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Procyclical Behavior of Hedge Funds: A Portfolio Manager and Investor's Perspective

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Procyclical risk analysis is one of the main concerns for researchers working in the field of financial institutions, especially in banking research and macro-prudential analysis (Shin 2009; Adrian and Shin 2010; Jacques 2010). Procyclicality may be defined in two ways. First, a time series is procyclical if it tends to co-move positively with the business cycle. Thus, it increases in expansionary periods and decreases during recessionary periods. Second, a time series is procyclical if it tends to increase the amplitude of the business cycle. Similarly, a financial institution generates procyclicality if the credit it grants gives rise to an amplification of the business cycle. In this scenario, procyclicality generates systemic risk or risk related to contagion. The term "procyclicality" is somewhat ambiguous in the economic and financial literature, so we will retain both definitions of procyclicality in this article.

According to many studies, the main drivers of procyclicality are the big banks, which are very involved in off-balance-sheet activities, investment bankers, and more globally, the actors in the shadow banking business. However, the cyclical behavior of hedge funds, which are a constituent of shadow banking, is often neglected in the financial literature. However, it is well known that the recent financial crisis was attributable to the procyclicality of credit. The role of hedge funds in this procyclicality must not be minimized. According to Adrian and Shin (2010), the share of hedge funds in the origination of U.S. subprime mortgages by the leveraged financial sector was as high as 32% before the crisis, which suggests that hedge funds may originate important financial shocks that have repercussions throughout the entire economy.

To study the procyclical behavior of hedge funds, we place our analysis in a dynamic setting (Racicot and Théoret, 2013). We first show that the spectra of hedge fund returns classified by strategies highlight fluctuations in the business cycle frequency, which provides evidence of procyclicality in the hedge fund industry. Since the spectrum is a way of capturing the autocorrelation of returns, we can conclude that there is persistence in the series of the strategy returns at the business cycle frequency. This result is useful because it means that hedge fund returns are not pure random walks and can thus be forecasted. Importantly, the spectra of hedge fund strategy returns are quite different from one strategy to the next, which suggests that strategies may be a way for the investor to diversify his or her portfolio.

We then conduct an empirical study on the procyclicality of two key financial parameters in portfolio management: the alpha and the beta of hedge fund strategies. Traditionally, these parameters are analyzed in a static way, in the sense that they are not time-varying. We make them time-varying by relying on two empirical methods applied to the Fama and French model (1992, 1993, 1997): the conditional regression and the Kalman Filter. We find that when classified by strategy, hedge fund portfolio managers tend to manage the risk of their portfolio, as measured by the time-varying beta, in a procyclical fashion. That is, the portfolio manager bears more risk (or leverages his portfolio) during expansion and bears less risk (or deleverages his portfolio) during recession. Importantly, strategies focusing on arbitrage, e.g., futures and distressed strategies, follow a different cyclical behavior. In this respect, it is interesting to note that the spectra of strategies based on arbitrage are different from those of the other strategies. Arbitrage strategies are also the ones whose returns are less easily captured by the Fama and French model (1992, 1993, 1997). The cyclical behavior of the alpha of arbitrage strategies is also dissimilar. Indeed, some strategies display a countercyclical behavior, which suggests that an absolute positive return may be obtained even in bad times. These results also indicate that hedge fund strategies may provide good diversification benefits. We complete our analysis of the diversification benefits provided by hedge fund strategies by studying the cyclical behavior of the cross-sectional dispersion of hedge fund strategy returns.

Data and Stylized Facts

Data

This study is based on a sample of the indices of U.S. Greenwich Alternative Investment (GAI) hedge fund strategies, a leader in hedge fund databases and collects data on the broad universe of hedge funds. Note that we compare hedge fund databases in some previous studies (Racicot and Théoret 2007a,b) and the empirical results are very close, especially with respect to the Hedge Fund Research (HFR) database. Descriptive statistics on this sample are reported in Exhibit 1. Our observation period for the monthly returns of these hedge fund indices runs from January 1995 to March 2010, for a total of 183 observations for each index (strategy). The risk factors that appear in the Fama and French equation (1992, 1993, 1997) - the market risk premium and the two mimicking portfolios: SMB and HML - are drawn from French's website. The interest rate used to test the models is the U.S. three-month Treasury bill rate and the selected market portfolio index is the S&P 500. The period we analyze was plagued by four major financial crises: (i) the Asian financial crisis (1997-1998); (ii) the Russian/LTCM crisis (1998); (iii) the bursting of the high-tech market bubble (2000); and (iv) the 2007-2009 subprime market crisis, related to high risk mortgages. Our period of analysis is, therefore, rich in major stock market corrections. Despite these market collapses, Exhibit 1 reveals that the GAI hedge funds performed quite well during this period. The mean monthly return of these indices is 0.71% over this period, for an annual rate of 8.5%. This rate is higher than the annual mean return of the S&P 500 over the same period, which amounted to 5.5%. The low performers over this period are the short-sellers, convertible arbitrage, and macro strategies while the high performers are the long-short, growth, and market-neutral strategies. In addition, the standard deviation of returns differs greatly from one index to the next. The standard deviations of the strategy returns are generally below those of the S&P 500.

Several researchers argue that the strategies followed by hedge funds are similar to option-based strategies (Fung and Hsieh, 1997, 2004; Weisman, 2002; Agarwal and Naik, 2000, 2004). And effectively, Exhibit 1 reveals that some hedge fund strategies are similar to hedged option strategies, like the covered call and protective put strategies. These option-based strategies have a beta that is quite low, in the order of 0.6 for at-the-money options, and yet may offer high returns that approximate those shown in Exhibit 1. The following strategies - equity market-neutral, arbitrage, futures, and distressed securities - have a very low beta compared to other funds. These strategies are more involved in arbitrage activities than the others. Their returns are also less tractable in the Fama and French model. Other risk factors are at play to explain the returns of these low-beta strategies.

In addition, plain vanilla puts, to which the short-seller strategy is linked, have a negative expected return. That might explain the low mean return of the short-seller index over the period of analysis. At a monthly 0.18%, it is well below the mean return of the whole set of strategies. Incidentally, the CAPM beta of the short-seller index, equal to -1.01, is negative and quite high in absolute value over the sample period. According to the CAPM, the excess return of a portfolio having a negative beta should be low and even negative: this is the

	Mean	Median	Max	Min	sd	Skew	Kurtosis	CAPM-beta
Distressed Securities	0.68	1.04	4.79	-7.44	2.06	-1.47	6.86	0.22
Equity Market-Neutral	0.87	0.80	8.10	-2.53	1.41	1.33	8.95	0.08
Futures	0.67	0.21	7.71	-6.80	3.10	0.18	2.72	-0.08
Macro Index	0.55	0.66	4.00	-2.95	1.45	0.29	3.06	0.27
Market-Neutral Group	0.93	0.92	7.20	-6.06	1.48	-0.61	8.99	0.20
Short-Sellers	0.18	-0.10	11.41	-6.88	3.61	0.56	3.46	-1.01
Value Index	0.61	1.11	5.68	-9.65	2.54	-1.21	5.94	0.56
Arbitrage Index	0.87	0.90	4.10	-8.58	1.38	-2.40	17.99	0.16
Convertible Arbitrage Index	0.31	0.60	6.55	-19.31	2.98	-3.78	26.43	0.40
Growth Index	1.04	1.19	20.10	-12.99	4.53	0.43	5.50	0.76
Long-Short	1.09	1.31	13.20	-9.24	3.02	0.04	5.20	0.52
Mean of indices	*0.71*	*0.78*	*8.44*	*-8.40*	*2.51*	*-0.60*	*8.65*	*0.19*
Weighted composite	0.56	0.90	4.75	-5.96	1.86	-1.01	5.18	0.37
S&P500	0.46	1.29	11.06	-18.47	4.62	-1.13	5.99	1.00

Notes: The statistics reported in this Exhibit are computed on the monthly returns of the GAI indices over the period running from January 1995 to March 2010. The weighted composite index is computed over the whole set of the GAI indices (strategies). The CAPM beta is estimated using the simple market model, that is: $R_{it} - R_{ft} = \alpha + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}$, where R_i is the return of the index i, R_m is the S&P500 return. R_f is the riskless rate and ε_i is the innovation.

Exhibit 1 Descriptive statistics of the GAI indices returns, 1995–2010

Source: GAI & Bloomberg

case of the short-seller index.

Furthermore, according to Exhibit 1, the composite index of hedge funds has lower kurtosis than the market index given by the S&P 500. However, this characteristic is not shared by all hedge fund strategies, the convertible arbitrage index having a kurtosis as high as 26.43. A high kurtosis means that rare or extreme events are more frequent than for the normal distribution, which suggests that the payoffs of strategies displaying high kurtosis in their returns are very nonlinear. Once more, we may relate these statistics to those associated with the cash-flows of option-based strategies. Their payoffs have a relatively low standard deviation, but a high degree of kurtosis compared to the returns of the stock market index, which is priced in their returns.

Stylized facts

The spectrum of a time series is a device to depict its persistence at different frequencies, the business cycle frequency being the most important . In other words, the spectrum detects persistence or autocorrelation in the time series over the frequencies varying on a time scale running from 0 to . When there is persistence over a time frequency, returns are predictable over this frequency. In this respect, the spectrum of a pure random variable—which by nature is not predictable—is flat (Exhibit 2). This kind of variable displays no persistence. Exhibit 3 shows the plot of the spectrum of a standard macroeconomic variable expressed in logarithm, like the logarithm of GDP or the logarithm of aggregate consumption. This kind of variable displays high persistence at very low frequencies, i.e., the trend

	r_{t-1}	$(Rm\text{-}Rf)_{t-1}$	VIX_{t-1}
Distressed Securities	-0.0014	0.0000	0.0043
	0.9172	*0.7714*	*0.0016*
Market-Neutral	-0.0145	0.0001	0.0027
	0.2183	*0.3054*	*0.0114*
Long-Short	-0.015	0.0001	0.0041
	0.030	*0.0484*	*0.0001*
Value Index	0.0072	0.0025	-0.0002
	0.5283	*0.0321*	*0.2502*
Growth Index	-0.0591	0.0055	0.0007
	0.0007	*0.0014*	*0.0014*
Futures Index	-0.1540	0.0108	0.0019
	0.000	*0.0001*	*0.000*
Weighted Composite	-0.0216	0.004	0.0002
	0.000	*0.000*	*0.000*

Notes: The Kalman Filter model used to estimate these coefficients is explained in the article. For each strategy, the first line of numbers provides the estimated coefficients of the variables and the second line gives the corresponding p-values (reported in italics).

Exhibit 2 Time-varying betas of some strategies estimated by the Kalman Filter

Source: Author's calculations

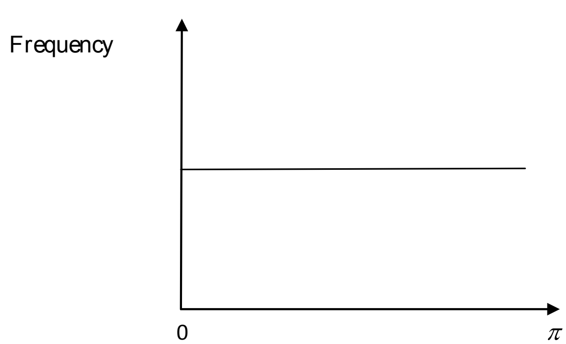

Exhibit 3 Spectrum of a random variable

Source: Author

of the variable is very pronounced. But it shows no fluctuation at higher frequencies, i.e., the trend dominates this time series. In Exhibit 3, the shaded area represents the business cycle frequency. As we see, a standard macroeconomic variable expressed in logarithm shows no fluctuation at this frequency. It must be transformed in order to study its cycle.

Exhibit 5 plots the spectrum of the hedge fund composite return. Since the spectrum has a peak at the business cycle frequency—always represented in the shaded area, it is the first indication that the return of a representative hedge fund is procyclical. It is thus persistent at the business cycle frequency. This result is not covered in the hedge fund literature. Note that the spectrum of the stock market return (S&P 500) is different (Exhibit 4). It shows fluctuations at a higher frequency than the business cycle one. This suggests that the stock market return is more unstable than the hedge fund composite return.

As mentioned previously, the behavior of hedge funds included in strategies focusing on arbitrage activities differs from the behavior of hedge funds mainly involved in other strategies. Exhibit 5 supports this hypothesis. Except for the futures strategy, strategies based on arbitrage show high fluctuations at low frequencies but much less fluctuation at higher frequencies. In this respect, the equity market-neutral spectrum is very similar to the one of a standard macroeconomic variable (Exhibit 3). It displays no fluctuation at the business cycle frequency, suggesting that the returns of this strategy are not procyclical. The spectrum of the futures strategy is quite different from the other three since it displays significant peaks at the business cycle frequency and at higher frequencies. Note that this strategy is sometimes classified in directional strategies although it has low beta, which might explain why the return delivered by the futures strategy displays fluctuations at the business cycle frequency.

We expect higher beta strategies to be more procyclical. Exhibit 6 plots the spectra of three of these strategies. Among all hedge fund strategies, the most conventional one is the long-short strategy. Its spectrum displays two peaks: one at low frequency and one at the business cycle frequency. Consequently, even if the returns of this strategy are partly procyclical, they are also related to the behavior of returns of arbitrage strategies. Therefore, a strategy may belong to many categories, which rep-

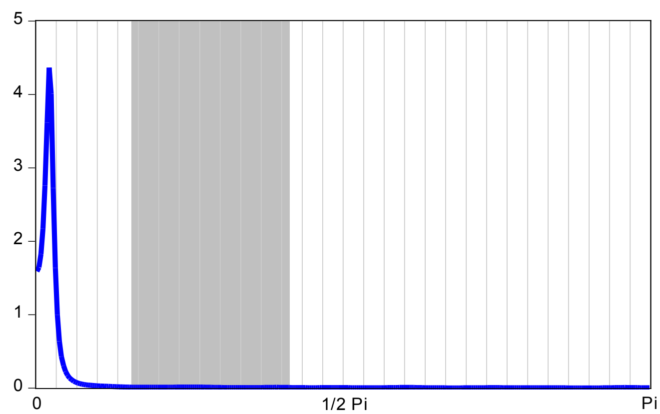

Exhibit 4 Spectrum of a standard macroeconomic variable

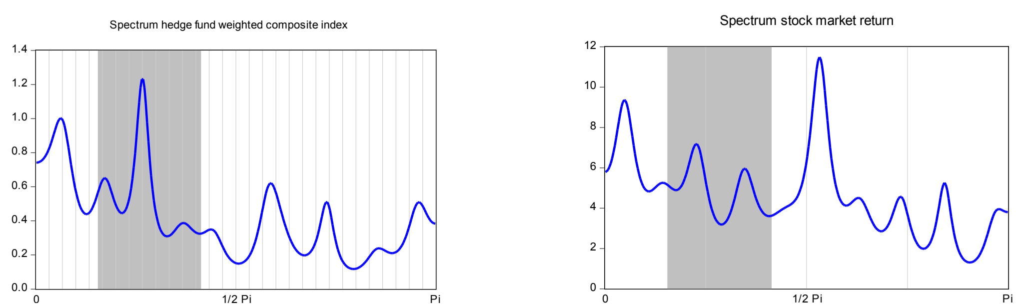

Exhibit 5 Spectra of the hedge fund composite return and the stock market return (S&P 500)

resents a good opportunity to diversify a portfolio. The spectrum of growth funds is quite similar to the one of the long-short strategy while the spectrum of the value index is more procyclical. From the investor's point of view, the growth strategy would be more appropriate in expansion than the other two strategies, although they may be beneficial in recession since they embed an arbitrage dimension. We know that the value strategy is associated with one market anomaly. Indeed, stocks related to this strategy incorporate a high dividend yield: these stocks tend to be undervalued. According to the spectrum, this dimension would be more valuable in expansion than in recession. The cyclical behavior of this anomaly is similar to the small firm anomaly. In this respect, Exhibit 6 shows that the spectrum of the SMB portfolio as computed by French - a portfolio long in firms with low capitalization and short in firms with high capitalization - is quite similar to the spectrum of the value index, even if it shows more fluctuations at higher frequencies. The SMB anomaly would thus be a better opportunity during an expansion than during a recession.

Overall, the analysis of the spectra shows that each strategy may embed many dimensions, even if it is classified as an arbitrage strategy or as a strategy more sensitive to the business cycle. These strategies may offer good diversification benefits to the investor. We examine this aspect more thoroughly in the following sections.

Return Models: The Conditional Model and the Kalman Filter Model

To further study the procyclicality of hedge fund behavior, we must simulate the time profile of strategies' alphas and betas. To do so, we rely on the standard conventional Fama and French model (1992, 1993, 1997), which reads as follows:

$$\left(R_{pi}-R_f\right)_t = \alpha_{it} + \beta_{1i,t}\left(R_m - R_f\right)_t + \beta_{2i,t} SMB_t + \beta_{3i,t} HML_t + \varepsilon_{it} \quad (1)$$

where $\left(R_{pi}-R_f\right)_t$ is the excess return of the portfolio of strategy i over the risk-free rate R_f; $\left(R_m - R_f\right)_t$ is the market risk premium; SMB_t is the "small firm anomaly"; HML is the "value stock anomaly"; α_{it} is the time-varying alpha; $\beta_{1i,t}$ is the time-varying beta, and ε_{it} is the innovation.

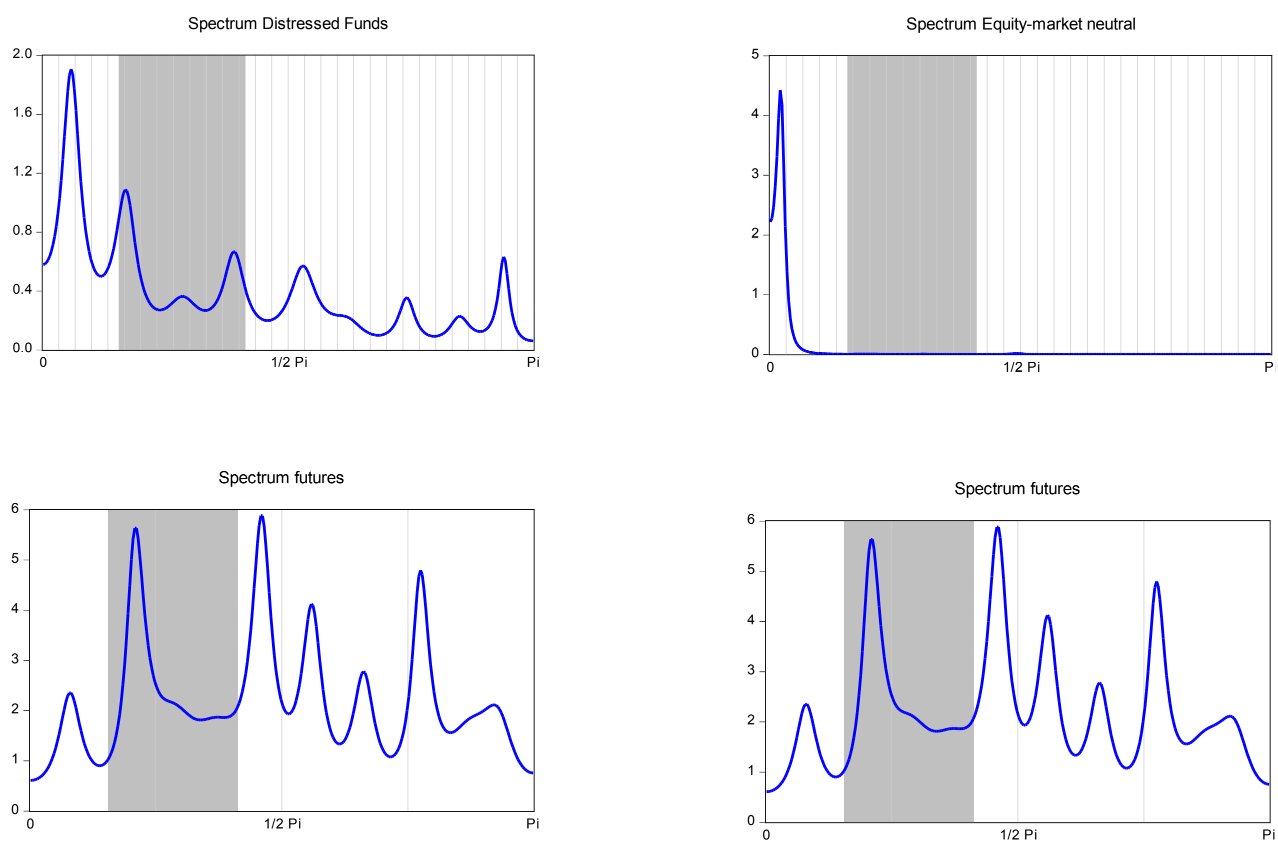

Exhibit 6 Spectra of some strategies focusing on arbitrage

We rely on two ways to compute the time-varying alpha and beta in equation (1). One way is to resort to the conditional model (Ferson and Schadt, 1996; Christopherson, Ferson and Glassman, 1998; Ferson and Qian, 2004). In line with this model, we express the conditional alpha and beta as follows:

$$\alpha_{it} = \alpha_{0i} + \phi_{1i} r_{t-1} + \phi_{2i}\left(R_m - R_f\right)_{t-1} \quad (2)$$

$$\beta_{1i,t} = \beta_{0i} + \phi_{3i} r_{t-1} + \phi_{4i}\left(R_m - R_f\right)_{t-1} + \phi_{5i} VIX_{t-1} \quad (3)$$

with r, the level of short-term interest, and VIX, the impliedvolatility of the S&P 500 index. The conditioning variables are lagged one period, our aim being to track the reaction of the time-varying coefficients to the conditioning market information. The selected financial variables are thus known at time t.

We thus postulate that the alpha and beta are under the control of the portfolio manager to a certain degree. Equation (3) indicates that the manager is involved in market timing, as he adjusts the beta of his portfolio according to the market risk premium. We may postulate that he bears more risk, or increases the beta of his portfolio, when the market risk premium increases. Conversely, he takes less risk, or decreases the beta, when the market risk premium decreases. Note that market-timing is usually studied by introducing the squared market risk premium in the return model (Treynor and Masuy, 1966; Henriksson and Merton, 1981). But we can easily verify that this is the case in our model by substituting equations (2) and (3) in equation (1). Aside the market risk premium, we also postulate that the beta is also sensitive to the short-term interest rate, which is viewed as an indicator of market conditions. The beta is also conditioned by the stock market volatility (VIX). The alpha responds to the risk market premium and the short-term interest rate.

To estimate the conditional model, we substitute equations (2) and (3) in equation (1). We can then rely on OLS (ordinary least-squares) to estimate the coefficients of equation (1). The coefficients of equations (2) and (3) are then exactly identified.

The Kalman filter is another method to estimate the time-varying alpha and beta. In this setting, equations (2) and (3) are transformed as follows:

$$\alpha_{it} = \alpha_{t-1,i} + \phi_{1i} r_{t-1} + \phi_{2i}\left(R_m - R_f\right)_{t-1} \quad (4)$$

$$\beta_{1i,t} = \beta_{t-1,i} + \phi_{3i} r_{t-1} + \phi_{4i}\left(R_m - R_f\right)_{t-1} + \phi_{5i} VIX_{t-1} \quad (5)$$

Compared to equations (2) and (3), the conditional al-

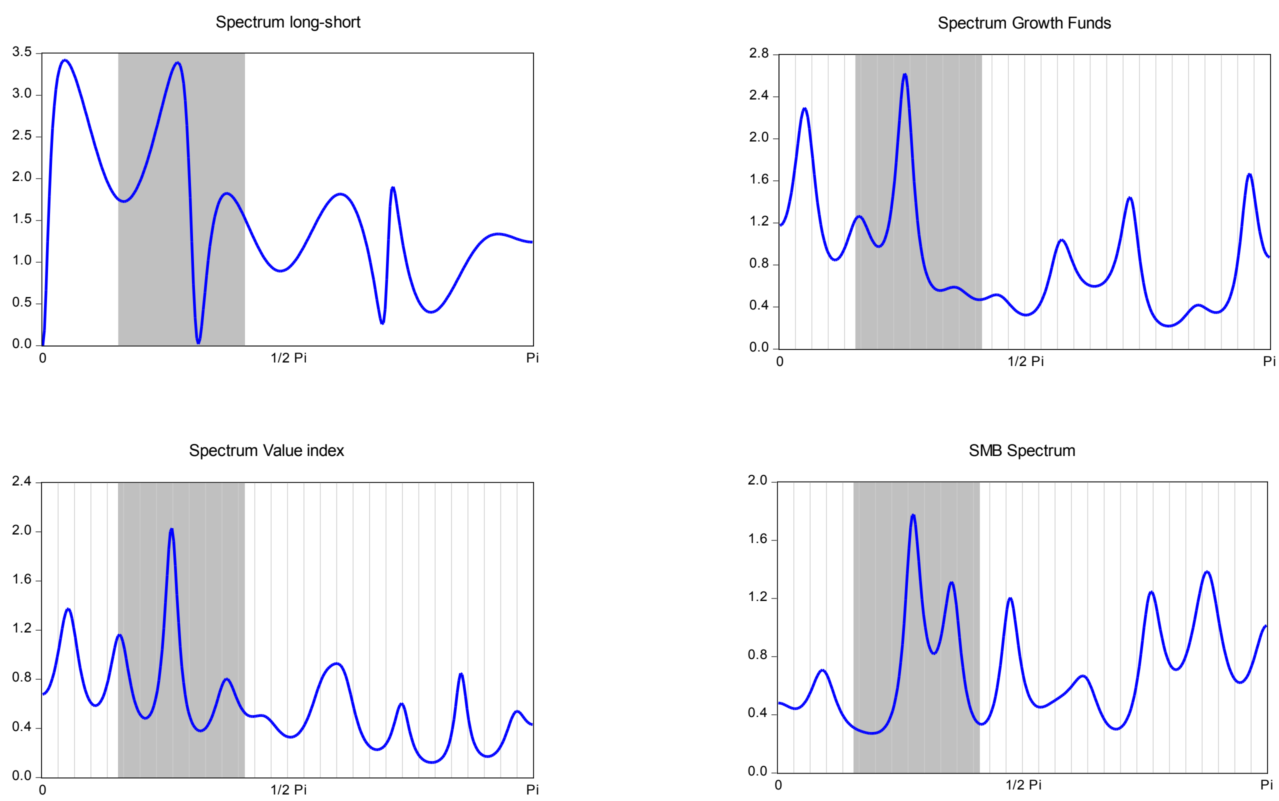

Exhibit 7 Spectra of some strategies having higher betas

pha and beta take a recursive form in the Kalman Filter model—i.e., the conditional alpha and beta are functions of their lagged values. In this model, the estimated alpha and beta ought to be smoother.

In the Kalman Filter model, equation (1) is the signal equation and equations (4) and (5) are the state equations. In this kind of model, these three equations are estimated simultaneously with a routine using the maximum likelihood method.

Empirical Results

Hedge fund portfolio managers and market timing

In this section, we focus on the time variability of the strategies' betas since it is the most important aspect of our article. In Exhibit 7, we note that the interest rate (r_f) has a negative impact on hedge funds betas, i.e., an increase in interest rate signals a market deterioration, which leads hedge funds to take less risk. Note however that this variable is not significant for strategies focusing on arbitrage, such as the distressed securities and market-neutral strategies. In other respects, according to the market variable (R_m - R_f), hedge funds take more risk when the market return, as measured by the S&P 500 index, increases. This result also indicates that hedge funds are good market-timers. However, as in the case of the interest rate conditioning variable, this effect is quite low and not significant for the distressed securities and market-neutral strategies.

Finally, financial market volatility, as measured by VIX, impacts positively and significantly on the market returns of all strategies except the value index strategy, for which the exposure to volatility is negative and insignificant. Hedge funds seem conditioned by the payoffs related to forward market volatility, the value of an option being dominated by its volatility.

Overall, the behavior of portfolio managers associated with arbitrage strategies seems different from that of managers associated with directional strategies. In the following section, we examine the time-varying behavior of the alphas and the betas of some representative strategies involved respectively in arbitrage activity and

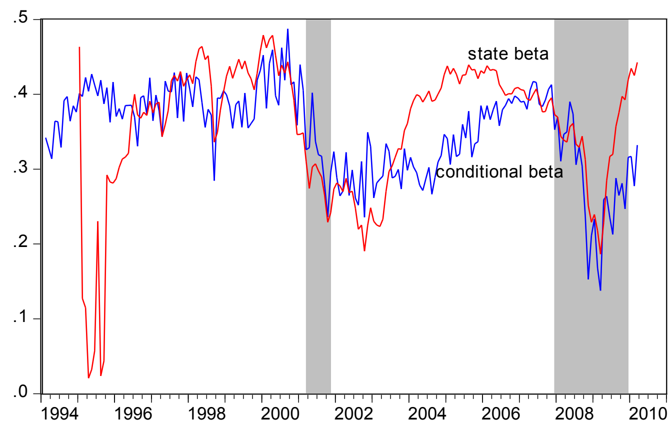

Exhibit 8 State beta and conditional beta for the GAI weighted composite index

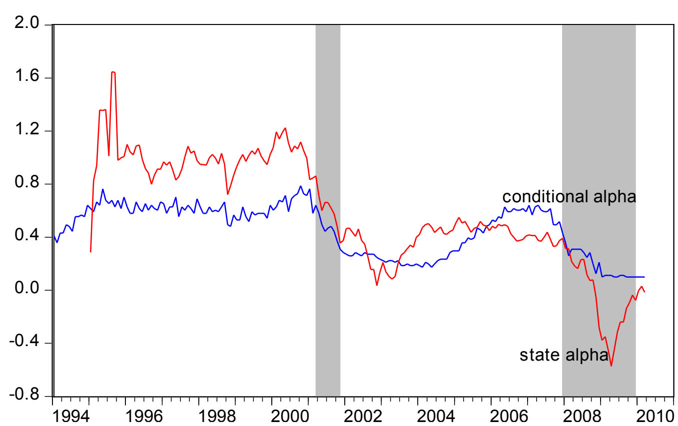

Exhibit 9 State alpha and conditional alpha for the GAI weighted composite index

market-oriented business lines in more detail.

The cyclicality of representative strategies' alphas and betas.

The plots of the betas indicate that they are far from being constant, as suggested by the conventional CAPM, and that many strategies exhibit a procyclical behavior with respect to the beta. As shown in Exhibit 8, the state beta of the weighted composite index decreased during the 1997 Asian crisis before resuming its rise in 1998. Thereafter, following the first U.S. recession of the millennium, the beta decreased from the beginning of 2000 until the end of 2002, which paved the way for a market recovery. The beta almost doubled from 2003 to the middle of 2005. It decreased progressively thereafter in expectation of an economic slowdown and in reaction to the corporate accounting scandals. This beta dynamics is comparable to the one obtained by McGuire et al. (2005) during the period from 1997-2004 with respect to hedge fund risk exposure, whereby funds lever their positions during the upward trend of the stock market or in economic expansions, and delever their positions during crises. Note that the profiles of the time-varying beta obtained by our two models - the conditional model and the Kalman Filter model - are quite close (Exhibit 9). Since the profiles of the strategy's conditional alpha and beta are also similar to the ones obtained with the Kalman filter, we only report the Kalman filter results in the ensuing discussion.

The state alpha related to the weighted composite index has a profile similar to the beta but is more volatile (Exhibit 8). The alpha decreased after the Asian crisis, the decrease gaining momentum during the technological bubble. During this episode, the estimated alpha dropped from a high of 1% (monthly) to a low close to 0%, which suggests that the alpha puzzle must be studied in a dynamic setting and might not be a puzzle after all. Our procyclical approach thus seems more relevant to track the alpha process than the one based on a static framework. As in the case of beta, the alpha profile is particularly interesting during the 2007–2009 subprime crisis. According to Exhibit 8, it decreases to a low of -0.5% in the middle of the crisis, before recovering thereafter - a profile similar to the beta. In summary, alpha and beta co-move positively, a result in line with the common factors that drive these two performance measures.

We reproduced the same plots for four representative strategies: two arbitrage strategies—the distressed securities and equity market-neutral strategies—and two

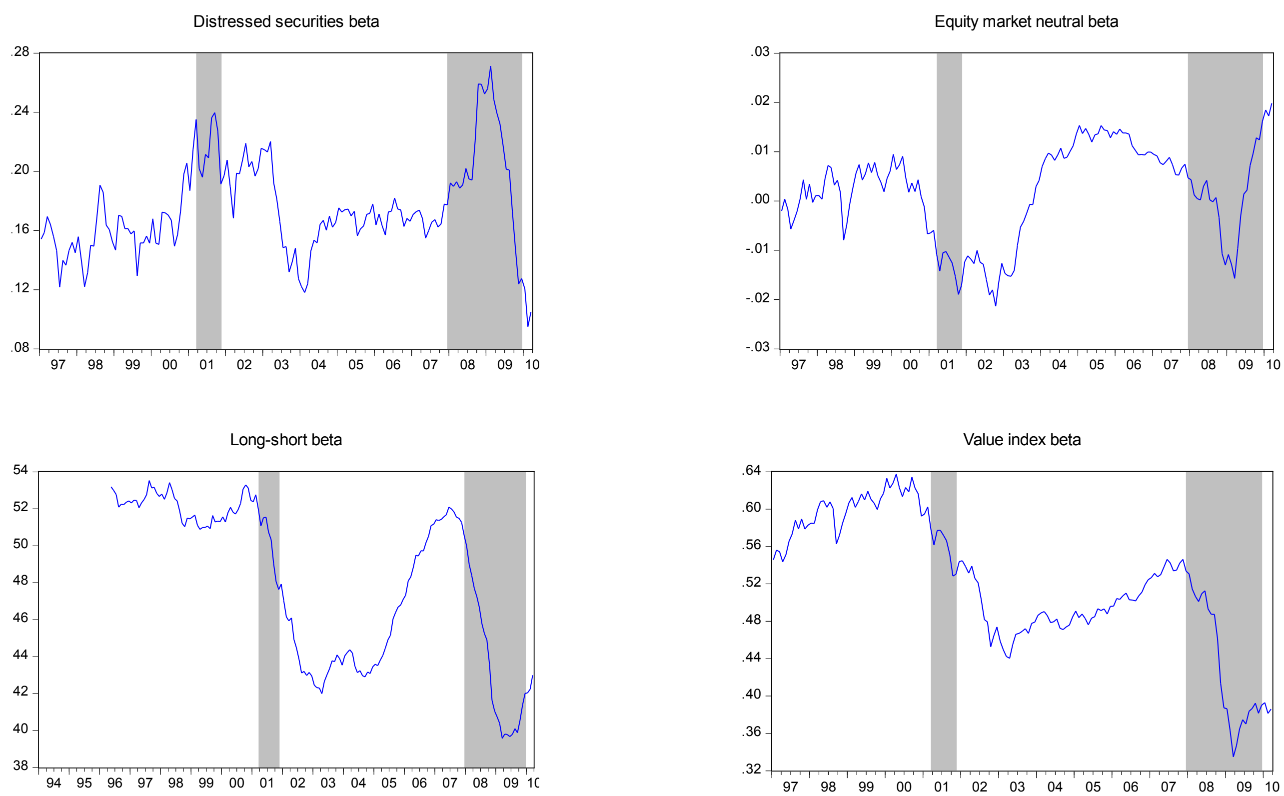

Exhibit 10 State betas for some strategies

directional strategies—the long-short and value index strategies. In Exhibits 10 and 11, we note that the cyclical behavior of the alphas and betas of these two groups of strategies is quite different. Exhibit 10 shows that the managers involved in the distressed securities strategy take more risk during periods of recession or financial turmoil. The jump of the beta of this strategy is particularly high during the subprime crisis. This result was expected since the managers of these funds are confronted with better opportunities, i.e., more businesses in bad shape, during these periods. However, the beta of the market-neutral strategy displays some procyclicality, even if it tends to remain close to zero. Indeed, it fluctuates in a very narrow range, comprised between -0.02 to 0.02.

The cyclical behavior of the beta of the two representative market-oriented hedge funds differs markedly. The beta of these two strategies collapses during episodes of crises. In this respect, the drop is very sharp during the subprime crisis. Interestingly, these betas seem forward-looking since their decrease tends to lead the crises, and they resume their increase before the start of an economic recovery. In times of expansion, the betas of the long-short and value index strategies tend to increase. In line with the conventional behavior of portfolio managers, the managers of these strategies use leverage to increase risk in periods of expansion and deleverage to reduce risk in periods of recession.

Exhibit 11 provides the corresponding plots of the time-varying alphas of our four strategies. In terms of alpha, the distressed securities strategy seems to benefit from periods of crises, when business opportunities are greater for this strategy. We also note a great compression of this strategy alpha during expansion. The distressed securities strategy is definitively more valuable to the investor in crisis episodes. The pattern of the alpha of the equity market neutral strategy is similar. However, the alpha of this strategy remains above 0.6 over the entire sample period, which seems to suggest an alpha puzzle for this strategy.

The time profile of the directional strategies' betas is quite similar since their sensitivity to common factors is comparable. As expected, the alphas of these strategies decrease in the first phase of a recession but resume their increase before the start of the following recovery. The alphas of these two strategies tend to trend downward during our sample period, suggesting an attenuation of the alpha puzzle.

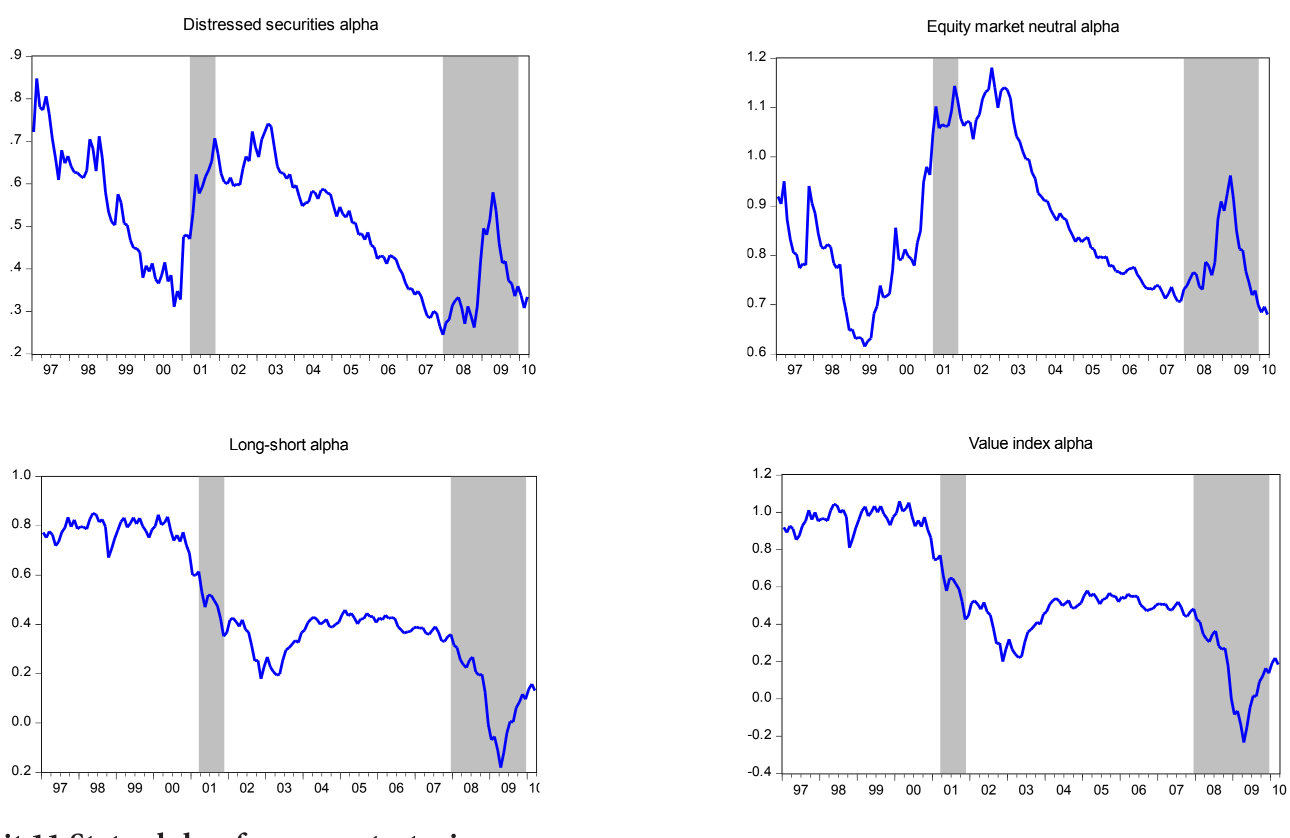

Exhibit 11 State alphas for some strategies

In summary, there are obvious differences in the behavior of hedge fund strategies' alphas and betas, especially between funds that focus more on arbitrage activity and funds that focus more on the direction of the stock market. This is good news for investors in search of yield and diversification opportunities.

Portfolio diversification across strategies

To track the co-movement of strategy returns, we rely on the cross-sectional standard deviation of strategy returns. Beaudry et al. (2001) rely on this indicator to study the co-movement of firm returns on investment. Solnik and Roulet (2000) also employ the cross-sectional dispersion to track the co-movement of the stock market returns. Sabbaghi (2012) transpose this indicator to the study of the co-movements of the returns of hedge fund indexes. The cross-sectional standard deviation, also labeled the cross-sectional dispersion, is defined as:

$$\forall t, \quad cs\_sd_t = \sqrt{\frac{1}{N}\mathbf{R}_{it}^{'}\mathbf{R}_{it}} \qquad (6)$$

Where N is the number of strategies, and $\mathbf{R}_{it}$ is the cross-sectional vector of the strategies' 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. Thus, there is a rise in the heterogeneity of the hedge fund strategies in this case. This is good news with respect 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 strategy returns move closer in this case.

Exhibit 12 plots the cross-sectional dispersion of our strategies' returns from 1997 to 2010. Since this indicator is quite unstable, we also plot a twelve-month moving average of the series. We note that the cross-sectional dispersion jumps in times of crises. The investor can thus diversify his portfolio across hedge fund strategies when diversification is needed the most. Surprisingly, the cross-sectional dispersion jumped less during the subprime crisis than during the tech bubble burst. This may be an indication that hedge fund strategies become more homogeneous through time. Hedge funds may also have relied on more hedging operations during the subprime crisis than in the past. This is a kind of learning-by-doing or maturation process at play in the hedge fund industry that is beneficial to the hedge fund investor, since it signals a decrease in systemic risk in the hedge fund industry.

Conclusion

The returns behavior over the business cycle of standard financial instruments like stocks and bonds is well known. However, papers on the cyclical dimensions of hedge fund returns are scarce. Contrary to many other

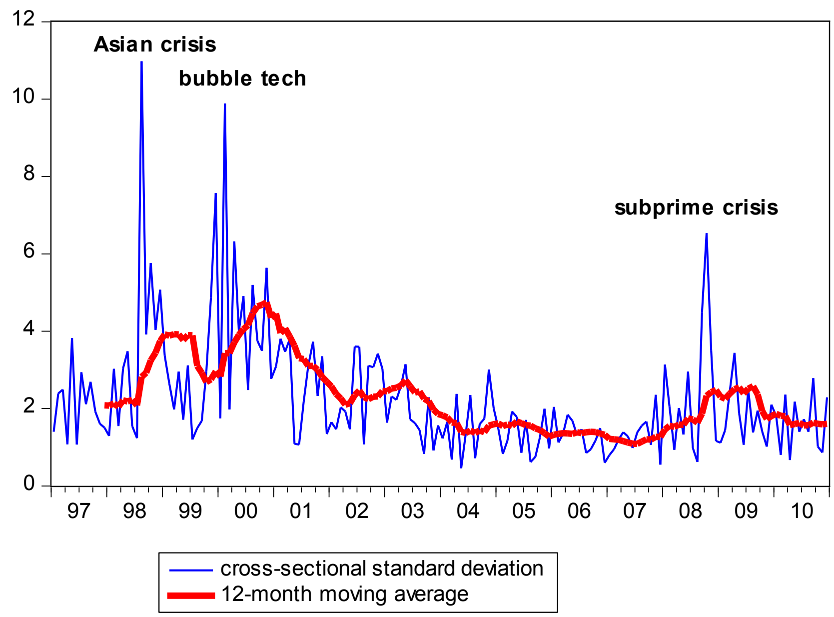

Exhibit 12 Cross-sectional standard deviation of strategies' returns

Source: GAI & author's calculations

financial institutions for which short-selling is restricted by the law, hedge funds may adopt investment strategies that deliver positive payoffs during crises. Some strategies, such as investment in distressed securities, short selling, and equity market-neutral, even benefit from a decline in stock markets. It is 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.

Our study provides important insights regarding the hedge fund portfolio managers and investors. Regarding portfolio managers, we find that the manager of a representative hedge-fund modifies his beta in line with the trend and the volatility of financial markets. While managers of hedge fund strategies tend to increase their beta when volatility increases, funds differ regarding their market-timing activities. In this respect, there is a sharp contrast between funds focusing on arbitrage activities and funds that are more market-oriented. The beta of the distressed securities strategy even increases in times of financial turmoil, while the portfolio manager of a representative hedge fund tends to decrease his beta during such periods.

Turning to the investor's point of view, the results of our study indicate that hedge fund strategies continue to provide good diversification benefits over the business cycle. First, hedge fund strategies differ in terms of the profile of their systematic risk over the business cycle. Second, in spite of the subprime crisis, the alpha of most strategies remains positive. In addition, some strategies benefit from this crisis, which suggests good opportunities for hedge fund investors, even in bad times. Finally, our diversification index, as measured by the cross-sectional dispersion of hedge fund returns, indicates that diversification opportunities seem to increase in times of crisis, when they are needed the most.

References

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, pp. 63-98.

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, pp. 648-662.

Calmès, C., and Théoret, R., 2014. "Bank Systemic Risk and Macroeconomic Shocks: Canadian and U.S. Evidence." Journal of Banking and Finance 40, pp. 388-402.

Fama, E.F., and French, K.R., 1992. "The Cross-Section of Expected Stock Returns." Journal of Finance 47, pp. 427-465.

Fama, E.F., and French, K.R., 1993. "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Financial Economics 33, pp. 3-56.

Fama, E.F., and French, K.R., 1997. "Industry Costs of Equity." Journal of Financial Economics 43, 153-193.

Fung, W., and Hsieh, D.A., 1997. "Empirical Characreristics of Dynamic Trading Strategies: The Case of Hedge Funds." Review of Financial Studies 10, pp. 275-303.

Fung, W., and Hsieh, D.A., 2004. "Hedge Fund Benchmarks: A Risk Based Approach." Financial Analyst Journal 60, pp. 65-80.

Henriksson, R., and Merton, R.C., 1981. "On Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills." Journal of Business 41, pp. 867-887.

Jacques, K., 2010. "Procyclicality, Bank Lending, and the Macroeconomic Implications of a Revised Basle Accord." The Financial Review 45, pp. 915-930.

McGuire, P., Remolona, E. and Tsatsaronis, K., 2005. "Time-Varying Exposures and Leverage in Hedge Funds." BIS Quarterly Review, pp. 59-72.

Racicot, F.E., and Théoret, R., 2007a. "A Study of Dynamic Market Strategies of Hedge Funds Using the Kalman Filter." The Journal of Wealth Management 10, pp. 94-106.

Racicot, F.E., and Théoret, R., 2007b. "The Beta Puzzle Revisited: A Panel Study of Hedge Fund Returns." Journal of Derivatives and Hedge Funds 13, pp. 125-146.

Racicot, F.E., 2011. “Low-Frequency Components and the Weekend Effect Revisited: Evidence from Spectral Analysis.” Aestimatio, the IEB International Journal of Finance, 3, pp. 8-26.

Racicot, F.E. Racicot, F.É., and Théoret, R., 2013. “The Procyclicality of Hedge Fund Alpha and Beta.” Journal of Derivatives & Hedge Funds 19 (2), pp. 109-128.

Sabbaghi, O., 2012. “Hedge Fund Return Volatility and Comovement: Recent Evidence.” Managerial Finance 38, pp. 101-119.

Shin, H.S., 2009. “Securitization and Financial Stability.” Economic Journal 119, pp. 309-332.

Solnik, B., and Roulet, J., 2000. “Dispersion as Cross-Sectional Correlation.” Financial Analysts Journal 56, pp. 54-61.

Treynor, J., and Mazuy, K., 1966. “Can Mutual Funds Outguess the Market? Harvard Business Review 44, pp. 131-136.

Weisman, A., 2002. “Informationless Investing and Hedge Fund Performance Measurement Bias.“ The Journal of Portfolio Management 28, pp.80-91.

Whaley, R.E., 2006. Derivatives: Markets, Valuation and Risk Management, Wiley & Sons, Inc..

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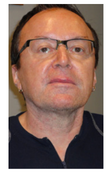

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