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Net Inflows and Time-Varying Alphas: The Case of Hedge Funds*

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Abstract

The growth in the size of the hedge funds industry has led some investors to worry about a decline in alphas, associated with reduced arbitrage opportunities in international financial markets. We introduce a multivariate components model for returns and net relative inflows into hedge funds, accounting for time-varying market premia. We estimate alpha as an unobserved component variable of the econometric model. We then assess whether several categories of hedge funds do produce extra profits and whether the flows of funds into the industry are dynamically related to returns. Our results point to a positive correlation between past returns and future flows, while the evidence concerning the linkage between past flows and future returns is mixed. However, we do not find any structural decline in alpha for most hedge fund categories.

Key words: Hedge funds, performance, asset pricing models, unobserved components models

JEL classification: G2; G11; G15; C32

1 Introduction

Hedge funds have become a mainstream investment. Although there is considerable imprecision, it is estimated that there are about 6,000 hedge funds in the world, corresponding to more than one trillion dollars of assets under management at the end of 2005. The excess capacity hypothesis claims that there are too many hedge fund managers chasing too few arbitrage opportunities in international financial markets and, as a consequence, lower returns for investors. Some academic studies implicitly support this view. Agarwal and Naik (2000)

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show that 28% of the funds considered in their sample has added value, with their active management strategies, in the late nineties, down from 38% of the early nineties. Similarly, Fung et al. (2005) report a general decline in the alphas produced by funds of hedge funds and by various styles of hedge funds between 1994-1998 and 2001-2004. Chan, Getmansky, Haas and Lo (2005) suggest that "the hedge-fund industry has grown tremendously over the last few years, fueled by the demand for higher returns in the face of stock-market declines and mounting pension-fund liabilities. These massive fund inflows have had a material impact on hedge-fund returns and risks in recent years, as evidenced by...reduced performance...".

Summary statistics also seem to confirm the excess capacity hypothesis. Yearly returns on the 9 categories of hedge funds monitored by Tremont (the data set that we use in our empirical analyses) have often been below long run average returns in the 2001-2005 period. A comparison of average returns over the period 2001-2005 with returns over the full period 1993-2005 reveals that in 60% of the cases the former returns have been lower than the latter returns. If the calculation is repeated excluding the year 2003 the percentage increases to 70%.

Mispricing should be almost nonexistent under ideal conditions. Dybvig (1983) considers a multifactor model and finds that return mispricing is bounded above by the variance of idiosyncratic noise, the supply of shares and by a function of the coefficient of absolute risk aversion. His "back-of-the-envelope" computations suggest that mispricing should be basically irrelevant, amounting to 0.04% on an annualized basis. A negative relation between assets under management and returns is consistent with the idea of limited arbitrage.[1] Hedge funds may be regarded as informed investors in the Grossman-Stiglitz sense, but their ability to arbitrage away risky opportunities may be constrained by various elements like short run risk, limited capital and risk aversion. An increase in the amount of assets under management by hedge funds might therefore be associated with a decline in their gross returns. Such a decline would be transmitted to the net returns perceived by investors if it were not offset by a decrease in the management fees. In the case of hedge funds, however, informal evidence shows that fees have not declined over time. Hedge funds charge high fees, often amounting to a fixed fee of 2% plus an incentive fee of 20%. Such fees have existed for a long time, i.e. they are not a transitory feature of the industry. Perhaps they have increased over time, since Ackermann, McEnally and Ravenscraft (1999) report a 1% annual management fee and an incentive fee equal to 14% at the end of the 1990s.

In equilibrium however rational investors should decide their portfolio allocation on the basis of the net returns. Petajisto (2005) allows for a layer of financial intermediaries, which specialize in acquiring information and exploiting it for portfolio formation purposes. Final investors allocate wealth between

[1] See Shleifer and Vishny (1997).

passive and active investors, taking into account the cost of acquiring information. Active investors in turn select stocks exploiting mispricing. The total amount of wealth actively chasing mispricing is therefore limited by the investment decision of the final investors. Petajsto's (2005) calibration shows that a standard one factor model produces a negligible mispricing for prices and returns, in line with Dybvig (1983). However, a more complex version of the model, allowing for costs of information, produces substantial deviations. A key parameter of his model is the fee charged by the institutional investor to manage assets: the larger the fee, the larger the equilibrium alphas on single stocks. Indeed, in equilibrium a higher fee can be only justified by higher excess return. A management fee equal to 1% produces an estimate of alpha between -1.6% and +1.6%, a non negligible value. This suggests that excess capacity may be a transitory phenomenon. High fees cannot be justified without a corresponding value creation, whose bases may largely be found in securities mispricing.

Hence, is there a general decline in hedge funds' alphas? In particular, have the large inflows of assets into the hedge funds industry undermined the ability of managers to overperform market indices? The question implies that alpha is a time-varying parameter and not a constant. Therefore, the standard performance evaluation model, which treats alpha as a constant, cannot be used to answer the question. In this paper we propose a performance evaluation model with a time varying intercept. In the model alpha is an unobserved variable, proxied every period by the observed return. In the context of such a generalized model, the question about the linkage between flows and performance can be properly answered, since the dynamics of alpha are an empirical phenomenon which can be described by the econometric model. The estimated time series of alphas can then be analyzed to assess the evidence in favor of trends, cycles and other regularities.

However, the time series of alphas by itself cannot shed light on the impact of the assets under management by the hedge funds industry. In order to study the relevance of the inflows into the industry, we consider a bivariate model including both returns, the proxy for alpha, and inflows into the hedge funds industry. We use inflows and not cumulative assets under management, i.e. the total net asset value, due to the different time series properties of alphas and assets under management. A simple plot of returns, a proxy for alphas, and assets under management in the hedge funds industry reveals a formidable increase in the latter but not in the former. In statistical terms, alpha is a stationary variable while total assets under management are a nonstationary variable. On the other hand, inflows (relative to past assets under management) is also a stationary variable, which can be meaningfully related to returns. A dynamic model incorporating both inflows and returns allows for the estimation of the effects of past alphas and inflows on current alphas and inflows, as well as the assessment of the contemporaneous covariance between alphas and inflows. In order to answer the particular question about the impact of inflows on alphas we need to estimate the marginal impact of inflows on alphas, keeping other variables constant. The two questions outlined at the beginning can, therefore, be reframed in the following ways. First, is there convincing evidence about time variability of alphas? Second, do inflows contribute in a systematic way to such time variability?

Empirically, one has to start from the observation that returns can be decomposed into a component due to the manager's skill, a component associated with a risk premium of the underlying assets, and a shock. The relative importance of the three components may vary across categories of hedge funds. Directional categories, which are on average long some underlying market, require estimation of a time-varying risk premium before measuring potential arbitrage opportunities, while non-directional categories may not present any market risk premium. We will measure the time-varying excess return in the context of an econometric model allowing for unobserved variables and for standard risk factors considered in the literature. The model will retrieve an estimate of excess returns under the mild assumption that it follows an autoregressive process, by using the actual (risk-adjusted) rate of return as the measurement variable. Importantly, our econometric techniques will not force us to separately estimate the model over various sub-periods.

The plan of the paper is as follows. After this introduction, we describe the econometric model and discuss its economic and statistical foundations. We then present the data and the empirical results, which can be summarized as follows. First, there is evidence of shock persistence in flows and excess returns, i.e. both processes are positively serially correlated. Second, flows tend to depend positively on lagged excess returns; the effects of returns and flows shocks peak within two quarters and are in general reabsorbed within ten quarters. In terms of forecast error variance decomposition, returns shocks are the most important determinant of returns fluctuations at all the horizons, noticeably contributing to flows fluctuations at all the horizons as well. Finally, and most importantly, we find no evidence of a negative trend in the excess returns produced by most styles, even though non-directional flows tend to have a negative effect on subsequent alphas.

2 The model

The model describes the joint dynamics of relative (to assets under management in the previous period) net flows (f_t) into a certain category of hedge funds and of the returns (r_t) obtained by the funds in that category. The state of the system is described by two unobserved variables (α_{1t}, α_{2t}), i.e. the arbitrage opportunity available to all the funds in the category and the relative net flow of funds into the category, respectively. Hence, the model can be written as two linear measurement equations and two transition equations[2]:

[2] Our model is similar to the latent VAR used by Brandt and Kang (2004) to study the relationship between the conditional mean and the volatility of stock returns, albeit in our case the state space model is linear and Gaussian.

$$
\begin{aligned}
r_t &= \alpha_{1t} + \theta_1 + \gamma' r_{F,t} + \varepsilon_{1t} && (1)\\
f_t &= \alpha_{2t} + \theta_2 + \varepsilon_{2t} && (2)\\
\boldsymbol{\alpha}_t &= \mathbf{T}\boldsymbol{\alpha}_{t-1} + \mathbf{u}_t && (3)\\
\boldsymbol{\varepsilon}_t &\sim N(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon) \quad \mathbf{u}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_u). && (4)
\end{aligned}
$$

The first equation decomposes the return to a specific category of hedge funds into the sum of a component representing arbitrage opportunities perceived by investors, but unobserved by the econometrician (α_{1t}), a fixed level component (θ_1), an i.i.d. Gaussian shock (ε_{1t}) and the sensitivity (γ') to a vector of returns on factor mimicking portfolios, $r_{F,t}$. Factor mimicking portfolios include both buy-and-hold portfolios and portfolios simulating dynamic option strategies.[3]

The specification employed allows for a contemporaneous relation between returns and flows shocks as well as for a lagged effect of flows on arbitrage opportunities, if any. The sign of the relation between lagged flows and current arbitrage opportunities is uncertain.[4] The capacity effect hypothesis assumes that the total amount of arbitrage opportunities is fixed, so that increases in flows decrease future alphas. This is more likely to take place in situations where assets under management by the hedge fund industry represent a large portion of the total capitalization of the securities usually traded by the hedge fund managers. However, financial innovations and increasing trading opportunities continuously expand total capitalization and trading opportunities. Therefore, flows may chase an expanding capacity.[5] According to recent estimates[6] hedge funds active in equity markets represent just about 1.5% of market capitalization and their role in fixed income markets is even lower than that. In these cases, therefore, there may not be a negative relation between inflows and future excess returns; on the contrary, the relation may even turn out to be positive. Our specification does not assume a priori a sign for the relation. The specification may even be non-existent. We let the data clarify this phenomenon.

The second equation decomposes the relative net flow into an unobserved component (α_{2t}) driving the systematic dynamics in flows, a fixed level component (θ_2), and an i.i.d. Gaussian shock (ε_{2t}). We allow for an unobserved component in flows for several reasons. The first is due to the presence of various time lags between the moment an investor decides to enter or exit hedge funds

[3] It is well known that following option replication strategies may induce the researcher to identify artificial market timing ability (Jagannathan and Korajczyk, 1986). Yet, the hedge funds performance evaluation literature has long recognized the importance of including option strategies among the regressors (Agarwal and Naik, 2000; Fung and Hsieh, 2004). Our econometric model significantly extends the standard model used in hedge funds performance measurement as it allows for time variability of the intercept. The following section will describe in detail the factor portfolios used for the various hedge fund categories.

[4] We thank one referee for pointing this issue to us.

[5] For instance, the dramatic growth in credit derivatives drew a lot of money into capital structure arbitrage, but the hedge fund dollars were flowing into a rapidly growing market – indeed the dollars were chasing perceived opportunities afforded by a new market. Similarly with emerging markets, where evolving capacity attracted investment.

[6] See Watson Wyatt (2005).

and the moment of the actual investment. Among the factors implying a difference between actual and desired flows are the time necessary for a due diligence of the candidate hedge fund manager and the redemption lag which may last up to 1 or 2 years. A second reason is due to uncertainty about the measurement of the variable representing the capacity effect. A plausible measurement could be given by assets under management by hedge funds or by the ratio between assets under management and total capitalization. However, assets under management cannot be meaningfully related with returns. In our sample assets under management are continuously increasing, i.e. they are a nonstationary variable, while returns fluctuate over time, i.e. they are stationary. Also, for most categories it is unclear what should be taken as the denominator of the ratio between assets under management and total capitalization. Our measure based on relative flows is therefore well suited to the analysis of returns. Allowing for measurement errors in both variables, our approach is robust to the possibility of imperfect measurement of total capacity.

The second equation also allows for a reaction of relative flows to past returns. There is much evidence for a relation between relative flows and past returns, both in the hedge funds and in the mutual funds literature. In the mutual funds literature the performance of managers is hardly predictable on the basis on past returns. However, individual net flows are correlated with past returns. Berk and Green (2004) show that these two elements are consistent with each other when final investors learn about managers abilities through past returns and at the same time flows negatively affect future returns because of decreasing returns to scale in the active management sector. Flows accrue to mutual funds to the point where there are no differences in expected returns.[7] In the case of hedge funds Agarwal, Daniel and Naik (2004) find that inflows chasing past returns may be described by a convex function, and that large hedge funds with larger inflows are associated with worse future performance, consistent with the hypothesis of decreasing returns to scale. Getmansky (2004) finds that a 10% increase in current return is associated with a 2% increase in inflows and that the relationship between current flows and past returns is concave, suggesting an optimal size to individual hedge funds. Getmansky (2004) also finds that hedge funds flows are influenced by the category they belong to, and that investors in directional hedge funds are more sensitive to past returns.

[7] Interestingly, a linear relation between aggregate flows and returns has also been found for mutual funds. For instance, Warther (1995) has found that, over the period 1984-1993, monthly stock returns are strongly correlated with concurrent unexpected flows to stock mutual funds, but not correlated with concurrent expected flows. Moreover, no evidence that aggregate fund flows are positively related to past returns is found, as well as that investors move money into funds in response to high returns (albeit such evidence has been found by other studies conducted at the micro level of the individual fund). However, Edelen and Warner (2001) have found a positive concurrent relation between returns and unexpected flows for the US, using daily data for the period February 2, 1998 through June 30, 1999. Evidence that aggregate flows follow market returns with a one-day lag has also been found, pointing to a positive feedback trading or as a common response to new information.

Moreover, Getmanski, Lo and Mei (2004) also find that attrition rates in the hedge funds industry are related to variables like past performance, volatility, style. Hence, these results lead us to expect interesting relationships at the aggregate level.

Finally, the third equation describes the state of the system. The non-diagonal transition matrix $\mathbf{T}$ imposes a latent VAR(1) structure to the vector $\boldsymbol{\alpha}_t = (\alpha_{1t}\ \alpha_{2t})'$, allowing the measurement of lagged linkages between flows and arbitrage opportunities. It also allows measurement of contemporaneous linkages through the non diagonal structure of the variance-covariance matrices of the Gaussian innovations $\boldsymbol{\varepsilon}_t$ where $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}\ \varepsilon_{2t})'$ [8].

Estimation of the model can be carried out by means of the Kalman filter applied to the following Gaussian state space representation (see Harvey, 1989):

$$\begin{aligned}
\mathbf{y}_t &= \mathbf{Z}_t\boldsymbol{\gamma}_t^* + \mathbf{c} + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon) \\
\boldsymbol{\gamma}_t^* &= \mathbf{T}\boldsymbol{\gamma}_{t-1}^* + \mathbf{u}_t^* \\
\mathbf{u}_t^{*'} &= \begin{bmatrix} \underset{(1\times 2)}{u_t'} & \underset{(1\times m)}{0} \end{bmatrix} \quad \mathbf{u}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_u).
\end{aligned}$$

$\mathbf{y}_t' = \begin{bmatrix} r_t & f_t \end{bmatrix}$, $\mathbf{Z}_t = \begin{bmatrix} I_2 & \mathbf{Z}_{2_t} \end{bmatrix}$, $\mathbf{Z}_{2_t} = \begin{bmatrix} r_{F,t}' \\ \mathbf{0}_{(1\times m)} \end{bmatrix}$, $\mathbf{c}' = \begin{bmatrix} \theta_1 & \theta_2 \end{bmatrix}$,

$\boldsymbol{\gamma}_t^{*\prime} = \begin{bmatrix} \alpha_{1,t} & \alpha_{2,t} & \gamma_{1,t} & \cdots & \gamma_{m,t} \end{bmatrix}$, $\mathbf{T} = \begin{bmatrix} \mathbf{T}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_m \end{bmatrix}$, $\mathbf{T}_1 = \begin{bmatrix} \theta_3 & \theta_4 \\ \theta_5 & \theta_6 \end{bmatrix}$, $\boldsymbol{\Sigma}_\varepsilon = \begin{bmatrix} \theta_7 & \theta_8 \\ \theta_8 & \theta_9 \end{bmatrix}$, $\boldsymbol{\Sigma}_u = \begin{bmatrix} \theta_{10} & \theta_{11} \\ \theta_{11} & \theta_{12} \end{bmatrix}$.

The key parameters in the model are contained in the transition matrix $\mathbf{T}$ and the variance-covariance matrices $\boldsymbol{\Sigma}_\varepsilon$ and $\boldsymbol{\Sigma}_u$. Coherent with the above discussion, we expect excess returns to be positively affected by past excess returns if arbitrage opportunities are persistent, i.e. $\theta_3 > 0$. Moreover we expect the impact of flows on excess returns to be negative ($\theta_4 < 0$) in the case that arbitrage opportunities fall as the amount of money invested in hedge funds

[8] The contemporaneous interrelation between flows and returns can be evaluated as follows. By projecting ε_{1t} onto ε_{2t}, i.e. $\varepsilon_{1t} = \beta_1\ \varepsilon_{2t} + \eta_{1t}$ with $\beta_1 = cov(\varepsilon_{1t}, \varepsilon_{2t})/var(\varepsilon_{2t})$, and noting that from (2) $\varepsilon_{2t} = f_t - \alpha_{2t} - \bar{f}$, we can write $\varepsilon_{1t} = \beta_1\ (f_t - \alpha_{2t} - \bar{f}\ ) + \eta_{1t}$. By substituting into equation (1), we get the reduced form for the return equation

$$r_t = E_t r_{t+1} + \alpha_{1t} + \bar{r} + \beta_1(f_t - \alpha_{2t} - \bar{f}\ ) + \eta_{1t}. \tag{5}$$

Similarly, the reduced form for the flows equation can be written as

$$f_t = \alpha_{2t} + \bar{f} + \beta_2(r_t - E_t r_{t+1} - \alpha_{1t} - \bar{r}) + \eta_{2t}. \tag{6}$$

From the reduced form equations it can noted that if the error terms in the measurement equations are correlated, i.e. $cov(\varepsilon_{1t}, \varepsilon_{2t}) \neq 0$, flows not only have a lagged impact on returns, but also a contemporaneous impact, with sign determined by the sign of the covariance between the error terms. Similarly, returns may contemporaneously affect flows, with the sign of the impact still depending on the sign of the covariance. In both cases, it is however the size of the ratios $\beta_1 = cov(\varepsilon_{1t}, \varepsilon_{2t})/var(\varepsilon_{2t})$ and $\beta_2 = cov(\varepsilon_{1t}, \varepsilon_{2t})/var(\varepsilon_{1t})$ which allows to determine whether such contemporaneous linkage is negligible or not.

increases. We also expect flows to be positively serially correlated ($\theta_6 > 0$), and to positively react to past returns ($\theta_5 > 0$), i.e. flows increasing with past funds performance. Since we employ quarterly observations, we expect the covariance component in the matrix $\mathbf{\Sigma}_\varepsilon$ to be different from zero. If arbitrage opportunities do not disappear with the quarter, flows and returns may be positively correlated.

2.1 Risk premia specification

In choosing the risk factors we have drawn from the available literature. The premium of dedicated short bias (DSB) is the stock market risk premium. Fung and Hsieh (2002) find that it is possible to explain 76% of the variability of CSFB/Tremont's dedicated short bias by using the return of the Wilshire 1750 small cap index and the return of the IFC composite index. We use the returns on the S&P500 index and on the MSCI Emerging Markets index. Following Agarwal and Naik (2004), we also allow for the size and value factors of Fama and French, and the momentum factor of Carhart. We augment this set of factors by considering option based strategies on the S&P500. We select an ATM option as the one with a strike price equal to the current value of the index, an OTM call (put) as the one with a strike which is 1% lower (higher) than the current value of the index. At the beginning of each quarter we compute the value of a 3-month option by using the Black and Scholes model. Volatility is estimated by means of the realized volatility of the previous quarter, obtained by daily data.[9]

Global macro (GM) hedge funds invest in a wide variety of asset classes which in principle may present a time-varying premium. Agarwal and Naik (2004) define such a strategy as one "....that seeks to capitalize on country, regional and/or economic change affecting securities, commodities, interest rates and currency rates. Asset allocation can be aggressive, and leverage and derivatives may be utilized. The method and degree of hedging can vary significantly". Relying on empirical work of Harvey, Solnik and Zhou (2002), pointing to two international risk factors, i.e. the return of the world stock market and the return on a currency exposure, we therefore allow for the possibility of a time-varying risk premium of a global nature. We use the returns on the S&P500 index, the MSCI Emerging Markets index, the Goldman Sachs Commodity Index, the Citigroup index for bonds with maturity between 1 and 3 years, the DM/US$ exchange rate. We augment the set of factors by including returns on option strategies consisting of call and put options on the S&P500 index, the Citigroup 1-3 years bond index and the DM/US$ exchange rate.

Long/short equity (LSE) should mainly use arbitrage techniques, but various studies suggest that on average they have a positive sensitivity to stock markets. Fung and Hsieh (2002) find that 72% of the variability of their returns is explained by a style analysis in which the only significant factor is the return

[9] See Andersen, Bollerslev, Diebold and Labys (2001).

of the Wilshire 1650 Small Cap index. We use the returns on the S&P500 index and options on the S&P500 index plus the size, momentum and value factors. Equity market neutral hedge funds are treated as LS funds.

Managed futures (MF) are characterized by the presence of momentum techniques and may therefore present a time-varying momentum premium if such a premium exists. On the other hand, the category of trend followers analyzed by Fung and Hsieh (2002) is systematically long volatility in currency, commodity and bond markets. In this case we consider a large set of factors, corresponding to that used in the analysis of global macro.

Event driven (ED) hedge funds are concerned with reacting to important events which may drive stocks, usually at the company level. One important event driven strategy is merger arbitrage (or risk arbitrage), where the investor tries to profit from the spread between the market prices of the acquiring company and the target company. If the merger is successful the investor profits from the trade, otherwise not. Mitchell and Pulvino (2001) show that this arbitrage is correlated with the level of the stock market because the merger is more likely to be successful in increasing markets. It follows that the return of event driven funds may have a time-varying premium associated with the market premium because the strategy involves elements of systematic put shortening. Fung and Hsieh (2002) find that there are several relevant factors like the stock market, the CSFB high-yield bond index, and the IFC Composite index. Agarwal and Naik (2004) find mainly stock market factors, including the return on a put strategy. We use the returns on the S&P500 index, the size, value momentum factors, the MSCI Emerging Markets index, the rate of return on the Lehman BAA bond index, call and put options on the S&P500 index.

Fixed-income arbitrage (FIA) funds seek to exploit pricing inefficiencies between related fixed-income securities while neutralizing exposure to interest rate risk. Fung and Hsieh (2002) have shown that two components describe the returns of this strategy, the first correlated to the spread between high-yield bonds and treasury returns, the second to the spread between convertible bond returns and treasury returns. We use high yield returns (from the Lehman high yield index), bond returns (Citigroup 1-3 years index), returns on call and put strategies written on the same Citigroup 1-3 bond index, returns to a butterfly strategy consisting of a portfolio that is long a one-year and a ten-year bond and short a three-year bond. The index from which the return of the butterfly strategy is computed are all from Citigroup World Government bond index for maturities 1-3 years, 3-5 years, 7-10 years. Litterman, Scheinkman and Weiss (1991) show that this return is strongly associated with volatility of the yield curve.

In the case of convertible arbitrage (CA), the risk factors are the returns on the S&P500, on call and put option strategies written on the S&P500 index, the returns to the size and value factors, the returns on the Citigroup index of government bonds and the returns on the Lehman high yield bond index.

Finally, for emerging markets (EM) the factors are the returns on the MSCI Emerging Markets index and on the S&P500 index, plus returns on option strategies written on the S&P500 index.

3 The data

The database we use has been assembled and kindly provided by Tremont Capital Management. It contains quarterly net asset flows into the following categories of hedge funds: convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF). Flows are computed by Tremont Capital Management as the change in assets under management net of the return effect, i.e. $f_{it} = A_{it} - A_{it-1}(1 + r_{it})$. In terms of total assets as of December 2005, the various styles are so represented in the data set: LSE 32%, ED 17%, GM 11%, FIA 7%, EM 4%, EMN 7%, CA 8%, MF 5%, DSB 1%. The database also contains quarterly net returns for the same categories. The number and importance of the hedge funds monitored by Tremont Capital Management are very large. The value of total assets reported at the end of 2005, see Tremont (2006), is equal to $813 billions, more than 50% of the total assets under management estimated for the hedge funds industry.

The returns to the option-based strategies are computed from prices retrieved from the Black- Scholes model. At the beginning of each quarter, calls and puts, both at-the-money and out-of-the-money, are evaluated by means of a Black-Scholes model fed by a volatility computed from the realized volatility of the previous quarter. The realized volatility is estimated by means of the daily data of the underlying. This approach does not assume the validity of a specific econometric model, like GARCH, and has been proposed and justified in various papers.[10]

The options have an initial life of 4 months when bought, and are sold at the end of the quarter, when their remaining life is equal to one month. Following Agarwal and Naik (2004), at-the-money options are characterized by a value of the underlying equal to the present value of the strike price, while the out-of-the-money call (put) options are characterized by a ratio of 0.99 (1.01). We extend the approach of Agarwal and Naik (2004) by computing returns of option strategies on several underlying markets, while Agarwal and Naik (2004) only consider the stock market. In particular, we consider the returns to option strategies on the bond market (where the underlying is the Citigroup weighted Government bond index[11]), the commodity market (where the underlying is the Goldman Sachs Commodity Index, GSCI), and the currency market (where the underlying is the DM/US$ exchange rate). Therefore, our model is also an extension of the seven-factor model of Fung and Hsieh (2004), which only includes options on bonds, commodities and currencies.

[10] See for instance Andersen, Bollerslev, Diebold and Labys (2001).

[11] The Datastream code for this latter variable is CGBI WGBI US ALL MATS - TOT RETURN IND.

4 Empirical results

In Table 1 we report some summary statistics for the performance of the funds and the (relative) flows. As shown by the Normality tests reported in Table 1, the assumption of Gaussian state space model seems to be appropriate for all the funds according to the Kolmogorov-Smirnov test, with the few rejections detected by the Bera-Jarque test being possibly due to serial correlation.

The quarterly average performance of the various categories over the period 1994:1-2005:4 is generally positive, apart from DSB. When positive, the average performance ranges between 1.5% (FIA) and 3.3% (GM). Yet, the dispersion of the return distribution is large, with standard deviations in the range 1.8%-10.4%. As expected, particularly high is the volatility of the directional funds, while the volatility of non-directional strategies is much lower. Of interest is also the minimal and maximal quarterly performance of the funds, the former ranging between -30.4% (EM) and -2.9% (EMN), and the latter between 4.8% (FIA) and 28% (EM). The relative flows are closer to normality. Their means over the sample are all positive, except for one case, but very different. Hedge funds belonging to EMN have a mean percentage increase of 6.1% a quarter, while funds belonging to EM have a 3% growth. Also the volatility is very different, with funds belonging to LSE showing a minimum volatility (3.4%).

The estimates of the econometric model are reported in Table 2. Robust standard errors have been computed using Monte Carlo simulation.[12] There is no evidence of serious misspecification, even though there is rejection of normality for the flow equation for EM, EMN, FIA, GM, LSE, and MF, and for the return equation for DSB and FIA. Moreover, apart from the flow equations of EM and FIA, there is no evidence of ARCH effects. This is compatible with our use of quarterly data, a frequency for which very often one does not find evidence of correlated volatility shocks even for standard markets like stocks, bonds and currencies. The estimated transition matrices also signal that the latent VAR(1) structure is appropriate for the various series. Most of the estimated coefficients are in fact statistically significant, pointing to bidirectional linkages between returns and flows.

[12] Monte Carlo simulation has been performed following Prichard and Theiler (1994). The approach is semiparametric and amounts to the generation of simulated data, which preserve the same mean, variance, covariance, correlation, autocorrelation and cross-correlation properties of the actual data, through randomization of the phase of the Fourier Transform (FT) of the series. In practice the FT of each couple of series is computed, and a random number uniformly chosen within the interval $[0,2\pi)$ is added to the phase differences for the related series at each frequency. In order to preserve the cross correlations, the same random number must be added to the phase of the related series. Then, the time domain version of the simulated data are obtained by means of inverse FT. The advantage of the procedure, relative to the standard parametric simulation, is not requiring the actual specification of the parametric model from which the data can be simulated. This is particularly important in the current framework, since in the light of the unobserved alphas, the data generating mechanism can not be accurately specified. A detailed description of the procedure can be found in Prichard and Theiler (1994). For comparison, jack-knife standard errors have also been computed. Since the two methods lead to the same results in terms of the statistical significance of the estimated parameters, only Monte Carlo standard errors have been reported in the tables. A full set of results is available upon request to the authors.

In view of the analysis and the results of Getmanski, Lo and Makarov (2003), it is important to notice that in none of the cases there is evidence of autocorrelation in the residuals. Getmanski, Lo and Makarov (2003) discuss several reasons why one might expect autocorrelation in hedge fund returns. Among these, of particular importance are the fee structure of hedge funds and the presence of illiquid securities in their portfolios. In the words of Getmanski, Lo and Makarov (2003), the fee structure, based on the combination of large incentive fees and the high-water mark mechanism, "can induce serial correlation in net-of-fee returns because of the path dependence inherent in the definition of the high-water mark". On the other hand, the presence of illiquid securities is usually associated with various return smoothing devices (like linear extrapolation of prices for thinly traded securities and sometimes performance-smoothing behavior), which cause autocorrelation in returns. Getmanski, Lo and Makarov propose an MA(3) structure to allow for such correlation or, alternatively and less efficiently, the inclusion of lagged returns in the performance evaluation equation. Our finding of no autocorrelation in quarterly returns suggest that none of these effects is relevant at the quarterly horizon. This is completely coherent with the findings of Getmanski, Lo and Makarov (2003) who find an MA(3) structure working with monthly returns. Liquidity and fee effects are therefore important within the quarter but are not so large to influence quarterly returns. This implies that our results on time-varying alphas, to be described next, cannot be explained by neglected liquidity and fee effects.[13]

In addition, alphas, estimated as the first unobservable variable in the model, are in general positively serially correlated, as shown by the estimated values of the parameter θ_3. Alphas are not significantly autocorrelated for LSE, and negatively correlated for DSB, FIA and GM . Flows are positively serially correlated in all of the cases (θ_6). The impact of the lagged flow component on the alphas (θ_4) is negative only in four out of nine cases (CA, ED, FIA, LSE), positive in four cases (DSB, EMN, GM, MF) and not significant in one case (EM). It is noteworthy that the impact of flows on excess returns is negative for some of the most well-known non-directional strategies, i.e. convertible arbitrage, event driven and fixed income arbitrage, for which the excess capacity hypothesis is more plausible. The impulse response function analysis plotted in Figure 5 and discussed in the final part of this section gives an indication of the dynamics of alphas following relative flow shocks for many future periods. The positive dependence of flows on lagged excess returns is significant in all of

the cases. Investors therefore choose hedge funds by correctly looking at past excess returns.

[13] Moreover, in order to corroborate our specification, according to which relative inflows depend on past returns only, we have also assessed the relevance of the square of lagged returns for future returns. Some literature, described in the second section, has found quadratic terms to be relevant to explain relative inflows into individual hedge funds. It would therefore be conceivable to find a convex relation between past returns and flows also at the aggregate level. However, the quadratic term is relevant for none of our nine hedge fund categories at the 5% significance level. This reinforces our choice of considering a simple linear relation between returns and inflows.

From the estimated covariance term in the variance-covariance matrix (θ_8) for the measurement equation residuals it is possible to conclude that contemporaneous linkages also characterize flows and returns. The contemporaneous impact of flows on returns is positive in four out of nine cases (EM, EMN, GM, MF), negative in two cases (DSB, LSE), and not statistically significant in the remaining three cases (FIA, ED, CA). The contemporaneous relation between flows and returns is therefore weaker than the lead-lag effects previously documented. This is not surprising given the long time lags associated between decisions to invest in hedge funds and actual investment.

Concerning the statistical significance (10% level) of the risk factors, from Table 2 (Panels C and D) it is possible to note that the risk factors in general tend to be statistically significant. The exceptions are the size factor for CA, the emerging markets factor for DSB, the put option on the S&P for DSB, the momentum factor for EMN and MF, the DM/US$ exchange rate and the call option on the DM/US$ exchange rate for GM, and the call options on bonds for MF.

We have also tested for the time variability of the sensitivities to the risk factors by means of a likelihood-ratio test, which allows for a direct comparison of time-varying parameter and constant parameter models. The estimated time-varying parameter model allows for random walk dynamics in the factors parameters. Although it may be argued that a stationary specification for the transition dynamics may be more appropriate, we had to resort to the non stationary representation for lack of degrees of freedom[14]. The results of the test favor the constant parameter model, since the p-value of the test (computed as in Davies, 1987) in none of the cases points to rejection of the null at the 1% significance level, albeit for EM and LSE the null of stability is very close to rejection.[15]

Figure 1 reports the estimated smoothed alphas for the 9 hedge fund categories, obtained from the first element of the vector γ_t^*. The picture compares the estimates of the alphas obtained from both the fixed and the time-varying factor sensitivity coefficients. There are two remarkable features. Firstly, the alphas may sometimes be negative. This is not inconsistent with the theory and with the empirical results reported by Fung et al. (2005). In various quarters the overall shocks which have hit financial markets have not been properly absorbed by the strategies of hedge funds, producing negative ex post excess returns. Most styles have suffered during the Summer and Autumn of 1998, particularly in the case of EM, ED, FIA, GM, LSE and MF. Many style have also suffered in 1994, i.e. CA, EM, ED FIA, GM, LSE, and MF. Some styles

[14]For instance, for the case of MF and GM we would otherwise have had more parameteres than observations.

[15]In order to control for the non standard asymptotic distribution of the LR test when the parameters under testing are present only under the alternative, as in the case at hand, an upper bound for the significance of the test has been computed following Davies (1987). The corrected p-values of the LR test are as follows: 1.000 for CA, DSB, EMN, ED, GM, MF ; 0.16 for FIA; 0.01 for EM and LSE. For reason of space we do not include detailed results concerning the stability tests and the estimated time-varying parameter models, which are however available upon request from the authors.

show some specific negative shock, i.e. CA in 2004, DSB in 2000-2003, EM and FIA in 1999, GM in 1999 and 2000, LSE in 2001 and 2002.

The second remarkable feature of our results is the absence of any trend in most of the categories. We do not find any evidence of a slow down in profit opportunities for most of the hedge funds categories. Rather, we find clear cycles of profitability. The alpha of convertible arbitrage hedge funds declined for most of the 2000-2004 period but has started to recover in 2005. For dedicated short bias hedge funds the alpha declined for most of the sample period but has started to increase from 2003. The contrary happens to emerging market hedge funds which reached their peak in profitability around 2003 to decline in the second part of the sample. Equity market neutral hedge funds are perhaps the only category showing a prolonged period of declining alpha after the steep rise of the mid-1990s, albeit a recovery in profitability can be noted since 2005. Event driven hedge funds show very short cycles in alpha. The decline which started in 2003 is not new: similar episodes took place in mid-1990s and around 2000. Fixed income arbitrage also shows a decline (in the context of overall stability), but a similar movement already took place in the second half of the 1990s. Global macro hedge funds show a recent decline following a strong increase between 2000 and 2003. Long short equity funds produce a rather constant alpha, while managed futures show ample cycles of changing alpha.

The broad stability of the excess returns is not inconsistent with the negative impact of flows on excess returns uncovered for CA, ED, FIA and LSE. In fact, one could expect that a long period of positive relative flows be associated with a long period of declining alphas. However, the evidence is not consistent with this view. Positive relative flows have gone together with cycling alphas as well as a negative short run effect of flows on alphas. This evidence can be reconciled with our econometric estimates if flows determine a small portion of the variability of excess returns. This is indeed the case. We have computed the partial coefficient of determination from a regression of the expected excess returns on the expected lagged flows and expected excess returns and have found that for three out of four cases where there is a negative impact of flows on returns the partial R^2 attributable to past flows are small, i.e. 23% for convertible arbitrage, 0.1% for fixed income arbitrage and 22% for long short equity. Only in the case of event driven the figure is as large as 73%.

Therefore, only in the case of Event Driven hedge funds there is strong impact of the variability of flows on the variability of excess returns, coherent with the econometric results. Figure 2 shows that the recent increase in flows has been parallel to a decline in excess returns. An independent verification of this relation between relative flows and alphas for Event Driven comes from an analysis of the relation between the time series of estimated alphas and the total yearly value of mergers and arbitrage. FactSet-Mergerstat provides the total annual value of worldwide mergers and arbitrage. Such a value can be thought of as the main "raw material" for the supply of arbitrage opportunities to hedge funds in the Event Driven category. The ratio between the assets under management of Event Driven hedge funds and the total value of mergers and acquisitions may be a better proxy for competition for alpha among managers.

This ratio was equal to 3.2% in 1995 and to 13.8% in 2005, a dramatic proof of the interest shown by hedge funds in this investment style. The correlation between the lagged value of such a ratio and the annual average alpha estimated from our econometric model is equal to -27%; the correlation between the first difference of the ratio and the annual average alpha is -32%. Both measures are coherent with our econometric model.

In Figures 3-6 we have plotted the impulse response functions of returns and flows to orthogonal unitary return and flow shocks, with 95% significance bands. As is shown in Figures 3 and 4 the largest effects of the own shocks are contemporaneous. Over time the effects of shocks then tend to disappear monotonically, also coherent with the stationarity of the return and flow series. Apart from MF and EMN, the impact of shocks is never statistically significant after ten quarters. In Figures 5 and 6 the effects of a flow shock on returns and of a return shock on flows are plotted. The effects of a flow shock on returns tend to quickly disappear over time, showing however a non monotonic pattern. In all of the cases the peak is reached between two and four quarters. The effects of shocks tend to disappear within 10 quarters, although they the can last longer in some cases (CA, EMN, MF, ED). Coherent with the estimated state space models, the effects of a flow shock is negative in only four out of nine cases (CA, ED, FIA, LSE). Moreover, a return shock has in general a positive transitory effect on flows growth, albeit a negative impact is found for EMN.

Finally, as shown in Table 3, returns tend to be largely affected by the own shock, while both the returns and flows shocks are important to explain fluctuations in flows at all the horizons (1 quarter - 5 years). In fact, while the returns shock tends to explain between 77% and 100% of returns fluctuations over all the horizons, the percentage of flows variance explained by the flows shock ranges between 30% and 80%, suggesting that innovations in returns are more important to determine fluctuations in flows than the other way around. Moreover, the importance of returns innovations for flows fluctuations seems to increase with the forecast horizon, with fluctuations being in generally explained by both returns and flows innovations already starting from the one year horizon.

5 Conclusions

In the paper we have studied the linkage between flows and excess returns for nine categories of hedge funds over the period 1994:1-2005:4. The key question we tried to answer was whether we are in a phase of excess capacity and declining alphas. To this aim we introduced an unobserved components model, with exogenous risk factors, which allows to model the interaction between flows and returns at different horizons. Overall, our findings can be summed up as follows. Firstly, there is evidence of shock persistence in flows and returns, i.e. both processes are positively serially correlated. Secondly, flows tend to depend positively on lagged excess returns, while excess returns tend to depend negatively on lagged flows mainly for the arbitrage oriented strategies. Thirdly, the effects of returns and flows shocks peak between two and four quarters and are in general reabsorbed within ten quarters. Fourthly, returns shocks are the most important determinant of returns fluctuations at all the horizons, noticeably contributing to flows fluctuations at all the horizons as well. Finally and most importantly, our results are not consistent with the view of a decline in the excess returns produced by the hedge funds industry: the impact of flows is not so strong to obscure the relevance of other factors which maintain open opportunities for hedge funds to perform profitable strategies. Hence, our results do not support the view according to which an excess supply of arbitrage capital exhausts the set of available opportunities. The wide variety of real world investors, including noise traders and investors with heterogenous time horizons and objectives, seems to provide plenty of opportunities for hedge funds managers to exploit: the limits of arbitrage do not seem to have been met yet. Of course we have obtained our results on the basis of an admittedly short sample. Future analyses might use more observations and change some of the results. Yet, we are confident that the econometric methodologies employed deliver reliable results, which are also intuitive and coherent with sound economics.

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Table 1, Panel A: Summary statistics, returns

	CA	DSB	EM	EMN	ED	FIA	GM	LSE	MF
$mean$	2.100	−0.147	2.357	2.384	2.762	1.544	3.343	2.954	1.727
$std.dev$	3.217	9.674	10.387	1.774	3.545	2.052	5.552	5.578	5.934
sk	−0.540	0.039	−0.432	−0.216	−2.532	−1.040	−0.415	1.322	0.305
ek	0.377	−0.586	1.821	0.230	9.912	0.917	0.604	3.940	−0.063
N_{BJ}	0.270	0.705	0.017	0.787	0.000	0.006	0.197	0.000	0.686
N_{KS}	0.517	0.458	0.707	0.571	0.883	0.677	0.753	0.670	0.467
min	−7.350	−21.56	−30.35	−2.930	−14.69	−4.720	−10.290	−7.350	−10.77
max	9.420	20.77	28.29	5.820	8.170	4.760	16.080	25.71	15.77

Table 1, Panel B: Summary statistics, relative flows

	CA	DSB	EM	EMN	ED	FIA	GM	LSE	MF
$mean$	5.704	4.752	2.997	6.112	4.158	5.239	−0.218	3.131	3.832
$std.dev$	7.638	9.102	5.824	7.977	4.079	9.005	5.416	3.409	6.152
sk	0.051	0.396	0.084	2.082	0.244	3.486	−0.585	3.148	1.092
ek	−0.557	1.325	1.134	6.411	0.094	17.78	2.209	15.23	0.820
N_{BJ}	0.726	0.092	0.269	0.000	0.782	0.000	0.002	0.000	0.004
N_{KS}	0.540	0.617	0.562	1.086	0.785	1.449*	0.646	1.222	1.012
min	−9.580	−17.59	−12.05	−4.800	−4.050	−9.560	−20.01	−2.410	−5.010
max	21.75	32.15	20.00	41.30	13.57	55.59	10.62	21.55	20.79

The table reports summary statistics for quarterly funds'performance (Panel A) and relative flows (Panel B) over the period 1994:1-2005:4. N_{BJ} and N_{KS} are the p-values of the Bera-Jarque test and the value of the Kolmogorov-Smirnov normality test (* denotes rejection at the 5% level). The following categories of hedge funds have been considered: convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF).

Table 2, Panel A: estimated parameters

	CA	DSB	EM	EMN	ED
θ_1	1.723	2.930	−0.304	2.447	1.586
	(0.183)	(0.081)	(0.132)	(0.057)	(0.068)
θ_2	5.979	4.598	2.608	3.957	3.915
	(0.692)	(0.186)	(0.572)	(0.363)	(0.159)
θ_3	0.801	−0.090	0.578	0.529	0.553
	(0.039)	(0.025)	(0.023)	(0.014)	(0.049)
θ_4	−0.070	0.128	−0.001	0.042	−0.290
	(0.012)	(0.026)	(0.013)	(0.002)	(0.058)
θ_5	1.013	0.995	1.406	3.892	0.932
	(0.180)	(0.022)	(0.247)	(0.159)	(0.077)
θ_6	0.564	0.303	0.408	0.307	0.593
	(0.031)	(0.035)	(0.014)	(0.014)	(0.054)
θ_7	3.987	0.049	33.69	1.472	2.188
	(0.530)	(0.001)	(0.596)	(0.057)	(0.211)
θ_8	−0.063	−0.973	9.111	0.773	0.332
	(0.649)	(0.045)	(0.532)	(0.087)	(0.282)
θ_9	0.002	19.55	2.464	0.405	8.378
	(0.998)	(2.908)	(0.259)	(0.139)	(1.209)
θ_{10}	1.800	29.92	3.283	0.340	1.190
	(0.553)	(0.048)	(0.457)	(0.059)	(0.231)
θ_{11}	2.711	0.105	−0.261	−1.006	−0.392
	(0.881)	(1.170)	(0.211)	(0.075)	(0.211)
θ_{12}	20.97	24.55	7.579	10.22	2.188
	(0.635)	(2.302)	(0.268)	(0.338)	(0.211)
BIC	12.919	14.899	14.241	11.829	12.027
$AR(1-4)$	0.639	0.724	0.079	0.307	0.475
	0.699	0.973	0.694	0.616	0.293
$ARCH(1)$	0.513	0.044	0.361	0.643	0.174
	0.995	0.978	0.000	0.254	0.063
N_{BJ}	0.520	0.006	0.025	0.154	0.929
	0.571	0.611	0.000	0.001	0.464

Table 2, Panel B: estimated parameters

	FIA	GM	LSE	MF
θ_1	0.503	-0.665	0.769	-0.381
	(0.141)	(0.318)	(0.042)	(0.138)
θ_2	3.890	-0.016	2.823	1.709
	(0.129)	(0.196)	(0.026)	(0.690)
θ_3	-0.108	-0.596	-0.073	0.401
	(0.046)	(0.008)	(0.052)	(0.053)
θ_4	-0.030	0.332	-0.152	0.048
	(0.008)	(0.025)	(0.024)	(0.007)
θ_5	1.541	0.655	0.359	3.660
	(0.165)	(0.042)	(0.047)	(0.289)
θ_6	0.400	0.577	0.274	0.434
	(0.030)	(0.010)	(0.023)	(0.053)
θ_7	0.000	13.06	$2E-4$	19.15
	(0.000)	(1.005)	(0.000)	(0.256)
θ_8	0.000	5.970	$-1E-4$	2.161
	(0.000)	(0.435)	(0.000)	(0.747)
θ_9	16.31	2.730	0.000	0.247
	(1.668)	(0.332)	(0.000)	(0.119)
θ_{10}	3.731	6.422	7.157	0.675
	(0.229)	(0.772)	(0.177)	(0.174)
θ_{11}	1.080	2.009	1.382	0.057
	(0.300)	(0.336)	(0.090)	(0.292)
θ_{12}	6.607	7.305	4.830	11.04
	(0.546)	(0.407)	(0.161)	(1.437)
BIC	12.170	14.184	11.621	14.656
$AR(1-4)$	0.088	0.973	0.048	0.322
	0.623	0.532	0.919	0.202
$ARCH(1)$	0.779	0.574	0.709	0.411
	0.001	0.763	0.065	0.026
N_{BJ}	0.000	0.079	0.419	0.010
	0.000	0.000	0.000	0.000

Table 2, Panel C: estimated parameters

	CA	DSB	EM	EMN	ED
γ_{em}	–	-0.011 (0.010)	0.481 (0.013)	-0.032 (0.002)	0.043 (0.006)
γ_{m}	0.047 (0.013)	-0.218 (0.012)	0.415 (0.011)	$3E-4$ (0.002)	0.111 (0.007)
γ_{s}	0.027 (0.017)	-0.658 (0.024)	0.280 (0.011)	-0.012 (0.003)	0.143 (0.012)
γ_{v}	0.092 (0.012)	0.078 (0.014)	0.130 (0.007)	-0.045 (0.003)	0.147 (0.009)
$\gamma_{S\&P}$	0.123 (0.035)	-1.085 (0.034)	0.107 (0.028)	0.015 (0.007)	0.136 (0.022)
γ_{b}	0.198 (0.039)	–	–	–	–
γ_{hy}	0.219 (0.021)	–	–	–	–
γ_{ba}	–	–	–	–	0.402 (0.039)
$\gamma_{c_{S\&P}}$	0.371 (0.138)	0.403 (0.129)	-0.479 (0.093)	0.313 (0.022)	0.145 (0.071)
$\gamma_{p_{S\&P}}$	-1.120 (0.141)	-0.231 (0.161)	-0.553 (0.104)	0.166 (0.029)	-0.980 (0.110)
$\gamma_{c_{em}}$	–	–	0.329 (0.035)	–	–
$\gamma_{p_{em}}$	–	–	-0.591 (0.048)	–	–

Table 2, Panel D: estimated parameters

	FIA	GM	LSE	MF
γ_{em}	–	−0.063 (0.012)	0.048 (0.004)	0.066 (0.005)
γ_{m}	–	0.180 (0.015)	0.372 (0.008)	0.011 (0.008)
γ_{s}	–	0.285 (0.020)	0.230 (0.007)	0.050 (0.010)
γ_{v}	–	0.200 (0.013)	0.021 (0.006)	0.049 (0.006)
$\gamma_{S\&P}$	–	−0.150 (0.032)	0.623 (0.018)	0.375 (0.017)
γ_{b}	1.166 (0.124)	3.030 (0.286)	–	1.507 (0.060)
γ_{bu}	−0.404 (0.217)	–	–	–
γ_{hy}	0.179 (0.022)	–	–	–
γ_{ba}	−0.401 (0.066)	–	–	–
γ_{c}	–	−0.390 (0.038)	–	−0.478 (0.021)
γ_{e}	–	0.022 (0.089)	–	1.681 (0.044)
$\gamma_{c_{S\&P}}$	–	0.325 (0.160)	−0.143 (0.066)	−2.404 (0.039)
$\gamma_{p_{S\&P}}$	–	−2.552 (0.204)	0.944 (0.063)	1.634 (0.050)
γ_{c_b}	−1.224 (0.125)	−2.992 (0.273)	–	−0.010 (0.052)
γ_{p_b}	1.085 (0.139)	1.501 (0.282)	–	1.249 (0.102)
γ_{c_g}	–	1.184 (0.180)	–	2.120 (0.040)
γ_{p_g}	–	−1.504 (0.171)	–	−1.331 (0.125)
γ_{c_e}	–	−0.138 (0.151)	–	−0.925 (0.047)
γ_{p_e}	–	1.302 (0.234)	–	4.568 (0.152)

The table reports the estimated parameters with jack-knife standard errors in parenthesis. The model is written as follows: $\mathbf{y}_t = \mathbf{Z}_t \boldsymbol{\gamma}_t^* + \mathbf{c} + \boldsymbol{\varepsilon}_t$, $\boldsymbol{\gamma}_t^* = \mathbf{T}\boldsymbol{\gamma}_{t-1}^* +$

$\mathbf{u}_t^*$, $\mathbf{u}_t^{*\prime} = \begin{bmatrix} \underset{(1\times 2)}{u_t'} & \underset{(1\times m)}{0} \end{bmatrix}$, $\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon)$, $\mathbf{u}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_u)$, $\mathbf{y}_t' = \begin{bmatrix} r_t & f_t \end{bmatrix}$, $\mathbf{Z}_t = \begin{bmatrix} I_2 & \mathbf{Z}_{2_t} \end{bmatrix}$, $\mathbf{Z}_{2_t} = \begin{bmatrix} r_{F,t}' \\ \mathbf{0}_{(1\times m)} \end{bmatrix}$, $\mathbf{c}' = \begin{bmatrix} \theta_1 & \theta_2 \end{bmatrix}$,

$\boldsymbol{\gamma}_t^{*\prime} = \begin{bmatrix} \alpha_{1,t} & \alpha_{2,t} & \gamma_{1,t} & \cdots & \gamma_{m,t} \end{bmatrix}$, $\mathbf{T} = \begin{bmatrix} \mathbf{T}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_m \end{bmatrix}$, $\mathbf{T}_1 = \begin{bmatrix} \theta_3 & \theta_4 \\ \theta_5 & \theta_6 \end{bmatrix}$, $\boldsymbol{\Sigma}_\varepsilon = \begin{bmatrix} \theta_7 & \theta_8 \\ \theta_8 & \theta_9 \end{bmatrix}$, $\boldsymbol{\Sigma}_u = \begin{bmatrix} \theta_{10} & \theta_{11} \\ \theta_{11} & \theta_{12} \end{bmatrix}$. The risk factors are as follows: MSCI Emerging Markets index (em), Carhart Momentum (m), Fama-French SMB (s), Fama-French HML (v), S&P500 index ($S\&P$), Lehman high-yield bond index (hy), Lehman BAA index (baa), Citigroup weighted 1-3-year Government bond index (b), Goldman-Sachs commodity price index (c), DM/US$ exchange rate (e), butterfly strategy computed by means of Citigroup World Government bond indexes for maturities 1-3 years, 3-5 years, and 7-10 years (bu), call (c_i) and put (p_i) options on the S&P500 ($i = S\&P$), Citigroup weighted 1-3-year Government bond index ($i = b$), Goldman-Sachs commodity price index ($i = c$), DM/US$ exchange rate ($i = e$), MSCI Emerging Markets index ($i = em$). The sample period is 1994:1 through 2005:4. The following categories of hedge funds have been considered: convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF). BIC is the Bayes-Schwartz information criterion, AR(1-4) is the Lagrange Multiplier test for serial correlation up to the 2nd order, ARCH(1) is the Lagrange Multiplier test for ARCH effects up to the 1st order, N_{BJ} is the Bera-Jarque normality test. For the diagnostics the first row refers to the return equation, while the second row to the flow equation.

Table 3, Panel A: forecast error variance decomposition, returns

	1 quarter		1 year		3 years		5 years	
	u_1	u_2	u_1	u_2	u_1	u_2	u_1	u_2
CA	0.970	0.030	0.889	0.111	0.844	0.156	0.844	0.156
DSB	0.986	0.014	0.986	0.014	0.986	0.014	0.986	0.014
EM	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
EMN	0.969	0.031	0.944	0.056	0.927	0.073	0.927	0.073
ED	0.898	0.102	0.766	0.234	0.768	0.232	0.768	0.232
FIA	0.999	0.001	0.998	0.002	0.998	0.002	0.998	0.002
GM	0.916	0.084	0.916	0.084	0.917	0.083	0.917	0.083
LSE	0.986	0.014	0.985	0.015	0.985	0.015	0.985	0.015
MF	0.969	0.031	0.944	0.056	0.927	0.073	0.926	0.074

Table 3, Panel B: forecast error variance decomposition, flows

	1 quarter		1 year		3 years		5 years	
	u_1	u_2	u_1	u_2	u_1	u_2	u_1	u_2
CA	0.317	0.683	0.455	0.545	0.480	0.520	0.481	0.519
DSB	0.517	0.483	0.526	0.474	0.526	0.474	0.526	0.474
EM	0.670	0.330	0.670	0.330	0.670	0.330	0.670	0.330
EMN	0.431	0.569	0.523	0.477	0.575	0.425	0.577	0.423
ED	0.199	0.801	0.455	0.545	0.454	0.546	0.454	0.546
FIA	0.591	0.498	0.609	0.301	0.609	0.301	0.609	0.301
GM	0.365	0.635	0.365	0.635	0.366	0.634	0.366	0.634
LSE	0.232	0.768	0.237	0.763	0.237	0.763	0.237	0.763
MF	0.413	0.587	0.564	0.436	0.628	0.372	0.630	0.370

The table reports the forecast error variance decomposition for quarterly funds'performance (Panel A) and relative flows (Panel B). The following categories of hedge funds have been considered: convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF).

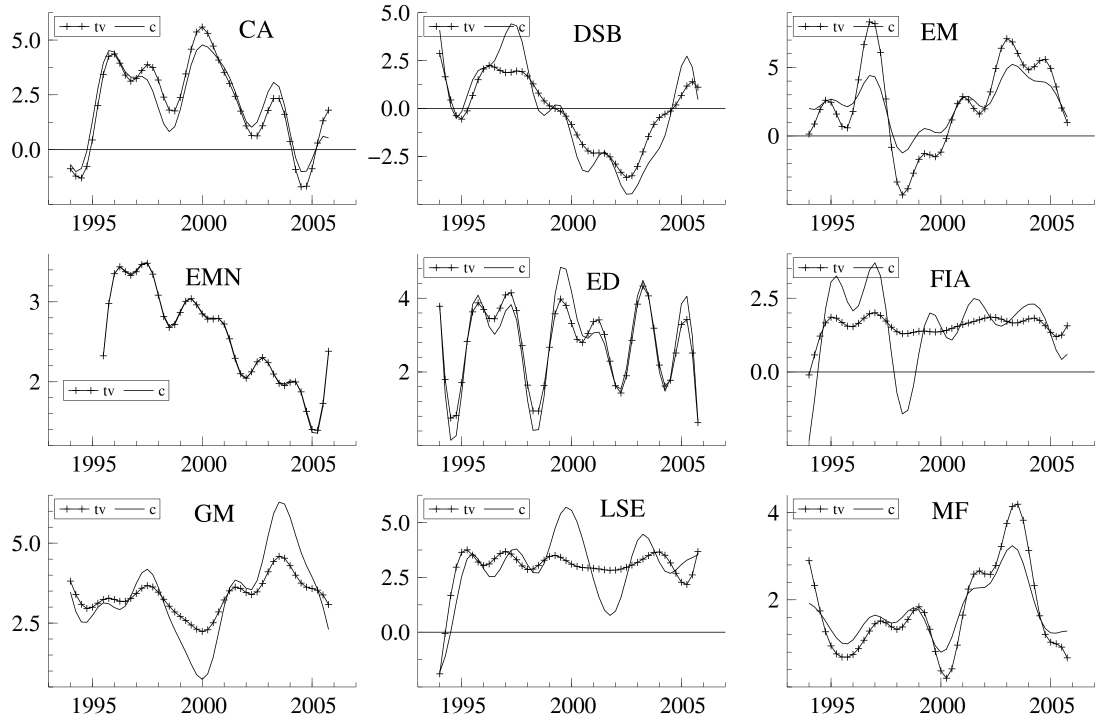

Figure 1: Smoothed unobserved component for returns from the constant parameter model (c) and the time-varying parameter model (tv) (convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF)).

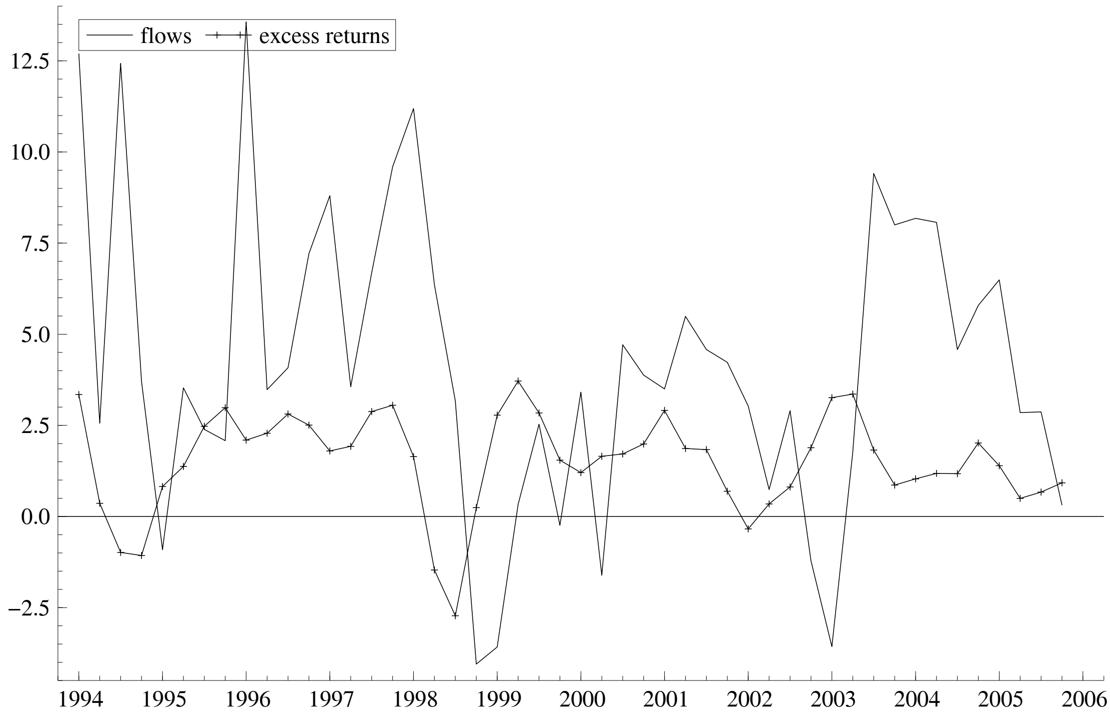

Figure 2: Flows and excess returns for ED category.

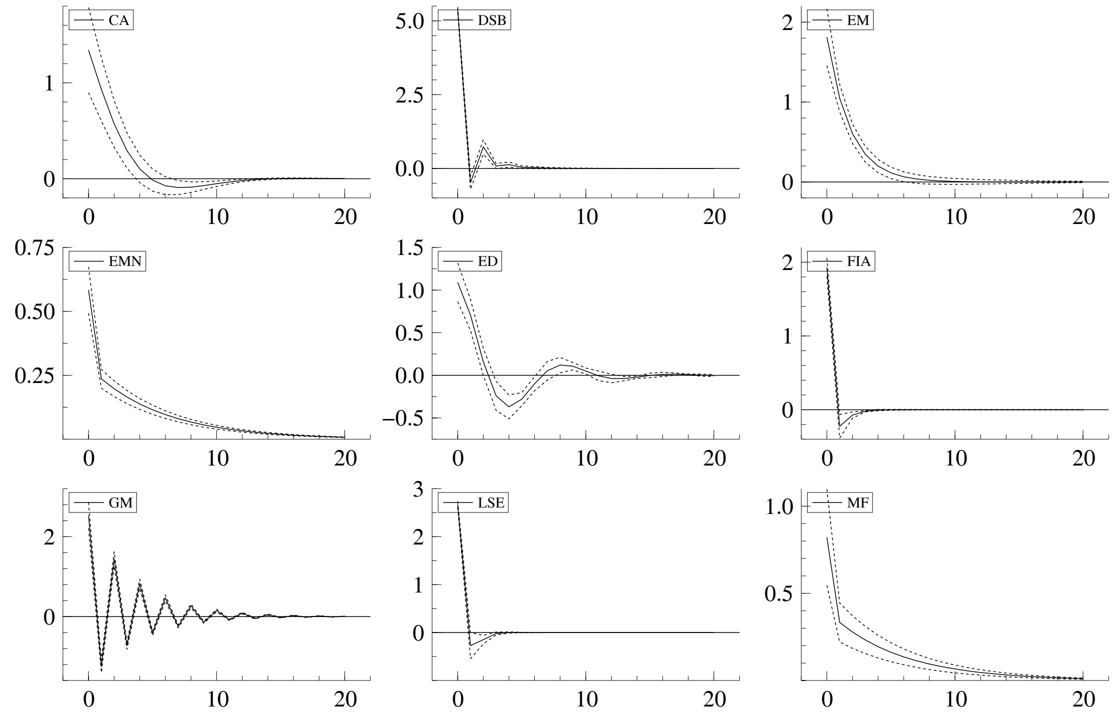

Figure 3: impulse responses of returns to returns' shock (convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF)).

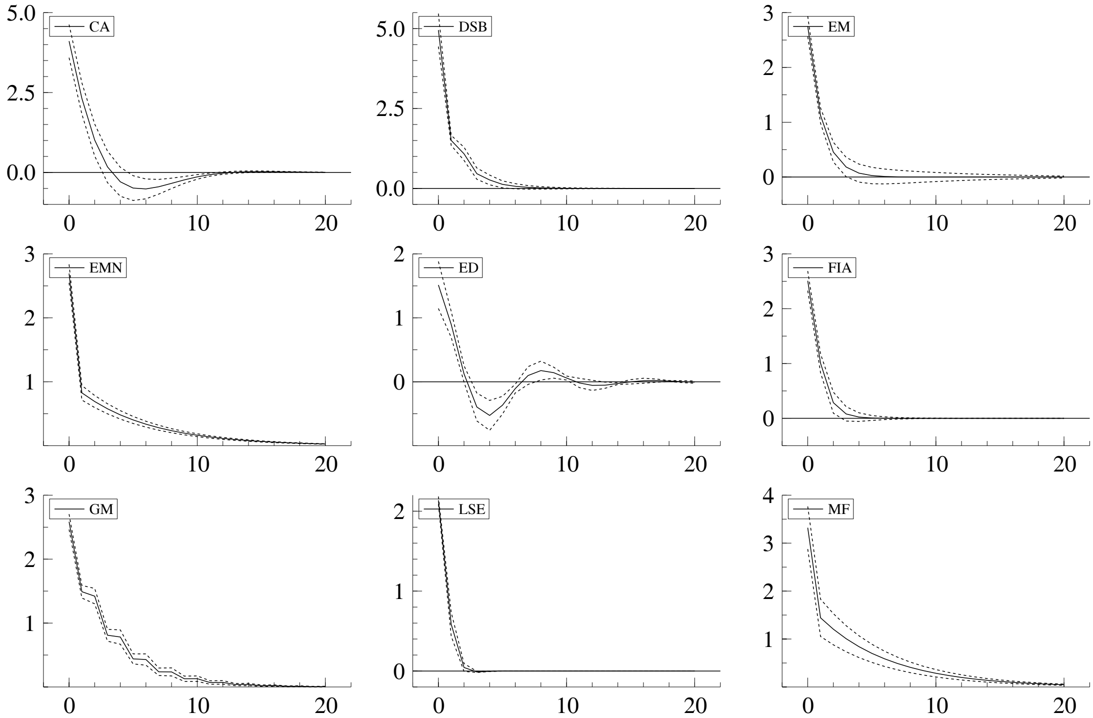

Figure 4: impulse responses of flows to flows' shock (convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF)).

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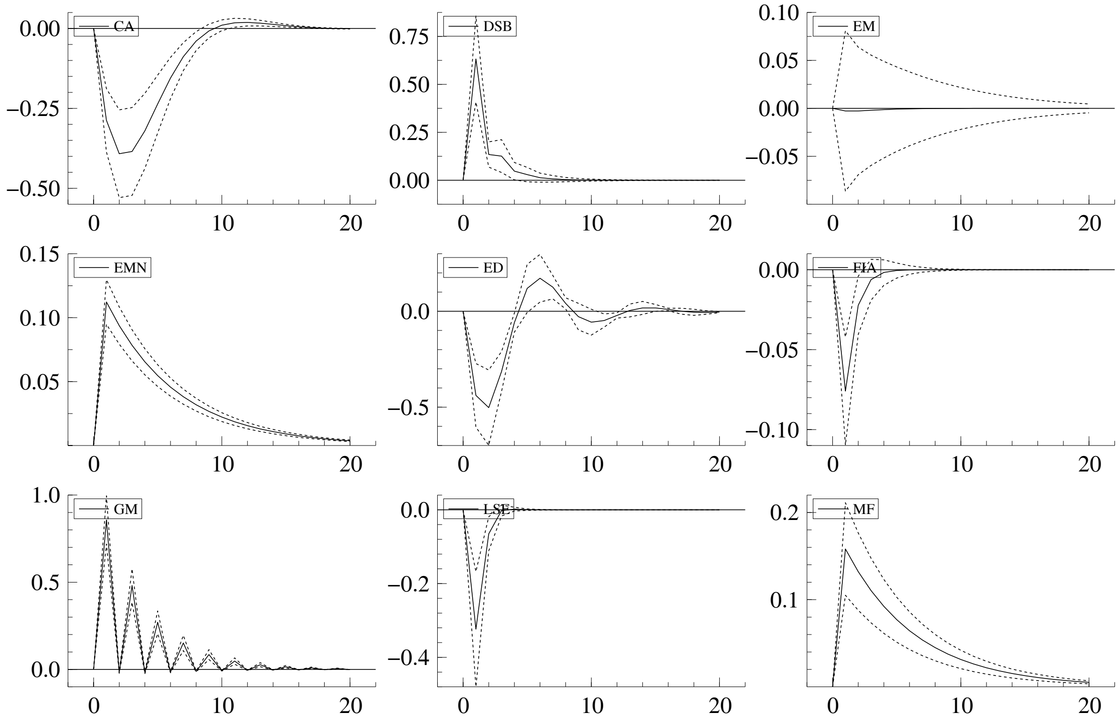

Figure 5: impulse responses of returns to flows' shock (convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF)).

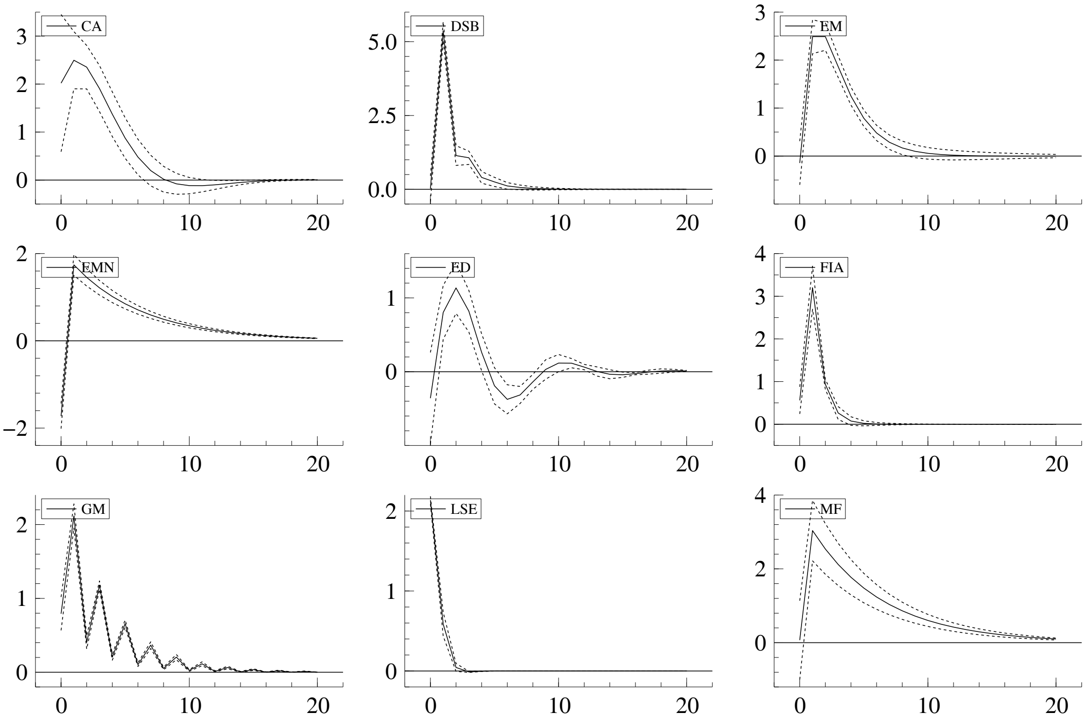

Figure 6: impulse responses of flows to returns' shock (convertible arbitrage (CA), dedicated short bias (DSB), emerging markets (EM), equity market neutral (EMN), event driven (ED), fixed income arbitrage (FIA), global macro (GM), long/short equity (LSE), managed futures (MF)).