Original Article

Procyclicality and diversification in the hedge fund industry in the aftermath of the subprime crisis

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ABSTRACT **Using an updated database that extends after the subprime crisis, we revisit the asymmetries of hedge fund behavior in recession compared with economic expansion. In this respect, we study the time-varying α's and β's associated with strategy returns using an innovative framework based on the Kalman filter and the multivariate GARCH. We find that hedge fund managers reduce drastically their risk exposure during financial crises while their behavior is much smoother in normal times. We also find 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' behavior in terms of α and β 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.**

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INTRODUCTION

Many researchers have analyzed the asymmetric behavior of hedge fund during bear markets compared with bull markets, the subprime crisis having fostered this kind of studies (Mitchell and Pulvino, 2001; Agarwal and Naik, 2004; Capocci *et al*, 2005; Billio *et al*, 2009; Bollen and Whaley, 2009; Bollen, 2011; Sandvik *et al*, 2011). According to Dewachter and Wouters (2014), asymmetry is related to the fact that 'the reaction of agents – here hedge funds – is much more pronounced during periods of recession (crises) while they behave much smoothly during booming business cycle periods'. In this respect, researchers found that hedge funds reduce drastically their risk exposures in periods of crisis. The signs of the factor loadings may even change, these factors accounting for other sources of risk in crises.[1]

Most authors study the asymmetric behavior of hedge funds across two states of nature: bull markets and bear markets (for example, Capocci *et al*, 2005; Sandvik *et al*, 2011). To perform these studies, the methods used go from simple regressions on these two states to regime-switching models. The analysis is quite static because the behavior of hedge funds is not monitored inside these states. A notable exception on that matter is the study of Bollen and Whaley (2009), who rely on the Kalman filter to track the autoregressive behavior of the hedge fund β across the states of nature.

In this study, we extend the framework of Bollen and Whaley (2009) by monitoring the *procyclical* behavior of the α's and β's of hedge fund strategies. 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. One of our contributions is to relate the time-varying α and β of each strategy to conditioning market information. In this respect, the β of a strategy is related to the payoffs of a lookback straddle defined as the first principal component of 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, 1966; Henriksson and Merton, 1981; Fung and Hsieh, 2001; Billio *et al*, 2009). The co-movements of hedge fund strategies' returns, β's and α's have also not been studied yet using a comprehensive approach accounting for the impact of business cycles.[2] These co-movements are related to the level of risk in the hedge fund sector.

In this article, we also focus on the dynamics of diversification benefits provided by the hedge fund strategies. The literature has opposite views on this topic. In this respect, some researchers (for example, Billio *et al*, 2009) argue that risk is greatly underestimated in the hedge fund industry, particularly in crisis periods. In contrast, other researchers (for example, Sandvik *et al*, 2011; Brown *et al*, 2012; Boyson *et al*, 2013) assess that there is any significant underperformance by the hedge fund industry during financial crises.[3] Moreover, some strategies – as the managed futures, global macro and short sellers ones – even offer good diversification benefits when these benefits are needed the most, that is, in periods of financial turmoil. Other strategies – for example, the trend followers – benefit from the stock market volatility that is often associated with a downward trend in stock market returns (Black, 1976; Fung and Hsieh, 1997, 2001, 2004)[4]. It is important to revisit the topic of diversification in a dynamic setting with more recent data and with improved methods since investors – especially pension funds that suffer from chronic undercapitalization – are in search of yield in a world plagued by lower expected returns on traditional assets.

In line with many recent studies (Zhong, 2008; Sandvik *et al*, 2011), our empirical work shows that the α's 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 α increased during the subprime crisis, suggesting that hedge fund strategies may display a good performance even in times of turmoil (Sandvik *et al*, 2011). In other respects, the β of hedge funds is quite procyclical but the strategies' β's behave more heterogeneously during crises, suggesting again diversification opportunities. Strategies' returns also tended to move less homogenously during the subprime crisis than during the three preceding ones – that is, the Asian, Russian-LTCM 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 ambiguous signals and thus ought to be interpreted with caution, an issue overlooked in many previous studies.

This article is organized as follows. The next section presents our empirical return model. The subsequent section reports our database and the stylized facts associated with the hedge fund strategies' returns. The penultimate section analyses the empirical results while the final section concludes.

THE EMPIRICAL RETURN MODEL

Our model aims at studying the procylicality of the hedge fund strategies over the period spanning January 1995–September 2012. To do so, we rely on a hedge fund return model estimated with the Kalman filter.[5] 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:

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

where r_{ft} is the risk-free return; α_{it} is the time-varying α; β_{it} is the time-varying β; R_{mt} is the market portfolio return; SMB_t is the return of a mimicking portfolio that 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 10-year constant maturity yield and the 3-month Treasury bills yield, which may be assimilated to a portfolio that is long in the long-term (10-year) interest rate and short in the short-term interest rate.

In equation (1), ($R_{mt}-r_{ft}$) and SMB_t are two important risk factors found in most hedge fund return models. Fung and Hsieh (2004) call them the equity ABS (asset-based-style) factors, which stand for the main drivers of the long/short hedge fund strategy – that is, the leading hedge fund strategy. To these two factors, we add the term spread ($Spread_t$), a variable that has gained strength in explaining returns in line with the development of shadow banking (Billio *et al*, 2009). An increase in the spread usually signals an increase in the risk premia on bonds and possibly on stocks, which tends to give rise 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.[6] 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 that 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:

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

where $E(r)$ is the expected future yield; λ_t is the price of risk, here market risk – that is, 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 equation (2) represents an adjustment term that accounts for the convexity linking the price of a bond to its yield. According to equation (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 that 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 equation (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[7] 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[8] (for example, 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.[9]

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

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

We relate the state space equations of α and β to macroeconomic and financial variables, given the importance of the timing of the α and β to these variables in the hedge fund literature (Chen and Liang, 2007; Avramov *et al*, 2011; Cai and Liang, 2012; Cao *et al*, 2013). We thus postulate that the α follows an autoregressive process augmented with conditioning market information. Equation (3) may be written in first differences, such as:

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

The updating of the α 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 β is:[10]

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

In addition to the two conditioning variables included in the state space equation of the α, the state space equation of the β includes the *pc_lookback* variable. This variable is the first principal component of Fung and Hsieh's option risk factors, which are lookback straddles[11] on stocks, bonds, short interest, commodities and foreign currencies. Fung and Hsieh (1997, 2001, 2004) rely on lookback straddles to study the behavior of trend followers[12] 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 α (θ_{1i}<0) and a decrease in the β (δ_{1i}<0), hedge funds reducing their exposure to market risk in times of economic slowdown. Second, an increase in the market risk premium ($R_{mt}-r_{ft}$) is viewed as a strengthening of the stock market. This may induce hedge funds to position themselves for an increase in their α, this behavior being related to the portfolio manager's skills. In this case, the sign of θ_{2i} is positive. However, if the α is not manageable, this coefficient should be close to zero. This should not be the case for the time-varying β, 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 β. We thus expect δ_{2i}>0. The sign of the coefficient of the *pc_lookback* factor in equation (5) will be discussed later.

DATA SOURCES AND STYLIZED FACTS

The data are taken from the database managed by Greenwich Alternative Investment (GAI). GAI has one of the oldest hedge fund databases, containing more than 13 500 records of hedge funds as of March 2010. Returns provided by the database are net of fees. The survivorship bias is accounted for in this database, as index returns for periods since 1994 include the defunct funds.

The data set 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.[13] We also report the indices of GAI strategy groups whose sample starts in January 1995. The market risk premium and the risk factor *SMB* are drawn from French's website.[14] The lookback-straddle option factors come from the Hsieh's database.[15]

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 per cent for the short sellers[16] to 1.07 per cent for the value index, and the standard deviation ranges from 1.29 per cent for the market neutral group to 5.83 per cent for the short sellers.

According to Table 1, the strategies having the lowest mean return before the crisis were the short sellers, macro and futures, their returns being −0.16, 0.57 and 1.01 per cent, respectively. However, these strategies performed the best during the subprime crisis, with returns equal to 0.94, 0.57 and 0.90 per cent, respectively. This asymmetry between the two periods for these strategies was reported by Sandvik *et al* (2011). Owing to the good performance of these strategies in periods of crisis, these authors consider them as good diversification outlets. However, the picture changes after the crisis. Indeed, the mean returns of the strategies remained below their pre-crisis level. Note that the return of the macro strategy is quite stable through time, a characteristic that is not shared with the other strategies.

In other respects, the hedge funds' β's are generally low, the average β computed over all strategies being equal to 0.22. Two strategies display a negative β: the short sellers (−0.91) and the futures strategy (−0.08).[17] The strategy with the highest positive β is the growth one (0.69) while the strategy with the lowest positive β 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 β.[18] 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 β 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 β but is usually considered as directional.[19] The value strategy might also be a candidate for this category since its β is quite high (0.53), but actually it is usually classified in the arbitrage category (Connor and Lasarte, 2005). The strategies with the highest β are usually the ones that display the highest adjusted R^2 in standard multifactor return models such as the Fama and French model. Conversely, the strategies with the lowest β – 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 β is usually moderate. Note that these categories are not exclusive as a strategy may belong to two categories, such as the distressed one that may also be considered as an arbitrage strategy.

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 per cent (Table 1). In fact, the standard deviation of the return of the weighted composite index seems to decline through time,

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

	Mean (in percentage)	*Median (in percentage)*	*Maximum (in percentage)*	*Minimum (in percentage)*	*sd (in percentage)*	*Skew*	*Kurtosis*	*Sharpe index*	*CAPM-β*
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–September 2012 period. The mean returns are reported on the following subperiods: January 1995–May 2007 (9501–0705); June 2007–December 2009 (subprime crisis, 0706–0912); January 2010–September 2012 (1001–1209). They are also reported over the whole sample. 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-β is computed by regressing an index excess return on the market excess return. The β 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.

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 the section 'Empirical results'.

Not surprisingly, the strategies' standard deviations are correlated positively to their β's (Figure 2). Note that short sellers are outside the regression line relating standard deviation to β but actually, their β – 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 β (Figure 3). According to the CAPM, the slope of this regression multiplied by the β 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.

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 per cent).[20]

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 that 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

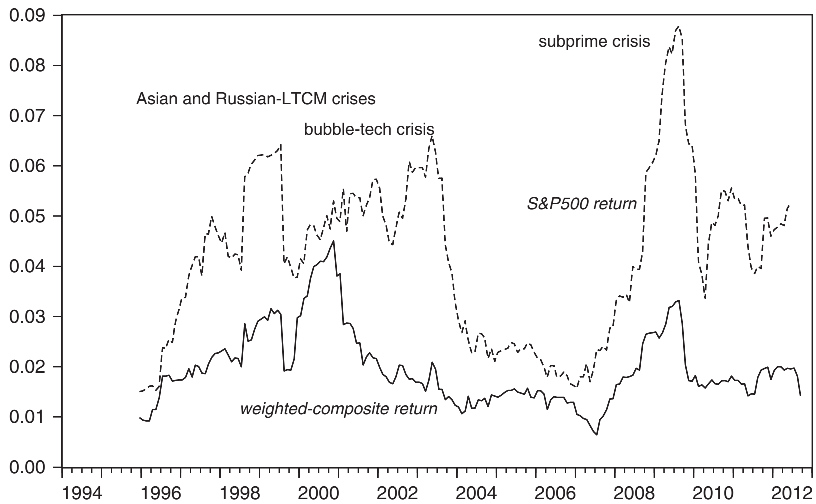

Figure 1: Rolling standard deviations: GAI weighted composite return and S&P 500 return.
Note: The standard deviation is computed on a rolling window of 12 months.

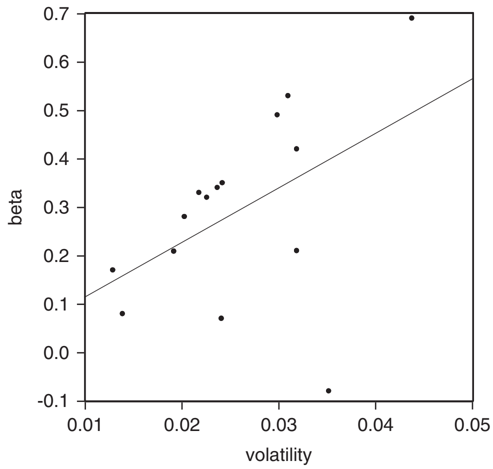

Figure 2: Strategies' β and return volatility.

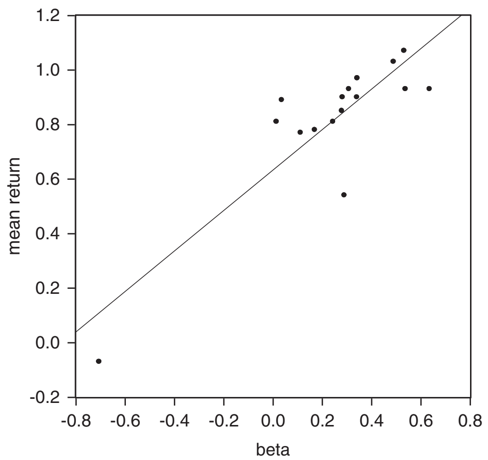

Figure 3: Strategies' mean return and β.

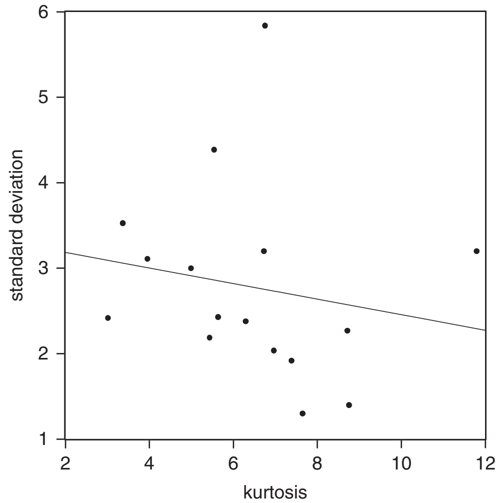

Figure 4: Strategies' kurtosis and return standard deviation.

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 – that is, 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.

Table 2 provides the correlation matrix between hedge fund strategy returns, the hedge fund global index and the three Fama and French risk factors. As a whole, most hedge funds have a high positive correlation with the market proxy and the *SMB* portfolio. The strategies having the highest correlation with the market are the value index, long–short and growth strategies. Short sellers and futures strategies are negatively correlated with the market, the correlation coefficients being −0.72 and −0.11, respectively. This observation is consistent with other studies (for example, Sandvik *et al*, 2011). Strategies that have a low correlation with the market tend also to exhibit a low correlation with *SMB*. It is especially the case for the equity market neutral and the futures

Table 2: Correlation matrix of strategies' returns and Fama and French risk factors

Correlation

t-statistic	*EMN*	*ED*	*DS*	*DED*	*LS*	*GR*	*OI*	*SS*	*VI*	*FUT*	*MACRO*	*MS*	*GI*	*MKT*	*SMB*	*HML*
EMN	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
ED	0.64	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	11.66	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
DS	0.48	0.83	1	—	—	—	—	—	—	—	—	—	—	—	—	—
	7.72	*20.73*	—	—	—	—	—	—	—	—	—	—	—	—	—	—
DED	0.64	0.98	0.74	1	—	—	—	—	—	—	—	—	—	—	—	—
	11.61	*79.33*	*15.30*	—	—	—	—	—	—	—	—	—	—	—	—	—
LS	0.62	0.89	0.69	0.91	1	—	—	—	—	—	—	—	—	—	—	—
	11.06	*28.01*	*13.42*	*29.99*	—	—	—	—	—	—	—	—	—	—	—	—
GR	0.60	0.84	0.59	0.87	0.96	1	—	—	—	—	—	—	—	—	—	—
	10.54	*21.87*	*10.36*	*24.35*	*51.46*	—	—	—	—	—	—	—	—	—	—	—
OI	0.68	0.88	0.68	0.89	0.95	0.92	1	—	—	—	—	—	—	—	—	—
	13.02	*25.73*	*12.84*	*26.85*	*40.64*	*32.44*	—	—	—	—	—	—	—	—	—	—
SS	−0.40	−0.71	−0.47	−0.73	−0.81	−0.86	−0.75	1	—	—	—	—	—	—	—	—
	−6.19	*−14.19*	*−7.50*	*−15.03*	*−19.41*	*−23.20*	*−16.05*	—	—	—	—	—	—	—	—	—
VI	0.56	0.86	0.69	0.87	0.97	0.91	0.88	−0.80	1	—	—	—	—	—	—	—
	9.44	*23.93*	*13.46*	*24.46*	*60.73*	*30.02*	*25.93*	*−18.85*	—	—	—	—	—	—	—	—
FUT	0.18	−0.02	−0.04	−0.02	−0.02	−0.03	0.00	0.13	−0.04	1	—	—	—	—	—	—
	2.55	*−0.33*	*−0.51*	*−0.27*	*−0.26*	*−0.44*	*−0.05*	*1.88*	*−0.53*	—	—	—	—	—	—	—
MACRO	0.39	0.48	0.36	0.47	0.51	0.50	0.51	−0.36	0.49	0.29	1	—	—	—	—	—
	5.94	*7.56*	*5.34*	*7.54*	*8.33*	*8.02*	*8.39*	*−5.34*	*7.97*	*4.32*	—	—	—	—	—	—
MS	0.48	0.74	0.53	0.76	0.82	0.80	0.76	−0.71	0.83	−0.11	0.44	1	—	—	—	—
	7.68	*15.52*	*8.66*	*16.12*	*20.42*	*18.51*	*16.50*	*−14.06*	*20.44*	*−1.53*	*6.92*	—	—	—	—	—

GI	0.67	0.92	0.71	0.92	0.98	0.95	0.95	−0.79	0.96	0.05	0.57	0.84	1	—	—	—
	12.62	*31.86*	*14.12*	*33.08*	*79.52*	*41.39*	*41.82*	*−18.28*	*47.61*	*0.67*	*9.80*	*21.29*	—	—	—	—
MKT	0.28	0.64	0.50	0.67	0.76	0.73	0.62	−0.72	0.79	−0.11	0.34	0.68	0.72	1	—	—
	4.12	*11.75*	*8.14*	*12.49*	*16.57*	*14.94*	*11.00*	*−14.71*	*18.10*	*−1.60*	*5.12*	*12.87*	*14.50*	—	—	—
SMB	0.07	0.25	0.20	0.25	0.28	0.27	0.18	−0.29	0.33	−0.03	0.26	0.23	0.27	0.14	1	—
	1.01	*3.57*	*2.93*	*3.69*	*4.13*	*4.00*	*2.53*	*−4.17*	*4.91*	*−0.41*	*3.75*	*3.31*	*3.90*	*1.91*	—	—
HML	0.00	−0.07	0.00	−0.09	−0.23	−0.32	−0.20	0.39	−0.23	0.10	−0.25	−0.32	−0.24	−0.18	−0.36	1
	0.05	*−1.02*	*0.04*	*−1.25*	*−3.33*	*−4.80*	*−2.89*	*5.99*	*−3.24*	*1.47*	*−3.61*	*−4.67*	*−3.39*	*−2.57*	*−5.40*	

Notes: The strategies are reported in the same order as in Table 1. These are: equity market neutral (*EMN*); event driven (*ED*); distressed securities (*DS*); diversified event driven (*DED*); long–short (*LS*); growth (*GR*); opportunistic (*OI*); short sellers (*SS*); value index (*VI*); futures (*FUT*); global macro (*Macro*); multi-strategy index (*MS*); hedge fund global index (*GI*); S&P500 return (*MKT*).

strategies. In other respects, the correlation between returns and *HML* is very low for the following strategies: equity market neutral, event driven, distressed securities and futures. Except for the short sellers, strategies tend to be negatively correlated with *HML*. As shown in the empirical section, this sign is related to crisis periods.

Some strategies have a high correlation with the hedge fund global index, the coefficient exceeding 0.8. These strategies are: long–short – that is, the strategy that weights the more in the global index – opportunistic index, event driven, value index and multi-strategy index. These strategies thus offer less diversification benefits when combined together. In contrast, the futures and macro strategies display the lowest correlation with the global index, and offer potentially good diversification opportunities. Sandvik *et al* (2011) have identified the same strategies as good potential providers of diversification benefits.

EMPIRICAL RESULTS

An overlook at the asymmetries

Table 3 provides the estimation of the three-factor Fama and French model for the GAI global index over subperiods in order to highlight the asymmetric impact of the subprime crisis. Before the crisis – that is, from January 1995 to May 2007 – the α is relatively high at 0.8 per cent monthly and significant at the 1 per cent level. Two risk factors impact positively and significantly on the global index: the market factor and the *SMB* factor. The market β of the global index is quite low at 0.35, suggesting the moderate exposure of the representative hedge fund to the market. In other respects, the positive

Table 3: Fama and French model applied to the GAI weighted composite index over key periods

	1995m01–2007m05	*2007m06–2009m12*	*2010m01–2012m09*	*1995m01–2012m09*
c	0.0080	0.0038	0.0001	0.0065
	5.90	*1.55*	*0.10*	*6.38*
MKT-rf	0.3548	0.3877	0.3067	0.3257
	10.16	*7.94*	*7.19*	*14.47*
SMB	0.1444	0.0203	0.0532	0.0979
	3.98	*0.19*	*0.57*	*3.28*
HML	−0.0244	−0.2881	−0.0287	−0.0888
	−0.53	*−3.46*	*−0.34*	*−2.76*
Adjuncted R^2	0.57	0.67	0.72	0.57
DW	1.59	2.02	1.83	1.60

Notes: The regressions are performed on the following periods: the pre-crisis period (January 1995–May 2007); the subprime crisis period (June 2007–December 2009); the post-crisis period (January 2010–September 2012); and the whole sample period (January 1995–September 2012).
The coefficients' *t* statistics are in italics.

sign for the *SMB* coefficient suggests that hedge funds prefer to buy the stocks of small firms. The *HML* factor is not significant before the crisis.

During the crisis, the α is not significantly different from 0, indicating that the representative hedge fund did not 'create' α during this crisis. The market β is higher than the one estimated during the pre-crisis period. However, according to previous studies (Capocci *et al*, 2005; Sandvik *et al*, 2011), it is well-known that hedge funds reduce their β (or deleverage) during a crisis. The higher β we observe in the subprime crisis is because of the fact that the β has culminated just before the subprime crisis. The apparent counter-result we obtain is thus because of the averaging implicit in a regression. In line with other studies (for example, Sandvik *et al*, 2011), the *SMB* factor loses its explanatory power during the subprime crisis. The exposure of hedge funds to small firms is thus quite reduced during a crisis. Moreover, *SMB* may be a proxy to liquidity risk in crisis periods (Billio *et al*, 2009) and hedge funds reduce their exposure to liquidity risk during these periods. Turning to *HML*, we note that the behavior of hedge funds is also strongly asymmetric in down-market versus up-market conditions. Indeed, its coefficient is significantly negative, at −0.2881, during the subprime crisis. Note also that the R^2 is much higher during the crisis than before. This result was also obtained in other studies like Billio *et al* (2009), Bollen (2011) and Sandvik *et al* (2011).

To get a better grasp of the time-varying nature of the model factor loadings, we re-estimate our model on a 15-month rolling window. The results appear in Figure 5. Regarding the α, we observe that it decreases during the Asian (June 1997–January 1998) and Russian-LTCM (August 1998–October 1998) crises but that it recovered thereafter. It hits its

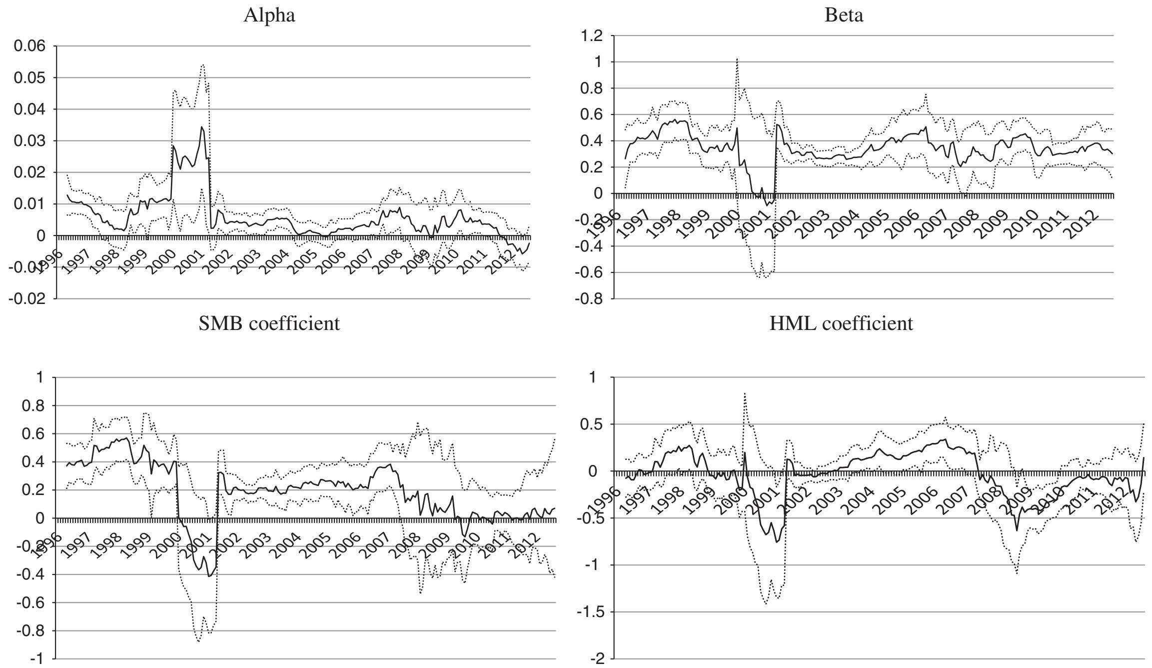

Figure 5: Recursive coefficients of the Fama and French model computed on a rolling window.
Notes: We run the simple Fama and French model on the GAI global return using a 15-month rolling window. The dotted lines enclose the confidence interval defined at the 5 per cent level. In this context, when the lower interval falls below zero, the corresponding coefficient is not significant at the 5 per cent level.

maximum at the beginning of the second millennium but it collapses toward 0 with the bursting of the bubble tech. Thereafter, the α fluctuated in a lower range than the one observed before the Asian crisis and its decrease was less pronounced during the subprime crisis than during the two preceding ones – especially the crisis associated with the bubble tech. Turning to the β, we note an important deleveraging process preceding the bubble-tech crisis but the β recovered quickly during the subsequent economic expansion. Hedge fund managers also reduced their exposure to the equity market during the subprime crisis, but, in line with the behavior of the α, the decrease of the β was much lower than during the bubble tech whereby it decreased to the 0 level. The reduction of the hedge fund β during crisis periods is mentioned in many studies (Cappoci *et al*, 2005; Billio *et al*, 2009; Bollen, 2011 and Sandvik *et al*, 2011).

In other respects, the behavior of the *SMB* loading over our sample is quite interesting. Similarly to the β, it collapsed during the bubble tech crisis, but recovered very quickly thereafter. However, its decrease was higher than the one of the β during the subprime crisis and it remained close to 0 thereafter. As noted earlier, *SMB* may be considered as a proxy for funding liquidity risk (Billio *et al*, 2009), especially during financial crises. During these periods, hedge funds are induced to reduce liquidity risk, and thus their exposure to *SMB*. Finally, *HML* loading also behaves asymmetrically in crisis periods compared with economic expansion ones. While its coefficient tends to be positive during expansion, it clearly turns negative during crises. In line with *SMB*, the coefficient of *HML* remained depressed at the end of our sample, that is, September 2012.

Estimation of the benchmark model

Table 4 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, which are shared with many other studies (for example, Sandvik *et al*, 2011) suggest that other specific risk factors are at play to explain the returns of these strategies whose payoffs seem to be highly non-linear.

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 *sv*2 in Table 4. As expected, the market risk premium is the factor that impacts the most hedge fund returns. The β's of the strategies are very close to the ones estimated with the standard market model (Table 1). The other factor that 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 stocks with a smaller capitalization. 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 (2000). In other respects, Figure 6 shows that the sensitivity of hedge fund strategies to *SMB* is quite correlated to their market β.

The term spread – which may be viewed as a portfolio long in the 10-year bond yield and short in the 3-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 per cent level. The strategies that 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.

Turning to the factors that explain the time variability of the β, Table 4 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 per cent level. The strategies that 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 β (systematic risk) when the yield on

Table 4: State space regressions of strategy index returns using the Kalman filter, January 1995–September 2012

	Time-varying α			*Time-varying β*				*SMB*	*Spread*	*dum_up*	*dum_down*	*L*	*AIC*
	sv1	*rf*	*(Rm-Rf)*	*sv2*	*rf*	*(Rm-Rf)*	*pc_lookback*						
Equity market neutral	0.0020	−0.153	0.0019	0.1129	−13.33	0.067	−0.7631	0.076	0.6144	0.0657	−0.0119	123.44	−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	−0.069	−0.0045	0.309	−0.0137	0.0602	−1.1818	0.166	−0.278	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	−0.026	−0.0095	0.282	1.6034	0.1321	−0.8958	0.109	0.0884	0.0427	−0.0406	556.55	−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	−0.088	−0.0032	0.3421	0.1112	0.0383	−0.9415	0.197	−0.323	0.0938	0.0386	568.97	−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	−0.156	0.0057	0.5375	−0.4142	0.1689	−0.9137	0.235	0.7583	0.1173	−0.0215	572.63	−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	−0.091	0.0037	0.636	0.1479	0.0798	−0.1245	0.291	2.7218	0.1931	0.0249	484.13	−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	−0.146	0.0014	0.4892	−0.6874	0.2074	−1.2879	0.191	1.0128	0.1746	−0.0301	528.86	−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	−0.17	−0.0002	0.7057	6.2219	0.054	1.0839	−0.38	−0.495	−0.2919	0.0431	395.52	−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	−0.197	0.0068	0.5322	−1.5835	0.0755	−1.2803	0.287	0.0849	0.0889	−0.0237	564.32	−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	−0.01	−0.1177	0.036	−2.3581	−0.0667	−2.4833	0.065	−1.442	0.0024	0.0477	378.41	−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	−6.4763	0.4231	−0.5451	0.255	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	−0.074	0.009	0.2804	−1.1724	−0.1303	−0.8577	0.125	1.6586	0.0571	−0.0224	538.18	−5.17
	1.13	*−1.68*	*2.00*	*12.09*	*−1.62*	*−1.27*	*−1.81*	*4.11*	*3.96*	*4.91*	*−2.63*		

Table 4: (*Continued*)

	Time-varying α			Time-varying β				*SMB*	*Spread*	*dum_up*	*dum_down*	*L*	*AIC*
	*sv*1	*rf*	*(Rm-Rf)*	*sv*2	*rf*	*(Rm-Rf)*	*pc_lookback*						
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	−0.03	−0.0013	0.0142	−3.5814	0.0728	−1.5416	0.085	0.0215	0.0501	0.0358	462.34	−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	−0.083	−0.0031	0.1704	0.1207	0.0688	−0.4647	0.099	0.4294	0.0407	−0.0347	692.15	−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 group	0.006	0.0039	0.0047	0.2441	−3.4073	0.0372	−0.7605	0.187	0.454	0.0543	−0.052	560.26	−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 index	0.0021	−0.1070	0.0021	0.3411	−1.1326	0.0770	−0.8560	0.1736	0.7194	0.0906	−0.0228	621.35	−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 US 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 US Federal Government securities; *pc_lookback*: the first principal component obtained with the Fung and Hsieh's US lookback returns on stocks, bonds, currencies, commodities and short interest; dum_up: a binary variable taking the value of 1 on February 2000 – an upside outlier related to the bubble tech – and 0 otherwise; dum_down: a binary variable taking the value of 1 in September and October 2008 – two outliers related to the subprime crisis – and 0 otherwise; *sv*1 is a state coefficient related to the α; *sv*2 is a state coefficient related to the β; *L* is the likelihood ratio and *AIC* is the Akaike statistics.
The coefficient' *t* statistics are in italics.

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 7).

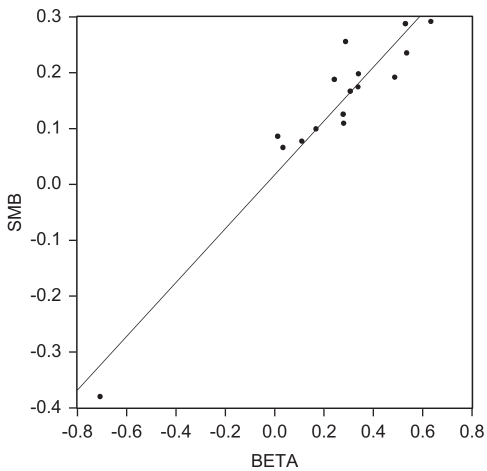

Figure 6: Strategies' *SMB* and β.

Note that this covariance – which is computed with a multivariate GARCH[21] (MGARCH) using a BEKK procedure (Bollerslev *et al*, 1988; Engle and Kroner, 1995) – is particularly high in periods 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 8 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.

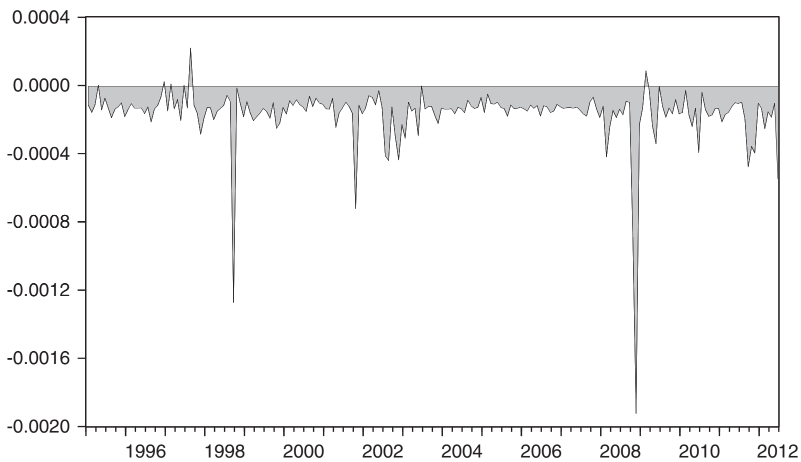

Figure 7: Conditional covariance between the *pc_lookback* and S&P 500 return.
Note: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al*, 1988; Engle and Kroner, 1995).

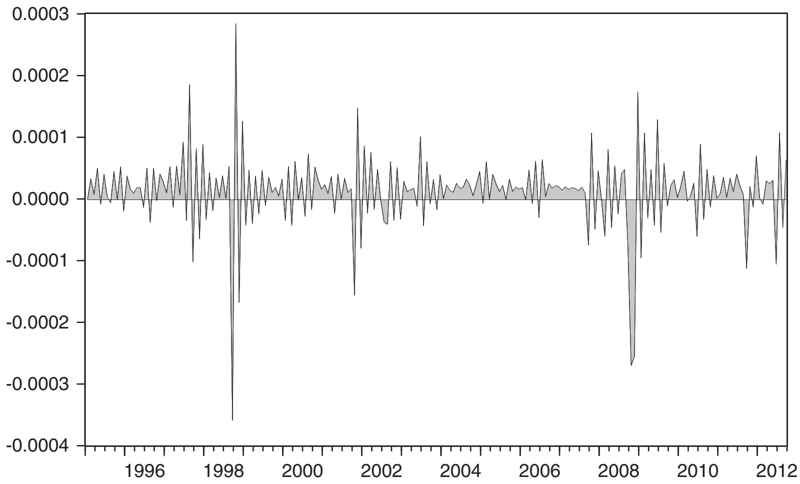

Figure 8: Conditional covariance between the *pc_lookback* and GAI weighted composite index. *Note*: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al*, 1988; Engle and Kroner, 1995).

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 an explanatory variable in the β's state equation. In Fung and Hsieh (2001), the lookback factors are not combined and constitute individual risk factors in the return equations.

Another interpretation of the link between the *pc_lookback* factor and a strategy's β hinges on the following argument. Recall that the *pc_lookback* factor is built with lookback straddles that provide greater positive payoffs when the financial markets are volatile. Figure 9 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 10 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 11 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 12 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.

To gain a better understanding of the link between the *pc_lookback* factor and the strategies'

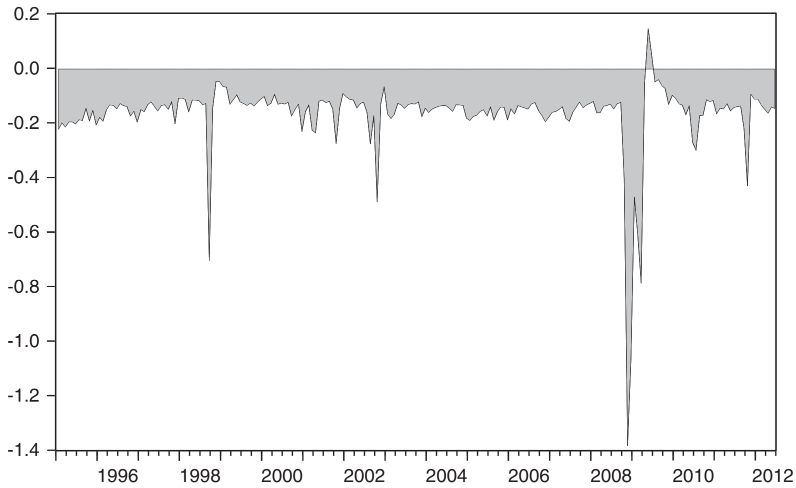

Figure 9: Conditional covariance between the *VIX* and S&P 500 return.
Note: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al*, 1988; Engle and Kroner, 1995).

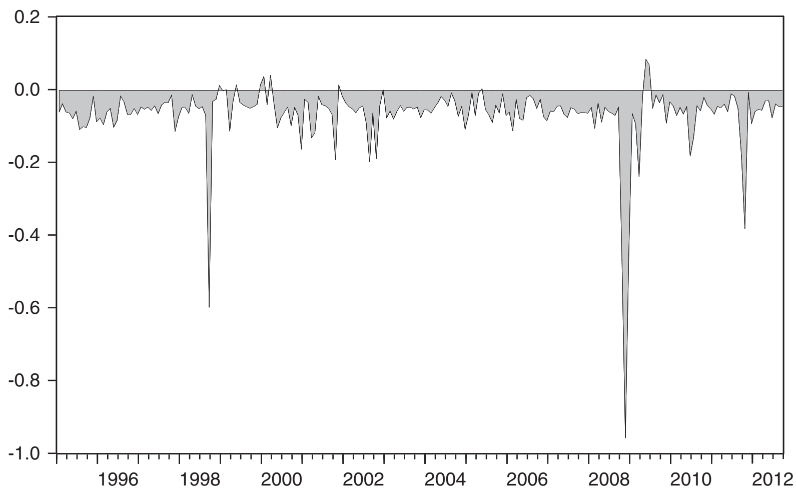

Figure 10: Conditional covariance between the *VIX* and the GAI weighted composite index.
Note: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al*, 1988; Engle and Kroner, 1995).

returns, we have computed the time-varying market β of this factor, relying on the simple market model estimated with the Kalman filter:

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

Figure 13, which plots the estimated β 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.

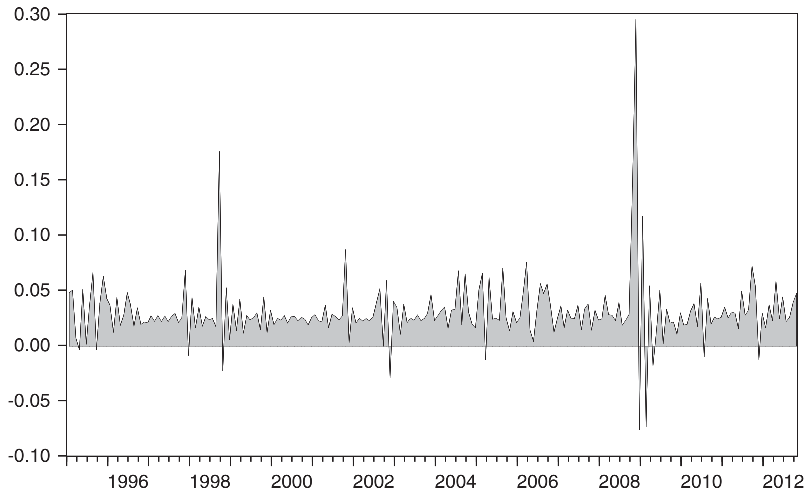

Figure 11: Conditional covariance between the *VIX* and the *pc_lookback.*
Note: The conditional covariance is computed using a multivariate GARCH based on a BEKK procedure (Bollerslev *et al*, 1988; Engle and Kroner, 1995).

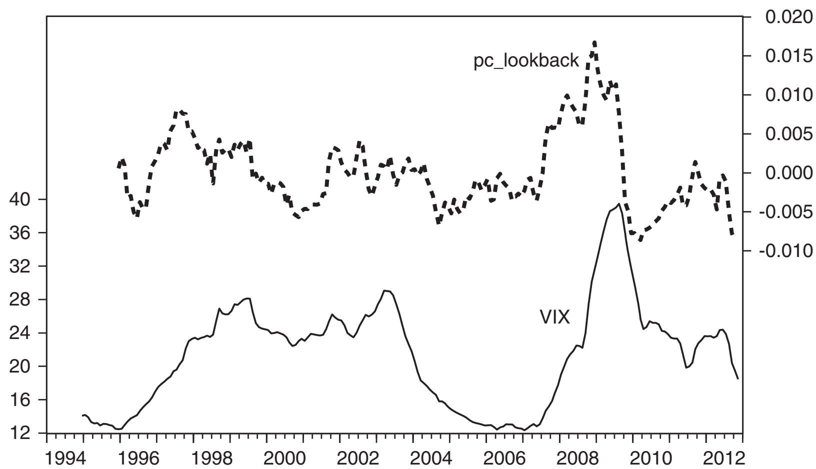

Figure 12: Moving average, *pc_lookback* and *VIX.*
Note: The moving average is computed on a rolling window of 12 months.

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: $\beta_{i,t}\delta_{3i}\beta_{t,pc\_look}(R_{mt}-r_{ft})^2$. Given our previous results, the coefficient of $(R_{mt}-r_{ft})^2$ is positive. The strategies that 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 $(R_{mt}-r_{ft})^2$) increases. These strategies thus share the nature of the Fung and Hsieh's (2001, 2004) trend

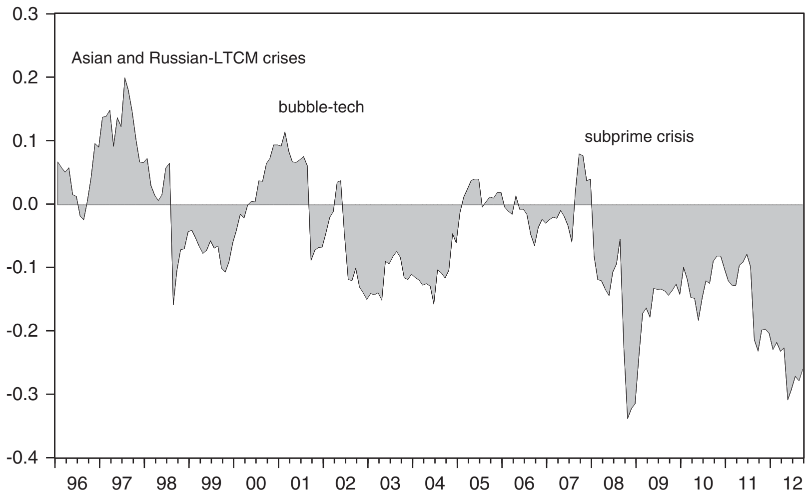

Figure 13: β of the *pc_lookback.*
Note: The time-varying β is computed with the Kalman filter applied to the simple market model.

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).

The level of the interest rate (r_f) also impacts negatively and significantly the β 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 β 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 β 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 β being estimated at 6.2219, significant at the 5 per cent level. Short sellers thus decrease their risk when the interest rate increases. Actually, they follow the same behavior as the other strategies since the short sellers' β is usually negative.

As indicated in Table 4, only few strategies' β's 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 per cent 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 per cent level.

Even if our sample includes the subprime crisis, Table 4 shows that the α puzzle seems unsolved over our estimation period (Racicot and Théoret, 2009, 2014). Most of the strategies display significant α's as measured by their estimated coefficients. Indeed, the average α ($sv1$)

computed over the 12 strategies is equal to 0.27 per cent on a monthly basis. The futures strategy displays the highest α (0.74 per cent) while the growth strategy displays the lowest one (−0.68 per cent). This is the only strategy endowed with a negative α. 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 α (Table 4). For instance, the short-sellers' strategy displays the highest estimated α after the futures strategy but has the lowest mean return over our sample period.

Strategies' α's 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 per cent level. In the same vein, the α's 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 α. 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 α.

Like in the case of the β analysis, few strategies display a link between their α 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 per cent level. This link can be easily explained since a deterioration in business conditions leads to an increase in business failures, a situation that 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).

Kalman-filtered time-varying α and β

Figure 14 plots the Kalman-filtered time-varying α's and β's[22] for the weighted index and the strategies over the period 1997–2012.[23] For most strategies, the β follows a mean-reverting or Ornstein-Uhlenbeck process. Also for most of them, the β trended upward during the economic expansion, which preceded the subprime crisis. Hedge funds thus take more risk when business conditions are improving. However, the β 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 β that moved back near its pre-crisis level at the end of 2012.

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

Turning to the time variability of the α, we first note that some strategies succeed in maintaining a high α 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 α has trended downward since 1999. The α puzzle thus tends to recede through time, at least over our sample period. This result is shared with many recent studies (for example, Zhong, 2008; Sandvik *et al*, 2011; Cay and Liang, 2012). It is attributed to decreasing returns to scale, increased

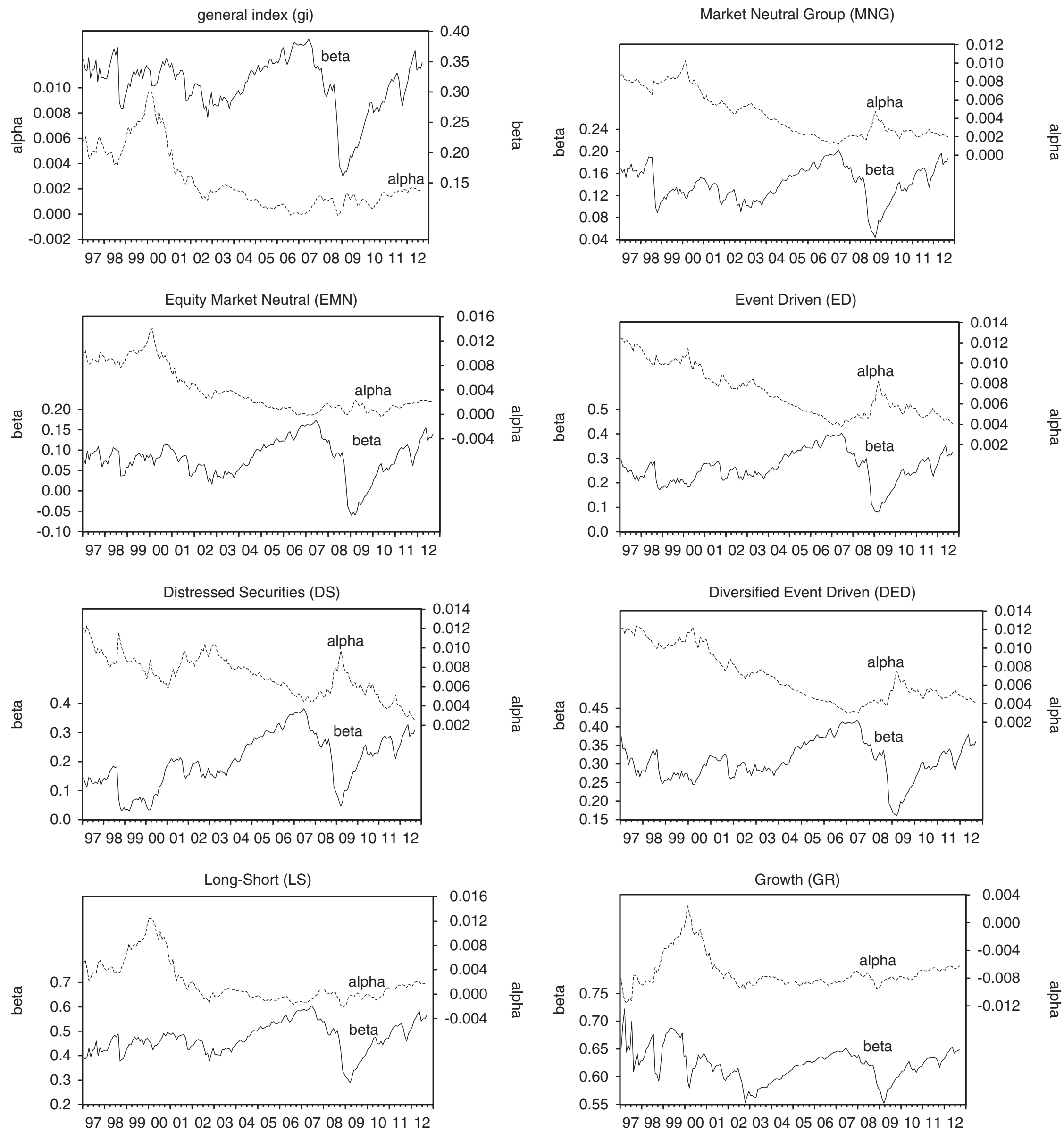

Figure 14: Strategies' time-varying α and β.
Note: The time-varying α and β are computed by applying the Kalman filter to the model given by equations (1)–(5).

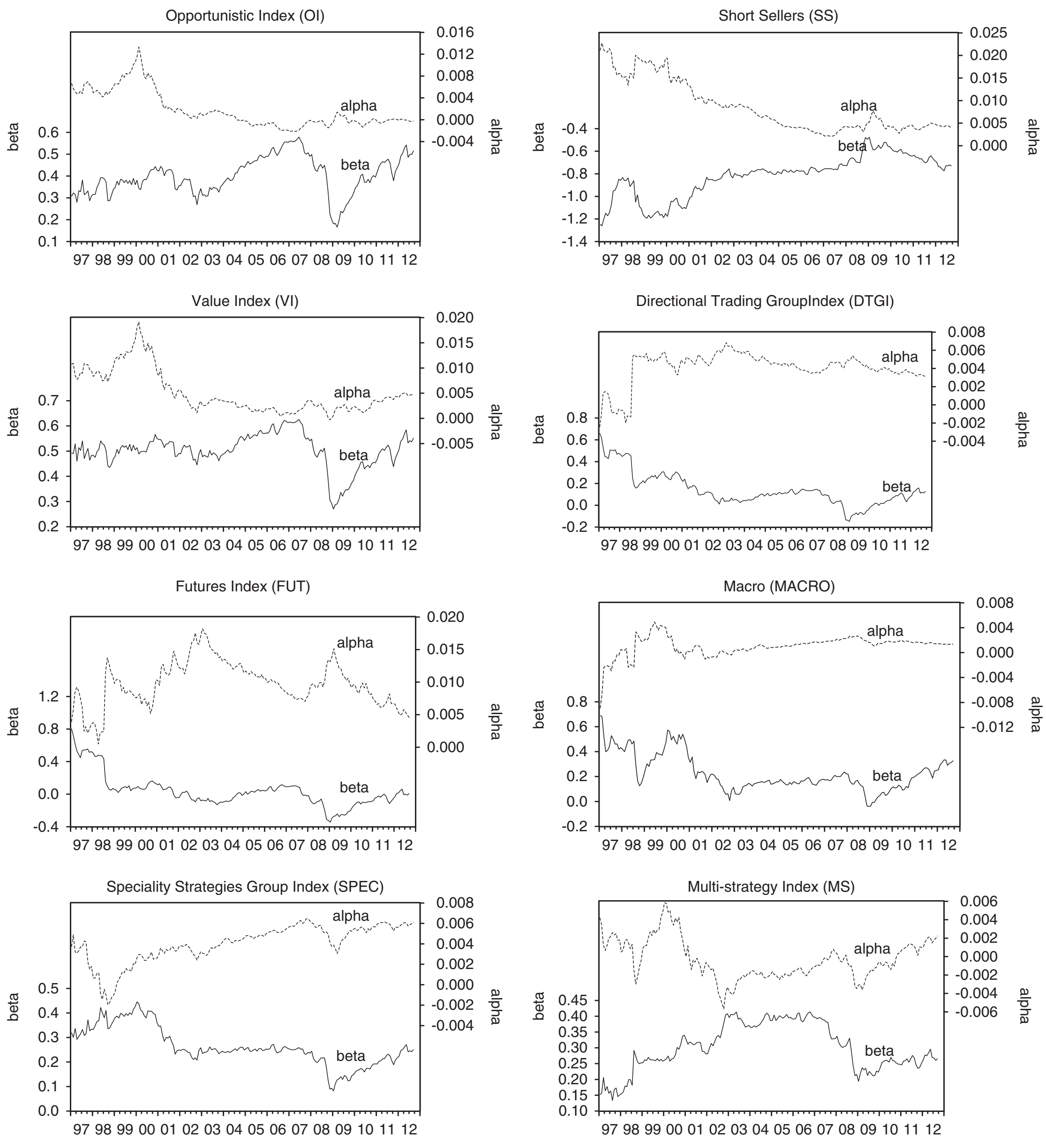

Figure 14: *continued*

competition in the hedge fund sector and the sheer growth of assets under management in this sector. However, the α 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' α's. On the contrary, the α of some strategies increased during the crisis. In this respect, the following strategies benefited from the crisis in terms of their α: 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 α

of the futures strategy jumps at each crisis that occurred during our sample period – that is, the Asian, bubble-tech and subprime crises. It is thus quite immune to crises (Sandvik *et al*, 2011). Finally, since the strategies' α's are not mean-reverting like most of their β's, we can induce than the α is less manageable than the β. It is more related to the particular situation of the hedge fund industry, like the low regulation in this sector.

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.[24] 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:

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

where N is the number of strategies, and $\mathbf{R}_{\mathrm{it}}$ 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:

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

where N is the number of strategies, $\mathbf{R}_{\mathrm{it}}$ 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).[25] 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.

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:

$$\forall t, \quad cs\_corr = \frac{cs\_cov_t}{cs\_var_t} \tag{9}$$

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.

Sabagghi (2012) relies on the three indicators of co-movement given by equations (7)–(9) in order to investigate the return co-movement of the strategy indices provided by Credit Suisse.[26] We reproduce this exercise for the GAI strategies. Figure 15 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 smaller one 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.

The signal sent by the cross-sectional deviation in regard to the co-movement of the strategies' returns is different. First, the time profile of the two co-movement series – that is, *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 the behavior 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 16). 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 15). 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 16). 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

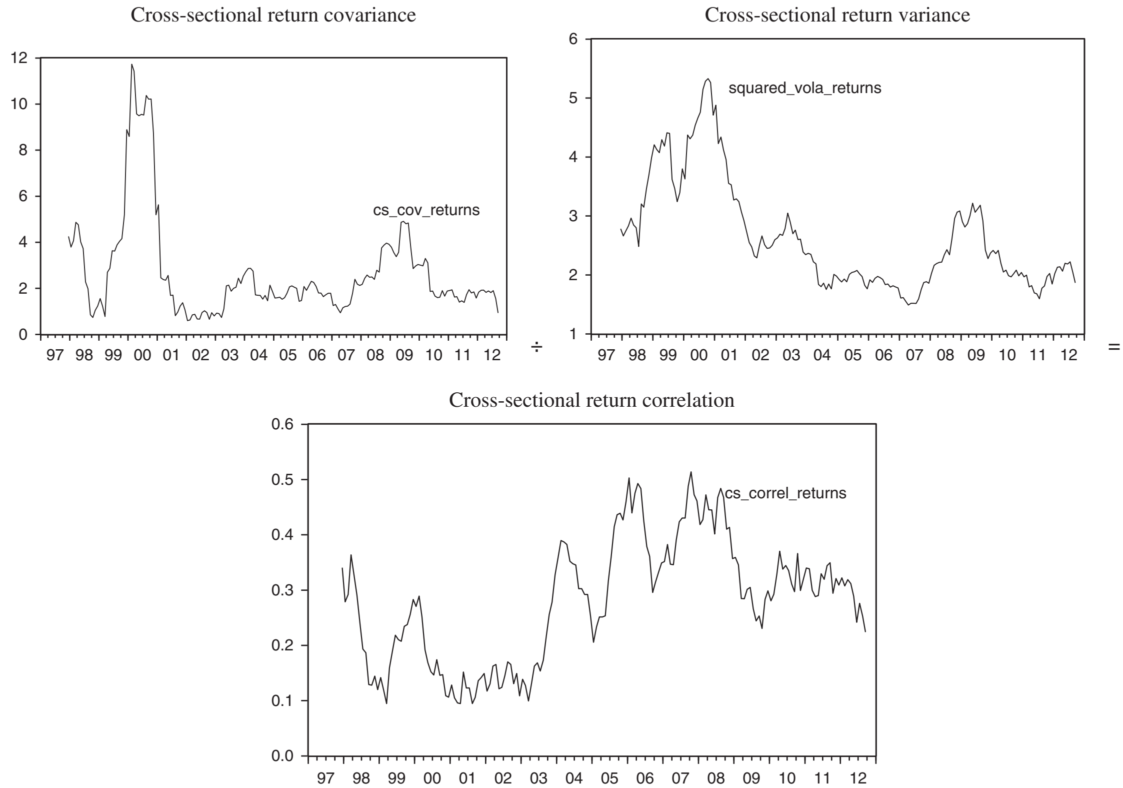

Figure 15: Cross-sectional correlation (*cs_corr*) of the strategies' returns and its components.
Note: The cross-sectional time series are computed using a moving average of 12 months.

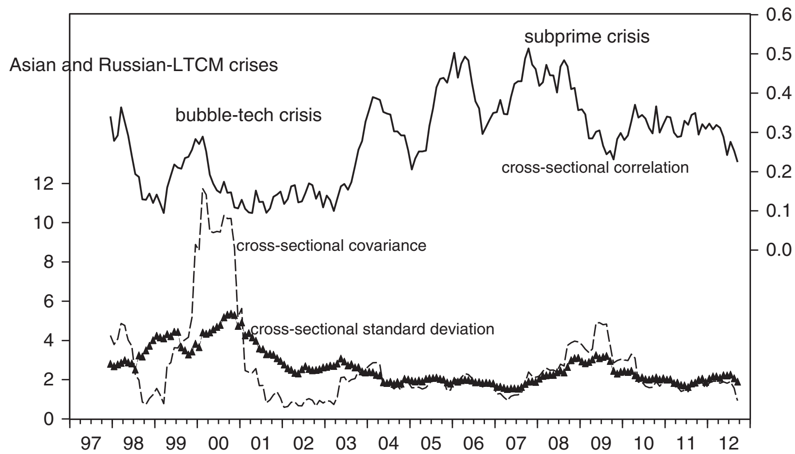

Figure 16: Financial crises and co-movements between strategies' returns.
Note: The cross-sectional time series are computed using a moving average of 12 months.

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 12 Almon lags of *cs_cov* shows that the sum of the lags is equal to 0.36, significant at the 1 per cent 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 gauge the co-movement of returns, it seems therefore more advisable to rely on *cs_cov*, a quite straightforward indicator of co-movement.

The α and β co-movements of the of hedge fund strategies

We also computed the same statistics for the strategies' β's and α's (Figure 17).[27] In times of economic expansion, the cross-sectional covariance of the strategies' β's shows a tendency to increase. The strategies' behavior thus becomes more homogenous in terms of β. This is the pattern we observed in the previous section in economic expansion. However, in times of crisis, the cross-sectional covariance of the β 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 β's,

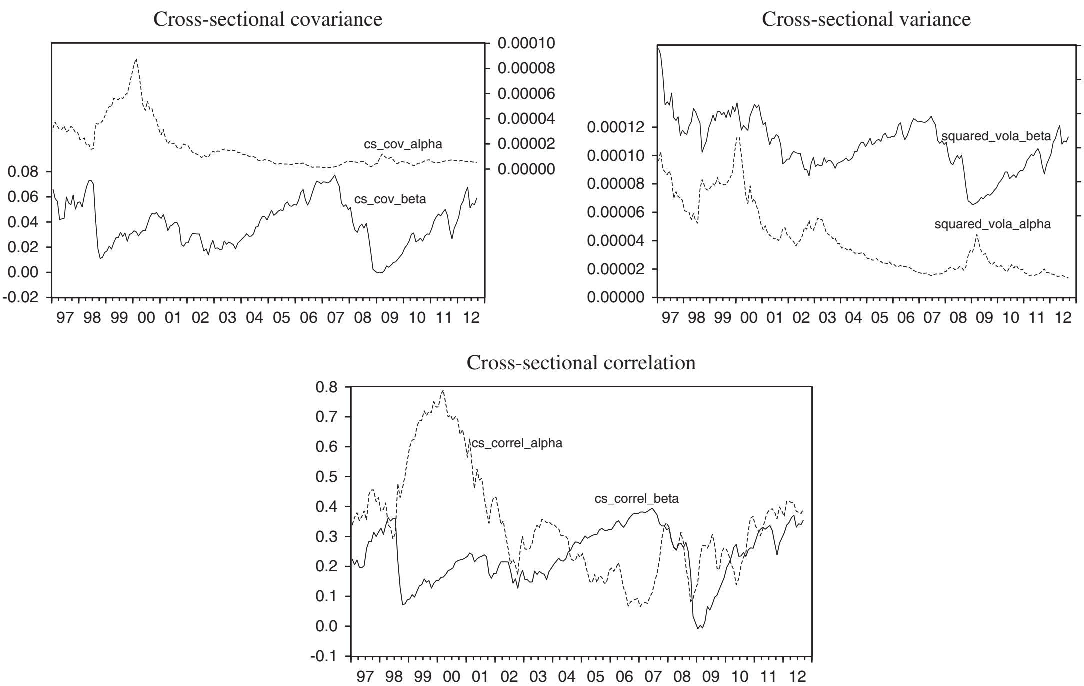

Figure 17: Cross-sectional correlation of the strategies' α's and β's.

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' β's increases during economic expansions, which suggests that the risk-taking behavior of the strategies is more homogenous during good times. However, the cross-sectional correlation of the β's decreased sharply during the subprime crisis, some strategies taking higher risk while others doing the opposite. A closer look at the link between the β's *cs_cov* and *cs_corr* shows that they are strongly and positively correlated (Figure 18). In other words, the *cs_sd* does not disturb the positive link between *cs_cov* and *cs_corr* for the β's as it was the case for returns.

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

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

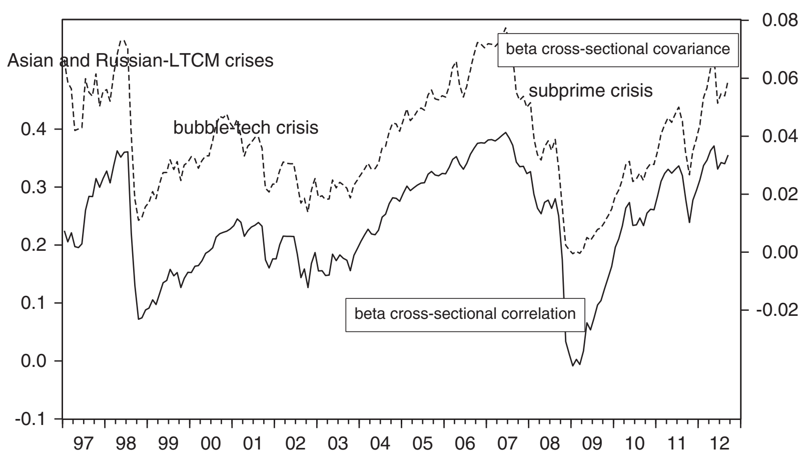

Figure 18: Financial crises and β's cross-sectional covariance and correlation.

CONCLUSION

While the returns' behavior 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 behavior of hedge fund strategies over the business cycle in order to pin down the dynamics of their risk-return trade-off.

In this respect, our contribution is two-fold. First, we study the cycles of the strategies' time-varying α's and β's using a Kalman filter approach that embeds conditioning information in the α's and βs' state equations. This information allows us to see how hedge funds adjust their risk level to market information. In this respect, our *pc-lookback* factor is particularly relevant to monitor the hedging operations of hedge funds. Moreover, we track the volatility of hedge fund during the business cycle using an innovative approach in this kind of study, that is, a MGARCH approach. Second, we study the behavior of the cross-sectional dispersions of returns and especially the ones of the α's and β's, another innovative approach relying on the Kalman filter to simulate the strategies' α's and β's.

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 α of most strategies remains positive. Some strategies benefited from this crisis, which suggests good opportunities for hedge fund investors even in bad times (Sandvik *et al*, 2011). Third, our results are consistent with the fact that hedge funds' portfolio managers modify their β's 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' α's and β's 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. More precisely, as noted by other researchers, there is no evidence of underperformance in the hedge fund industry during the subprime crisis and no indication that hedge funds induce fire sales in the subprime crisis – fires sales being an important amplification channel during financial crises (Sandvik *et al*, 2011; Shleifer and Vishny, 2011; Brown *et al*, 2012; Boyson *et al*, 2013; Gennaioli *et al*, 2013). This development may suggest a decrease in *systemic* risk in the hedge fund industry, which is often because of contagion or herding – that is, a greater homogeneity in the behavior 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 (Racicot and Théoret, 2013). One promising avenue for further research is to model the co-movements of the returns, α's and β's of the hedge fund strategies. Indeed, how macroeconomic shocks or uncertainty do impact these co-movements?[28] This is an important question that must be addressed to gain a better understanding of the hedge fund time-varying risk-return trade-off.

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NOTES

1 In this respect, the *SMB* factor in the Fama and French model may be seen as a proxy for funding liquidity risk in periods of crisis, which is not the case in normal times (Billio *et al*, 2009).

2 Sabbaghi (2012) investigates 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 analysis of the co-movements of strategies' α's and β's.

3 In this respect, Brown *et al* (2012) argue that few hedge funds failed during the subprime crisis. Similarly, Boyson *et al* (2013) provide evidence that hedge funds did not induce fire sales in the subprime crisis – fires sales being a powerful amplification channel during financial crises (Shleifer and Vishny, 2011; Gennaioli *et al*, 2013).

4 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 amplitude of return volatility depends on the sign of the innovation in return models. When the sign of the innovation is negative – that is, in times of bad news – return volatility is higher than when the sign of the innovation is positive – that is, in times of good news. For further detail on this asymmetry, see Nelson (1991).

5 For an EViews application of the Kalman Filter, see Racicot and Théoret (2010).

6 This relationship is in line with the well-known theory of asset substitution.

7 The broad credit channel regroups the traditional lending channel and the balance sheet channel.

8 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.

9 Veronesi (2010) casts equation (2) in a macroeconomic model where the price of risk depends on the business cycle.

10 Bollen and Whaley (2009) do not introduce conditioning information in their state β equation. The time-varying β follows a simple random walk in their model.

11 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).

12 Mainly managed futures or CTA funds.

13 GAI strategies are described in the following document available on GAI's

website: *Greenwich Global Hedge Fund Index Construction Methodology*.

14 Kenneth French's website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

15 Hsieh' s database website is https://faculty.fuqua.duke.edu/~dah7/HFData.htm.

16 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 per cent as opposed to 40 per cent for a long call in Hull's (2012) example.

17 Selling short may thus be a dominant strategy of futures hedge funds.

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

19 See: Greenwich Alternative Investments, *Greenwich Global Hedge Fund Index Construction Methodology*.

20 The equity market neutral strategy was considered as one of the leading hedge fund strategies in many papers (for example, Capocci *et al*, 2005) but its performance suffered recently from the Madoff affair (Sandvik *et al*, 2011).

21 See the appendix for the technical aspects of the multivariate GARCH procedure.

22 Or state α's and β's.

23 Yu and Sharaiha (2007) rely on the cross-sectional dispersion to study investment opportunities in terms of α.

24 Baum *et al* (2004, 2009) rely on the cross-sectional standard deviation of the loans-to-assets ratio to study the herding behavior in the banking sector. In complement to this study, Calmès and Théoret (2014) study the cross-sectional dispersion of bank non-interest income – a proxy for fee-based activities.

25 Note that we transposed the Adrian's formula in matrix notation so it can be used in programming (for example, in Visual Basic (Excel)).

26 Formerly known as the Credit Suisse/Tremont Hedge Fund Indexes.

27 Yu and Sharaiha (2007) rely on the cross-sectional dispersion to study investment opportunities in terms of α.

28 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) and Calmès and Théoret (2014) use a similar approach to study the bank herding behavior in the market for loanable funds and in fee-based activities.

29 For an EViews application of the MGARCH model see Racicot (2012). See also Calmès and Théoret (2013) for an application of the MGARCH model to investigate the product-mix diversification of US and Canadian banks.

References

Adrian, T. (2007) Measuring risk in the hedge fund sector. Current issues in economics and finance. *Federal Reserve Bank of New York* 13(3): 1–7.

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

Agarwal, V. and Naik, N.Y. (2004) Risk and portfolio decisions involving hedge funds. *Review of Financial Studies* 17(1): 63–98.

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

Avramov, D., Kosowski, R., Naik, N.Y. and Teo, M. (2011) Hedge funds, managerial skill and macroeconomic variables. *Journal of Financial Economics* 99(3): 672–692.

Baum, C.F., Caglayan, M. and 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. and Ozkan, N. (2009) The second moment matters: The impact of macroeconomic uncertainty on the allocation of loanable funds. *Economics Letters* 102(2): 87–89.

Beaudry, P., Caglayan, M. and Schiantarelli, F. (2001) Monetary instability, the predictability of prices, and the allocation of investment: An empirical investigation using panel data. *American Economic Review* 91(3): 648–662.

Billio, M., Getmansky, M. and Pellizon, L. (2009) Crises and hedge fund risk. Working Paper, University of Venice.

Black, F. (1976) Studies of stock price volatility of changes. *American Statistical Association Journal*: 177–181.

Bollen, N.P.B. (2011) The financial crisis and the hedge fund returns. *Review of Derivatives research* 14(2): 117–135.

Bollen, N.P.B. and Whaley, R.E. (2009) Hedge fund risk dynamics: Implications for performance appraisal. *Journal of Finance* 64(2): 985–1035.

Bollerslev, T. (1986) Generalized autoregressive conditional hetetoskedasticity. *Journal of Econometrics* 31(3): 307–327.

Bollerslev, T., Engle, R.F. and Woodridge, J.M. (1988) A capital asset pricing model with time-varying covariances. *Journal of Political Economy* 96(1): 116–131.

Boyson, N., Helwege, J. and Jindra, J. (2013) Crises, liquidity shocks, and fire sales at hedge funds. Working Paper, Northeastern University.

Brown, G., Green, J. and Hand, J. (2012) Are hedge funds systemically important. *Journal of Derivatives* 20(2): 8–25.

Cai, L. and Liang, B. (2012) On the dynamics of hedge fund strategies. *Journal of Alternative Investments* 14(4): 51–68.

Calmès, C. and Théoret, R. (2013) The change in banks' product mix, diversification and performance: An application of multivariate GARCH to Canadian data, Chaire d'information financière et organisationnelle, ESG-UQAM, Cahier de recherche 2013-01.

Calmès, C. and Théoret, R. (2014) Bank systemic risk and macroeconomic shocks: Canadian and U.S. evidence. *Journal of Banking and Finance* 40: 388–402.

Cao, C., Chen, Y., Liang, B. and Lo, A.W. (2013) Can hedge funds time market liquidity? *Journal of Financial Economics* 109: 493–516.

Cappoci, D., Corhay, A. and Hübner, G. (2005) Hedge fund performance and persistence in bull and bear markets. *European Journal of Finance* 11(5): 361–392.

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

Chen, Y. and Liang, B. (2007) Do market timing hedge funds time the market? *Journal of Financial and Quantitative Analysis* 42(4): 827–856.

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

Dewachter, H.D. and Wouters, R. (2014) Endogenous risk in a DSGE model with capital-constrained financial intermediaries. *Journal of Economic Dynamics & Control* 43: 241–268.

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(4): 987–1007.

Engle, R.F. and Kroner, K.F. (1995) Multivariate simultaneous GARCH. *Econometric Theory* 11(1): 122–150.

Fung, W. and Hsieh, D.A. (1997) Empirical characteristics of dynamic trading strategies: The case of hedge funds. *Review of Financial Studies* 10(2): 275–302.

Fung, W. and Hsieh, D.A. (2001) The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies* 14(2): 313–341.

Fung, W. and Hsieh, D.A. (2004) Hedge fund benchmarks: A risk based approach. *Financial Analysts Journal* 60(5): 65–80.

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

Gennaioli, N., Shleifer, A. and Vishny, R. (2013) A model of shadow banking. *Journal of Finance* 68(4): 1331–1363.

Haiss, P.R. (2005) Banks, herding and regulation: A review and synthesis, Working paper, Europe Institute.

Henriksson, R. and 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. and 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 edn. New York: Pearson.

McGuire, P., Remolona, E. and Tsatsaronis, K. (2005) Time-varying exposures and leverage in hedge funds. *BIS Quarterly Review*, March, pp. 59–72.

Mitchell, M. and Pulvino, T. (2001) Characteristics of risk and return in risk arbitrage. *Journal of Finance* 56(6): 2135–2175.

Nelson, D.B. (1991) Conditional heteroskedasticity in asset returns: A new approach. *Econometrica* 59(2): 347–370.

Racicot, F.E. (2012) Notes on nonlinear dynamics. *Aestimatio, the IEB International Journal of Finance* 5: 162–221.

Racicot, F.E. and Théoret, R. (2009) Integrating volatility factors in the analysis of the hedge fund alpha puzzle. *Journal of Asset Management* 10(1): 37–62.
Racicot, F.E. and Théoret, R. (2010) Forecasting the stochastic volatility using the Kalman: An application to the Canadian interest rate and price-earnings ratio. *Aestimatio, the IEB International Journal of Finance* 1: 28–47.
Racicot, F.E. and Théoret, R. (2013) The procyclicality of hedge fund alpha and beta. *Journal of Derivatives & Hedge funds* 19(2): 109–128.
Racicot, F.E. and Théoret, R. (2014) Cumulant instrument estimators for hedge fund return models with errors in variables. *Applied Economics* 46(10): 1134–1149.
Sabbaghi, O. (2012) Hedge fund return volatility and comovement: Recent evidence. *Managerial Finance* 38(1): 101–119.
Sandvik, S.H., Frydenberg, S., Westgaard, S. and Heitmann, R.K. (2011) Hedge fund performance in bull and bear markets: Alpha creation and risk exposure. *The Journal of Investing, Spring* 20(1): 52–77.
Shleifer, A. and Vishny, R.W. (2011) Fire sales and finance and macroeconomics. *Journal of Economic Perspectives* 25(1): 29–48.
Solnik, B. and Roulet, J. (2000) Dispersion as cross-sectional correlation. *Financial Analysts Journal* 56(1): 54–61.
Treynor, J.L. and Mazuy, K. (1966) Can mutual funds outguess the market? *Harvard Business Review* 44(4): 131–136.
Veronesi, P. (2010) *Fixed Income Securities: Valuation, Risk, and Risk Management*. New Jersey: Wiley.
Wagner, W. (2010) Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation* 19(3): 272–286.
Yu, W. and Sharaiha, Y.M. (2007) Alpha budgeting – Cross-sectional dispersion decomposed. *Journal of Asset management* 8(1): 58–72.
Zhong, Z. (2008) Why does hedge fund alpha decrease over time? Evidence from individual hedge funds. Working Paper, SSRN, http://ssrn.com/abstract=1108817.

APPENDIX

The multivariate GARCH[29]

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:

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

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:

$$vec(H_{\mathrm{t}}) = vec(C) + Avec(e_t e_{t-1}') + Bvec(H_{\mathrm{t}-1})$$

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 that 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:

$$H_{\mathrm{t}} = C + A(\varepsilon_t \varepsilon_{t-1}^{'})A' + BH_{\mathrm{t}-1}B'$$

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