The Performance of European Equity Mutual Funds*

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Abstract

Despite significant growth in the European mutual fund industry and the integration of European financial markets during recent years, the performance of European equity mutual funds is largely an unexplored area of research. This paper shows that macroeconomic state variables can be used to identify a significant time-varying alpha component among a large sample of funds with a Pan-European, European country, or European sector focus. Specifically, the default yield spread, term spread, dividend yield, and short interest rate, as well as macroeconomic variables tracking consumer price inflation and economic sentiment prove valuable in identifying, ex-ante, funds with superior performance. Most of the alpha that these state variables generate comes from their ability to identify superior Pan-European funds, as well as to generate returns from country selection.

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1 Introduction

The European-domiciled mutual fund industry has grown very significantly over the last several years. Measured by total net assets, European funds grew from a little over \$3 trillion in 2000 to nearly \$9 trillion in 2007. By the end of 2007, this amounted to nearly three-quarters of the size of the U.S. mutual fund industry, which, over the same period, grew from \$7 trillion in assets to \$12 trillion. Further, there were 35,000 European-domiciled funds by the end of 2007 (Investment Company Institute, 2008).

Despite the economic significance of the European mutual fund industry, European-domiciled funds remain very much an under-researched area. Some studies have been conducted at the individual country level−e.g., for funds that invest in the UK, Germany, Italy or France. However, there is no comprehensive study that has simultaneously examined the performance of stock funds that invest across Europe (Pan-European funds), funds that invest in specific countries or regions (e.g., Germany or Scandinavia), or funds that invest in specific sectors (e.g., telecommunications) over a long time period that includes the integration of European financial markets of the past ten years.[1] This is an important omission, since investors in any European state find it increasingly easy and inexpensive to invest in mutual funds incorporated in other countries as a result of this market integration and the adoption (by many developed European countries) of the common Euro currency. In turn, investors should now compare the performance of mutual funds investing in any European nation.

Accordingly, this paper conducts a study of monthly returns for mutual funds having a (developed-market) European equity focus over the 1988 to 2008 period. Building on recent papers such as Avramov and Wermers (2006) and Moskowitz (2000), we allow for the possibility of time-varying mutual fund alphas and betas. Following Christopherson, et al. (1998) and Ferson and Schadt (1996), we model such time-variation using a publicly available set of conditioning state variables. Thus, one of the major objectives of our study is to explore which, if any, macroeconomic variables are helpful in identifying funds with superior future skills. The vast majority of studies that have considered this question have focused on funds with a U.S. equity objective, but it is clearly important to see if these results generalize to other markets, in part to corroborate the U.S. results, and in

[1] We note, however, that Otten and Bams (2002) examine 506 open-end equity funds in five major European countries prior to 1998.

part to see if there are differences in how the macroeconomic environment affects the performance of funds in Europe.

We first construct European factors to represent the broad stock market within each developed country, and Pan-European size, book-to-market, and momentum risk factors for stocks. Then, we document the average performance of European mutual funds over our time period using these benchmarks. Our findings are similar to those of many studies of U.S. mutual funds (e.g., Carhart, 1997 and Wermers, 2000). Specifically, the average fund exhibits a one-factor alpha of -0.48%/year, and a four-factor alpha of -1.2%/year–this finding indicates that our benchmarks successfully control for common factors in European equity mutual fund returns.

Our main contribution is to determine whether a European investor can actively select Pan-European, regional, and sector funds with persistent performance, relative to our European risk factors. Given the modest costs of trading most open-ended mutual funds, if successful, such a strategy would be attractive to many investors in European funds. By including funds whose investment objectives focus on a particular country or sector, as well as funds that invest in the entire European region, we allow for our strategies to generate abnormal returns by timing countries or sectors, or by identifying funds with superior security selection within each of these categories. Thus, we can determine whether specialist country or sector funds outperform, during certain phases of the business cycle, generalist funds that invest more broadly across countries and sectors in Europe. Further, our models determine which macroeconomic factors seem to be most useful in identifying superior European mutual funds.

Our analysis considers over 4,000 European-domiciled equity mutual funds during the period from 1988 to 2008.[2] To our knowledge, we cover the longest time period and the broadest cross-section of funds ever studied in Europe. We study the strategies of types of investors in mutual funds. These four types have differing views regarding the ability of mutual funds to generate abnormal returns, as well as whether alphas and betas of funds are time-varying. The investment performance of these four types are compared with the performance of a dogmatic investor who does not believe that funds can generate abnormal performance (alpha), relative to the CAPM.

Our main empirical findings are as follows. First, we find that a range of financial and macroeconomic variables prove helpful in selecting funds that are capable of generating future alphas.

[2] Our current sample includes a number of funds that invest in Europe, but are not Europe-domiciled. However, the vast majority of funds in our sample are domiciled in developed European countries.

In particular, we find evidence that a number of investment strategies generate alphas in excess of 7%/year (after fund-level trading costs, but before other fund expenses), when measured with a single-factor model or, alternatively, with a four-factor model that controls for fund exposures to size, value, and momentum (Carhart (1997)). These results are generated by an out-of-sample exercise in which investors use the first five years of our sample (1988-1992) to obtain initial estimates, then revise their beliefs recursively as new data arrive, using Bayesian updating rules. Moreover, the results are robust to the choice of sample period, and hold in separate out-of-sample portfolio selection experiments conducted on the periods 1993-2000 and 2001-2008.

We also find that the ability to identify superior performing funds critically depends on allowing for a time-varying alpha component. Our baseline results assume a standard set of state variables previously identified on U.S. data (Avramov and Wermers (2006))–the dividend yield, default spread, short-term interest rate and term spread. These variables also prove valuable in selecting funds with superior performance in Europe. However, we also find that additional variables, such as a measure of consumer confidence, the prevailing inflation rate, or a proxy for market volatility (VDAX), are able to identify funds with superior performance.[3]

To better understand the sources of outperformance, we undertake an attribution analysis that decomposes investor returns into returns from three selection and one market timing source, namely selection of Pan-European funds, country funds, and sector funds, and timing of country weights. This analysis suggests that the superior returns associated with the active investment strategies mainly arise from the selection of superior country funds and, to a lesser degree, from the selection of superior Pan-European funds. In contrast, returns from selection of sector funds and timing of country weights does not substantially enhance returns.

In addition to identifying funds with superior performance, our model proves capable of identifying funds with inferior performance. Thus, a strategy that only allows short positions is capable of generating systematic negative alphas, and a self-financing long-short strategy adds further to the long-only strategy, while controlling the exposure to the systematic risk factors. This finding indicates that mimicking the portfolio holdings of funds, where securities held by inferior funds are shorted, may outperform our basic long-only fund-level strategy (depending on the impact of the delay in public availability of fund holdings information).

[3] This finding of a different set of important macroeconomic variables that forecast mutual fund performance in Europe, relative to the U.S., presents a new and intriguing question for future research.

We adopt a Bayesian approach in our paper, so the choice of investor priors is an issue. We find that investors do best when they allow the data to completely determine the parameters that they use in their portfolio analysis. Further, by evaluating the impact of different beliefs for different investor-types, we show that the macro-economic contribution to fund performance predictability plays a large role in allowing our investors to generate significant outperformance.

Our paper proceeds as follows. Section 2 reviews our data, and describes the economic state variables used in the study. Section 3 reviews the investor types considered in our study, and provides details on the methodology. Section 4 presents the main empirical results, while Section 5 provides a robustness analysis. Finally, Section 6 concludes. Details on data sources are provided in an appendix.

2 Data

2.1 Mutual fund data

Our data was obtained from Lipper and comprises monthly returns on European equity mutual funds over the period from June 1988 to February 2008, a total of 237 observations. It includes funds that were alive at the end of the sample as well as dead funds. We include actively managed funds as well as specialist funds with a more passive investment objective (e.g., ishares).

Table 1 lists the number of funds over time by investment objective. The number of funds in our sample rose sharply from just over 200 in 1988 to more than 4,400 at the end of the sample, doubling or more than doubling during the first three five-year periods. A similar, if less pronounced, pattern has been observed in the U.S. fund industry.

Funds with a country or regional investment objective, shown in Panel B, dominate our sample. In particular, there were 2,900 such funds in 2008. By far the largest group of funds in this category is Pan-European funds which are allowed to invest across all the developed European stock markets (get definition). This category rose faster than the other types of funds to comprise more than half of the total number of funds in our sample by 2008. Other important country-investment funds include the UK (631 funds in 2008), Scandinavia (316), and France (276).

Turning to the sector funds shown in Panel C, there are fewer of these, only 300 by 2008. Among these, only Real Estate, Banks and Financial, Information Technology, and Cyclical Goods and Services have more than 20 funds in 2008. Interestingly, with the exception of real estate funds, there were very few funds that specialized in particular European sectors prior to 2003.

We should emphasize that the division between sector funds and country funds is less clear-cut than may seem the case. The reason is that some of the smaller European stock markets are dominated by a few firms and one or two sectors (e.g., Nokia in the Finnish stock market).

We do not have data on many of the individual funds' expenses and fees, particularly during the early part of the sample. However, for the last decade or so, we do have this data on a sizeable fraction of the funds. In Panel D of Table 1, we show that the average expenses and fees have been quite stable over the period from 1998-2008 and ranged between 1.4% and 1.6% per annum.

2.2 State variables and risk factors

Following the large literature on mutual fund performance, we control for risk exposure in measuring the funds' ability to outperform. In particular, we adopt the four factor approach advocated by Carhart (1997). The four factors are a market risk factor, measured here by the MSCI Europe total return index; a size factor (small minus big, or SML) which captures the difference between returns on the Europe STOXX Small Cap Return Index and the Europe STOXX Large Cap Return Index; a value factor (high minus low, or HML) computed as the difference between European value and European growth portfolios. Finally, a momentum factor constructed from the return difference between the top and bottom six sectors from the Dow Jones STOXX 600 Super Sector Indices is included. For comparison, we also report results from a more conventional single-factor approach that only includes the market factor.

Recent studies suggest that funds' ability to generate alpha varies over time, in a way that can be tracked by means of macroeconomic or financial state variables. Moreover, fund exposure to risk factors may also be state- and time-dependent. To capture such effects we consider the following state variables. First, we use the slope of the term structure of interest rates, measured as the difference between the yield of a 10-year Euro area government bond and the 1-month Euribor yield. Second, we consider the dividend yield for a portfolio of European stocks. Third, we use the default spread on European bonds, calculated as the difference between the yields of corporate bonds and yields on government debt. Fourth, we consider the level of the short risk-free rate, measured as the 1-month Euribor. These variables have been widely used in the literature on time-varying investment opportunities (e.g. Fama and French (1993)) and played a key role in the study on U.S. mutual funds by Avramov and Wermers (2006).

In addition to this list, we also consider a set of new macroeconomic variables. First, we use the level of volatility in the stock market, measured as the change in the VDAX index for the German stock market. We also use the level of inflation, measured as the year-on-year change in the European Consumer Price Index; the 12-month change in the level of industrial production, and the change in the economic sentiment indicator obtained from opinion surveys conducted by the European Central Bank.

Notice that, with a few exceptions, we use European as opposed to country-specific state variables. This is dictated by our desire to keep the number of state variables limited.

Data sources as well as a brief characterization of the properties of the key state variables used in the study are provided in Appendix 1.

3 Investor Types

Building on the analysis in Avramov and Wermers (2006), this Section presents the model for capturing predictability in mutual fund returns and the prior beliefs for the four types of Bayesian optimizing investors analyzed throughout the paper in addition to a conventional investor who holds strong beliefs in the CAPM.

3.1 Dynamic Return Generating Process for Returns

The general mutual fund return generating model takes the form

$$r_{it} = \alpha_{i0} + \alpha_{i1}' z_{t-1} + \beta_{i0}' f_t + \beta_{i1}' \left(f_t \otimes z_{t-1} \right) + \upsilon_{it}. \tag{1}$$

Here r_{it} is the month-t return on mutual fund i, measured in excess of the risk-free rate; z_{t-1} is a set of state variables in the information set, which contains M business cycle variables observed at the end of month $t-1$, f_t is a set of K zero-cost benchmarks (risk factors), β_{i0} is the fixed or constant component of fund risk loadings, while β_{i1} is its time-varying counterpart, and υ_{it} is a fund-specific event, assumed to be uncorrelated across funds and over time, as well as being normally distributed with mean zero and variance σ_i.

The risk factors are assumed to follow a simple autoregressive process with persistence controlled by the matrix A_f

$$f_t = a_f + A_f z_{t-1} + \upsilon_{ft}. \tag{2}$$

Finally, the state variables, many of which are quite persistent, also follow an autoregressive process:

$$z_t = a_z + A_z z_{t-1} + \upsilon_{zt}. \tag{3}$$

The innovations υ_{ft} and υ_{zt} are assumed to be independently and normally distributed over time and are also mutually independent.

We consider five investor types throughout the paper. These differ in their beliefs about the parameters in equation (1) of the return generating process that represent manager skills in stock selection and benchmark timing, captured by the excess returns generated by individual manager, α_{i0},excess returns from stock selection based on market conditions, $\alpha_{i1}' z_{t-1}$, and the time-varying factor loadings, $\beta_{i1}' \left(f_t \otimes z_{t-1}\right)$.

The most restrictive view is held by the dogmatist CAPM investor, who believes that no fund manager has skill or predictable factor loadings and the benchmark returns are not predictable. This investors's beliefs can therefore be represented as $\alpha_{i0} = 0$, $\alpha_{i1} = 0$, $\beta_{i1} = 0$, and, $A_F = 0$.

A slightly less restrictive view is held by the Skeptic investor, who believes that fund factor loadings and benchmark returns are not predictable, so that $\beta_{i1} = 0$ and $A_F = 0$, but places a prior belief that $\alpha_{i0} + \alpha_{i1}' z_{t-1} \sim N\left(0, \sigma_\alpha^2\right)$ that effectively shrinks the Skeptic's expectation for the manager's skill.

Still less restrictive is the Agnostic Macro-Alpha (AMA) investor, who allows for predictability in the benchmark returns while maintaining the belief that fund factor loadings are not predictable, so that $\beta_{i1} = 0$. The AMA investor places no restrictions on α_{i1}, but imposes a prior belief that $\alpha_{i0} \sim N\left(0, \sigma_\alpha^2\right)$ to shrink their expectation for a fund manager's individual skill.

The Agnostic Predictable Market Loading (APML) investor further relaxes the model by allowing the fund manager to have predictable market factor loadings, but maintains the belief that the $K-1$ other benchmark factor loadings are not predictable, so that the entries in β_{i1} corresponding to the interactions between the macro factors and the non-market benchmark entries are restricted to be zero. As with the AMA investor, the APML investor places no restrictions on α_{i1} and maintains the prior belief that $\alpha_{i0} \sim N\left(0, \sigma_\alpha^2\right)$ on a monthly basis.

Lastly, the Agnostic Predictable Factor Loading (APFL) investor makes no restrictions on α_{i1}or β_{i1}, placing the only restriction on the return generating process through their prior belief that $\alpha_{i0} \sim N\left(0, \sigma_\alpha^2\right)$ on a monthly basis. In the baseline analysis we set $\sigma_\alpha = 0.1$.

Below we summarize the investor types, moving from the least restrictive to the most restrictive prior beliefs:

Investor type	α_{i0}	α_{i1}	β_{i1}	A_f
APFL	$\alpha_{i0} \sim N(\bar{\alpha}_{i,0}, \sigma^2_\alpha)$	unconstrained	unconstrained	unconstrained
APML	$\alpha_{i0} \sim N(\bar{\alpha}_{i,0}, \sigma^2_\alpha)$	unconstrained	$\beta_{i1} \neq 0$	unconstrained
AMA	$\alpha_{i0} \sim N(\bar{\alpha}_{i,0}, \sigma^2_\alpha)$	unconstrained	0	unconstrained
Skeptic	$\alpha_{i0} + \alpha'_{i1} z_{t-1} \sim N(\bar{\alpha}_{i,0}, \sigma^2_\alpha)$		0	0
CAPM	0	0	0	0

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3.2 Predictive moments for Investor Models

In this section, we present the predictive moments used to form portfolios for each of our investor models, building on the work by Avramov & Wermers (2006).

3.2.1 The Agnostic Predictable Factor Loading (APFL) Investor

Our model for the Agnostic Investor with Time-Varying Factor Loadings is identical to the PA-4 investor in Avramov & Wermers (2006), who show that the Bayesian predictive mean is given by:

$$E\left\{r_{T+1}|D_T\right\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}_T \tilde{A}'_F x_T, \tag{4}$$

where $\tilde{\alpha}_0$, $\tilde{\alpha}_1$, and $\tilde{\beta}_T$ are the all-fund versions of $\tilde{\alpha}_{i0}$, $\tilde{\alpha}_{i1}$, and $\tilde{\beta}_i\left(z_T\right) = \tilde{\beta}_{i0} + \left(I_K \otimes z'_T\right)\tilde{\beta}_{i1}$. Using the natural conjugate relationship, $\tilde{\alpha}_{i0}$, $\tilde{\alpha}_{i1}$, $\tilde{\beta}_{i0}$, and $\tilde{\beta}_{i1}$ are the first element, the next M elements, the next K elements, and the last $K \times M$ elements in the vector $\tilde{\Gamma}_i = \left(G'_i G_i + \Upsilon\right)^{-1}\left(G'_i r_i + \Upsilon \Gamma_{i0}\right)$, where $G_i = \left[G'_{t_i}, ..., G'_{t_i+T_i-1}\right]$, with $G_t = \left[1, z'_{t-1}, f'_t, f'_t \otimes z'_{t-1}\right]'$, Υ is a $(KM+K+M+1) \times (KM+K+M+1)$ square matrix with zeros everywhere except the $(1,1)$ element, which is equal to s^2/σ^2_α, and $\Gamma_{i0} = [\bar{\alpha}_{i,0}, 0, ..., 0]'$.

We assume that investors center their prior beliefs $\bar{\alpha}_{i,0} = -\frac{1}{12}\left(\textit{expense} + 0.01 \times \textit{turnover}\right)$ when that information is available, otherwise substituting in zeros for the expense and turnover when they are missing. Lastly, $\tilde{A}_F = \hat{A}_F = \left(X'X\right)^{-1} X'F$, where $X = \left[x'_0, ..., x'_{T-1}\right]'$, $x_t = [1, z_t]$, and $F = [f'_1, ..., f'_T]'$.

The predictive variance-covariance matrix for returns is given by:

$$V\left\{r_{T+1}|D_T\right\} = \left(1+\delta_T\right)\tilde{\beta}_T \hat{\Sigma}_{ff} \tilde{\beta}'_T + A_T, \tag{5}$$

where $\delta_T = \frac{1}{T}\left[1 + (\bar{z} - z_T)' \hat{V}_z^{-1} (\bar{z} - z_T)\right]$ with $\hat{V}_z = \frac{1}{T}\sum_{t=1}^{T} (z_t - \bar{z})(z_t - \bar{z})'$ and, $\hat{\Sigma}_{ff} = F' Q_X F / (T - K - M - 2)$ with $Q_X = I_T - X (X'X)^{-1} X$. The matrix A_T is diagonal with (i,i) element equal to

$$\tilde{\psi}_{i2} \begin{pmatrix} 1 + tr\left[\hat{\Sigma}_{ff}\tilde{\Omega}_i\right](1 + \delta_T) + x_T' \Omega_i^{11} x_T \\ +2x_T \left[\Omega_i^{12} + \Omega_i^{13}(I_K \otimes z_T)\right] \tilde{A}_F' x_T + tr\left[\tilde{A}_F' x_T x_T' \tilde{A}_F \tilde{\Omega}_i\right] \end{pmatrix} \tag{6}$$

where $\tilde{\psi}_{i2} = \tilde{\psi}_i / (T_i - K - M - KM - 2)$, $\tilde{\psi}_i = r_i' \, r_i + \Gamma_{i0}' \Upsilon \Gamma_{i0} - \tilde{\Gamma}_i' (G_i' G_i + \Upsilon) \tilde{\Gamma}_i$, $\tilde{\Omega}_i = \Omega_i^{22} + \Omega_i^{23}(I_k \otimes z_T) + (I_k \otimes z_T') \Omega_i^{32} + (I_k \otimes z_T') \Omega_i^{33} (I_k \otimes z_T)$, and the quantities Ω_i^{mn} are based upon the partitions of $G_{it} = [1, z_{t-1}; f_t'; f_t' \otimes z_{t-1}]'$ given by

$$(G_i' G_i + \Upsilon)^{-1} = \begin{pmatrix} \Omega_i^{11} & \Omega_i^{12} & \Omega_i^{13} \\ \Omega_i^{21} & \Omega_i^{22} & \Omega_i^{23} \\ \Omega_i^{31} & \Omega_i^{32} & \Omega_i^{33} \end{pmatrix}.$$

3.2.2 The Agnostic Predictable Market Loadings (APML) Investor

The Agnostic Investor with time-varying factor loadings needs to estimate a very large number of parameters to account for the full set of interactions between macro factors and benchmark factors, resulting in a relatively over-parameterized model. To address this, we investigated the behavior of an agnostic investor who assumes the non-market factor loadings are constant, effectively limiting the interactions to those between macro factors and the market benchmark return.[4] Note that this investor type maintains a belief that market returns are predictability using the information in z_{t-1}.

The predictive moments are effectively the same as those for the APFL investor, except that β_{i1}now has only M elements instead of KM elements. We redefine $G_t = \left[1, z_{t-1}', f_t', r_{m,t} z_{t-1}'\right]'$, where $r_{m,t}$ is the excess return on the market portfolio in period t and Υ is now an $(M + 2K + 1) \times (M + 2K + 1)$ matrix. All other formulas from section remain unchanged.

3.2.3 The Agnostic Macro-Alpha (AMA) Investor

The Agnostic Investor with Constant Factor Loadings believes that although a manager's alpha may depend on the macroeconomic environment, managers do not shift their exposure to benchmark

[4] The resulting agnostic investor with time-varying market factor loadings is a restricted version of the PA-4 investor in Avramov & Wermers (2006).

factors in response to macroeconomic indicators. This investor effectively restricts the parameter β_{i1} to be equal to zero so that $\beta_T = \beta_0$.

The restriction on β_{i1} affords some simplification to the above formulas. In particular, the expected returns now take the form

$$E\left\{r_{T+1}|D_T\right\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}_0 \tilde{A}_F' x_T. \tag{7}$$

Similar to the restriction that non-market benchmark factor loadings are constant as described previously, we redefine $G_t = \left[1, z_{t-1}', f_t'\right]'$ and Υ is now a $(M+K+1)\times(M+K+1)$ matrix. The variance-covariance matrix is given by:

$$V\left\{r_{T+1}|D_T\right\} = (1+\delta_T)\,\tilde{\beta}_0 \hat{\Sigma}_{ff} \tilde{\beta}_0' + A_T, \tag{8}$$

where now the matrix A_T is diagonal with a simplified (i,i) element:

$$\tilde{\psi}_{i2}\begin{pmatrix} 1 + tr\left[\hat{\Sigma}_{ff}\Omega_i^{22}\right](1+\delta_T) + x_T'\Omega_i^{11}x_T + 2x_T\Omega_i^{12}\tilde{A}_F'x_T \\ +tr\left[\tilde{A}_F'x_T x_T'\tilde{A}_F\Omega_i^{22}\right]\end{pmatrix}. \tag{9}$$

3.2.4 The Skeptic Investor

Our Skeptic investor believes that the benchmark returns and benchmark factor loadings are not predictable and is skeptical of whether fund managers can generate predictable alpha. As such, this investor exactly matches the Skeptic investor from Avramov & Wermers (2006), who follow Pastor & Stambaugh (2002) in using the conjugate prior relationship to model the investor's prior beliefs as a sample of returns that reflects their prior belief in no manager skill. Avramov & Wermers (2006) show the investor's predictive means are given by:

$$E\left\{r_{T+1}|D_T\right\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}\bar{f}, \tag{10}$$

where $\tilde{\alpha}_0$, $\tilde{\alpha}_1$, and $\tilde{\beta}$ are the all-fund versions of $\tilde{\alpha}_{i0}$, $\tilde{\alpha}_{i1}$, and $\tilde{\beta}_i$. The individual fund's $\tilde{\alpha}_{i0}$, $\tilde{\alpha}_{i1}$, and $\tilde{\beta}_i$ are the first element, the next M elements, and the last K elements in the vector $\tilde{\Gamma}_i = (G_i'G_i + G_{i0}'G_{i0})^{-1}(G_i'r_i + [G_{i0}'G_{i0}]\,\Gamma_{i0})$, where $G_i = \left[G_{t_i}', ..., G_{t_i+T_i-1}'\right]$, with $G_t = [1, z_{t-1}, f_t']'$. The skeptic investor's prior beliefs are centered on $\Gamma_{i0} = \left[\bar{\alpha}_{i0}, 0', \bar{\beta}_{i0}'\right]'$, where as above, $\bar{\alpha}_{i0} = -\frac{1}{12}$ (expense+$0.01\times$turnover) when that information is available, otherwise substituting in zeros for the expense and turnover when they are missing, and $\bar{\beta}_{i0} = (F'F)^{-1}(F'r_i) - T_i (F'F)^{-1}\bar{f}\bar{\alpha}_{i0}$

. Lastly,

$$\left[G_{i0}'G_{i0}\right]^{-1} = \frac{1}{T_0}\begin{bmatrix} 1+\bar{z}'\hat{V}_z^{-1}\bar{z}+\bar{f}'\hat{V}_F^{-1}\bar{f} & -\bar{z}'\hat{V}_z^{-1} & -\bar{f}'\hat{V}_F^{-1} \\ -\hat{V}_z^{-1}\bar{z} & \hat{V}_z^{-1} & 0 \\ -\hat{V}_F^{-1}\bar{f} & 0 & \hat{V}_F^{-1} \end{bmatrix}. \tag{11}$$

The value $T_0 = \frac{s^2}{\sigma_\alpha^2}\left(1+M+SR_{max}^2\right)$ represents the size of the hypothetical sample used to update the skeptic investor's beliefs using a conjugate-prior model of beliefs and T_i refers to the number of return observations for fund i. Next, Avramov & Wermers (2006) show that the variance-covariance matrix is given by:

$$V\left\{r_{T+1}|D_T\right\} = \left(1+\frac{1}{T^*}\right)\tilde{\beta}\tilde{V}_f\tilde{\beta}+A_T, \tag{12}$$

with the (i,i) element of the diagonal matrix A_T equal to:

$$A_T\left(i,i\right) = \tilde{\psi}_{i3}\left(1+\text{tr}\left[\tilde{V}_f\Omega_i^{22}\right]\left(1+\frac{1}{T^*}\right)+x_T'\Omega_i^{11}x_T+2x_T\Omega_i^{12}f+\text{tr}\left[\bar{f}\bar{f}'\Omega_i^{22}\right]\right)$$

with,

$$\tilde{V}_f = \frac{T^*\hat{V}_f}{T^*-K-3}, \tilde{\psi}_{i3} = \frac{\left(T_i^*/T_i\right)r_i'r_i-\tilde{\Gamma}_i'\left(G_i'G_i+G_{i0}'G_{i0}\right)\tilde{\Gamma}_i}{T_i^*-K-M-2},$$

$T^* = T+T_0$, $T_i^* = T_i+T_0$, and the Ω_i^{mn} matrices obtained by partitioning $\left(G_i'G_i+G_{i0}'G_{i0}\right)^{-1}$.

4 Empirical Results

We next turn to a description of our empirical results.

4.1 Historic Return Performance

Table 2 reports the raw return performance as well as the risk-adjusted return performance measured for the full sample and for various subsamples.

Panel A lists performance results for the equal-weighted universe of funds in our sample and the benchmark MSCI Europe index. Over the full sample, 1988-2008, the equal-weighted portfolio of funds returned 10.2% per annum, 85 basis points below the benchmark which returned 11.05% per annum. This average underperformance reflects very different performance of the funds in the first part of the sample, 1988-1998, a period during which they significantly trailed the benchmark, against a period of outperformance relative to the benchmark during the latter sample from 1999 to 2008.

Turning to the risk-adjusted alphas, displayed for the single-factor model in Panel B and for the four-factor model in Panel C, we observe underperformance both on average and for the median fund during the full sample period. In the case of the single-factor model, the average underperformance was -48 basis points per annum. This number does not convey the large differences in alpha performance during the five-year subperiods, however. For example, during the five-year period from 1988-1992, the average single-factor alpha was negative , at -4.68%, while conversely it was positive at 0.96% during the five-year period from 1999 - 2003.

Similar conclusions can be drawn from the four-factor alphas which are negative on average, with the median fund returning -24 basis points per annum and the equal-weighted alpha coming in at -1.08% per annum.

These results are consistent with findings reported for the U.S.. It is generally found that mutual funds on average underperform by between 50 and 100 basis points per annum. These results also indicate that survivorship bias is not overly important in our sample. To further explore this point, we also report quantiles for the alpha distribution. If survivorship bias was a key concern, we would expect the left-tail quantiles to be much smaller than those observed in the right tails (as under-performing funds are excluded from the sample). This is not what we observe. In fact, the cross-sectional distribution of single-factor alphas, which arguably is the most relevant comparison, is largely symmetric.

We conclude from these historical or in-sample performance results that although the average fund underperformed both on a raw return basis and also on a risk-adjusted basis, many funds were able, ex-post, to generate large and positive alphas. From an active investment perspective, however, the key question is whether such funds could have been identified ex-ante and selected as part of a portfolio strategy to produce performance superior to that available from passive investment strategies. We next address that question.

4.2 Portfolio Performance

To address the out-of-sample portfolio performance of the various investor types described in the previous section, Table 3 reports performance results for an expected utility maximizing investor with mean-variance preferences and coefficient of risk aversion equal to 2.94, the value advocated by Avramov and Wermers (2006).

The baseline portfolio results shown in Table 3 are based on the following assumptions. First we use as macro factors a similar set of variables as those adopted by Avramov and Wermers (2006), namely the term spread, dividend yield, default spread and the short-term interest rate. The parameter σ_α, which represents the degree to which investors believe in their prior, is set to 0.1, or 10% per month. Moreover, we assume quarterly rebalancing and a cap of 25% on the holdings in individual funds. Short sales are not allowed. The expected utility maximization used to derive the optimal holdings considers the top 50 funds ranked by their conditional Sharpe ratio.

To capture portfolio performance, we present conventional measures such as the geometric and arithmetic mean as well as the volatility, Sharpe ratio and the percentage of months where a particular investor type's portfolio outperformed the benchmark. In addition we report the alphas, their t-statistics, and factor risk exposures.

First consider the raw return performance reported in the first four lines of Table 3. The market index returned 10.50% per annum at a volatility of 20.4% and produced a Sharpe ratio of 0.31. The APFL investor produced slightly higher mean returns of 11.8% per annum, for a Sharpe ratio of 0.47, roughly f0% higher than that of the benchmark. The APML, AMA and Skeptic investors saw mean returns seven percent or more above that of the benchmark. This improvement in the mean return only came at the cost of a marginally elevated level of volatility and so these investors' portfolios generated Sharpe ratios, ranging from 0.62 to 0.68, more than twice the level estimated for the benchmark.

Finally, the very restrictive portfolio strategy associated with the CAPM Investor delivered very poor mean returns of 7.5% per annum and a Sharpe ratio of only 0.27, far below that of the benchmark portfolio.

4.2.1 Alphas

Turning to the alpha estimates, over the full sample the APFL, APML, AMA and Skeptic investors all generate economically large positive single-factor alphas ranging from 5.6% per annum to 11.9% per annum. Moreover, three of the four alphas are statistically significant at conventional levels, with only the APFL investor's alpha being insignificant. In contrast, the single-factor alpha estimate for the CAPM investor is much smaller at 0.52% and statistically insignificant.

Even larger alpha performance is observed when the four-factor model is used as the benchmark for risk-adjustment. For this case the alphas from the four active investor types range from 11.7% to 18.2% per annum, with the skeptic investor once again coming out on top. All alphas are highly statistically significant as well. Once again, the CAPM investor produces a much smaller alpha of 3% per annum that is also statistically insignificant.

To understand the investment strategies, note that the four investor types all have positive loadings on the market portfolio, the small cap (size) factor and the momentum factor, but load negatively on the value factor. Hence these strategies tend to be overweighted in small growth stocks and also are exposed to momentum.

Our sample covers very different market conditions, spanning the run-up in stock prices during the nineties, followed by the market crash in 2000, the recovery from 2003 and, more recently, the financial crisis from 2007. To test if the performance associated with the various investor types varied across these very different market conditions, we split our sample into two sub-periods, namely 1993-2000 and 2001-2008. Reassuringly, Table 3 shows that the four strategies under consideration generated positive alpha in both subsamples, irrespective of whether the single-factor or four-factor model is used for benchmarking. This suggests that the ability to identify funds with superior performance does not solely hinge on one type of market environment.

To gain further insights into the performance of the various portfolios through time, Figure 1 plots the rolling twelve-month returns of the market portfolio against the returns on the portfolios managed by the four active investor types and the CAPM investor. The plot confirms that although a significant portion of the portfolios' outperformance materialized during the period around 1999-2000, the portfolios of the four active investor types consistently outperformed the benchmark during much of the sample.

Figure 2 shows the cumulative growth in one Euro invested in the benchmark or in each of the portfolios managed by the five investor types. One Euro invested in 1993 would have grown to a little under 4 Euros in 2008 in the benchmark portfolio. In contrast, one Euro would have grown to more than 12 Euros in 2008 in the portfolios managed by the AMA, APML and skeptic investors.

5 Portfolio weights and attribution analysis

To understand which factors led to the superior performance of the actively managed portfolios of mutual funds, we next consider the country and sector allocations in the portfolios and we perform an attribution analysis that explores which components were accountable for the investment performance.

5.1 Country and Sector Allocations

We first consider the portfolio allocation of the various investor types through time. To this end, Table 4 shows snapshots of the portfolio weights by region/country and by sector. The country/regional funds obtain by far the highest weights through time, but it should be recalled from Table 1 that there are very few European sector funds prior to 2003. Among the country/region funds, Pan European funds generally obtain the largest weights, which is again unsurprising given that these funds constitute the single largest category among our universe of funds. At the end of the sample, Pan-European funds accounted for between 43% and 63% of the overall portfolio weight, depending on the investor type.

Interestingly, we see considerable variation in the portfolio weights across the four investor types. For example, in 2008 the skeptic and AMA investors allocated 25% (the maximum allowed) to tech, media and telecommunication sector funds, whereas the APFL and APML investors allocated zero to this sector. Similarly, Swiss funds took up a large proportion of the skeptic, AMA and APML investors' funds in 2008, compared with a zero allocation for the APFL investor who instead allocated a large portion to UK funds.

The finding that country and sector allocations vary considerably over time for the four investor types shows that they clearly pursue very active strategies. Moreover, the large variation in portfolio allocations across investor types suggests that there is not just a single way to identify funds with superior performance.

5.2 Selection of Individual Funds

Table 4 does not show the identity of the individual funds that were selected by the four investor types. These are instead presented in Table 5, using data as of February 2008. The portfolio held by the APFL investor is most diversified across funds, whereas the other three investor types hold close to three-quarters of their portfolios in three funds, in many cases coming up against the maximum of 25% holdings in one fund. There is a substantial overlap in the funds selected by the septic and AMA investors, but considerably less overlap among the other investor types.

5.3 Decomposition of Returns

To evaluate the source of outperformance for our portfolios, we decompose the abnormal return performance into four components plus a residual. The return for the portfolio is first decomposed into the Pan-European (including Sector Funds) and C Country-Specific returns as:

$$r_P = w_{Euro,P} * r_{Euro,P} + w_{Sect,P} * r_{Sect,P} + \sum_{i=1}^{C} w_{Ctry_i,P} * r_{Ctry_i,P}. \tag{13}$$

We compare this return to the return on the MSCI Europe Benchmark, which is decomposed into its C Country-Specific components as:

$$\begin{aligned} r_B =& w_{Euro,P} r_B + w_{Sect,P} r_B \\ &+ (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} * r_{Ctry_i,B} \\ &+ (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} \left(r_B - r_{Ctry_i,B} \right) \end{aligned} \tag{14}$$

The weights for each country in the benchmark were computed using the market capitalizations for each country's equity market, taken from the World Bank's Development Indicators and the benchmark country returns are taken from the MSCI European Country Indices. Note that we only decompose the proportion of the benchmark that the portfolio invests in country funds. This split implicitly assumes that the Pan-European and sector funds do not take active country positions, which seems reasonable in the absence of a detailed analysis of fund constituent data and the relatively small sector exposure of the portfolio through the majority of the sample period. The third term in the benchmark decomposition is a residual reflecting the small mismatch between the MSCI country index and the MSCI Europe benchmark returns.

The contribution of Pan-European stock selection and Sector stock selection to our portfolio's performance is given by the difference of the first terms in the portfolio return decompositions. These components reflect the ability of the portfolio to select funds that outperform the benchmark and are computed as

$$r_{European\ Selection} = w_{Euro,P} * \left(r_{Euro,P} - r_B \right) \tag{15}$$

$$r_{Sector\ Selection} = w_{Sect,P} * \left(r_{Sect,P} - r_B \right). \tag{16}$$

The contribution of country fund selection to the portfolio's abnormal performance captures the ability of the portfolios to select country-specific funds that outperform the country benchmark. This component is given by the difference between the portfolio-weighted returns on country funds in the portfolio and the benchmark country return, weighted by the benchmark portfolio weights. In the common occurrence that the portfolio did not invest in a particular country, we use the benchmark country return for the portfolio country return (so that no contribution is accounted for by those countries). The formula for the country selection component of abnormal performance is

$$r_{Country\ Select} = (1 - w_{Euro,P}) \sum_{i=1}^{C} w_{Ctry_i,B} * (r_{Ctry_i,P} - r_{Ctry_i,B}) . \tag{17}$$

The contribution of timing country weights is given by the active position of the fund in countries weighted by the benchmark returns for the country. This contribution reflects the ability of the fund to move into countries in response to the macroeconomic state variables. This is

$$r_{Country\ Time} = \sum_{i=1}^{C} ((1 - w_{Euro,P}) w_{Ctry_i,B} - w_{Ctry_i,P}) r_{Ctry_i,B}. \tag{18}$$

Finally, the residual for the abnormal portfolio performance is given by the traditional Brinson, Beebower, & Hood residual component minus the residual in the benchmark return composition:

$$\begin{aligned} r_{resid} = & \sum_{i=1}^{C} ((1 - w_{Euro,P}) w_{Ctry_i,B} - w_{Ctry_i,P}) (r_{Ctry_i,P} - r_{Ctry_i,B}) \\ & - (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} (r_B - r_{Ctry_i,B}) \end{aligned} \tag{19}$$

Table 6 presents the results of this decomposition for our five investor types. We see that country-specific fund selection contributed strongly to the performance of all investor types. The Skeptic investor had a significant contribution from Pan-European fund selection, but this component did not help many of the other investor types. The remaining components did not contribute much to the abnormal performance of the portfolio, reflecting that the real advantage of the portfolio lay in finding very good country funds.

5.4 Macro Variables

To address which macrovariables are important in generating the alpha for the four active investor types, we next present alphas and alpha t-statistics when different predictor variables are included, one by one, in the model. The results, shown in Table 7, suggest that a variety of macro variables are useful in generating alpha, with the term spread, dividend yield and the consumer price index being among the most important ones.

6 Robustness of Results

In this section we undertake a range of robustness checks to see how sensitive the findings from the baseline case is to changes in the universe of funds, rebalancing frequency, constraints on the portfolio weights and prior beliefs.

6.1 Universe of Funds

First consider the universe of funds included in the investment analysis. Table 8 shows the effect on four-factor alphas of going from the full set of regional, country and sector funds (Panel A) to a setting where the sector funds are excluded (Panel B) or the country funds are excluded (Panel C). The results clearly show that regional funds can be omitted without any major deterioration in the investment performance. In sharp contrast, once the country funds are dropped, the alphas typically decline by levels at or below half their previous levels. Even in the latter scenario, it should be noted that the skeptic and AMA investors manage to generate alphas close to 6% per annum.

These results are consistent with our findings that sector funds get relatively small weights in most portfolios, at least up to the very end of the sample, whereas country funds play a more prominent role in the allocations. They also reflect the absence of European sector funds up to around 2003.

6.2 Construction of Momentum Factor

We do not have access to a momentum factor constructed at the individual stock level. Instead we formed the momentum factor based on the previous 12-month performance for the 18 Dow Jones

STOXX 600 Super Sectors indices. The momentum factor is then formed from the spread between returns on the top six and the bottom six sectors.

Alternatively, we could make use of a country momentum factor. To explore if this can help explain our results, we constructed this as follows. Again we considered the performance of each of the 16 European countries included in the analysis over the previous 12-month period.[5] We then computed the return differential between the three countries with the highest previous return and the three countries with the lowest previous returns.

Table 9 explores whether it makes a difference to our results if we use the sector- or country-based momentum factor. The results under the separate momentum factors are very similar, so we conclude that our findings are robust to whether momentum is defined along sector or country lines..

6.3 Constraints on Portfolio Optimization

Our baseline results assumed that the mean-variance investor optimizes the portfolio allocation across the top 50 funds, ranked by their conditional Sharpe ratio. One could alternatively extend the set of funds considered in the optimization. Table 10 shows that expanding the set of fund used in the optimization to include 250 rather than 50 has a very marginal effect on the results.

Limiting the portfolio weights so that sales cannot exceed a certain amount per quarter provides one way to reduce the portfolio turnover. Table 10 further shows that limiting the sales of individual funds to 15% per quarter has very little impact on the results.

Table 10 also shows that lifting the constraint of a maximum 25% of the portfolio invested in any one fund increases the alpha performance by between 3% and 5% for the skeptic, AMA and APML investor types but leaves the alpha performance of the APFL investor unchanged. These findings are encouraging as they suggest that there is significant value in the signals used to select funds based on their conditional alphas. The greater the signal value, the more one would expect that essentially ad-hoc constraints should reduce the portfolio performance.

[5] The 16 countries included in the analysis are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

6.4 Effect of Priors

Our baseline results assumed a prior of $\sigma_\alpha = 10\%$ per month. This is not a very tight or informative prior, and so the investor types (with the exception of the CAPM investor) are open-minded about the possibility of abnormal performance. It is clearly important, however, to explore the effect of different priors on portfolio selection (see Baks et al. (2001). In particular, we investigate to what extent tightening the priors of the investor to $\sigma_\alpha = 1\%$ per month or $\sigma_\alpha = 0.1\%$ per month affects the returns, as the investor becomes increasingly skeptical about the possibility of finding abnormal performance and puts less weight on the data.

Table 11 shows that as σ_α gets smaller and so the priors get tighter, the alpha performance decline quite substantially for the skeptic investor in particular, whereas a smaller decline is observed for the APFL, AMA and APML investor types.

To interpret these findings notice that when we tighten σ_α for the APFL investor, α_0 is effectively limited to be zero, although we still consider alpha generated by the manager's macroeconomic-related skill since there are no restrictions on α_1. When we tighten σ_α for the skeptic investor, we shrink the total α $(\alpha_0 + \alpha_1 z_t)$ toward zero. The relative sensitivity of the skeptic's performance to increasing the precision of his belief therefore provides further evidence that the $\alpha_1 z_t$ component is critical to the model's performance.

6.5 Identifying Under-performing Funds

Table 12 considers the performance of a range of alternative investment strategies such as short-only results, 130-30 and self-financing portfolios. The short-only results tell us whether the model is capable of identifying underperformers among the hedge funds. In this regard, the model again seems to be doing well, particularly when the four-factor benchmark is used for risk-adjustment. The alphas are quite smaller for the single-factor model, ranging from -1.27% to -4.37%, but at close to minus eight percent per annum, the four-factor alphas are quite substantial across all investor types.

Encouraged by these findings, we also considered the performance of a self-financing portfolio strategy which allows for both long and short positions. Across all four investor types, the single-factor alphas for the self-financing strategy are far higher than those observed for the long-only strategy, increasing the latter by between four and seven percent. Moreover, the betas associated with the self-financing long-short strategy are close to zero, showing that this strategy is basically market neutral.

The results are somewhat different when the four-factor model is adopted. For this case the long-only and long-short self-financing portfolio alphas are very similar. Since the four-factor long-only alphas were already very high, this is not, however, an indication of poor performance for the self-financing strategy. Moreover, the self-financing strategy has very low exposure to the market and SMB factors, but retains a negative exposure to the HML factor and a large, positive exposure to the momentum factor.

7 Conclusion

Despite their significant growth in recent years, the performance of European equity mutual funds is a largely unexplored area of research. This paper shows that macroeconomic state variables can be used to identify a significant time-varying alpha component among a large sample of Pan-European, European country and sector funds. State variables such as the default yield spread, the term spread, the dividend yield and the short risk-free rate as well as macroeconomic variables tracking consumer price inflation and economic sentiment are useful in identifying superior performance among funds. Most of the alpha that these state variables help identify using ex-ante information comes from their ability to select superior Pan-European funds and generate returns from country selection.

References

[1] Avramov, Doron and Russ Wermers, 2006, Investing in mutual funds when returns are predictable. Journal of Financial Economics 81, 339-377.

[2] Baks, Klaas P., Andrew Metrick, and Jessica Wachter, 2001, Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation, *Journal of Finance* 56, 45-85.

[3] Carhart, Mark, 1997, On persistence in mutual fund performance. Journal of Finance 52, 57-82.

[4] Carhart, Mark M., Jennifer N. Carpenter, Anthony W. Lynch, and David K. Musto, 2002, Mutual fund survivorship, *Review of Financial Studies* 15, 1439-1463.

[5] Christopherson, Jon A., Wayne E. Ferson, and Debra A. Glassman, 1998, Conditioning manager alphas on economic information: Another look at the persistence of performance, *Review of Financial Studies* 11, 111-142.

[6] Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[7] Ferson, Wayne E., and Rudy W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425-461.

[8] Investment Company Institute, 2008, *Mutual fund fact book* (Washington, D.C.).

[9] Moskowitz, Tobias, 2000, Discussion: mutual fund performance: an empirical decomposition into stock-picking talent, style , transactions costs, and expenses. Journal of Finance 55, 1695-1703.

[10] Otten, Roger, and Dennis Bams, 2002, European mutual fund performance, *European Financial Management* 8, 75-101.

Appendix: Data Sources and Definitions

Variable	Definition	Source
Market	MSCI Europe Total Return Index	Global Financial Database
Small-Minus-Big	Difference between Europe STOXX Small Cap Return Index and Europe STOXX Large Cap Return Index	Global Financial Database
High-Minus-Low	Difference between Europe Value and Growth Portfolios*	Ken French's Data Library
Momentum	Difference between top and bottom 6 sectors from Dow Jones STOXX 600 Super Sector Indices (18 sectors)**	Dow Jones STOXX Website
Term Structure	Difference between "10-year Euro area Government Benchmark Bond Yield' and Euribor 1 month.	European Central Bank
Dividend Yield	Europe Dividend Yield	Global Financial Database
Europe Default Spread	Difference between Yields on Corporate bonds and Yields on Public debt securities.	Bundesbank Website
Volatility	squared 1 month difference on the Germany VDAX index	Global Financial Database
Consumer Price Index	Annual Change in the European Consumer Price Index	European Central Bank
Industrial Production	%12m from Industrial Production index (excluding construction)	European Central Bank
Economic Sentiment	1 month difference on the Economic sentiment indicator from the Opinion Surveys from European Central Bank	European Central Bank
Risk free Rate	1-month Euribor from ECB***	European Central Bank

*Through 4Q07. Jan-Feb 2008 computed using difference between S&P Citigroup Europe BMI Value and Growth Indices from S&P Citigroup Global Equity Indices website

**Top and bottom sectors are selected based on performance over the previous 12 months. Portfolios are rebalanced on amonthly basis.

***Backfilled with "GFD Euribor 1 month' an interbank rate for the ECU prior to 1999) recovered from Global Financial Database for the period (02/1988-12/1993)

Table A-1: Descriptive Statistics for Benchmark and Macroeconomic Factors

Panel A. Risk Factors

	Market	Size	Book-to-market	Sector Momentum
Mean	0.95	-0.41	0.39	0.34
Median	1.55	-0.33	0.37	0.43
Maximum	12.97	7.07	11.15	13.14
Minimum	-16.41	-9.03	-12.08	-14.72
Standard Deviation	4.61	2.52	2.65	3.32
Skewness	-0.78	-0.10	-0.07	-0.30
Kurtosis	4.59	3.33	5.95	5.84
Autocorrelation	0.07	0.23	0.20	0.23

Panel B. Macroeconomic Variables

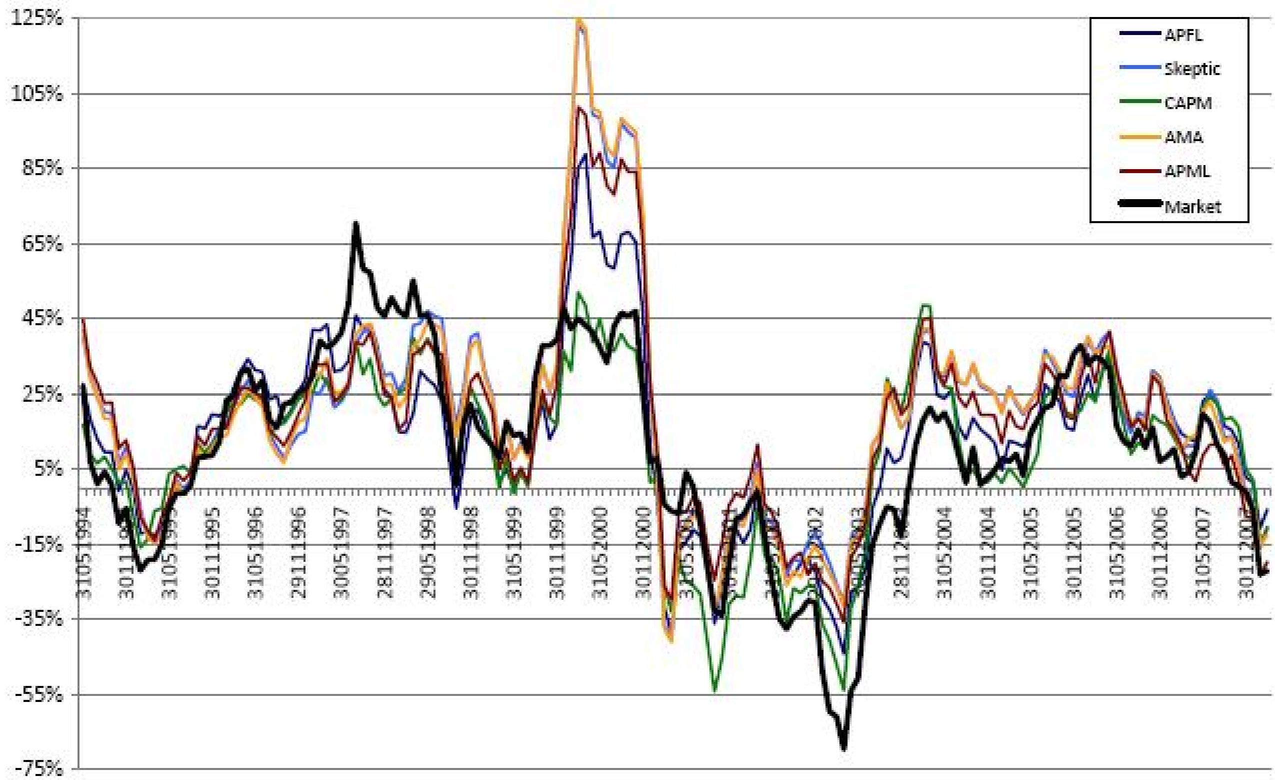
	Dividend Yield	Default Spread	Short Rate	Term Spread
Mean	3.05	0.58	5.51	1.09
Median	3.00	0.50	4.51	1.19
Maximum	4.80	2.80	13.69	3.28
Minimum	1.70	-0.20	2.04	-3.67
Standard Deviation	0.72	0.46	2.86	1.00
Skewness	0.09	1.40	0.64	-0.64
Kurtosis	2.40	5.86	2.19	4.29
Autocorrelation	0.97	0.90	0.99	0.90

Note: Based on monthly series

This table shows descriptive statistics for the risk factors as well as for the predictor variables used to track time-variations in the conditional alpha. All statistics are based on monthly observations for the factors and state variables.

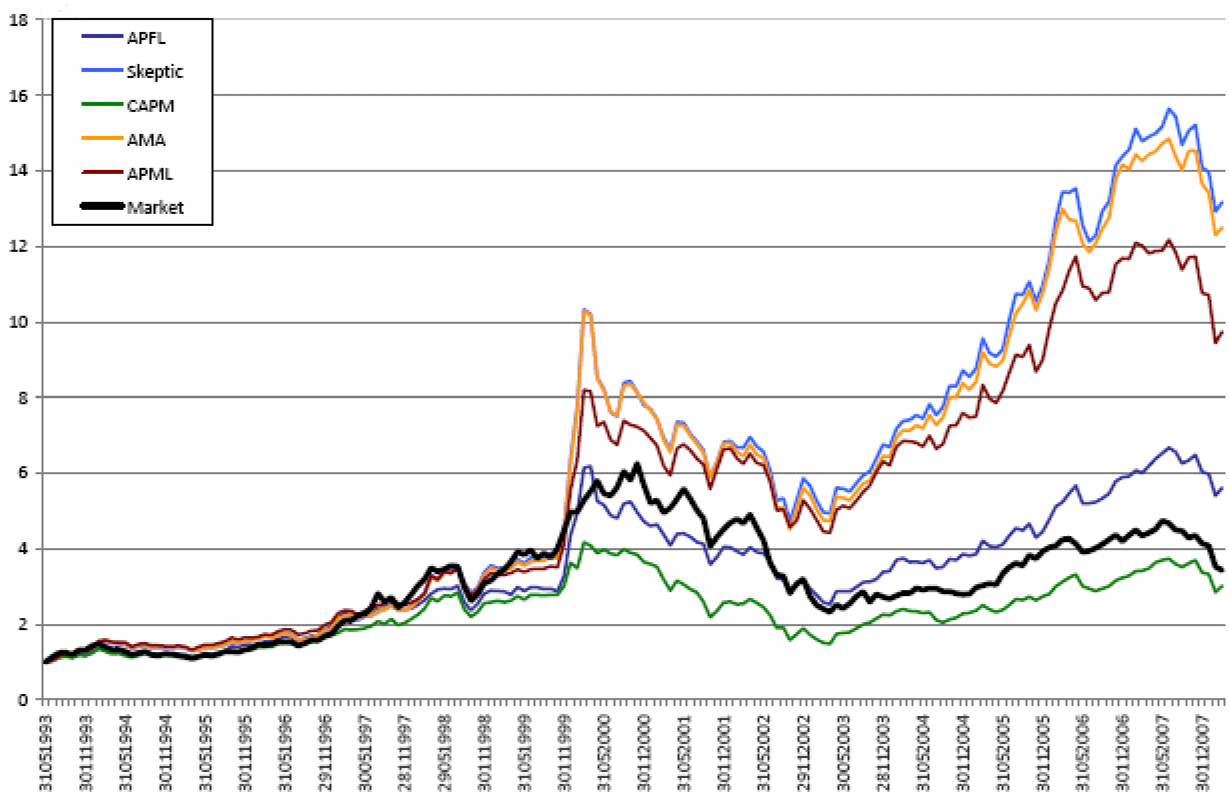
Tables and Figures

Figure 1: Portfolio Strategies Trailing 12 Month Return



This figure shows the rolling 1-year return performance for the conditional alpha investment strategies and the benchmark MSCI Europe portfolio. In each case the results are based on out-of-sample analysis covering the period 06/1993-02/2008.

Figure 2: Portfolio Strategies Cumulative Performance



This figures shows how \$1 invested in the conditional alpha or the benchmark MSCI Europe portfolio would have evolved over time, assuming zero transaction costs.

Table 1: Number of Funds over Time by Investment Objective

Panel A: Fund Counts

	1988	1993	1998	2003	2008
I. Universe	229	726	1,441	3,400	4444
II. Regional Funds					
Austria	1	4	7	12	18
Benelux	3	25	45	73	62
France	2	86	166	277	276
Germany	17	43	78	113	116
Italy	2	19	54	94	96
Pan-Europe	58	237	502	1,656	2,358
Scandinavian	18	52	141	271	316
Spain/Portugal	0	26	69	113	145
Switzerland	8	24	55	104	156
UK	119	198	300	509	631
III. Sector Funds					
Banks & Financial	0	0	1	24	31
Basic Industries	0	0	0	7	12
Cyclical Goods & Services	0	0	0	10	21
General Industry	0	0	0	7	11
Information Technology	0	0	0	25	21
Natural Resource	0	0	0	8	12
Non Cyclical Con	0	0	0	15	17
Pharma & Health	0	0	0	8	8
Real Estate	1	12	21	48	108
Tech Media & Tele	0	0	1	12	10
Telecom Services	0	0	1	7	7
Utilities	0	0	0	7	12

Panel B: Fund Expenses and Fees

	1998	2003	2008
Average	1.46	1.63	1.50
Median	1.48	1.59	1.61
Standard Deviation	0.55	0.94	0.62
No of Expense Obs	486	1,528	931

This table shows snapshots of the number of funds included in our sample as of year-end 1988, 1993, 1998, 2003 and February 28, 2008. The funds are grouped according to their investment objectives by country, region or sector. Panel B reports snapshots of the expenses and fees in 1998, 2003 and 2008.

Table 2: Fund Universe Sample Performance

	Full Sample	1988-1992	1993-1998	1999-2003	2004-2008
	A. Annual Average Return Performance				
Eq Weight Universe	10.11%	7.63%	18.36%	1.78%	11.11%
Benchmark	11.05%	12.41%	22.41%	-0.44%	6.88%
	B. Single-Factor Alpha (Annualized)				
Universe Average	-0.48%	-4.68%	-1.80%	0.96%	-1.08%
5% - Quantile	-8.16%	-22.68%	-19.56%	-8.64%	-8.88%
10% - Quantile	-5.52%	-16.68%	-10.68%	-5.88%	-6.24%
25% - Quantile	-3.00%	-8.64%	-4.56%	-3.24%	-3.60%
50% - Quantile	-0.84%	-3.24%	-1.32%	-0.12%	-1.56%
75% - Quantile	1.80%	0.12%	2.16%	4.80%	1.20%
90% - Quantile	5.76%	3.24%	6.84%	10.56%	5.28%
95% - Quantile	8.88%	6.12%	12.36%	15.00%	8.40%
	C. Four-Factor Alpha (Annualized)				
Universe Average	-1.20%	0.60%	8.40%	2.40%	-2.40%
5% - Quantile	-7.56%	-20.40%	-14.64%	-8.40%	-8.40%
10% - Quantile	-5.04%	-12.12%	-7.68%	-5.88%	-5.88%
25% - Quantile	-2.64%	-5.64%	-2.52%	-3.12%	-3.48%
50% - Quantile	-0.24%	-0.72%	4.20%	0.24%	-1.44%
75% - Quantile	3.12%	4.56%	13.32%	5.64%	1.56%
90% - Quantile	8.04%	13.92%	28.08%	12.60%	6.24%
95% - Quantile	11.28%	23.28%	51.24%	18.36%	10.20%

This table shows the return performance both tor the entire sample period, 1988-2008, as well as during four sub-periods, 1988-92, 1993-98, 1998-2003 and 2004-2008. Panel A reports raw return performance for the equal-weighted universe of funds and the MSCI Europe benchmark. Panels B and C show in-sample single-factor and four-factor alpha values for the corresponding sample periods.

Table 3: Out of Sample Portfolio Performance (06/1993 - 02/2008)

	Benchmark	APFL	APML	AMA	Skep	CAPM
		Panel A: Full Sample Results				
Geometric mean	8.39%	11.76%	15.53%	17.24%	17.61%	7.52%
Arithmetic mean	10.50%	13.79%	17.82%	19.85%	20.22%	9.46%
Volatility	20.42%	20.60%	22.05%	23.78%	23.77%	19.72%
Sharpe ratio	0.314	0.471	0.623	0.663	0.679	0.273
Outperformance Frequency		53%	51%	54%	55%	52%
Single-Factor Alpha		5.68%	9.44%	11.38%	11.89%	0.52%
Single-Factor Alpha t-Stat		1.34	2.08	2.28	2.38	0.15
Single-Factor Beta		0.64	0.68	0.71	0.71	0.73
Four-Factor Alpha		11.74%	15.86%	17.42%	18.26%	3.11%
Four-Factor Alpha t-Stat		2.98	3.73	3.72	3.91	0.92
Beta - Market		0.67	0.71	0.75	0.75	0.74
Beta - SMB		0.48	0.50	0.50	0.51	0.21
Beta - HML		-0.13	-0.10	-0.20	-0.17	0.03
Beta - Momentum		0.27	0.28	0.29	0.32	0.03
		Panel B: Sub-Sample Results - 1993-2000				
Geometric mean	23.42%	20.88%	26.48%	27.85%	27.71%	17.39%
Arithmetic mean	25.53%	23.40%	29.24%	31.32%	31.16%	18.97%
Volatility	20.63%	23.27%	24.65%	27.92%	27.78%	18.04%
Sharpe ratio	0.993	0.789	0.981	0.941	0.940	0.772
Outperformance Frequency		52%	47%	47%	51%	47%
Single-Factor Alpha		5.83%	9.61%	11.22%	11.65%	0.61%
Single-Factor Alpha t-Stat		0.82	1.29	1.28	1.34	0.14
Single-Factor Beta		0.65	0.72	0.75	0.74	0.67
Four-Factor Alpha		31.05%	37.93%	43.09%	43.67%	10.89%
Four-Factor Alpha t-Stat		5.55	6.72	6.63	6.76	2.76
Beta - Market		0.57	0.65	0.66	0.65	0.63
Beta - SMB		0.79	0.95	1.05	1.03	0.27
Beta - HML		-0.04	-0.09	-0.15	-0.11	0.02
Beta - Momentum		0.88	0.91	1.11	1.14	0.43
		Panel C: Sub-Sample Results - 2001-2008				
Geometric mean	-6.96%	2.38%	4.31%	6.37%	7.24%	-2.61%
Arithmetic mean	-5.05%	3.85%	6.00%	7.99%	8.90%	-0.37%
Volatility	19.31%	17.09%	18.52%	18.09%	18.36%	21.05%
Sharpe ratio	-0.421	0.045	0.158	0.271	0.317	-0.164
Outperformance Frequency		60%	56%	61%	60%	52%
Single-Factor Alpha		4.92%	7.34%	9.79%	10.53%	1.44%
Single-Factor Alpha t-Stat		1.08	1.40	2.04	2.14	0.27
Single-Factor Beta		0.63	0.65	0.68	0.68	0.82
Four-Factor Alpha		3.58%	5.57%	8.12%	8.80%	-0.33%
Four-Factor Alpha t-Stat		0.84	1.13	1.80	1.90	-0.07
Beta - Market		0.53	0.51	0.54	0.55	0.68
Beta - SMB		0.41	0.30	0.12	0.19	0.31
Beta - HML		0.27	0.45	0.42	0.43	0.37
Beta - Momentum		-0.10	-0.10	-0.17	-0.15	-0.23

This table shows the portfolio performance for the four active conditional alpha investors as well as for the CAPM investor during the out-of-sample period 06/1993–02/2008 (Panel A) as well as for two sub-samples, 1993-2000 and 2001-2008. The arithmetic and geometric mean returns, the volatility and the Sharpe ratio are all annualized. The outperformance frequency shows the percentage of months during which the various investor types generated returns higher than the benchmark return. Results are based on the benchmark out-of-sample portfolio selection exercise that reviews portfolio weights every quarter, limits the maximum holdings in any one fund to 25%, rules out short-selling and uses the short-term Euribor, the default spread, the term spread and the dividend yield to capture time-variations in the conditional alpha and factor loadings with beliefs specified so that σ_α=10%/Month.

Table 4: Portfolio Country & Sector Rotation

	APFL				APML				AMA				Skeptic			
	1993	1998	2003	2008	1993	1998	2003	2008	1993	1998	2003	2008	1993	1998	2003	2008
A. Regional/Country Weight																
Austria	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Benelux	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
France	-	-	-	-	-	25%	1%	-	-	25%	-	-	-	25%	-	-
Germany	-	-	2%	-	-	-	7%	-	-	25%	-	-	-	25%	-	-
Italy	25%	-	-	-	-	11%	-	-	-	-	-	-	-	-	-	-
Pan-Europe	28%	27%	83%	43%	-	36%	75%	50%	25%	25%	44%	60%	25%	25%	50%	63%
Scandinavian	24%	42%	11%	13%	25%	-	18%	25%	25%	0%	45%	1%	46%	-	31%	1%
Spain/Portugal	-	31%	-	-	-	25%	-	-	3%	25%	-	-	2%	25%	-	-
Switzerland	-	-	-	-	-	3%	-	25%	-	-	-	14%	-	-	-	12%
UK	23%	-	-	31%	75%	-	-	-	47%	-	-	-	27%	-	-	-
Total Regional/Country	100%	100%	96%	87%	100%	100%	100%	100%	100%	100%	88%	75%	100%	100%	81%	75%
B. Sector Weight																
Banks & Financial	-	-	-	12%	-	-	-	-	-	-	1%	-	-	-	8%	-
Basic Industries	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Cyc Goods & Services	-	-	-	-	-	-	-	-	-	-	11%	-	-	-	11%	-
General Industry	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Information Technology	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Natural Resource	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Non Cyclical Con	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Pharma & Health	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Real Estate Europe	-	-	4%	-	-	-	-	-	-	-	-	-	-	-	-	-
Tech Media & Telecomm	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	25%
Telecom Services	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Utilities	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Total Sectors	-	-	4%	12%	-	-	-	-	-	-	12%	25%	-	-	19%	25%

This table presents portfolio weights for each of the four investor types considered in the analysis. Weights are reported as of June 30th, 1993, 1998, 2003 and 2008 and are based on the benchmark out-of-sample portfolio selection exercise that reviews portfolio weights every quarter, limits the maximum holdings in any one fund to 25%, rules out short-selling and uses the short-term Euribor, the default spread, the term spread and the dividend yield to capture time-variations in the conditional alpha and factor loadings with beliefs specified so that σ_α=10%/Month.

Table 5: Optimal Portfolio Weights (end of February, 2008)

	APFL	APML	AMA	Skept
Dexia Equities B Europe Small Caps C Cap	-	-	23.9%	25.0%
Ethis Vitalite	-	-	3.1%	6.7%
Holberg Norge	13.2%	-	1.2%	0.6%
Eurovalor Europa, FI	13.6%	2.5%	-	6.2%
EasyETF Euro Media Cap/Dis	-	-	25.0%	25.0%
Skandia European Opportunities A	-	-	25.0%	25.0%
Durlacher Growth Plus B Acc	16.9%	-	-	-
iShares SMI (DE)	0.3%	25.0%	14.3%	11.5%
Deka-EuropaValue CF	14.4%	-	-	-
Focused Fund - Equities EMU Flexible I	-	20.8%	-	-
Credit Suisse Equity (Lux) European Growth B	1.2%	1.8%	7.6%	-
Marlborough UK Micro Cap Growth	14.0%	-	-	-
MULTI-AXXION - STOCKPICKER	6.1%	-	-	-
ABN AMRO Europe Opportunities A EUR	7.0%	24.9%	-	-
OP-Eurooppa Kasvu A	1.1%	-	-	-
ABN AMRO Indeks	-	25.0%	-	-
ING (PL) Srodkowoeuropejski Sektora Finans Plus	12.3%	-	-	-

This table presents the portfolio holdings at the end of the sample (02/2008) for the four active, conditional alpha investors. Results are based on the benchmark out-of-sample portfolio selection exercise that reviews portfolio weights every quarter, limits the maximum holdings in any one fund to 25%, rules out short-selling and uses the short-term Euribor, the default spread, the term spread and the dividend yield to capture time-variations in the conditional alpha and factor loadings with beliefs specified so that σ_α=10%/Month.

Table 6: Out of Sample Performance Attribution (06/1993-02/2008)

	Benchmark	APFL	APML	AMA	Skep	CAPM
Arithmetic mean	10.50%	13.79%	17.82%	19.85%	20.22%	9.46%
Return from Pan-Euro Fund Selection		-1.52%	-0.70%	1.55%	6.13%	-1.46%
Return from Country Fund Selection		7.74%	11.05%	9.68%	3.80%	4.12%
Return from Sector Fund Selection		0.46%	-1.03%	-1.33%	0.42%	-0.43%
Return from Timing Country Weights		-2.05%	-0.93%	2.24%	-0.35%	0.61%
Residual		-1.35%	-1.08%	-2.78%	-0.29%	-3.88%
Total Outperformance		3.29%	7.32%	9.35%	9.72%	-1.03%

This table decomposes the abnormal return performance into four components, plus a residual. The differential return is measured relative to the benchmark MSCI Europe portfolio whose arithmetic mean return was 10.50% over the sample period. It comprises three selectivity components, namely returns from pan-European fund selection, country fund selection and sector fund selection. In addition there are returns from timing the country weights.

Table 7: Predictability Generated by Individual Macro Variables

Panel A: Agnostic Predictable Factor Loadings (APFL)

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Alpha	Alpha t-Statistic	Beta
1 - Short Rate Yield	13.66%	15.69%	20.67%	0.56	7.85%	1.80	0.61
2 - Term Spread	15.66%	17.36%	18.73%	0.71	9.80%	2.55	0.58
3 - Dividend Yield	15.33%	17.65%	22.10%	0.61	9.29%	2.02	0.67
4 - Default Spread	14.31%	16.11%	19.22%	0.63	8.04%	2.07	0.61
5 - Volatility	12.96%	14.84%	19.54%	0.55	6.61%	1.69	0.63
6 - Inflation	17.47%	19.47%	20.32%	0.76	11.47%	2.70	0.61
7 - Industrial Production	12.47%	14.57%	20.96%	0.50	6.46%	1.48	0.63
8 - Economic Sentiment	13.14%	14.69%	17.66%	0.60	7.11%	1.95	0.54

Panel B: Agnostic Predictable Market Loadings (APFL)

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Alpha	Alpha t-Statistic	Beta
1 - Short Rate Yield	13.00%	15.15%	21.25%	0.52	7.06%	1.59	0.64
2 - Term Spread	16.75%	18.53%	19.18%	0.75	10.98%	2.77	0.59
3 - Dividend Yield	15.42%	17.80%	22.46%	0.61	10.17%	2.13	0.65
4 - Default Spread	13.28%	15.21%	19.96%	0.56	7.29%	1.76	0.61
5 - Volatility	14.07%	15.78%	18.62%	0.63	7.82%	2.13	0.61
6 - Inflation	15.56%	17.52%	20.09%	0.67	9.65%	2.34	0.62
7 - Industrial Production	14.30%	16.63%	22.44%	0.56	8.64%	1.75	0.61
8 - Economic Sentiment	12.79%	14.30%	17.46%	0.59	6.83%	1.86	0.52

Panel C: Agnostic Macro Alpha (AMA)

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Alpha	Alpha t-Statistic	Beta
1 - Short Rate Yield	13.78%	15.88%	21.03%	0.56	7.76%	1.76	0.63
2 - Term Spread	15.81%	17.56%	19.03%	0.71	10.08%	2.56	0.58
3 - Dividend Yield	15.21%	17.54%	22.08%	0.61	9.83%	2.13	0.66
4 - Default Spread	13.13%	15.11%	20.25%	0.54	7.18%	1.71	0.62
5 - Volatility	16.45%	18.22%	19.00%	0.74	9.90%	2.70	0.63
6 - Consumer Price Index	15.76%	17.60%	19.50%	0.69	10.06%	2.41	0.56
7 - Inflation	14.93%	17.24%	22.33%	0.59	9.49%	1.93	0.61
8 - Economic Sentiment	17.45%	19.64%	21.93%	0.71	11.85%	2.43	0.58

Panel D: Skeptic

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Alpha	Alpha t-Statistic	Beta
1 - Short Rate Yield	13.52%	15.65%	21.19%	0.55	7.65%	1.72	0.64
2 - Term Spread	15.81%	17.55%	19.03%	0.71	10.08%	2.56	0.58
3 - Dividend Yield	15.64%	18.03%	22.37%	0.62	10.37%	2.24	0.68
4 - Default Spread	13.18%	15.15%	20.24%	0.55	7.24%	1.72	0.62
5 - Volatility	16.13%	17.79%	18.45%	0.74	9.89%	2.68	0.59
6 - Inflation	15.16%	17.01%	19.62%	0.66	9.47%	2.25	0.56
7 - Industrial Production	15.15%	17.45%	22.30%	0.60	9.71%	1.98	0.61
8 - Economic Sentiment	17.44%	19.64%	21.96%	0.71	11.84%	2.42	0.58

This table presents key performance statistics when the four investor types use a single state variable to track time-variations in the conditional alphas and factor loadings. Results are reported for the sample period 06/1993 – 02/2008 and assume the setup from the baseline investment exercise, i.e. no short-selling, individual fund holdings capped at 25% of the total holdings, quarterly rebalancing, and $\sigma_\alpha = 10\%$ per month. The short rate yield is measured by the 1-month Euribor; the term spread is the difference between the 10-year Euro area government benchmark bond yield and the 1-month Euribor; the dividend yield is the 12-month moving average of dividends divided by the current stock price; the default spread is the difference between yields on corporate bonds and yields on public debt securities; volatility is the squared 1-month change in the VDAX index; the inflation rate is the annual rate of change in the European consumer price index; industrial production is the annual rate of change in industrial production index for Europe (excluding construction); finally, the Economic sentiment indicator is measured as the monthly change in the Economic sentiment indicator for the opinion surveys tracked by the European Central Bank.

Table 8: Robustness to the Universe of Funds

Panel A: Regional & Country Funds Only

	Bmk	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	11.90%	16.62%	17.32%	17.33%	8.46%
Arithmetic mean	10.50%	13.92%	18.96%	19.97%	19.97%	10.37%
Volatility	20.42%	20.56%	22.24%	23.89%	23.83%	19.53%
Sharpe ratio	0.314	0.48	0.67	0.67	0.67	0.32
Beta		0.63	0.69	0.72	0.72	0.73
Alpha		5.87%	10.51%	11.33%	11.58%	1.53%
Alpha t-Stat		1.39	2.31	2.27	2.32	0.45
Outperformance Frequency		55%	53%	55%	56%	50%
Total No of Funds	4,930					

Panel B: Regional & Sector Funds Only

	Bmk	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	7.70%	7.51%	12.03%	11.84%	8.16%
Arithmetic mean	10.50%	9.27%	9.27%	14.09%	13.88%	9.87%
Volatility	20.42%	17.88%	18.88%	20.76%	20.66%	18.43%
Sharpe ratio	0.314	0.29	0.27	0.48	0.47	0.31
Beta		0.62	0.66	0.67	0.66	0.72
Alpha		1.26%	1.23%	6.03%	5.86%	1.10%
Alpha t-Stat		0.37	0.35	1.45	1.41	0.37
Outperformance Frequency		51%	51%	49%	50%	52%
Total No of Funds	3,010					

This table shows the effect on portfolio performance due to the exclusion of sector funds (Panel A) or country funds (Panel B). All other assumptions are identical to those from the baseline scenario, i.e., portfolio weights are set every quarter, maximum holdings in individual funds is capped at 25%, short-selling is ruled out and the state variables used to capture time-variations in the conditional alpha and factor loadings are the term spread, the dividend yield, the default spread, and the short-term interest rate with beliefs specified so that σ_α=10%/Month.

Table 9: Robustness to Country Momentum Factor

	Benchmark	APFL	APML	AMA	Skep	CAPM
Geometric mean		10.63%	15.07%	16.29%	16.90%	7.52%
Arithmetic mean	10.50%	12.65%	17.48%	18.90%	19.49%	9.46%
Volatility	20.42%	20.45%	22.58%	23.83%	23.71%	19.72%
Sharpe ratio		0.419	0.593	0.622	0.650	0.273
Beta		0.68	0.71	0.73	0.72	0.73
Alpha		4.34%	8.97%	10.23%	11.01%	0.52%
Alpha t-Stat		1.09	1.95	2.07	2.23	0.15
Outperformance Frequency		51%	50%	53%	55%	49%

This table shows the sensitivity of our results with regard to changing how the momentum factor in the four-factor alpha model is constructed. The baseline analysis assumes that the sector momentum factor is constructed based on the prior-12-month return performance of the 18 super sectors tracked by the STOXX indices. It then constructs the realized momentum factor as the difference between the equal-weighted return on the top-six and the bottom-six sectors. This exercise is then repeated every month to get a time-series of momentum realizations. The country momentum factor uses the same methodology, but now applied to the 16 MSCI Europe country indices. For this case we consider the equal-weighted return on the top-three countries relative to the equal-weighted return on the bottom-three countries. All other assumptions from the baseline scenario remain valid.

Table 10: Robustness to Investor Trading Strategy Restrictions

Panel A: Limit Sales to 15%/Quarter

	Benchmark	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	10.96%	15.57%	17.18%	16.95%	7.40%
Arithmetic mean	10.50%	12.90%	17.79%	19.67%	19.38%	9.26%
Volatility	20.42%	20.03%	21.66%	23.09%	22.74%	19.28%
Sharpe ratio	0.314	0.440	0.633	0.675	0.673	0.269
Beta		0.63	0.67	0.70	0.70	0.73
Alpha		4.82%	9.41%	11.24%	11.04%	0.33%
Alpha t-Stat		1.18	2.13	2.34	2.35	0.10
Outperformance Frequency		53%	51%	54%	54%	50%

Panel B: Portfolios Formed with No Weight Restrictions

	Benchmark	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	11.59%	17.57%	21.58%	21.67%	7.49%
Arithmetic mean	10.50%	13.93%	20.52%	24.83%	25.05%	9.43%
Volatility	20.42%	22.44%	25.48%	26.79%	27.42%	19.69%
Sharpe ratio	0.314	0.439	0.645	0.774	0.765	0.272
Beta		0.64	0.74	0.75	0.77	0.74
Alpha		5.78%	11.83%	16.30%	16.49%	0.45%
Alpha t-Stat		1.20	2.18	2.80	2.78	0.13
Outperformance Frequency		53%	51%	55%	54%	50%

Panel C: Portfolios of 250 Funds with Highest Conditional Alpha

	Benchmark	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	11.60%	15.43%	17.21%	17.74%	9.35%
Arithmetic mean	10.50%	13.70%	17.70%	19.81%	20.35%	11.14%
Volatility	20.42%	20.88%	21.98%	23.77%	23.75%	18.91%
Sharpe ratio	0.314	0.461	0.620	0.662	0.685	0.374
Beta		0.66	0.68	0.71	0.71	0.72
Alpha		5.39%	9.34%	11.34%	12.03%	2.45%
Alpha t-Stat		1.28	2.06	2.27	2.41	0.77
Outperformance Frequency		53%	51%	54%	55%	52%

This table shows the effect of imposing different constraints on the portfolio weights. All results are based on performance during the out-of-sample period from 06/1993 – 02/2008. The baseline scenario selected the 50 funds with the highest conditional alpha and assumed no restrictions on the changes in the weights, but capped holdings in individual funds to a maximum of 25% of the portfolio. Panel A restricts changes in the portfolio weights so the fund cannot divest more than 15% per quarter (e.g., a fund can go from 20% to a minimum of 5% over a three-month period). This has the effect of reducing turnover. In contrast, Panel B lifts the constraints on the portfolio weights which are no longer capped at 25%, although short sales are still ruled out. Finally, Panel C tests the portfolio performance when the initial sort selects the 250 funds with the highest conditional alphas. All other assumptions are identical to those from the baseline scenario, i.e., portfolio weights are set every quarter and the state variables used to capture time-variations in the conditional alpha and factor loadings are the term spread, the dividend yield, the default spread, and the short-term interest rate with beliefs specified so that σ_α=10%/Month.

Table 11: Robustness to Investor Beliefs

Panel A: Investor Belief $\sigma_\alpha = 1\%$/Month

	Benchmark	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	12.7%	13.6%	15.9%	14.6%	7.8%
Arithmetic mean	10.50%	14.7%	15.7%	18.4%	16.7%	9.4%
Volatility	20.42%	20.7%	21.5%	23.5%	20.9%	18.0%
Sharpe ratio	0.314	0.51	0.54	0.61	0.60	0.30
Beta		0.65	0.67	0.70	0.63	0.68
Alpha		6.55%	7.39%	9.98%	8.77%	0.98%
Alpha t-Stat		1.55	1.70	2.03	2.01	0.32
Outperformance Frequency		54%	52%	57%	53%	50%

Panel B: Investor Belief $\sigma_\alpha = 0.1\%$/Month

	Benchmark	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	12.7%	13.5%	15.7%	10.6%	7.8%
Arithmetic mean	10.50%	14.8%	15.7%	18.2%	12.1%	9.4%
Volatility	20.42%	20.7%	21.4%	23.4%	17.7%	18.0%
Sharpe ratio	0.314	0.52	0.54	0.60	0.45	0.30
Beta		0.65	0.67	0.70	0.58	0.68
Alpha		6.63%	7.36%	9.80%	3.93%	0.98%
Alpha t-Stat		1.57	1.69	1.99	1.14	0.32
Outperformance Frequency		54%	52%	57%	53%	50%

This table shows how the tightness of investor priors affects the portfolio weights. All results are based on performance during the out-of-sample period from 06/1993 – 02/2008. The baseline analysis assumes that $\sigma_\alpha = 10\%$. In Panels A and B, we change this assumption and instead set $\sigma_\alpha = 1\%$ per month (Panel A) or 0.1% per month (Panel B). All other assumptions are identical to those from the baseline scenario, i.e., portfolio weights are set every quarter, maximum holdings in individual funds is capped at 25%, short-selling is ruled out and the state variables used to capture time-variations in the conditional alpha and factor loadings are the term spread, the dividend yield, the default spread, and the short-term interest rate.

Table 12: Out-of-Sample Long-Short Model Portfolio Performance (06/1993-02/2008)

Panel A: Short-Only Performance

	Benchmark	APFL	APML	AMA	Skep	CAPM
Geometric mean	8.39%	-6.28%	-7.20%	-5.83%	-5.19%	-8.43%
Arithmetic mean	10.50%	-3.85%	-4.98%	-3.15%	-2.45%	-8.16%
Volatility	20.42%	22.32%	21.37%	23.46%	23.75%	7.36%
Sharpe ratio	0.314	-0.355	-0.424	-0.308	-0.275	-1.663
Outperformance Frequency		43%	43%	42%	41%	36%
Single-Factor Pricing						
Alpha		-3.07%	-4.37%	-2.11%	-1.27%	-11.88%
Alpha t-Stat		-0.72	-1.07	-0.47	-0.28	-6.12
Beta		-0.75	-0.72	-0.78	-0.80	-0.01
Four-Factor Pricing						
Alpha		-7.92%	-8.96%	-8.30%	-7.76%	-12.29%
Alpha t-Stat		-1.96	-2.27	-1.94	-1.82	-6.36
Beta - Market		-0.76	-0.73	-0.79	-0.81	0.00
Beta - SMB		-0.44	-0.43	-0.54	-0.56	0.02
Beta - HML		-0.14	-0.02	-0.12	-0.17	-0.13
Beta - Momentum		0.16	0.11	0.11	0.13	-0.04

Panel B: Self-Financing Long/Short Portfolio

Geometric mean	8.39%	12.65%	15.62%	18.63%	19.68%	3.75%
Arithmetic mean	10.50%	14.02%	16.92%	20.78%	21.85%	5.38%
Volatility	20.42%	16.93%	16.59%	21.59%	21.63%	18.08%
Sharpe ratio	0.314	0.587	0.774	0.774	0.822	0.072
Outperformance Frequency		47%	49%	47%	47%	47%
Single-Factor Pricing						
Alpha		10.74%	13.19%	17.39%	18.74%	-3.23%
Alpha t-Stat		2.44	3.04	3.08	3.32	-1.14
Beta		-0.12	-0.04	-0.07	-0.09	0.72
Four-Factor Pricing						
Alpha		11.60%	14.69%	16.90%	18.28%	-1.36%
Alpha t-Stat		2.94	3.62	3.22	3.53	-0.48
Beta - Market		-0.09	-0.02	-0.04	-0.06	0.73
Beta - SMB		0.02	0.05	-0.07	-0.08	0.20
Beta - HML		-0.28	-0.13	-0.34	-0.35	-0.11
Beta - Momentum		0.42	0.37	0.40	0.44	-0.02

This table presents performance statistics for portfolios that allow short-selling of mutual funds. Panel A considers the ability of the stock selection methodology to identify underperformers by studying a portfolio with short-only positions. Panel B reports the performance of a 130-30 strategy with limited short-selling. Panel C considers the performance of a self-financing portfolio that allows for higher-still short selling of underperforming funds.