. Wiley, New Jersey.
Treynor, J., Mazuy, K., 1966. Can mutual funds outguess the market? Harvard Business Review 44, 131-136.
Wagner, W., 2010. Diversification at financial institutions and systemic crises. Journal of Financial intermediation 19, 272-286.
Yu, W., Sharaiha, Y.M., 2007. Alpha budgeting—cross-sectional dispersion decomposed. Journal of Asset management 8, 58-72.