Mutual Fund Return Predictability in Segmented Markets*

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Abstract

This paper studies the predictability of equity mutual fund performance in segmented markets. Specifically, we use macroeconomic variables to predict the performance of equity funds in Europe, including Pan-European, country, and sector funds. We find that macro-variables are useful in locating funds with future outperformance, and that country-specific mutual funds provide the best opportunities for fund rotation strategies using macroeconomic information. Specifically, our baseline long-only strategies provide four-factor alphas of 7-12%/year over the 1993-2008 period. Our study provides new evidence on the benefits of local asset managers in segmented markets, as well as how macroeconomic information can be used to locate and exploit these benefits.

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1 Introduction

A vast literature focuses on the predictability of U.S. and international stock returns using macroeconomic variables, such as the short government interest rate or the yield spread between defaultable and government bonds. For instance, Ferson and Harvey (1993) find that international stock indexes are predictable using macroeconomic indicators as conditioning variables. More strikingly, Ferson and Harvey (1999) find that broad economic variables explain the cross-sectional variation in U.S. individual stock returns better than the Fama and French (1993) factors.[1] Avramov and Chordia (2006) extend this literature by showing that substantial alphas are derived from choosing individual stocks based on macroeconomic conditioning variables. All of the aforementioned papers indicate that substantial gains in portfolio choice may be obtained from the use of such macroeconomic information.

Another literature examines whether asset managers or sell-side analysts are better able to collect private information on stocks in their geographic area. For instance, Coval and Moskowitz (1999) find that fund managers are better able to select stocks of firms headquartered close by, while Cohen, Frazzini, and Malloy (2008) find that fund managers with past educational ties to corporate managers overweight and outperform in the stocks of those corporations. This literature suggests that geographic proximity and/or social networks may aid the transfer of private information. Further, Sonney (2009) finds that European sell-side analysts with a country specialization outperform analysts with an industry specialization, suggesting that an understanding of local product markets is crucial to analyzing stock valuation.

These two seemingly unrelated bodies of research suggest that professional asset managers may be better able to choose local stocks under certain macroeconomic conditions. For instance, during the recent financial crisis, we might expect that active UK asset managers would be valuable because of their superior abilities in the face of large asymmetric information on the value of banking stocks. On the other hand, during the technology collapse, we might prefer to invest in active Scandinavian managers due to their special knowledge of telecommunication companies–thus, helping to sort out which firms might recover most quickly. Hence, a rotation among asset managers

[1] Ferson and Harvey (1999) show that macroeconomic variables explain the cross-section of stock returns better than the Fama and French factors even when the loadings on the factors are conditioned on the same macroeconomic variables. Thus, even conditional Fama and French risk variables cannot capture conditional cross-sectional returns as well as macroeconomic variables.

with local expertise as macroeconomic conditions evolve may outperform strategies involving either local expertise or macro indicators alone to choose active managers.

This paper brings these issues to a unique dataset that contains the monthly returns of European-domiciled equity mutual fund managers over a 20-year period. Specifically, we ask whether an investor can outperform when she has access to country-specific managers across several developed European markets, and is allowed to rotate the portfolio allocation among the countries and managers as macroeconomic conditions in Europe evolve. We believe that our paper uniquely addresses this question, since European stock markets are segmented (although decreasingly so over the past few years), and since our dataset contains returns for both Pan-European active funds as well as country-specialized active funds. Specifically, we ask under which conditions a generalist fund (the Pan-European fund) should be chosen due to its ability to time various countries and sectors (perhaps itself using macroeconomic information); conversely, we ask when a specialized country or regional fund should be chosen due to its greater knowledge of industries or stocks in its local geographic area.

Our paper, in studying the monthly returns for over 4,000 mutual funds having a (developed-market) European equity focus over the 1988 to 2008 period, covers the recent period of market integration across Europe. This market integration brings several interesting questions to the issue of active management. For example, it is natural to wonder whether the reduced frictions of investing across Europe have decreased the usefulness of country-specific investing skills. And, we may further wish to know whether active managers that specialize in different country equity markets exhibit varying skills during different European business cycle conditions. Our study also has significant economic real-world implications. European funds grew from a little over \$3 trillion during 2000 to nearly \$9 trillion during 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 to \$12 trillion. Further, there were 35,000 European-domiciled funds by the end of 2007 (Investment Company Institute, 2008), far more than the number of U.S.-domiciled funds, indicating that the European market is highly fragmented. Clearly, European investors have a confusing array of decisions to make in choosing their stock portfolio managers, including country allocations, sector allocations, and specialized vs. generalist European stock managers. Our study brings a new method of fund selection to bear to the complex problem of mutual fund manager choice in segmented markets; we illustrate the potential gains from our methodology in European mutual fund markets.[2]

Our study also adds evidence to the debate on whether countries or sectors are more segmented in financial markets in light of the aforementioned integration of European markets. For instance, Roll (1992) argues that industry structure explains a large portion of country stock index returns, while Heston and Rouwenhorst (1994) argue that country effects are a stronger influence. Further evidence is provided by Sonney (2009), who finds that stock analysts who are country specialists benefit from an informational advantage over sector specialists due to the country analysts' superior knowledge about industries and firms that are geographically proximate. In studying the expertise of country-specific vs. sector-specific asset managers in Europe, we bring fresh evidence to the more general asset pricing question of country vs. industry.

We focus on the dynamics of active management skills and how an investor might optimally invest in active funds during varying business conditions. 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 by active managers in Europe. 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 state 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 provide an out-of-sample test relative to the U.S. results, and in part to see if there are differences in how the macroeconomic environment affects the performance of funds in a segmented market such as Europe.

[2] Despite the economic significance and fragmentation 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, or some combination of these countries. One such widely known study is Otten and Bams (2002). 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), and 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. 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.

Moreover, a major contribution of our paper is that we generalize existing models for Bayesian fund selection by allowing not only for predictability in alphas, factor loadings, and benchmark returns, but also by considering both integrated market models, which assume a single common European equity risk factor, and (building on Bekaert and Harvey, 1995) partially segmented models that allow both pan-European and individual European country risk factors to affect country mutual fund returns. We do so in a unified framework that nests many existing models as special cases. This part of our analysis takes advantage of a unique aspect of our study–our dataset has funds categorized by country investment objectives.

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 median one-factor and four-factor alphas are -0.84%/year and -0.24%/year, respectively. This finding indicates that our benchmarks successfully control for common variation in European equity mutual fund returns.

We next move to our main contribution, which 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, and to identify if and how macroeconomic information helps to improve the selection of these funds in a segmented market environment. Given the modest costs of trading most open-ended mutual funds, such a strategy would be attractive to many investors in European funds if it is successful. By including funds whose investment objectives focus on a particular region or sector, as well as funds that invest in the entire European region, we allow our strategies to generate abnormal returns by timing countries or sectors, or by identifying funds with superior security selection within each of these investment objective categories. Thus, we can determine whether specialist country or sector funds, during certain phases of the business cycle, outperform 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.

Following recent work in the mutual fund literature (e.g., Pastor and Stambaugh, 2002a,b), we study European mutual fund choice through the lenses of four different types of Bayesian investors. These four types have differing prior views of (1) the ability of mutual funds to generate abnormal returns, and (2) 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. In particular, we find evidence that a number of investment strategies (that use macroeconomic variables to predict fund returns) generate alphas from 4-8%/year (after fund-level trading costs and fees, except for load fees), when measured with a single-factor model, and from 7-12%/year with a four-factor model that controls for fund exposures to size, book-to-market, 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 model parameter estimates, then revise their prior beliefs recursively through time 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 tests conducted over the periods 1993-2000 and 2001-2008.

For investor types believing that active managers may be able to generate abnormal returns, we also find that the ability to identify superior performing funds is improved by considering market segmentation effects. Our baseline analysis, which constrains the portfolio weight of each fund to a maximum 10% of the strategy portfolio, finds CAPM alpha enhancements of 2-5% per year from using macroeconomic state variables to choose funds, while allowing for segmentation in market risk factors generally leads to improvements of 0.5-2% per year.

These baseline results assume a standard set of macroeconomic state variables previously used to analyze U.S. mutual fund return predictability by Avramov and Wermers (2006)–the dividend yield, default spread, short-term interest rate, and term spread. We find that these variables prove valuable in selecting funds with superior performance in Europe, giving them important out-of-sample credibility. Interestingly, we find that some additional variables, such as growth in industrial production, inflation, or a proxy for stock market volatility, are useful in identifying funds with superior performance. The predictive success of these additional macro variables is consistent with their documented power in predicting market returns over historical periods prior to most of our time series by Fama and Schwert (1981) (inflation), Pesaran and Timmermann (1995) (industrial production), and Welch and Goyal (2008) (volatility).[3]

[3] Our finding that a different set of macroeconomic variables forecast mutual fund performance in a segmented

To better understand the sources of outperformance, we undertake an attribution analysis that decomposes investor returns into that from (1) the selection of Pan-European funds, (2) the selection of country funds, (3) the selection of sector funds, and (4) the timing of country weights implied by the selection of country funds. This analysis shows that the superior returns associated with the macroeconomic-driven strategies arise from the last three sources of performance, and not from choosing Pan-European funds. These Pan-European funds, while providing lower-cost diversification, do not exhibit exploitable alphas, either time-varying or unconditional.[4] As such, our study adds weight to the conjecture that European markets have a stronger country segmentation than industry segmentation–similar to the findings for sell-side analysts of Sonney (2009).

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 largely determine the parameters that they use in their portfolio analysis, that is, when we designate diffuse priors. Further, by evaluating the impact of different beliefs for different investor-types, and different assumptions regarding market integration or segmentation, we show that macroeconomic information and partial segmentation both play important roles in allowing investors to generate significant outperformance.[5] Indeed, while a large part of the improved performance against a CAPM benchmark comes from a fixed (constant) alpha component, modeling time-varying alphas substantially helps to improve performance from country fund selection and from timing country weights.

In addition to identifying funds with superior performance, our model proves capable in identifying funds with inferior performance, that is, funds least likely to hold outperforming stocks. Thus, a self-financing long-short strategy adds further to the performance of a long-only strategy, while controlling the exposure to systematic risk factors. This finding indicates that mimicking the portfolio holdings of European funds, where securities held by inferior funds are shorted, may

market–Europe–relative to the U.S., presents a new and intriguing question for future research on conditional asset pricing. We also note that results for all macro variables that we considered are included in this paper. We did not selectively include results based on the success of the particular macro variable.

[4]Although macro variables do not appear to be particularly successful in timing passive country equity markets, they do perform an important role in finding which country-specific active funds are most likely to generate alpha under current economic conditions. Thus, our models do perform well in timing countries with the most promising active managers.

[5]Indeed, there is a substitution effect between our country-specific risk factors (used in the segmented models) and our macroeconomic variables. That is, macroeconomic variables show a lower impact (although still significant) when we use a model with both Pan-European and country-specific market risk-factors.

outperform our basic long-only fund-level strategy (depending on stock trading costs, as well as the impact of the delay in public availability of fund holdings information–which may be longer in Europe than in the U.S.). We leave this issue as a promising avenue for further research.

To summarize, our study provides the first evidence of the value of specialized regional skills by active fund managers in segmented markets. Further, we show that these specialized skills are time-varying, and are best captured through the use of macroeconomic variables. And, to answer our earlier question, country funds continue to be important to capture time-varying alpha, even with the reduced frictions of investing across Europe during the latter part of our sample.

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

This section describes our data on European-domiciled equity mutual funds in addition to the macroeconomic state variables used in the analysis.

2.1 Mutual fund data

Our data is from Lipper, and consists of monthly returns with dividends reinvested at the end of the day that they are paid on European-domiciled equity mutual funds with a European investment focus (either Pan-European or country/region/sector specific) over the period June 1988 to February 2008, a total of 237 monthly observations. These returns are net of fees and trading costs, i.e., these are returns actually experienced by investors in the funds (ignoring any load charges). The sample includes funds that were alive at the end of the sample, as well as non-surviving funds−about 15% of the funds were discontinued during our sample. We include actively managed funds as well as specialist funds with a more passive investment objective (e.g., exchange-traded funds based on an index).

Table 1 lists the number of funds at five-year intervals by investment objective. The number of funds in our sample rose sharply from just over 200 in 1988 to 4,200 at the end of the sample, at least doubling during each of 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 are shown in section II of Table 1. In particular, there were 3,936 such funds in 2008, compared with only 264 sector funds. By far, the largest group of regional funds is Pan-European funds−these are funds that are allowed to invest across all the developed European stock markets. The number of Pan-European funds increases faster than any other category, comprising more than half of the total number of funds in our sample by 2008.[6] Important country- or region-specific funds include the UK (625 funds in 2008), Scandinavia (314), and France (275).

Our database contains relatively few European sector funds (shown in section 3)–only 264 by 2008. Among these, only Real Estate, Banks and Financial, Information Technology, and Cyclical Goods and Services have 20 or more funds in 2008. Interestingly, with the exception of real estate funds, there are very few funds that specialize in particular European sectors prior to 2003.

It is worth noting that the division between sector funds and country funds is less clear-cut than may first seem the case. Indeed, 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). Thus, investors likely used country funds to invest in certain industries during earlier periods of our time-series.

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 B of Table 1, we show that the average expenses and fees have been quite stable over the period from 1998-2008, and have ranged between 1.4% and 1.6% per annum. Although our sample includes low-fee passive funds, it is still evident that fees on European funds exceed those in the U.S. during the later years, on average.

2.2 State variables and risk factors

We control for risk exposures in measuring the funds' ability to outperform following the four factor approach advocated by Carhart (1997). It is something of a challenge to determine the

[6]These Pan-European funds often tend to have specialized investment objectives similar to many U.S. mutual funds–such as growth, high dividend, or small capitalization. An further examination of the fund names indicates that Pan-European funds, in general, do not appear to specialize along industry or broad sector lines (which would imply a particular regional focus, such as telecom stocks in Scandinavia).

proper benchmarks to use in Europe, as markets have become more integrated over the 20 years that we study. However, we start with a Pan-European four-factor model. The four factors include a market risk factor, measured by the MSCI Europe total return index minus the 1-Month Euribor short rate, a size factor (small minus big, or SMB) 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 growth portfolios. Finally, our momentum factor is constructed from the following month return difference between the six top and six bottom 12-month lagged return sectors (out of a total of 18 sectors) from the Dow Jones STOXX 600 Super Sector Indices.[7] For comparison, we also analyze results (but do not construct strategies) using a more conventional single-factor approach that only includes the market factor.[8]

Recognizing that European equity markets were somewhat segmented over at least part of our time period, we also employ some augmented models in our analysis. Specifically, we add, to the four-factor model above, country-specific market indexes in some of our analysis to country-focused funds. For instance, when we turn to such models, a UK fund will have, in addition to the Pan-European factors, a UK market index in a five-factor model.[9]

Recent studies suggest that funds' ability to generate alpha varies over time, in a way that can be predicted with macroeconomic state variables. Moreover, fund exposures to risk factors may also be state- and time-dependent.[10] 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 on a 10-year Euro area government bond and the 1-month Euribor rate. Second, we consider the dividend yield for a portfolio of European stocks.[11] Third, we use the default

[7]This follows the Moskowitz and Grinblatt (1998) evidence in the U.S. that industry momentum is stronger than individual stock momentum.

[8]Further details on the data sources and construction of these variables are provided in the appendix.

[9]Our country specific market factors use the Euribor short rate as a proxy for the local riskfree rate, since local rates are not available for some countries for the majority of the time-period of our study.

[10]Mamaysky et al. (2007) use a time-varying coefficient model to capture time-varying alphas, while Kosowski (2006) uses a regime-switching model of alphas. Ferson and Schadt (1996), Christopherson et al. (1998), and Lynch and Wachter (2007) model alphas and/or betas as functions of observable state variables. Avramov and Wermers (2006) find that such macroeconomic state variables are useful in identifying time-varying skill among mutual fund managers.

[11]The monthly dividend yield for Europe, obtained from the Global Financial Database, is based on large capitalization stocks in each country that represent about 75% of the capitalization of that market. Dividend data are based

spread on European bonds, calculated as the difference between the yields on corporate bonds and yields on government debt. Fourth, we consider the level of the short risk-free rate, measured as the 1-month Euribor. Similar variables defined for the U.S. have been widely used in the literature on time-varying investment opportunities (e.g., Ferson and Harvey, 1999) and play a key role in the study of U.S. mutual funds by Ferson and Schadt (1996) and Avramov and Wermers (2006).

We note that, while several studies use the above-mentioned macro variables in the U.S., the macro variables that best predict asset returns in Europe are less known, and may be different. Therefore, in addition to the above list, we also consider a set of new macroeconomic variables, all motivated by past research. First, we use the level of volatility in the stock market (Welch and Goyal, 2008), measured as the change in the VDAX index for the German stock market. We also use the level of inflation, measured as the year-over-year change in the European Consumer Price Index (Fama and Schwert, 1981), the 12-month change in the level of industrial production (Pesaran and Timmermann, 1995), and the change in the economic sentiment indicator obtained from opinion surveys conducted by the European Central Bank (David and Veronesi, 2009). We also explore the effect of a new currency risk factor which tracks the importance of local currency volatility, measured against parity rates such as the ECU prior to year 2000 and the Euro thereafter, and weighted by each local currency's equity market share. This currency factor is especially useful for separating currency returns from local returns measured in the numeraire currency (ECU) during the early part of our sample period, when currency markets were more segmented across countries.

In the benchmark analysis, we use European as opposed to country-specific state variables. This is dictated by our desire to keep the number of state variables limited. However, as mentioned above, the correct macro variables to use in such a partially segmented market is not clear from prior research. Thus, in a subsequent analysis, we also consider country-specific macro state variables. Data sources as well as a brief characterization of the properties of the key state variables used in the study are provided in the appendix.

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upon the dividends reported for the trailing twelve months, when the dividends are known by the market. Fourth quarter dividends, for example, are generally not reported until February, and only at this point are fourth quarter dividends included in the dividend yield calculations.

3 Methodology

This section first presents the model for capturing skills among mutual fund managers, then continues to describe the different investor types characterized by their prior beliefs concerning manager skills. Finally, we explain how we account for market segmentation in the context of our models.

3.1 Dynamic Return Generating Process

The general return generating model for our sample of mutual funds takes the following form:

$$\begin{aligned} r_{i,t} =& \alpha_{i0} + \alpha'_{i1} z_{t-1} + \beta'_{i0G} r_{G,t} + \beta'_{i0S} r_{S,t} + \beta'_{i1} \left(r_{B,t} \otimes z_{t-1} \right) + \varepsilon_{i,t} \\ \equiv& \theta'_i \begin{bmatrix} x_t \\ r_{G,t} \\ r_{S,t} \\ r_{B,t} \otimes z_{t-1} \end{bmatrix} + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

for $\theta_i = (\alpha_{i0}\ \alpha'_{i1}\ \beta'_{i0G}\ \beta'_{i0S}\ \beta'_{i1})'$, $x_t = (1\ z'_{t-1})'$, and $\varepsilon_{i,t} \sim N(0, \sigma_i^2)$. Here, $r_{i,t}$ is the month-t return on mutual fund i, measured in excess of the risk-free rate, and z_{t-1} is a set of m state variables known to investors at time $t-1$, used to measure the state of the economy. We split the vector denoting the excess returns for our set of k zero-cost benchmarks, $r_{B,t}$, into a set of k_G globally integrated benchmarks, denoted $r_{G,t}$, and k_S locally segmented (country) benchmarks, denoted $r_{S,t}$.

The coefficient parameter α_{i0} represents a constant abnormal return due to individual fund manager skill, net of expenses, while α_{i1} captures the sensitivity (predictability) of individual manager skill with respect to lagged business cycle variables, z_{t-1}. The risk factor loadings, β_{i0}, are separated into integrated (β_{i0G}) and locally segmented (β_{i0S}) loadings, and represent the constant components of fund risk exposures. Moreover, β_{i1} measures the degree to which fund risk exposures vary predictably with business cycle variables. In our tests to come shortly, we focus on models where we assume $\beta_{i1} = 0$ with respect to local market factors (but not with respect to the MSCI Europe index) in our segmented models (to preserve degrees-of-freedom). Finally, $\varepsilon_{i,t}$ is a fund-specific return component that is assumed to be uncorrelated across funds and over time, as well as being normally distributed with mean zero and standard deviation σ_i.

The risk factors are assumed to follow a simple autoregressive process with predictability in benchmark returns characterized by the matrix A_B:

$$\begin{bmatrix} r_{G,t} \\ r_{S,t} \end{bmatrix} \equiv r_{B,t} = \alpha_B + A_B z_{t-1} + \varepsilon_{B,t}. \tag{2}$$

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

$$z_t = \alpha_Z + A_z z_{t-1} + \varepsilon_{z,t} \tag{3}$$

Finally, the innovations $\varepsilon_{B,t}$ and $\varepsilon_{z,t}$ are assumed to be independently and normally distributed over time, and mutually independent of $\varepsilon_{i,t}$.

3.2 Incorporating Restrictions and Beliefs from Asset Pricing Models

Given the linear return generating process, (1) - (3), the Bayesian framework provides a flexible approach to modeling the implications of asset pricing models either through dogmatic restrictions on parameter values, prior beliefs on those parameter values, or some combination of the two. All of our investor models incorporate informative investor beliefs that some linear combination of the parameters governing the return generating process is centered at a given value. Frequently, these priors relate information solely about an individual parameter, but we can also consider priors that relate information in the form of cross-parameter restrictions. For example, an investor may hold conditional beliefs that the total contribution of macroeconomic predictability to a fund's expected return, $\alpha'_{i1} z_{t-1}$, has mean zero and standard deviation σ_α. By analyzing this general case, we provide a unifying framework for characterizing predictive expected returns, variances, and covariances for portfolio selection.

We often want to explicitly restrict parameters, a priori, on theoretical grounds to limit the effects of estimation error on our posterior moments.[12] We can incorporate such restrictions within a natural conjugate framework as the limit of conditional normal-gamma prior beliefs. Recalling that m is the number of macro or state variables and k is the number of benchmarks, there are

[12] In practice, when implementing restrictions on the coefficient for a single variable, it is often best to simply remove those variables from the set of regressors. This is especially important if the number of observations may be less than the total number of regressors resulting in an unidentified regression. For instance, if the model contains 4 macro factors, 4 benchmarks, and 11 country indices, it would involve a total of 80 regressors. If we have less than 80 observations, the likelihood would imply zero idiosyncratic variance, no variance for coefficient estimates, and so consequently, the Bayesian restrictions would not take hold.

$1+m+k+km$ parameters in (1), so we can represent d dogmatic restrictions on these parameters by forming the $d \times (1+m+k+km)$ matrix, F_R. Denoting a $d \times d$ matrix of zeros by $0_{(d\times d)}$, we then express our prior beliefs in the context of the standard Normal-Gamma model:

$$F_R\theta_i|\sigma_i^2 \sim N\left(0, \sigma_i^2 0_{(R\times R)}\right); \;\; \sigma_i^{-2} \sim G\left(\underline{s}^{-1}, \underline{t}\right). \tag{4}$$

We specify the gamma-distributed beliefs on the conditioning idiosyncratic variance as diffuse so that $\underline{s}$ is any constant with degrees of freedom $\underline{t}$= 0.

In cases where we do not wish to *dogmatically* impose the restrictions implied by asset pricing models, we can incorporate the implications of those models through a set of p informative priors. This can again be done through the the $p \times (1+m+k+km)$ matrix, F_I:

$$F_I\theta_i|\sigma_i^2 \sim N\left(f_{I,i}, \sigma_i^2\Omega\right); \;\; \sigma_i^{-2} \sim G\left(\underline{s}^{-1}, \underline{t}\right), \tag{5}$$

where Ω reflects the tightness of the prior beliefs. Of particular interest will be investor priors with regard to the components of manager skill, $\alpha_{i0} + \alpha_{i1}' z_{t-1}$, in the return equation, (1). We'll often refer to the prior standard deviation for these beliefs as σ_α. This parameter measures how strong an investor's views are concerning the possibility that managers have the ability to consistently outperform, with smaller values indicating increasing skepticism about manager skills.

To complete the characterization of investors' beliefs, we augment the linear combinations of parameters for which we have dogmatic restrictions or informative priors with additional uninformative priors over independent linear combinations of parameters to span the parameter space. We do this through a set of uninformative priors, F_U, so that the complete set of priors is represented by the following $(1+m+k+km) \times (1+m+k+km)$ matrix, F, and the parameters $\underline{f}$, $\underline{\Phi}$:

$$F = \begin{bmatrix} F_R \\ F_I \\ F_U \end{bmatrix}; \;\; \underline{f_i} = \begin{bmatrix} 0_{(d\times 1)} \\ f_{I,i} \\ 0_{(1+m+k+km-d-p)} \end{bmatrix},$$

$$F\theta_i|\sigma_i^2 \sim \lim_{c\to\infty} N\left(\underline{f_i}, \sigma_i^2 \begin{bmatrix} 0_{(d\times d)} & 0 & 0 \\ 0 & \Omega & 0 \\ 0 & 0 & cI_{(1+m+k+km-d-p)} \end{bmatrix}\right) \equiv N\left(\underline{f_i}, \sigma_i^2 \underline{\Phi}\right). \tag{6}$$

The matrix F_U can take any form, as long as the partitioned matrix F has full rank, $|F| > 0$.

To facilitate characterizing posterior expectations using standard updating formulae, it is convenient to express the priors in the form:

$$\theta_i|\sigma_i^2 \sim N\left(\underline{\theta}_i, \sigma_i^2\underline{V}\right). \tag{7}$$

where $\underline{\theta}_i$ is the prior expectation for θ_i and $\sigma_i^2\underline{V}$ is the variance covariance matrix for prior beliefs. This prior can be constructed from the representation of beliefs in equation (6) by observing that, for any non-singular matrix $\tilde{F}$,

$$\tilde{F}\theta_i|\sigma_i^2 \sim N\left(\tilde{F}\underline{\theta}, \sigma_i^2\tilde{F}\underline{V}\tilde{F}'\right).$$

Hence, to translate the beliefs from equation 6 into a natural conjugate specification, define $(\underline{\theta}_i, \underline{V})$ so that:

$$F\underline{\theta}_i = \underline{f}_i; |F| > 0 \Rightarrow \underline{\theta}_i = F^{-1}\underline{f}_i \tag{8}$$

$$\sigma_i^2 F\underline{V}F' = \sigma_i^2\underline{\Phi} \Rightarrow \underline{V} = F^{-1}\underline{\Phi}F'^{-1}, \tag{9}$$

where the implied equalities require non-singularity of F. This transformation projects our prior beliefs onto the parameter space:

$$\theta_i|\sigma_i^2 \sim N\left(F^{-1}\underline{f}_i, \sigma_i^2 F^{-1}\underline{\Phi}F'^{-1}\right); \quad \sigma_i^{-2} \sim G\left(\underline{s}^{-2}, \underline{t}\right). \tag{10}$$

With these transformed priors in place, the updating process is straightforward as we next show.

3.3 Posterior Distribution for Fund Return Generating Process

The prior specification from the previous section is completely standard, allowing us to express the posterior expectation for factor loadings in closed form. Using superscript bars to indicate posteriors, subscript bars to denote priors, and "hats" to denote least-squares estimates, we have:

$$\theta_i, \sigma_i^{-2}|D \sim NG\left(\overline{\theta}_i, \overline{V}_i, \overline{s}_i^2, t_i + \underline{t}\right), \tag{11}$$

$$\overline{\theta}_i = \left(F\underline{\Omega}^{-1}F' + G_i'G_i\right)^{-1}\left(G_i'G_i\hat{\theta}_i + F\underline{\Omega}^{-1}F'F^{-1}\underline{f}_i\right) \tag{12}$$

$$\overline{V}_i = \left(F\underline{\Omega}^{-1}F' + G_i'G_i\right)^{-1} \tag{13}$$

$$(t_i + \underline{t})\,\overline{s}_i^2 = \underline{t}\underline{s}^2 + t_i s^2 + \left(\hat{\theta}_i - F^{-1}\underline{f}_i\right)'\left[F^{-1}\underline{\Omega}F'^{-1} + \left(G_i'G_i\right)^{-1}\right]^{-1}\left(\hat{\theta}_i - F^{-1}\underline{f}_i\right)$$

$$\underline{\Omega}^{-1} \equiv \lim_{c\to\infty} \begin{bmatrix} cI_{(d\times d)} & 0 & 0 \\ 0 & \Omega^{-1} & 0 \\ 0 & 0 & 0_{(1+k+m+km-d)} \end{bmatrix}, \tag{14}$$

where $D = \{r_{i\tau}, r_{B\tau}, z_{\tau-1}\}_{\tau=1}^{t}$ is the history of the observed data. G_i is the $t_i \times (1+m+k+km)$ matrix of explanatory variables in the right hand side of the return generating process in equation (1) corresponding to the t_i periods in which $r_{i,t}$ is observed, in information set D. The vector r_i denotes this sample of returns so that the least squares estimate of $\hat{\theta}_i$ is simply $\hat{\theta}_i = (G_i'G_i)^{-1}G_i'r_i$, and $s^2 = t_i^{-1}(r_i - G_i'\hat{\theta}_i)'(r_i - G_i'\hat{\theta}_i)$. We maintain an uninformative prior for σ_i so that, as before, $\underline{s}$ is any constant and $\underline{t} = 0$.[13]

3.4 Predictive Moments for Portfolio Selection

Given the posterior distribution for the parameters governing the return generating process, we can now state the predictive expectations and variance-covariance matrix for the return generating process. These are similar to, but generalize, the results in Avramov and Wermers (2006), equations (14) and (15), though expressed in a somewhat more compact notation:

$$\begin{aligned} E\left[r_t|D_{t-1}\right] &= \bar{\alpha}_0 + \bar{\alpha}_1 z_{t-1} + \overline{\beta}_0 \hat{A}_F' x_{t-1} + \overline{\beta}_1 \left(I_K \otimes z_{t-1}\right) \hat{A}_F' x_{t-1} \\ &\equiv \bar{\alpha}_0 + \bar{\alpha}_1 z_{t-1} + \overline{\beta}_{t-1} \hat{A}_F' x_{t-1}, \end{aligned} \tag{15}$$

$$V\left[r_t|D_{t-1}\right] = \left(1+\delta_{t-1}\right)\overline{\beta}_{t-1}\hat{\Sigma}_B\overline{\beta}_{t-1}' + \Psi_{t-1}. \tag{16}$$

Here, $\hat{A}_F' = [\hat{\alpha}_B \;\; \hat{A}_B]$ represents least squares estimates of the VAR parameters in equation (2). Denoting the time-series average of the macro-variables in D_{t-1} by $\overline{z}$, the remaining variables are defined as:

$$\begin{aligned} \delta_{t-1} &= \frac{1}{t-1}\left\{1 + \left(z_{t-1} - \bar{z}\right)\hat{V}_z^{-1}\left(z_{t-1} - \bar{z}\right)\right\} \\ \hat{V}_z &= \frac{1}{t-1}\sum_{\tau=1}^{t-1}\left(z_{\tau-1} - \bar{z}\right)\left(z_{\tau-1} - \bar{z}\right)' \end{aligned}$$

[13]To compute the variance-covariance matrix requires that F_R is orthogonal to F_I and F_U, otherwise $\overline{V}_i^{-1}$ will have arbitrarily large off-diagonal elements. The leading specification of F_R, though, is one that restricts individual parameters to be equal to zero. Then the posterior variance and all related covariances for these restricted parameters will be zero.

$$\hat{\Sigma}_B = \frac{1}{\tau_B}\sum_{\tau=1}^{t-1}\hat{\varepsilon}_{B,\tau}\hat{\varepsilon}'_{B,\tau}; \quad \hat{\varepsilon}_{B,\tau} = r_{B,\tau} - \hat{\alpha}_B - \hat{A}_B z_{\tau-1}$$

$$\Psi_{t-1\{i,i\}} = \left(\frac{t_i + \underline{t}}{\tau_i}\right)\bar{s}_i\left\{1 + tr\left\{\hat{\Sigma}_B \Upsilon'_{\beta,t-1}\overline{V}_i \Upsilon_{\beta,t-1}\right\}(1+\delta_{t-1}) + x'_{t-1}\Upsilon'_{t-1}\overline{V}_i\Upsilon_{t-1}x_{t-1}\right\}$$

$$\Psi_{t-1\{i,j|i\neq j\}} = 0; \quad \tau_i = t_i + \underline{t} - k - m - km - 2 + d; \quad \tau_B = t - k - m - 2$$

$$\Upsilon_{\beta,t-1} = \begin{bmatrix} 0_{(M+1\times K)} \\ I_K \\ (I_K \otimes z_{t-1}) \end{bmatrix}; \quad \Upsilon_{t-1} = \begin{bmatrix} I_{M+1} \\ \hat{A}'_B \\ \left(\hat{A}_B \otimes z'_{t-1}\right)' \end{bmatrix}.$$

3.5 Investor Models for Manager Skill and Segmentation

Five investor types are considered throughout the paper. These types differ in their beliefs about the parameters in equation (1) of the fund return generating process. Recall that this model allows for constant (non time-varying) manager skills, $\alpha_{i,0}$, excess returns from stock selection based on macroeconomic conditions, $\alpha'_{i,1}z_{t-1}$, and excess returns from factor loadings that vary with macroeconomic conditions, $\beta'_{i,1}(r_B \otimes z_{t-1})$.

The most restrictive view is held by the dogmatist CAPM investor, who believes that no fund manager has skill, time-varying or constant, and that neither benchmark returns nor benchmark factor loadings are predictable. This investor type's beliefs can, therefore, be represented as $\alpha_{i,0} = 0$, $\alpha_{i,1} = 0$, $\beta_{i,1} = 0$, and $A_B = 0$.[14] A slightly less restrictive view that allows for non time-varying manager skill, but precludes predictability in the return generating process, is held by our Bayesian CAPM, or BCAPM, investor. This investor's beliefs are modeled after Pastor and Stambaugh (2002a,b), where the investor holds a prior belief that the average actively managed fund underperforms by the level of the expense ratio. This investor type's beliefs maintain the restrictions $\alpha_{i,1} = 0$, $\beta_{i,1} = 0$, and $A_B = 0$, and introduce the informative prior $\alpha_{i,0} \sim N\left(-\exp_i, \sigma^2_\alpha\right)$, where $\exp_i$ is one-twelfth of fund i's annual expense ratio. σ^2_α is the uncertainty of the investor in his prior, which determines the weight the investor will give to this prior, relative to the data.

The Bayesian Skeptical Macro-Alpha, or BSMA, investor-type allows for manager skill and predictability, but is skeptical of the total contribution of skill to a fund's return, and does not

[14] Since the CAPM investor dogmatically does not allow for the possibility of benchmark predictability, the contribution of macro-factor deviation from its mean to the variance in the benchmark expected return is removed from the predictive variance of fund returns, so that $\tau_{B,CAPM} = t - 1$ and $\delta_{t-1,CAPM} = \frac{1}{t-1}$.

believe risk factor loadings vary with macroeconomic conditions. This investor only restricts $\beta_{i,1} = 0$, allows A_B to be unrestricted, and introduces a conditional prior restricting the total manager skill generated either through constant or time-varying (predictable) skill, which can be represented as $\alpha_{i,0} + \alpha'_{i,1} z_{t-1} \sim N\left(0, \sigma^2_\alpha\right)$.

Allowing for predictability in manager skill and benchmark returns, the Bayesian Agnostic Macro Alpha, or BAMA, investor-type maintains an informative belief about a fund manager's constant skill and dogmatically believes fund factor loadings are not predictable. Like the BSMA investor, the BAMA investor restricts $\beta_{i,1} = 0$, but, in addition to allowing A_B to be unrestricted, the BAMA investor brings diffuse priors to $\alpha_{i,1}$, letting the data completely determine her beliefs about time-varying skills. The BAMA investor's informative prior restricting constant manager skills is represented identically to the BCAPM prior: $\alpha_{i,0} \sim N\left(-\exp_i, \sigma^2_\alpha\right)$.

Still less restrictive beliefs are held by the Bayesian Agnostic Macro Alpha with predictable market factor loadings (BAMAP) investor. The BAMAP investor allows 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 $\beta_{i,1}$ corresponding to the interactions between the macro factors and the non-market benchmark entries are restricted to be zero.[15] As with the BAMA investor, the BAMAP investor places no restrictions on $\alpha_{i,1}$, and maintains the prior belief $\alpha_{i,0} \sim N\left(-\exp_i, \sigma^2_\alpha\right)$.

Our five investor types are summarized in the following table:

Pricing Models	Benchmark Risk Premia	Factor Loadings	Manager Skill	Prior Belief Restrictions
CAPM	Not Predictable	Constant	None	$\alpha_{0,i} = 0$; $\alpha_{1,i} = 0$; $\beta_{1,i} = 0$; $A_B = 0$
BCAPM	Not Predictable	Constant	Not Predictable	$\alpha_{i,0} \sim N\left(-\exp_i, \sigma^2_\alpha\right)$; $\alpha_{1,i} = 0$; $\beta_{1,i} = 0$; $A_B = 0$
BSMA	Predictable	Constant	Predictable	$\alpha_{i,0} + \alpha'_{i,1} z_{t-1} \sim N\left(0, \sigma^2_\alpha\right)$; $\beta_{1,i} = 0$
BAMA	Predictable	Constant	Predictable	$\alpha_{i,0} \sim N\left(-\exp_i, \sigma^2_\alpha\right)$; $\beta_{1,i} = 0$
BAMAP	Predictable	Predictable Market Loading	Predictable	$\alpha_{i,0} \sim N\left(-\exp_i, \sigma^2_\alpha\right)$ $\beta_{1,i,j} = 0$ if $\beta_{1,i,j}$ does not correspond to the market factor

[15] Allowing for predictability of non-market risk factors, while interesting, greatly adds to the complexity of the model and its use of degrees-of-freedom.

In short, going from the orthodox CAPM investor-type to the BCAPM investor-type means allowing managers to have constant skills. Moving from BCAPM through BSMA to BAMA investors means allowing for manager skills that are time-varying and related to the macroeconomic state variables. Finally, going from BAMA to BAMAP investors means further allowing for time-varying factor loadings.

3.6 Market Segmentation

In each of the five investor models above, we also maintain the restriction implied by capital market integration that segmented benchmarks do not contribute to individual fund returns. That is, we restrict $\beta_{i0S} = 0$. In addition to these integrated market-models, we include a partially segmented market model for each investor type, labeled CAPM-S, BCAPM-S, and so forth. In the segmented market models, we impose the restriction that a fund's returns are generated by the integrated market benchmarks in addition to a local market benchmark (total stock market risk-factor only), but not by market benchmarks for other (non-local) countries. For example, a German-focused fund would have the MSCI Europe factor, the SMB, HML, and UMD factors (for Europe), and a German stock market factor (the MSCI Germany index). This approach closely follows the setup in Bekaert and Harvey (1995), and allows for "partial segmentation," since both the integrated market index *and* the relevant country index affect returns. This choice is dictated by the fact that we would, at most, expect partial segmentation for the European markets, which become increasingly integrated during our sample period.

4 Empirical Results

This section discusses the empirical results obtained from using the various investor models from the previous section to form portfolios of European equity mutual funds. We first describe the effect on portfolio performance of allowing for manager skill, followed by an analysis of the importance of considering information on macroeconomic state variables. Finally, we turn to the importance of market segmentation.

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 twenty-year sample, 1988-2008, the equal-weighted portfolio of funds returned 10.19% per annum, 86 basis points below the benchmark which returned 11.05% per annum. This negative average return performance conceals substantial variations in the returns from active management across sub-samples. Prior to 1998, on average, our sample of mutual funds out-performed the benchmark by 400-500 basis points per annum, while they under-performed the index by 200-400 basis points per annum in the 10-year period that followed.

These numbers refer to raw return performance. It is more relevant to consider risk-adjusted performance, as measured by the single-factor and four-factor alphas reported in panels B and C. In the case of the single-factor model, we observe underperformance, both on average and for the median fund. The average underperformance during the sample was -36 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, the mean alpha was positive at 1.20% during the five-year period from 1999-2003.

Turning to the results for the four-factor model, the median fund generated an alpha of -24 basis points per annum, while the equal-weighted alpha was 36 basis points per annum. Interestingly, this underperformance is similar to the U.S. equity fund underperformance over the 1980-2006 period, as documented by Barras, Scaillet, and Wermers (2010). Note that the four-factor alpha is unusually high during 1993-1998, relative to the CAPM alpha. During this period, the funds, in aggregate, overweighted small- and mid-cap stocks, relative to the value-weighted MSCI Barra market benchmark.[16] While these stocks underperformed in general, the funds apparently were successful in choosing stocks within those segments that outperformed their cohorts.

The results 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

[16]MSCI announced on December 10, 2000 that it would adjust its equity indices using free float adjusted market capitalization weights.

a key concern, we would expect the mass in the left-tail quantiles of the histogram to be much smaller than those observed in the right tails (as under-performing funds are dropped if there is survival-bias in 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 reasonably symmetric in the full sample, and highly left-skewed in the two five-year periods, 1988-1992 and 1993-1998.

We conclude from these historical, 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 the perspective of an active investor, 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. Based on the dynamic features of performance of the fund universe generally, a conditional framework provides an appealing mechanism with which to investigate this question. We address this issue in the next section.

To get a sense of variations in the average performance of funds in our universe, Figure 1 presents the cross-sectional average conditional expectations of excess returns as well as alphas, using the four models discussed in the previous section that allow for fund manager skill. At each point in time, these plots reveal how difficult it is for our model to identify funds with superior performance−the lower the average alpha, the narrower the set of funds with positive alphas will tend to be.

The plots highlight some interesting differences in the expected returns from the point-of-view of each of our investor models. Looking at the BCAPM model in Panel (a), we see no dynamic features (outside of the learning process) that causes the investor to update their posterior about individual fund (non-time-varying) alphas as new data arrives. The BSMA model in Panel (b) implements a conditional prior on total manager skill that allows for substantial time-variation in the components generating alpha, while shrinking the total alpha available to the fund manager. As such, the BSMA perspective allows for large swings in the proportion of alpha generated by constant vs. time-varying manager skill, but restrains the combined alpha contribution to expected returns so that the total alpha is relatively stable.

The BAMA investor model in Panel (c) further relaxes restrictions on the dynamic features of the model, restricting only the degree to which non-time-varying manager skill contributes to fund return performance. In this way, the α_0 contribution to expected returns is rather stable and relatively small, with the majority of dynamic return features driven by variation in the macroeconomic state variables, which drive manager selection without the constraint of a restrictive prior. Lastly, the BAMAP investor model in Panel (d) allows for a dynamic factor loading on the market benchmark return, introducing another dynamic feature to the model's expected returns. Note the large amount of volatility in benchmark-derived expected returns, which is due to the low predictability of benchmark returns relative to the alpha component.

One trend across these graphs is a decline in expected returns and, in particular, manager outperformance over the sample period. This feature is consistent with the recent findings of Barras, Scaillet, and Wermers (2010). Importantly, the degrading alphas are mainly due to decreases in the ability of fund managers to generate "all-weather" (non-time-varying) alphas as time-varying alphas continue to generate opportunities for alpha during the later years of the time period.

4.2 Portfolio Performance

We next turn to our five investor types that are described in the prior section, CAPM, BCAPM, BSMA, BAMA, and BAMAP. Recall that CAPM allows no active management skills (the "dogmatist"), while BCAPM, BSMA, BAMA, and BAMAP allow active management skills. BSMA, BAMA, and BAMAP allow macroeconomic variables to influence management skills with successively looser priors, and BAMAP also allows macro variables to influence risk factor loadings and excess returns. We are interested in determining whether macroeconomic variables can improve the selection of fund managers, i.e., whether BSMA, BAMA, and BAMAP exhibit higher performance than the other strategies.

To address the out-of-sample portfolio performance of these investor types, we follow Avramov and Wermers (2006) and assume that investors are endowed with a mean-variance utility function defined over terminal wealth:

$$U(W_t, R_{p,t+1}, a_t, b_t) = a_t + W_t R_{p,t+1} - \frac{b_t}{2} W_t^2 R_{p,t+1}^2, \tag{17}$$

where W_t is the wealth at time t, $R_{p,t+1}$ is one plus the portfolio return, and b_t characterizes the investor's absolute risk aversion. As shown by Avramov and Wermers, this is equivalent to choosing the optimal portfolio weights, ω_t^*, as the solution to

$$\omega_t^* = \arg\max_{\omega_t} \left\{ \omega_t' \mu_t - ((1 - b_t W_t)/b_t W_t - r_{ft})^{-1} \omega_t' [\Sigma_t + \mu_t \mu_t'] \omega_t / 2 \right\}, \tag{18}$$

where μ_t, Σ_t are the mean returns and the covariance matrix, both obtained from the posterior predictive distribution of mutual fund returns.

Table 3 reports performance results for an expected utility maximizing investor with mean-variance preferences and coefficient of risk aversion set equal to 2.94, the value advocated by Avramov and Wermers (2006). The baseline portfolio results shown in this table are based on the following assumptions applied using a four-factor European model. First, we use a set of European macro variables similar to those adopted by Avramov and Wermers (2006) in their study of US funds, namely the term spread, dividend yield, default spread and the short-term interest rate–all defined in the Appendix. Thus, we first provide a large-scale out-of-sample test of the Avramov and Wermers (2006) U.S. equity fund results, which is important, given that Ferson, Simin, and Sarkissian (2003) demonstrate that a highly persistent predictive variable (such as our macroeconomic variables, which vary slowly over time) can spuriously appear to predict a dependent variable (fund returns) if the predictive variable has been "data-mined."

The parameter σ_α, which represents the degree to which investors believe in their prior about either time-varying or constant manager skill, is set to 10% per month. Note that this very high level of uncertainty allows the data to almost completely influence the portfolio choice. Later in this paper, we explore variations, both tighter and looser, of the assumed value for σ_α to verify robustness.

We cap our strategies at a maximum of 10% invested in a single fund at any particular month; in addition, we assume quarterly rebalancing to constrain the turnover of funds by the strategies. Both of these constraints are imposed to avoid strategies that would be difficult to implement in practice. In addition, we do not allow short positions, since it is typically not possible to short-sell mutual funds.[17,18]

[17] To simplify the computations, the expected utility maximization used to derive the optimal holdings only considers the top 50 funds ranked by their conditional alpha (in a first-stage estimation process). However, our results are not very sensitive to this assumption, as shown by robustness tests later in this paper.

[18] Among the selected funds, the rate of attrition is generally considerably lower than for the full universe of funds (15%), namely 10% for the CAPM/BCAPM models, 4-6% for the BSMA model, 8% for the BAMA model, and 12-16% for the BAMAP model. When a selected fund is discontinued, we reallocate the weight allocated to that fund proportionally to the weight of other funds in the portfolio. To illustrate, suppose we assigned 10% each to Funds one through five and 5% each to funds six through 15, and the first fund is discontinued in the first out of sample month. Then we calculate returns for a portfolio that assigns 11.11% each to funds two through six and 5.55% to funds six through 15.

To measure the performance of the resulting "fund of funds," 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 single- and four-factor alphas, their t-statistics, and factor risk exposures.

First, consider the raw return performance reported in the first five lines of Table 3. The MSCI Europe benchmark index returned 11.4% arithmetic average return, with a volatility of 16.3% and produced a Sharpe ratio of 0.45. Compared with this, the CAPM investor who does not believe in active management skills produced somewhat smaller mean returns (8.6%), but also lower volatility (14.9%), for a somewhat lower Sharpe ratio of 0.3.

In contrast, every investor type who believes that some managers may be skilled, succeeded in generating raw return performance better than that of the MSCI Europe benchmark. For the four Bayesian investor types, arithmetic mean returns lie between 13.6% and 18.8% per annum, with volatilities close to or slightly above 20%, and Sharpe ratios between 0.49 and 0.69, significantly higher than that of the market index.

4.2.1 Alphas of the Baseline Strategies

Turning to the alpha estimates, consistent with the raw return figures, the dogmatic CAPM investor generates a negative single-factor alpha estimate of -1.97% per annum. This finding is not surprising, since the CAPM investor is not seeking to identify funds with superior performance and is clearly at a disadvantage (if active skills do actually exist) by being constrained to form a portfolio comprising actively managed funds (with zero alphas perceived by this investor) with higher expenses than the passive benchmark. In fact, the dogmatist loses, relative to the benchmark, an amount that is slightly higher than the average expense ratios that we observe in Table 1, perhaps due to excessive trading costs.

A very different conclusion emerges for the investor types that allow for some degree of manager skill. In particular, the Bayesian CAPM (BCAPM) investor who believes that individual managers may have (constant) skills generates a single-factor alpha of 2.47% per annum. This level of performance is quite remarkable, since BCAPM does not allow for any time variation in manager skills. Indeed, these results indicate that some managers have long-term alphas that do not vary much with macroeconomic cycles.

Moving to the skeptic macro alpha (BSMA) investor who believes that managers' ability to generate alpha may be state-dependent and time-varying, but continues to shrink the total (net) alpha contribution towards zero, the single-factor alpha grows by over 5%, to 7.78%/year. For the macro-alpha investor type who puts weaker constraints on the time-varying portion of the alphas, the single-factor alpha is slightly lower, 6.32%/year. The results indicate that the macro state variables are very important in identifying skill, since including them (for the BSMA and BAMA investors) leads to 4-5%/year of additional alpha–almost a tripling of the alpha of the BCAPM investor, who does not use macro variables.

Interestingly, similar to the U.S. results of Avramov and Wermers (2006), further relaxing the model to allow for time-varying factor loadings, as is done in the BAMAP model, does not lead to better performance than the otherwise similar BSMA model. The likely explanation for this is that time-variations in the factor loadings are difficult to identify with much precision and could be dominated by parameter estimation error, since the BAMAP model has 25 parameters in the equation specifying the conditional mean (and many funds only have data for part of our sample).

Even larger alpha performance for the macroeconomic models is observed when the four-factor model is used as the benchmark for risk-adjustment. With the exception of the CAPM alpha which, at -1.71%/year, does not change much, the estimated alphas from the four active investor types range from 7.47% to 12.04%/year. Note that macro variables continue to be important: Comparing the alpha estimates for the BCAPM and BSMA investors, we see that allowing for time-varying alpha (α_{1i}) with diffuse priors results in an additional 4.57%/year of alpha. Once again, allowing for predictable market factor loadings does not generate higher alpha estimates, and even results in a slight deterioration in performance.

In part because of such level differences, the statistical significance is stronger for the four-factor, relative to the one-factor alpha estimates. Clearly, a comparison of the single-factor and four-factor results tells us that fixed and time-varying skills are better predicted with a more robust model that includes equity characteristics (size, value/growth, and momentum/contrarian), since the funds in our database tend to tilt toward smaller-cap, growth, and momentum stocks, as indicated in the average factor loadings in Table 3, relative to the MSCI Europe index.[19] As such, much of the four-factor alpha is driven by some fund managers' ability to deliver positive returns despite this

[19] It is also worth noting that the positive alphas observed here do not simply arise as a result of underestimated loadings on the market risk-factor, a point emphasized by Mamaysky, Spiegel and Zhang (2007). In fact, the investor type with the highest alpha, namely the BSMA investor, has a single-factor beta which is indistinguishable from one.

period being very difficult for European Growth and Momentum stocks. Between 1993 and 2000, the SMB benchmark delivered an average annual return of -11.3% while the MOM benchmark returned -1.2%, presenting a significant drag on most of the strategies' gross return performance.

Our sample covers very different market conditions, spanning the bull market of the nineties, followed by the market crash in 2000, the recovery from mid-2002 and, more recently, the financial crisis beginning in mid-2007. To test if the performance associated with the various investor types varied across these very different market conditions, Panels B and C split our sample into two subperiods, namely 1993-2000 and 2001-2008. The four investor types under consideration (BCAPM, BSMA, BAMA, and BAMAP) generate positive alphas in both subsamples, regardless 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.

The sub-sample results also show the importance of controlling for more than one risk factor. While the single-factor and four-factor alpha estimates are very similar during the second subsample (2001-2008), as compared to the earlier subsample (1993-2000)–which is dominated by the bull market of the late nineties–the four-factor alphas are far greater than the single factor alphas during the earlier subsample, reflecting the importance of controlling for the style tilts of the funds. Note that the loadings of the optimal portfolios of funds on SMB is close to unity for the four investor types using predictive variables (BCAPM, BSMA, BAMA, and BAMAP), indicating that these strategies strongly prefer funds holding smaller capitalization stocks, where pricing inefficiencies are more likely to exist.

4.3 Market Segmentation

We next turn to the issue of whether allowing for partial market segmentation−i.e., the inclusion of individual country benchmarks in addition to the pan-European benchmark−further helps to locate active managers with true skills. For an investor who believes that markets are segmented along country borders, adding a country risk-factor will improve the identification of truly skilled managers within that country. For an investor who believes that markets are sufficiently integrated, however, adding a country risk-factor may reduce the profits from tilting toward countries with persistent, but temporarily high returns.[20]

[20] Alternatively, adding country risk factors leads to a richer covariance matrix under the segmentation model and so affects the precision of the covariance matrix estimates. See also Pastor and Stambaugh (2002a) for a related

We, therefore, compare the performance results for a fully integrated model which only includes the Pan-European equity benchmark index against a partially segmented model that, for all of the funds with country-specific investment objectives, includes the Pan-European equity and the relevant country index. Hence, for a mutual fund with a predominantly German stock focus, the segmented model would include returns on the MSCI Europe and the MSCI Germany stock indices. For Pan-European funds, we only include the MSCI Europe equity index.

Using the integrated and segmented market models, we compare results for three different universes of funds. First, to verify that there are no gains from investing in purely passive index funds, we consider an investment strategy that is restricted to the underlying 11 MSCI country indices. Second, we consider the full sample of funds, including pan-European, country and sector funds. Third, we consider a sample restricted to country funds. If manager skills tend to be country-specific (and not pan-European), we would expect that any segmentation effects should be strongest for this third set of funds.

Table 4 shows results from this analysis. First, for the universe comprising only passive index funds, single-factor and four-factor alpha estimates are always economically small−in all cases, falling at or below 1.6%/year–and statistically insignificant. This holds across all four investor types, suggesting that there are no gains to be made from a pure market timing strategy that seeks to vary the weights on the passive country index funds, with or without macroeconomic variables. This result indicates that our pan-European market factor properly captures country market risks, and does not allow alphas from trading passive funds.

Second, there appear to be additional gains from applying the market segmentation model, especially for the BCAPM and BAMAP models whose one-factor alphas increase by 1.8%/year. One-factor gains for the two other investor types that allow for some state-dependency in skills (BSMA and BAMA) are lower, at about 0.5%/year.

The larger alphas from the segmented models indicate that controlling for temporary, country-specific shocks (not related to macrofactor shocks) can help to more precisely identify skilled managers. This result is consistent with the framework of Pastor and Stambaugh (2002a,b), who add an unpriced benchmark to improve fund performance evaluation. We should expect this improvement, as many European countries are heavily tilted toward certain industries. We conclude from this analysis that some active managers have skills, and that both macro and segmentation variables

theme based on persistent, unpriced factors.

are helpful in identifying skills among European equity mutual fund managers.

5 Portfolio weights and attribution analysis

To understand which variables produce the superior performance of the portfolio of actively managed mutual funds, we next consider the country and sector allocations in the optimized portfolios. We also perform an attribution analysis that explores which components account 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 5 shows snapshots of the portfolio weights by region or country. The strategies generally allocate low weights to Pan-European funds, with the exception of the CAPM and BCAPM strategies. These two strategies apparently find less costly diversification opportunities in Pan-European funds, since they disregard time-varying skills of country funds.[21]

This result indicates that the biggest opportunity for exploiting time-varying alphas consists of large allocations to country-specific funds.[22] In turn, this indicates that country fund managers have a superior ability to generate alphas, but that their advantage is fleeting over time. This finding is consistent with time-varying opportunities that are out of phase across different countries in finding underpriced stocks. For instance, the BSMA strategy finds the best potential for managers in Scandinavian funds during the beginning of the technology/telecommunications boom in 1993, but reduces that weight by 1998.

Further, allocations are never evenly spread among the country funds, indicating that skills are not only time-varying, but country-varying–i.e., consistent with the opportunities for finding underpriced stocks being out-of-phase (or, more accurately, not perfectly in-phase across countries). This finding is interesting, in light of the industry rotation found to be present in the time-varying strategies of the Avramov and Wermers (2006) study of U.S. equity funds. Indeed, in untabulated tests, we generate estimated industry allocations of the strategies, using rolling Sharpe (1992)

[21] Although Pan-European managers may also have country-timing skills, it is likely that they cannot change the country tilt of their portfolios as quickly as that implied by our country manager strategies.

[22] 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.

regressions.[23] We find that the macro-variable strategies, BSMA, BAMA, and BAMAP, allocate much more to technology stocks (through their selection of mutual fund managers) during 1993-1998, and less to the automotive industry during 2004-2008 than the non-macro strategies, CAPM and BCAPM. Our prior finding of little predictability in pure country index funds indicates that time-varying opportunities in industries as a whole do not drive the success of macro strategies. Rather, the macro strategies focus on funds within certain industries to find alpha-generating opportunities. Correlated with this approach, the macro strategies often pick funds that focus on certain countries; industry and country choices are correlated, but imperfectly.

Note, also, the correlation in country allocations across the macro strategy investor types, BSMA, BAMA, and BAMAP. This consistency in region allocations indicates that the macro variables are picking up similar opportunities in these three models, with some differences due to the exact specification of the models.

There are also some large differences in the country allocations of the integrated models (panel A) versus the segmented models (panel B). Note that, in general, the allocations to Pan-European funds increase, since the model attributes some of the time-variation in country fund returns to time-variation in segmentation effects. For instance, during 2003, all three models (BSMA, BAMA, and BAMAP) significantly lower their exposure to Scandinavian funds, apparently because the Scandinavian market factor (relative to other country market factors) exhibited temporary outperformance relative to the non-segmented risk-factors of Panel A.

Sector funds mainly play a role towards the end of the sample, which is to be expected, given that there are very few sector funds prior to 2003. Interestingly, all three macro strategies allocate at least 70% to sector funds in 2007. Our prior-mentioned industry analysis (using Sharpe (1992) regressions) indicates that sector funds are used to focus strategies on combinations of certain industries, which are not easy to accomplish through country funds alone.[24]

Overall, the finding that country and sector allocations vary considerably over time, especially

[23] We generated three sets of Sharpe constrained regressions for our portfolio excess returns against the excess returns on 14 DJStoxx sector indices taken from the Global Financial Database. We estimated full-sample sector weights as well as split-sample and rolling five-year weights by constrained least squares. Following the convention of mimicking portfolio weights, these regressions are restricted so the factor loadings sum to 1 and the coefficients are non-negative. The results of these estimations are available upon request from the authors.

[24] For example, the BSMA strategy chooses an allocation of 19% toward industrial stocks, but 0% toward financials. This mix may be difficult to achieve by investing in, e.g., German or French country funds.

for the three macro strategies (BSMA, BAMA, and BAMAP) shows that they clearly pursue very active strategies to exploit macroeconomic information in picking managers.

5.2 Selection of Individual Funds

Table 5 does not show the identity of the individual funds that were selected by the four investor types. An example is presented in Table 6, using data as of February 2008 (the end of our return sample). As expected, the allocations vary widely across strategies. However, all strategies seem to hold the maximum 10% of the chosen funds. This result indicates that a small subgroup of funds are deemed superior by all investment strategies, although the exact composition of these superior funds is different, depending on the model used by the strategy. These "corner solutions" indicate that even greater performance may be achieved without the holdings constraints, a point we shall return to later.

For each investor type, there is a substantial (but nothing close to perfect) overlap in the funds selected, regardless of whether the integrated or the segmented market models are used. Again, this indicates that some (but not all) of the performance exploited by the strategies is not captured by segmentation in the market risk-premia (which, in turn, might be exploited, for example, through the macroeconomic variables). Our prior-mentioned industry analysis shows considerable differences in industry allocations between the integrated and segmented models, indicating that different funds are selected (in Table 5) to effect changes in industry allocations.

5.3 Decomposition of Returns

To evaluate the source of abnormal performance for our portfolios, we decompose the abnormal return performance into four components plus a residual. Portfolio returns are first decomposed into Pan-European, sector fund, and C country-specific returns as follows:

$$r_P = w_{Euro,P} r_{Euro,P} + w_{Sect,P} r_{Sect,P} + \sum_{i=1}^{C} w_{Ctry_i,P} r_{Ctry_i,P} + \varepsilon_P, \tag{19}$$

where, for example, $w_{Euro,P}$ is the portfolio allocation to pan-European funds by the investor, and $r_{Euro,P}$ is the (value-weighted) return on the Pan-European funds chosen. Note that ε_P captures actual fund weights chosen by the investor, relative to value-weights.We compare this return to the return on the MSCI Europe Benchmark, which is decomposed into C country-specific components as:[25]

$$
\begin{aligned}
r_B = & w_{Euro,P} r_B + w_{Sect,P} r_B && (20)\\
& + (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} * r_{Ctry_i,B} && (21)\\
& + (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} \left(r_B - r_{Ctry_i,B}\right).
\end{aligned}
$$

The weights for each country in the benchmark, $w_{Ctry_i,B}$, were computed using the market capitalizations for each country's equity market (taken from the World Bank's Development Indicators); the benchmark country returns are taken from the MSCI Europe 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 fund exposure of the portfolio through most of our sample. The third term in the benchmark decomposition is a residual reflecting the small mismatch between the capitalization weighted Europe index (based on MSCI country indexes) and the MSCI Europe benchmark returns.[26]

The contribution of Pan-European fund selection and sector fund selection to our portfolio's performance is given by the difference of the first two terms in the portfolio return decompositions of Equations (19) and (20), respectively. These components reflect the ability of the portfolio to select funds that outperform the benchmark and are computed as:

$$r_{European\ Selection} = w_{Euro,P} * \left(r_{Euro,P} - r_B\right) \tag{22}$$

$$r_{Sector\ Selection} = w_{Sect,P} * \left(r_{Sect,P} - r_B\right). \tag{23}$$

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.

[25]Note that we do not have returns for sectors within the MSCI Europe index, thus, we apply sector weights to the entire MSCI Europe return.

[26]Specifically, differences are attributable to MSCI using non capitalization-weighted country allocations in their MSCI Europe index.

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:

$$r_{Country\ Select} = (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} * (r_{Ctry_i,P} - r_{Ctry_i,B}). \tag{24}$$

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

$$r_{Country\ Time} = \sum_{i=1}^{C} (w_{Ctry_i,P} - (1 - w_{Euro,P} - w_{Sect,P})\, w_{Ctry_i,B})\, r_{Ctry_i,B}. \tag{25}$$

Finally, the residual for the abnormal portfolio performance is given by the traditional Brinson, Hood, and Beebower (1986) residual component (the interaction of country allocation with country stock-selection) minus the residual in the benchmark return composition:

$$\begin{aligned} r_{resid} = &\sum_{i=1}^{C} (w_{Ctry_i,P} - (1 - w_{Euro,P} - w_{Sect,P})\, w_{Ctry_i,B})\,(r_{Ctry_i,P} - r_{Ctry_i,B}) \\ &- (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B}\,(r_B - r_{Ctry_i,B}). \end{aligned} \tag{26}$$

Panel A of Table 7 presents the results of this decomposition for each of the investor types. We see that portfolio outperformance is driven by a combination of fund selection in country and sector funds, coupled with some skill in timing country allocations. The investors that keep an open mind about time-varying alphas (BSMA, BAMA, and BAMAP) generate more than twice the performance in these three attribution categories. Thus, time-varying macroeconomic strategies are successful, in part because they better identify country-specific managers with superior skills at a particular point in the business cycle. This interaction effect of timing coupled with selection is also apparent in the relatively large residuals for the conditional Bayesian investors, particularly in the segmented model (Panel B). Note, also, that the attribution components do not change much when we move to the segmented models. Clearly, the strategies are able to locate skilled managers, controlling for possible time-varying segmentation effects.

Also, the time-varying strategies achieve some performance by timing country weights. Given that our earlier results show that timing passive country funds does not work, this finding indicates that using macroeconomic variables helps to identify the countries with the best active managers at a given point in time. Again, this is quite interesting in light of the industry concentration of some of the countries–certain industries (which are concentrated in certain countries) represent the most fertile territory to search for manager skills, perhaps because of the large degree of asymmetric information in these industries at certain points of the business cycle. For instance, the outlook for technology firms varied substantially during the period surrounding the peak of the technology boom. The allocations of our strategies indicate that the macroeconomic-based investment strategies were able to identify the most promising industries as well as to select the portfolio managers with the best skills in those industries during a particular macroeconomic phase.[27]

6 Robustness of the Results

In this section we undertake a range of robustness checks to see how sensitive the findings from the baseline case are to changes in the macroeconomic variables used, the universe of funds considered, the construction of the momentum factor, the rebalancing frequency, the constraints on the portfolio weights, and the prior beliefs.

6.1 Macro Variables

To avoid concerns related to possible data mining, so far we have only considered a single set of macro variables, comprising four standard predictor variables used throughout the finance literature. However, it is interesting to address which types of macrovariables are capable of generating superior performance for the active investor types. To this end, Table 8 presents alpha estimates and alpha t-statistics for these four as well as five other predictor variables for the three investor types who believe that macro variables matter in identifying manager skills, namely the BSMA, BAMA and BAMAP investors, concentrating on the segmented market model in the interest of brevity. For comparison, the table also shows results at the bottom for the BCAPM investor who assumes constant alphas.

[27] We do not consider currency effects in our attribution analysis since these are likely to have been small during our sample. Prior to 1999, most currencies (with the exception of the Swiss Franc) moved tightly together relative to the ECU parity rate, whereas, after the introduction of the Euro in 1999, the national currencies in our sample disappeared, with the exception of the British pound, the Danish and Norwegian Krone, and the Swiss Franc.

To measure the marginal effect of each predictor variable, we show results when different predictor variables are included, one by one, in the model. Since these are univariate results, we would expect some decline in performance relative to the benchmark model that includes four state variables. The appendix describes how each of the variables is measured.

Many of the individual macro variables are able to generate superior performance, with the most consistent and largest effects obtained for the short rate yield, industrial production, and inflation. Conversely, the currency factor, volatility and the dividend yield do not show much promise. Interestingly, for the smaller model with fewer state variables, the BAMAP model that allows for time-varying factor exposures tends to generate the best performance overall. This supports our earlier conclusion that this model fails to perform well with four macro variables mainly because of the resulting rise in the number of parameters that require estimation.

In addition to single macro-factor specifications, we also consider models that condition on country-specific macroeconomic factors at the top of each panel. These results show the effect of using the same four macro factors for each country fund in our analysis, namely the term-spread, dividend yield, default spread and short-term interest rate, but using country-specific versions of these four macro factors.[28] We find, in general, that the alphas from the time-varying strategies are slightly lower using local macro factors. This suggests no gains from using local macro variables over using Europe-wide measures, perhaps because of the larger measurement error in these local indicators.

6.2 Construction of Momentum Factor

We do not have access to a momentum factor constructed at the individual stock level. However, following Moskowitz and Grinblatt (1999) in the U.S., we form the momentum factor based on the previous 12-month performance for each of the 18 Dow Jones STOXX 600 Super Sector indices. The momentum factor is then formed from the spread between equal-weighted 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 construct this as follows. Here, we consider the performance of each of the 16

[28]The BAMAP investor-type is dropped from this analysis because of the very large number of parameters needed in this model to estimate A_B and A_F. This means that only a short sample is available for out-of-sample evaluation.

European countries over the previous 12-month period.[29] We then compute the return differential between the three countries with the highest 12-month lagged returns and the three countries with the lowest 12-month lagged returns.

In untabulated results, we find that the performance of our strategies, using country-based momentum factors, are very similar to those in Table 3, 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 the mean-variance investor optimizes the portfolio allocation across the top 50 funds, ranked by their conditional alpha, subject to restrictions that preclude short positions and impose a maximum of 10% that the strategy can invest in a single fund. We next relax these assumptions, first on the pre-screened size of the universe, and, then, on the positions the investor can take.

Table 9 reports on the role of the universe pre-screen on portfolio performance. Panel A shows that expanding the set of funds used in the optimization to include 250, rather than 50, actually reduces the alpha somewhat for the strategies. This reduction is even more pronounced in Panel B, which reports investor portfolio performance when there is no pre-screening for manager skill, although the four-factor alphas remain statistically significant for most models. This dilution effect in portfolio alpha can be explained by two effects. First, estimation error means that forming portfolios from a larger universe that includes funds with low alphas may lead to worse performance when such funds are assigned non-zero weights due to sampling variation. Second, the objective of our portfolio allocation problem is not to directly maximize the expected alpha, but rather to maximize the expected utility of a mean-variance investor (i.e., maximize Sharpe Ratio). In fact, the investor's average realized utility (not shown here) actually increases as the investable universe grows.

Panel A of Table 10 shows that eliminating the maximum weight constraint for investment in any one fund increases the alpha performance by 5-8% per year, depending on the strategy. 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

[29]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.

expect that essentially ad-hoc constraints should reduce the portfolio performance. The findings also suggest that a very small number of fund managers have very sharp (predictable) abilities to generate alpha at varying times during the business cycle.

Panel B of Table 11 illustrates the effect of tightening the 10% maximum on portfolio holdings of a single fund to only 5%. As expected, tightening this constraint hinders portfolio performance, further illustrating the signal value of the conditional estimates for a fund's expected returns, standard deviation, and correlations. Nevertheless, these more diversified and balanced portfolios continue to perform well, and generate highly significant four-factor alphas between 7 and 10%/year.

Lastly, beyond quarterly rebalancing, our baseline models placed no constraints on portfolio turnover. Panel C of Table 11 shows that limiting the sales and purchases of individual funds to 5% per fund per quarter results in a slight deterioration in the alphas of the strategies that use macroeconomic information (BSMA, BAMA, and BAMAP). These results are qualitatively consistent with those of Panel A.

6.4 Effect of Priors

Our baseline results assumed a prior of $\sigma_\alpha = 10\%$ per month. Under this choice the investor types (with the exception of the CAPM investor) are very 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 $\sigma_\alpha = 0.1\%$ per month or loosening them to effectively represent uninformative priors (e.g. $\sigma_\alpha = 100\%$) affects the returns, as we vary the investor's degree of skepticism about the possibility of finding abnormal performance.

Table 11 shows that as σ_α gets smaller and, so, the priors get tighter, the alpha performance declines quite substantially for all investor types, and especially so for the BSMA investor. To interpret these findings, notice that when we tighten σ_α for the BCAPM investor, α_0 is effectively limited to be zero. When we tighten σ_α for the BSMA investor, we shrink the total α $(\alpha_0 + \alpha_1 z_{t-1})$ toward zero. However, for the BAMA investor, we shrink only α_0, and not $\alpha_1 z_{t-1}$. The higher sensitivity of BCAPM and BSMA to increasing the precision of prior beliefs, relative to BAMA, provides further evidence that the time-varying $\alpha_1 z_{t-1}$ component is critical to the model's performance, relative to α_0.

6.5 Identifying Underperforming Funds

Table 12 considers the performance of two different strategies that involve locating underperforming funds. Panel A shows results when our investors attempt to identify underperformers among the mutual 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 substantially negative for all investor types, and more so for the BSMA, BAMA, and BAMAP macro-strategies, not because these funds are attempting to underperform, but because our models identify funds that are likely to underperform in the current economic climate due to difficulties in successfully implementing their strategies in such a climate.

Encouraged by these findings, we also consider the performance of a self-financing portfolio strategy which allows for both long and short positions. In Panel B of Table 12, we allow the investor to form a 2 to 1 leveraged portfolio (long 200%, short 100%) in 50 funds with the highest conditional alpha financed by shorting the benchmark and country index portfolios (in the proportion indicated by the fund loadings and tilts). We find these leveraged portfolios generating exceptional performance, with geometric means of roughly 18%/year (for macroeconomic strategies) and single-factor alphas of roughly 10%/year. Panel C takes a purely self-financing approach, with the addition that the investor forms their portfolios subject to the constraint that their expected exposure to the benchmark factors be zero. This constraint hinders the portfolio's ability to generate alpha by directing more of the short position toward the market benchmark and away from the style indices. Even so, the models that allow for a time-varying alpha continue to generate single-factor alphas around 8-10%/year and four-factor alphas around 9-11%/year.

6.6 Breadth of Predictability in Fund Manager Performance

Our results illustrate that predictability in fund manager performance presents an opportunity to investors in equity mutual funds to aid in global portfolio diversification and enhance performance. However, one concern is that many of the portfolios appeared to be quite concentrated (see Table 6), and, so, could be overly sensitive to the availability of individual funds for investment. The fact that such concentrated strategies perform well need not be a concern, of course, since concentrated strategies that differ from common benchmarks have been found to be associated with better performance (see, for example, Cremers and Petajisto, 2009). To address the robustness of our strategies' ability to rank the entire cross-section of funds, we present evidence from a simple sorting test conducted on funds after computing their expected performance under each model.

Specifically, in Table 13, we report the performance of equal-weighted portfolios formed by sorting, each quarter, the universe of funds into deciles based on the t-statistic for the conditional alpha.[30] The models that allow for predictability generate spreads in both mean return performance and four-factor alphas of 3-5% per year between top and bottom deciles of funds. We also report the results of a Patton-Timmermann (2010) test for a monotonically decreasing pattern in the four factor alphas as we move from the top to the bottom ranked decile funds. This test rejects, i.e. results in a low p-value, if there is evidence of a monotonic pattern in the hypothesized direction. For all the segmented Bayesian models, we find that the test strongly suggests a monotonic relationship, with the top funds delivering higher alphas than the lower-ranked funds. The evidence is slightly weaker for the Bayesian models that assume integrated markets, thus, testifying to the advantage of allowing for segmentation.

The last column of Table 13 compares these results with the performance of a momentum strategy that sorts funds based on their trailing 12-month returns. Note that, while the momentum strategy generates attractive spreads between the high and low deciles, there is little evidence supporting a monotonic relationship between momentum and fund manager performance. Moreover, for the sub-sample from 1993-2000, the momentum strategy generated a negative spread between the winners minus losers portfolio, indicating that this strategy does not deliver consistent abnormal performance.

Table 14 evaluates the degree to which predictability in fund manager skill is concentrated in just a few funds by reporting the performance of equal-weighted portfolios formed from the N funds with the highest conditional alpha, where we let N vary from 10 to 500. We see that models allowing for predictability generate the most attractive return properties when they are allowed greater concentration. Again, this suggests that the Bayesian alpha models are capable of successfully ranking the funds' risk-adjusted performance.

[30] The $t-$statistic of alpha is a more reliable measure than the alpha estimate, which can be dominated by funds with very volatile returns.

6.7 Augmenting the Models for Currency

We try two last specifications, obtained by adding a currency macroeconomic variable and a currency "risk factor," respectively, to our baseline specifications that used four macro variables and four risk factors. This currency risk factor is constructed as described in the Appendix. These results, available on request from the authors, are qualitatively similar to our baseline results: adding a currency macro variable or risk factor does not substantially reduce the alphas attained by our time-varying alpha strategies. This is not surprising, since currencies in developed Europe were closely fixed together during our time period.

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 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 growth in industrial production 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 generate returns from country and sector fund selection, as well as from timing country weights. Thus, time-varying strategies appear to be successful, partly because they better identify country- and sector-specific managers with superior skills at a particular point in the business cycle. This finding suggests that there exists managers with superior country- and sector-specific skills, but that these skills may vary with the state of the economy. The fact that the strategies obtain positive returns from timing country weights further show that economic and financial markets in Europe are not perfectly synchronized and remain partially segmented despite the overall trend towards more integrated markets.

We also find that timing passive country funds does not work. The positive contribution from timing country weights achieved by the time-varying strategies, therefore, indicates that using macroeconomic variables helps to identify the countries with the best active managers at a given point in time rather than from timing country indexes. Again, this is quite interesting in light of the industry concentration of some of the countries.

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Appendix: Data Sources and Definitions

Variable	Definition	Source
Market	MSCI Europe, Nordic Countries, UK, France, Spain, Portugal, Italy, Austria, Switzerland, Belgium, Netherlands and Germany (Total Return Indices)	MSCI Barra
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 rate	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 change in the german VDAX index	Global Financial Database
Consumer Price Index	12-month rate of change in the European Consumer Price Index	European Central Bank
Industrial Production	12-month rate of change in the European Industrial Production Index (excluding construction)	European Central Bank
Economic Sentiment	1-month change in the Economic Sentiment Indicator from the opinion surveys collected by the European Central Bank	European Central Bank
Risk free Rate	1-month Euribor***	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 a monthly basis.

***Backfilled with "GFD Euribor 1 month,' an interbank rate for the ECU 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

This table shows descriptive statistics for the european 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. The market factor is represented by the MSCI Europe index.

Figures and Tables

Table 1: Number of Funds over Time, Grouped by Investment Objective

Panel A: Fund Counts

	1988	1993	1998	2003	2008
I. Universe	228	716	1397	3225	4200
II. Regional Funds					
Austria	1	4	7	12	18
Benelux	3	25	45	73	62
France	2	86	166	277	275
Germany	17	43	77	112	113
Italy	2	19	54	94	96
Pan-Europe	57	228	461	1491	2133
Scandinavian	18	52	140	271	314
Spain/Portugal	0	26	69	113	144
Switzerland	8	24	55	104	156
UK	119	197	299	504	625
III. Sector Funds					
Banks and 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	23	20
Natural Resource	0	0	0	8	12
Non Cyclical Con	0	0	0	15	17
Pharma and Health	0	0	0	8	8
Real Estate	1	12	21	46	103
Tech Media and 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

	1988	1993	1998	2003	2008
Average			1.46	1.63	1.49
Median			1.47	1.59	1.61
Standard Deviation			0.55	0.94	0.62
No of Expense Obs			483	1524	925

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, measured in percent per annum.

Table 2: Fund Universe Sample Performance

	Full Sample	1988-1992	1993-1998	1999-2003	2004-2008
	A. Annual Average Return Performance				
Eq Weight Universe	10.19%	7.65%	18.41%	1.90%	11.24%
Benchmark	11.05%	12.41%	22.41%	-0.44%	6.88%
	B. Single-Factor Alpha (Annualized)				
Universe Average	-0.36%	-4.68%	-1.92%	1.20%	-0.96%
5% - Quantile	-7.80%	-22.32%	-18.96%	-8.28%	-8.76%
10% - Quantile	-5.28%	-16.32%	-10.44%	-5.64%	-6.12%
25% - Quantile	-2.88%	-8.64%	-4.56%	-3.12%	-3.60%
50% - Quantile	-0.84%	-3.24%	-1.32%	0.00%	-1.44%
75% - Quantile	1.92%	0.12%	2.16%	4.92%	1.32%
90% - Quantile	5.88%	3.12%	6.72%	10.80%	5.40%
95% - Quantile	9.00%	6.12%	12.00%	15.12%	8.52%
	C. Four-Factor Alpha (Annualized)				
Universe Average	0.36%	0.48%	8.40%	2.52%	-0.84%
5% - Quantile	-7.08%	-20.28%	-13.92%	-7.92%	-8.28%
10% - Quantile	-4.80%	-12.12%	-7.44%	-5.64%	-5.76%
25% - Quantile	-2.52%	-5.64%	-2.40%	-3.00%	-3.36%
50% - Quantile	-0.24%	-0.72%	4.32%	0.36%	-1.44%
75% - Quantile	3.24%	4.56%	13.32%	5.76%	1.68%
90% - Quantile	8.16%	13.92%	27.60%	12.84%	6.24%
95% - Quantile	11.40%	22.32%	48.48%	18.60%	10.32%
	D. Single Factor Beta				
Universe Average	0.96	0.91	0.85	0.95	1.06
5% - Quantile	0.68	0.56	0.51	0.61	0.82
10% - Quantile	0.76	0.69	0.60	0.70	0.89
25% - Quantile	0.85	0.81	0.74	0.80	0.97
50% - Quantile	0.97	0.92	0.87	0.95	1.04
75% - Quantile	1.07	1.05	1.01	1.07	1.15
90% - Quantile	1.17	1.12	1.08	1.21	1.26
95% - Quantile	1.25	1.15	1.12	1.30	1.33

This table shows the return performance both for 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	CAPM	BCAPM	BSMA	BAMA	BAMAP
Panel A: Full Sample Results						
Geometric mean	10.06%	7.50%	11.76%	16.68%	15.28%	14.11%
Arithmetic mean	11.40%	8.62%	13.61%	18.79%	17.39%	16.09%
Volatility	16.28%	14.89%	19.39%	21.18%	21.20%	20.34%
Sharpe ratio	0.449	0.303	0.491	0.693	0.627	0.589
Outperformance Frequency		36%	55%	53%	50%	50%
Single-Factor Alpha		-1.97%	2.47%	7.78%	6.32%	4.77%
Single-Factor Alpha t-Stat		(1.703)	0.771	2.097	1.707	1.496
Single-Factor Beta		0.873	0.927	0.975	0.978	1.005
Four-Factor Alpha		-1.71%	7.47%	12.04%	10.28%	8.44%
Four-Factor Alpha t-Stat		(1.541)	2.803	3.710	3.137	3.021
Beta - Market		0.836	0.978	1.027	1.034	1.045
Beta - SMB		(0.012)	0.641	0.556	0.525	0.470
Beta - HML		0.119	(0.411)	(0.359)	(0.359)	(0.285)
Beta - Momentum		0.005	0.141	0.249	0.235	0.228
Panel B: Sub-Sample Results - 1993-2000						
Geometric mean	18.33%	15.34%	17.72%	23.49%	23.23%	21.65%
Arithmetic mean	19.49%	16.33%	19.71%	26.00%	25.73%	23.93%
Volatility	15.31%	14.16%	20.44%	23.55%	23.51%	22.23%
Sharpe ratio	0.941	0.795	0.716	0.888	0.879	0.848
Outperformance Frequency		43%	48%	45%	43%	43%
Single-Factor Alpha		-0.78%	0.86%	6.47%	6.27%	3.50%
Single-Factor Alpha t-Stat		(0.407)	0.160	0.991	0.956	0.633
Single-Factor Beta		0.852	0.941	1.019	1.009	1.076
Four-Factor Alpha		-2.17%	18.34%	25.35%	25.12%	19.26%
Four-Factor Alpha t-Stat		(1.219)	4.947	5.442	5.368	4.697
Beta - Market		0.831	0.811	0.859	0.851	0.962
Beta - SMB		(0.069)	0.887	0.907	0.906	0.779
Beta - HML		0.153	(0.444)	(0.511)	(0.519)	(0.452)
Beta - Momentum		(0.049)	0.484	0.674	0.674	0.499
Panel C: Sub-Sample Results - 2001-2008						
Geometric mean	1.17%	-0.94%	5.34%	9.35%	6.74%	6.00%
Arithmetic mean	2.65%	0.26%	7.01%	10.98%	8.38%	7.60%
Volatility	16.99%	15.36%	18.11%	18.14%	18.16%	17.88%
Sharpe ratio	(0.023)	(0.181)	0.219	0.437	0.293	0.255
Outperformance Frequency		28%	62%	62%	58%	56%
Single-Factor Alpha		-2.89%	4.12%	8.74%	6.02%	5.13%
Single-Factor Alpha t-Stat		(2.381)	1.246	2.666	1.889	1.730
Single-Factor Beta		0.889	0.914	0.932	0.944	0.941
Four-Factor Alpha		-2.61%	4.62%	10.26%	7.32%	6.37%
Four-Factor Alpha t-Stat		(2.237)	1.539	3.321	2.381	2.296
Beta - Market		0.881	0.912	0.859	0.879	0.891
Beta - SMB		0.081	0.454	0.189	0.109	0.108
Beta - HML		0.004	(0.211)	0.155	0.162	0.193
Beta - Momentum		0.029	0.014	0.071	0.056	0.144

This table shows the portfolio performance for the different strategies 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 strategies 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 10%, 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 $\sigma_\alpha = 10\%$/Month.

Table 4: Segmented versus Integrated Pricing Models

Asset Universe	Passive Index Funds		All Funds		Country Funds Only		Passive Index Funds		All Funds		Country Funds Only	
Market Model	Integrated	Segmented	Integrated	Segmented	Integrated	Segmented	Integrated	Segmented	Integrated	Segmented	Integrated	Segmented
	Panel A: BCAPM						Panel B: BSMA					
Geometric mean	11.09%	11.11%	11.76%	13.48%	11.59%	11.88%	10.17%	10.97%	16.68%	17.03%	13.34%	13.78%
Arithmetic mean	12.26%	12.27%	13.61%	15.13%	13.09%	13.31%	11.64%	12.39%	18.79%	19.03%	15.11%	15.48%
Volatility	15.25%	15.23%	19.39%	18.29%	17.43%	16.93%	17.08%	16.80%	21.18%	20.62%	19.10%	18.71%
Sharpe ratio	0.535	0.536	0.491	0.603	0.516	0.544	0.441	0.494	0.693	0.724	0.576	0.608
Outperf. Frequency	53%	53%	55%	54%	53%	51%	49%	50%	53%	54%	54%	51%
Single-Factor Pricing												
Alpha	1.60%	1.61%	2.47%	4.26%	2.27%	2.77%	0.49%	1.31%	7.78%	8.20%	3.90%	4.47%
Alpha t-Stat	1.311	1.329	0.771	1.451	0.858	1.085	0.299	0.836	2.097	2.239	1.293	1.484
Beta	0.892	0.892	0.927	0.889	0.872	0.851	0.977	0.965	0.975	0.938	0.938	0.907
Four-Factor Pricing												
Alpha	0.85%	0.84%	7.47%	9.09%	6.07%	6.91%	-0.18%	0.89%	12.04%	12.96%	7.54%	9.37%
Alpha t-Stat	0.715	0.720	2.803	3.818	2.717	3.293	(0.114)	0.606	3.710	4.236	2.888	3.920
Beta Market	0.909	0.908	0.978	0.942	0.918	0.893	0.987	0.975	1.027	1.017	0.991	0.969
Beta SMB	(0.071)	(0.073)	0.641	0.625	0.494	0.528	(0.071)	(0.043)	0.556	0.648	0.483	0.642
Beta HML	(0.010)	(0.009)	(0.411)	(0.411)	(0.331)	(0.335)	0.026	0.018	(0.359)	(0.485)	(0.339)	(0.440)
Beta MoM	0.057	0.059	0.141	0.129	0.135	0.123	0.159	0.169	0.249	0.229	0.184	0.171
	Panel C: BAMA						Panel D: BAMAP					
Geometric mean	10.08%	11.04%	15.28%	15.64%	13.19%	13.44%	10.75%	10.14%	14.11%	15.63%	12.40%	11.86%
Arithmetic mean	11.55%	12.46%	17.39%	17.60%	14.98%	15.17%	12.31%	11.65%	16.09%	17.42%	14.33%	13.43%
Volatility	17.05%	16.79%	21.20%	20.41%	19.17%	18.85%	17.59%	17.29%	20.34%	19.25%	19.95%	17.79%
Sharpe ratio	0.437	0.498	0.627	0.661	0.567	0.587	0.467	0.437	0.589	0.692	0.513	0.524
Outperf. Frequency	49%	50%	50%	53%	50%	52%	48%	47%	50%	51%	50%	50%
Single-Factor Pricing												
Alpha	0.38%	1.35%	6.32%	6.79%	3.69%	4.09%	0.95%	0.43%	4.77%	6.57%	2.53%	2.25%
Alpha t-Stat	0.233	0.868	1.707	1.895	1.235	1.348	0.581	0.265	1.496	2.118	0.881	0.942
Beta	0.974	0.965	0.978	0.936	0.947	0.915	1.011	0.994	1.005	0.938	1.026	0.939
Four-Factor Pricing												
Alpha	-0.32%	0.90%	10.28%	11.12%	7.26%	8.89%	0.56%	0.14%	8.44%	10.48%	5.94%	5.95%
Alpha t-Stat	(0.204)	0.619	3.137	3.656	2.816	3.713	0.357	0.092	3.021	4.037	2.405	3.023
Beta Market	0.985	0.975	1.034	1.013	1.002	0.981	1.017	0.997	1.045	0.985	1.063	0.962
Beta SMB	(0.075)	(0.047)	0.525	0.591	0.476	0.634	(0.045)	(0.036)	0.470	0.507	0.435	0.455
Beta HML	0.030	0.019	(0.359)	(0.451)	(0.342)	(0.447)	0.030	0.038	(0.285)	(0.319)	(0.262)	(0.236)
Beta MoM	0.161	0.172	0.235	0.233	0.192	0.188	0.151	0.181	0.228	0.261	0.227	0.169

This table presents key performance statistics for four investor types when we use both segmented and integrated pricing models and we consider three different fund universes: passive index funds, country funds and our complete sample of funds. Results are reported for the out- of- 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 10% of the total holdings, quarterly rebalancing. The short-term Euribor, the default spread, the term spread and the dividend yield are used as predictive variables, and beliefs are specified so that $\sigma_\alpha = 10\%$/Month.

Table 5: Portfolio Country and Sector Rotation

	CAPM				BCAPM				BSMA				BAMA				BAMAP			
	1993	1998	2003	2007	1993	1998	2003	2007	1993	1998	2003	2007	1993	1998	2003	2007	1993	1998	2003	2007
Austria	-	-	-	-	2%	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-
Benelux	-	14%	-	-	10%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
France	-	6%	10%	23%	-	-	16%	-	-	40%	-	-	-	33%	-	-	-	10%	-	-
Germany	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	10%	-	-	-	10%
Italy	-	-	-	-	-	-	3%	-	-	20%	-	-	-	13%	-	-	-	18%	-	-
Pan-Europe	10%	-	30%	60%	28%	10%	32%	6%	10%	10%	-	10%	10%	10%	-	10%	17%	20%	-	10%
Scandinavian	-	-	-	-	18%	90%	50%	58%	60%	21%	100%	-	60%	34%	100%	-	21%	52%	94%	-
Spain/Portugal	-	-	-	-	-	-	-	10%	-	9%	-	10%	-	10%	-	10%	-	-	-	10%
Switzerland	-	10%	10%	-	9%	-	-	-	10%	-	-	-	10%	-	-	-	28%	-	-	-
UK	90%	70%	50%	17%	33%	-	-	0%	20%	-	-	-	20%	-	-	-	25%	-	-	-
Sectors	-	-	-	-	-	-	-	26%	-	-	-	70%	-	-	-	70%	-	-	6%	70%

	CAPM - S				BCAPM - S				BSMA - S				BAMA - S				BAMAP - S			
	1993	1998	2003	2007	1993	1998	2003	2007	1993	1998	2003	2007	1993	1998	2003	2007	1993	1998	2003	2007
Austria	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Benelux	-	20%	10%	-	10%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
France	10%	30%	30%	30%	-	20%	30%	-	10%	58%	10%	-	10%	51%	10%	-	10%	10%	-	-
Germany	-	-	-	-	7%	-	-	-	-	-	10%	-	-	-	10%	-	-	-	-	10%
Italy	-	-	-	-	-	-	-	-	-	10%	-	-	-	10%	-	-	-	10%	-	-
Pan-Europe	42%	-	30%	60%	27%	10%	25%	5%	30%	4%	19%	10%	30%	9%	20%	12%	38%	40%	10%	2%
Scandinavian	-	5%	-	-	16%	70%	45%	65%	20%	19%	52%	-	30%	20%	48%	1%	20%	40%	78%	9%
Spain/Portugal	-	-	-	-	-	-	-	-	-	10%	-	-	-	10%	-	-	-	-	-	-
Switzerland	-	20%	10%	10%	-	-	-	-	10%	-	-	-	10%	-	-	-	12%	-	-	-
UK	48%	25%	20%	-	40%	-	-	10%	30%	-	-	10%	20%	-	0%	10%	20%	-	12%	9%
Sectors	-	-	-	-	-	-	-	20%	-	-	9%	80%	-	-	11%	78%	-	-	0%	70%

This table presents portfolio weights for the investor types considered in the analysis. Weights are reported as of end of May, 1993, 1998, 2003 and end of November 2007 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 10%, 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 $\sigma_\alpha = 10\%$/Month.

Table 6: Optimal Portfolio Weights (February, 2008)

	CAPM	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Etoile Alimentation Europe	0%	0%	0%	10%	10%	10%	10%	10%	10%
SKARBIEC-RYNKU NIERUCHOMOSCI FIZ	0%	0%	0%	10%	10%	10%	10%	10%	10%
StreetTRACKS MSCI Europe Telecom Svcs ETF	0%	0%	0%	10%	10%	10%	10%	5%	10%
iShares DJ EURO STOXX Telecomm (DE)	0%	0%	0%	10%	10%	10%	10%	0%	10%
Postbank Megatrend	0%	0%	0%	10%	2%	10%	8%	10%	2%
iShares TecDAX (DE)	0%	0%	0%	10%	0%	10%	0%	10%	10%
Fideuram Fund Europe Listed Cons Staples Eq	0%	0%	0%	0%	10%	0%	10%	10%	10%
Holly	0%	0%	10%	0%	10%	0%	10%	0%	9%
StreetTRACKS MSCI Europe Info Tech ETF	0%	0%	0%	10%	0%	10%	0%	10%	0%
Fideuram Fund Europe Listed TT Equity	0%	0%	0%	0%	10%	0%	10%	0%	10%
Etoile Collectivites Europe	0%	0%	0%	0%	10%	0%	0%	10%	10%
Santander Aggressive Spain, FI	0%	0%	0%	10%	0%	10%	0%	10%	0%
iShares DJ EURO STOXX Technology (DE)	0%	0%	0%	9%	0%	7%	0%	9%	0%
Fortis L Equity Telecom Europe Cap	0%	0%	0%	1%	9%	3%	10%	0%	0%
CSIMF Universe F	0%	6%	5%	0%	8%	0%	4%	0%	0%
KBC Multi Track Euro Telecom Acc	0%	0%	0%	10%	0%	10%	0%	2%	0%
Odin Eiendom	0%	10%	10%	0%	0%	0%	0%	0%	0%
FIM Fenno	0%	10%	10%	0%	0%	0%	0%	0%	0%
Holberg Norge	0%	10%	10%	0%	0%	0%	0%	0%	0%
DnB NOR SMB	0%	10%	10%	0%	0%	0%	0%	0%	0%
Pareto Aksje Norge	0%	10%	10%	0%	0%	0%	0%	0%	0%
WarrenWicklund Norge	0%	10%	10%	0%	0%	0%	0%	0%	0%
Sparinvest Europaeiske Finansielle Aktier	0%	6%	10%	0%	0%	0%	0%	0%	0%
Kaupthing Investment Fund - Icelandic Equity	0%	6%	6%	0%	0%	0%	0%	0%	0%
Anima European Equity B	10%	0%	0%	0%	0%	0%	0%	0%	0%
European Equity Index Pool	10%	0%	0%	0%	0%	0%	0%	0%	0%
SGAM Index Euro	10%	0%	0%	0%	0%	0%	0%	0%	0%
Lyxor France Index 1	10%	0%	0%	0%	0%	0%	0%	0%	0%
Andorfons Anglaterra	10%	0%	0%	0%	0%	0%	0%	0%	0%
Andorfons Europa	10%	0%	0%	0%	0%	0%	0%	0%	0%
Andorfons Franca	10%	0%	0%	0%	0%	0%	0%	0%	0%
AXA WF Euro Value Equities A Cap	10%	0%	0%	0%	0%	0%	0%	0%	0%
Barclays EF Euro Blue Chip A	10%	0%	0%	0%	0%	0%	0%	0%	0%
Eurovalor Bolsa Espaola, FI	0%	10%	0%	0%	0%	0%	0%	0%	0%
iShares DJ STOXX 600 Basic Resources (DE)	0%	10%	0%	0%	0%	0%	0%	0%	0%
Odin Finland	0%	0%	0%	0%	0%	0%	0%	0%	9%
SEBinvest Danske Aktier	0%	0%	9%	0%	0%	0%	0%	0%	0%
iShares DJ STOXX 600 Automobiles & Parts (DE)	0%	0%	0%	0%	1%	0%	8%	0%	0%
Aberdeen Global-UK Opportunities A Acc	7%	0%	0%	0%	0%	0%	0%	0%	0%
SGAM Index Tech Euro	0%	0%	0%	0%	0%	0%	0%	4%	0%
Oddo Quant France A Cap	3%	0%	0%	0%	0%	0%	0%	0%	0%
Storebrand Optima Norge A	0%	1%	0%	0%	0%	0%	0%	0%	0%
OP-Delta A	0%	0%	0%	0%	0%	0%	1%	0%	0%

This table presents the portfolio holdings at the end of the sample (02/2008) for the different strategies. 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 10%, 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 $\sigma_\alpha = 10\%/\text{Month}$.

Table 7: Out-of-Sample Performance Attribution

Panel A: Integrated Model

	CAPM	BCAPM	BSMA	BAMA	BAMAP
Arithmetic mean	8.62%	13.61%	18.79%	17.39%	16.09%
Return from Pan-Euro Fund Selection	2.21%	0.06%	-0.54%	-0.17%	-1.44%
Return from Country Fund Selection	-0.69%	1.34%	3.13%	2.01%	2.15%
Return from Sector Fund Selection	0.00%	0.55%	2.94%	2.50%	1.87%
Return from Timing Country Weights	-1.62%	1.19%	2.21%	2.10%	3.25%
Residual	-2.68%	-0.94%	-0.35%	-0.45%	-1.14%
Total Outperformance	-2.78%	2.21%	7.39%	5.99%	4.69%

Panel B: Segmented Model

	CAPM-S	BCAPM-S	BSMA-S	BAMA-S	BAMAP-S
Arithmetic mean	8.91%	15.13%	19.03%	17.60%	17.42%
Return from Pan-Euro Fund Selection	1.86%	-1.22%	-0.90%	-0.58%	-0.81%
Return from Country Fund Selection	-0.79%	1.36%	3.19%	2.09%	2.04%
Return from Sector Fund Selection	0.00%	1.45%	3.12%	2.68%	2.65%
Return from Timing Country Weights	-1.41%	1.26%	1.51%	1.33%	1.77%
Residual	-2.15%	0.89%	0.71%	0.68%	0.38%
Total Outperformance	-2.49%	3.73%	7.63%	6.20%	6.02%

This table decomposes the abnormal return performance of our integrated and segmented models into four components, plus a residual. The differential return is measured relative to the benchmark MSCI Europe portfolio whose arithmetic mean return was 11.40% 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 8: Predictability Generated by Individual and Local Macro Variables

Panel A - BSMA-S

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Single-Factor Alpha	Single-Factor Alpha t-Statistic	Beta
Local Macro Variables	13.23%	14.88%	18.23%	0.592	4.01%	1.373	0.887
1 - Short Rate Yield	15.22%	17.24%	20.42%	0.644	6.06%	1.755	0.963
2 - Term Spread	14.38%	15.96%	17.93%	0.661	4.97%	1.872	0.909
3 - Dividend Yield	13.52%	15.24%	18.71%	0.595	4.70%	1.470	0.876
4 - Default Spread	14.68%	16.41%	18.88%	0.652	5.47%	1.818	0.924
5 - Volatility	14.54%	16.29%	18.76%	0.650	4.85%	1.779	0.957
6 - Inflation	15.48%	17.08%	18.08%	0.718	6.39%	2.182	0.875
7 - Industrial Production	15.92%	17.76%	19.66%	0.695	7.00%	2.020	0.899
8 - Economic Sentiment	15.67%	17.54%	19.73%	0.681	6.61%	1.911	0.903
9 - Currency Factor	12.02%	13.55%	17.70%	0.534	3.01%	1.019	0.840

Panel B - BAMA-S

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Single-Factor Alpha	Single-Factor Alpha t-Statistic	Beta
Local Macro Variables	14.93%	16.89%	20.35%	0.628	6.19%	1.707	0.923
1 - Short Rate Yield	15.02%	17.00%	20.19%	0.639	5.91%	1.710	0.943
2 - Term Spread	14.39%	15.97%	17.95%	0.661	4.98%	1.871	0.909
3 - Dividend Yield	13.35%	15.04%	18.53%	0.590	4.55%	1.440	0.869
4 - Default Spread	14.73%	16.46%	18.91%	0.653	5.52%	1.826	0.924
5 - Volatility	14.53%	16.28%	18.76%	0.649	4.84%	1.776	0.957
6 - Inflation	15.33%	16.94%	18.12%	0.709	6.25%	2.125	0.875
7 - Industrial Production	15.91%	17.76%	19.69%	0.694	6.99%	2.015	0.899
8 - Economic Sentiment	15.71%	17.58%	19.78%	0.681	6.66%	1.913	0.903
9 - Currency Factor	12.03%	13.56%	17.63%	0.536	3.01%	1.031	0.839

Panel C - BAMAP-S

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Single-Factor Alpha	Single-Factor Alpha t-Statistic	Beta
1 - Short Rate Yield	16.03%	18.07%	20.63%	0.677	6.88%	1.975	0.974
2 - Term Spread	14.08%	15.68%	18.13%	0.639	4.91%	1.708	0.888
3 - Dividend Yield	13.16%	15.11%	19.94%	0.552	4.00%	1.192	0.942
4 - Default Spread	14.82%	16.58%	19.09%	0.653	5.69%	1.827	0.921
5 - Volatility	13.31%	15.15%	19.31%	0.572	3.71%	1.246	0.957
6 - Inflation	15.41%	17.30%	19.72%	0.669	6.26%	1.888	0.932
7 - Industrial Production	15.74%	17.55%	19.44%	0.692	6.63%	2.003	0.912
8 - Economic Sentiment	13.85%	15.49%	18.31%	0.622	4.72%	1.612	0.893
9 - Currency Factor	10.58%	11.85%	15.93%	0.486	1.65%	0.664	0.785

Panel D - Reference Portfolios

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Single-Factor Alpha	Single-Factor Alpha t-Statistic	Beta
Benchmark	10.06%	11.40%	16.28%	0.449			
CAPM	7.50%	8.62%	14.89%	0.303	-1.97%	(1.703)	0.873
BCAPM-S	13.48%	15.13%	18.29%	0.603	4.26%	1.451	0.889

This table presents key performance statistics when the three investor types, based on segmented pricing models, 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 10% 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 the 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. The local Macro Variable specification show the effect estimating the model with country-specific macroeconomic variables (term spread, dividend yield, default spread, and short-term interest rate) following the pan-European specification of these variables from the Global Financial Database.

Table 9: Robustness to Fund Universe Size

Panel A: Portfolios of 250 Funds with the Highest Conditional Alpha

	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	10.06%	8.18%	8.21%	12.56%	13.17%	13.59%	14.36%	13.47%	14.19%	12.94%	14.12%
Arithmetic mean	11.40%	9.25%	9.40%	14.04%	14.51%	15.04%	15.74%	14.94%	15.57%	14.43%	15.47%
Volatility	16.28%	14.61%	15.35%	17.21%	16.40%	17.21%	16.74%	17.40%	16.77%	17.41%	16.53%
Sharpe ratio	0.449	0.353	0.345	0.577	0.635	0.636	0.695	0.623	0.684	0.593	0.688
Outperformance Frequency		39%	37%	51%	53%	51%	55%	50%	54%	51%	54%
Single-Factor Alpha		-1.13%	-1.61%	2.94%	3.67%	4.28%	5.01%	4.09%	4.77%	3.47%	4.72%
Single-Factor Alpha t-Stat		(0.832)	(1.773)	1.315	1.805	1.879	2.311	1.770	2.215	1.587	2.366
Single-Factor Beta		0.837	0.917	0.918	0.888	0.917	0.897	0.925	0.900	0.941	0.904
Four-Factor Alpha		-0.80%	-1.25%	6.58%	7.29%	7.43%	8.69%	7.24%	8.39%	6.55%	7.92%
Four-Factor Alpha t-Stat		(0.623)	(1.436)	3.605	4.465	3.858	5.108	3.693	4.970	3.542	5.026
Beta - Market		0.792	0.891	0.951	0.913	0.941	0.925	0.950	0.928	0.963	0.920
Beta - SMB		(0.012)	0.012	0.461	0.451	0.394	0.460	0.395	0.453	0.381	0.390
Beta - HML		0.140	0.076	(0.280)	(0.258)	(0.216)	(0.259)	(0.219)	(0.255)	(0.203)	(0.187)
Beta - Momentum		(0.028)	(0.013)	0.118	0.091	0.164	0.157	0.166	0.163	0.159	0.180

Panel B: Portfolios of All Funds

	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	10.06%	8.49%	9.13%	10.09%	10.22%	10.22%	10.19%	10.26%	10.23%	10.15%	10.15%
Arithmetic mean	11.40%	9.66%	10.36%	11.35%	11.48%	11.46%	11.43%	11.49%	11.47%	11.38%	11.39%
Volatility	16.28%	15.21%	15.61%	15.76%	15.79%	15.68%	15.69%	15.68%	15.70%	15.67%	15.72%
Sharpe ratio	0.449	0.366	0.401	0.460	0.467	0.469	0.467	0.472	0.469	0.465	0.464
Outperformance Frequency		42%	47%	53%	50%	50%	51%	50%	51%	50%	51%
Single-Factor Alpha		-1.28%	-0.74%	0.23%	0.36%	0.45%	0.41%	0.47%	0.44%	0.37%	0.36%
Single-Factor Alpha t-Stat		(1.621)	(0.907)	0.232	0.360	0.442	0.402	0.462	0.426	0.363	0.357
Single-Factor Beta		0.915	0.940	0.940	0.942	0.933	0.934	0.933	0.935	0.934	0.937
Four-Factor Alpha		-0.52%	0.39%	1.81%	2.01%	1.98%	2.09%	2.00%	2.12%	1.90%	1.98%
Four-Factor Alpha t-Stat		(0.703)	0.520	2.106	2.333	2.202	2.349	2.243	2.382	2.139	2.242
Beta - Market		0.898	0.931	0.938	0.939	0.932	0.932	0.932	0.933	0.932	0.935
Beta - SMB		0.069	0.122	0.181	0.188	0.175	0.193	0.176	0.193	0.176	0.186
Beta - HML		0.021	(0.026)	(0.066)	(0.066)	(0.064)	(0.073)	(0.064)	(0.072)	(0.064)	(0.068)
Beta - Momentum		(0.020)	(0.006)	0.032	0.023	0.056	0.037	0.057	0.038	0.043	0.034

This table shows the efect of imposing diferent constraints on the universe of funds available for forming the investor's portfolios. 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 10% of the portfolio. Panel A tests the portfolio performance when the initial sort selects the 250 funds with the highest conditional alphas. Panel B tests the portfolio performance when there is no initial sort based on a funds conditional alpha.

Table 10: Robustness to Investor Trading Strategy Restrictions

Panel A: No Maximum Weight Restrictions

	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	10.06%	7.81%	7.26%	16.13%	15.78%	22.53%	22.05%	21.43%	21.26%	17.76%	19.36%
Arithmetic mean	11.40%	9.07%	8.81%	18.06%	17.65%	25.85%	25.37%	24.76%	24.53%	20.46%	22.29%
Volatility	16.28%	15.74%	17.46%	19.96%	19.66%	27.08%	27.09%	27.12%	26.84%	23.99%	25.08%
Sharpe ratio	0.449	0.315	0.270	0.699	0.689	0.803	0.785	0.762	0.761	0.682	0.725
Outperformance Frequency		46%	42%	56%	58%	58%	59%	56%	58%	54%	52%
Single-Factor Alpha		-1.02%	-2.96%	7.50%	7.28%	14.43%	14.29%	13.08%	13.55%	8.78%	11.06%
Single-Factor Alpha t-Stat		(0.653)	(1.803)	1.988	1.948	2.597	2.507	2.392	2.383	1.940	2.203
Single-Factor Beta		0.886	0.995	0.851	0.834	1.041	0.999	1.070	0.977	1.026	1.001
Four-Factor Alpha		-1.34%	-3.18%	12.77%	12.40%	20.23%	19.72%	18.14%	18.70%	14.04%	16.17%
Four-Factor Alpha t-Stat		(0.901)	(1.938)	3.874	3.790	4.056	3.926	3.629	3.723	3.572	3.767
Beta - Market		0.846	0.982	0.869	0.849	1.046	1.067	1.065	1.052	1.059	1.026
Beta - SMB		(0.081)	(0.040)	0.636	0.615	0.690	0.714	0.588	0.688	0.649	0.621
Beta - HML		0.148	0.061	(0.294)	(0.274)	(0.240)	(0.432)	(0.167)	(0.445)	(0.316)	(0.247)
Beta - Momentum		(0.051)	0.008	0.201	0.214	0.424	0.473	0.412	0.474	0.379	0.546

Panel B: 5% Maximum Weight

	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	10.06%	8.78%	8.49%	11.97%	12.69%	14.71%	14.54%	13.77%	14.49%	13.73%	13.85%
Arithmetic mean	11.40%	9.93%	9.80%	13.78%	14.25%	16.46%	16.19%	15.52%	16.14%	15.51%	15.43%
Volatility	16.28%	15.12%	16.09%	19.10%	17.72%	19.08%	18.43%	19.13%	18.46%	19.21%	17.91%
Sharpe ratio	0.449	0.386	0.354	0.507	0.573	0.648	0.656	0.597	0.653	0.594	0.633
Outperformance Frequency		40%	42%	54%	52%	51%	54%	49%	53%	50%	52%
Single-Factor Alpha		-0.85%	-1.47%	2.53%	3.44%	5.58%	5.41%	4.61%	5.36%	4.46%	4.55%
Single-Factor Alpha t-Stat		(0.876)	(1.706)	0.846	1.257	1.893	1.906	1.556	1.870	1.579	1.805
Single-Factor Beta		0.900	0.968	0.941	0.879	0.953	0.921	0.954	0.918	0.982	0.931
Four-Factor Alpha		-0.36%	-0.98%	7.26%	8.26%	9.02%	9.88%	8.16%	9.65%	8.05%	8.32%
Four-Factor Alpha t-Stat		(0.391)	(1.151)	2.931	3.810	3.516	4.322	3.135	4.115	3.325	4.082
Beta - Market		0.871	0.956	0.989	0.929	1.001	0.981	1.002	0.979	1.026	0.977
Beta - SMB		0.024	0.046	0.605	0.618	0.455	0.590	0.467	0.570	0.467	0.489
Beta - HML		0.076	0.013	(0.386)	(0.400)	(0.312)	(0.414)	(0.323)	(0.408)	(0.306)	(0.319)
Beta - Momentum		(0.015)	(0.012)	0.140	0.118	0.187	0.150	0.161	0.154	0.186	0.181

Panel C: Limit Buy/Sell to 5% per Quarter

	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	10.06%	8.39%	7.97%	11.93%	12.94%	14.76%	14.31%	13.46%	13.87%	13.57%	13.51%
Arithmetic mean	11.40%	9.52%	9.21%	13.73%	14.54%	16.52%	15.96%	15.24%	15.56%	15.36%	15.12%
Volatility	16.28%	14.96%	15.66%	19.05%	17.92%	19.14%	18.43%	19.21%	18.62%	19.26%	18.09%
Sharpe ratio	0.449	0.362	0.326	0.505	0.582	0.649	0.643	0.580	0.615	0.584	0.609
Outperformance Frequency		42%	45%	54%	54%	49%	54%	47%	53%	47%	47%
Single-Factor Alpha		-1.11%	-1.83%	2.73%	3.93%	5.63%	5.20%	4.35%	4.68%	4.35%	4.29%
Single-Factor Alpha t-Stat		(1.076)	(2.054)	0.904	1.398	1.908	1.805	1.459	1.627	1.535	1.658
Single-Factor Beta		0.887	0.939	0.937	0.887	0.956	0.914	0.956	0.928	0.984	0.935
Four-Factor Alpha		-0.51%	-1.38%	7.46%	8.81%	9.07%	9.61%	7.83%	8.97%	7.92%	7.96%
Four-Factor Alpha t-Stat		(0.518)	(1.591)	2.973	3.937	3.520	4.142	2.986	3.811	3.244	3.735
Beta - Market		0.858	0.919	0.984	0.936	1.003	0.975	1.007	0.991	1.029	0.984
Beta - SMB		0.038	0.030	0.604	0.625	0.453	0.584	0.462	0.571	0.465	0.480
Beta - HML		0.068	0.047	(0.382)	(0.400)	(0.307)	(0.411)	(0.327)	(0.413)	(0.307)	(0.326)
Beta - Momentum		(0.016)	(0.007)	0.144	0.128	0.188	0.168	0.164	0.156	0.183	0.179

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 10% of the portfolio. Panel A lifts the constraints on the portfolio weights which are no longer capped at 10%, although short sales are still ruled out. Panel B limits the maximum position in individual funds to 5% of the portfolio. Panel C restricts changes in the portfolio weights so the fund cannot divest more than 5% per quarter. This has the effect of reducing turnover. All other assumptions are identical to those from the baseline scenario.

Table 11: Robustness to Investor Beliefs

	Sigma Alpha						Sigma Alpha					
	0.10%	1.00%	5.00%	10.00%	50.00%	100.00%	0.10%	1.00%	5.00%	10.00%	50.00%	100.00%
	Panel A: BCAPM-S						Panel B: BSMA-S					
Geometric mean	11.52%	13.78%	13.48%	13.48%	13.49%	13.49%	14.45%	15.15%	17.38%	17.03%	16.84%	16.84%
Arithmetic mean	12.74%	15.32%	15.13%	15.13%	15.15%	15.15%	15.75%	16.75%	19.39%	19.03%	18.85%	18.85%
Volatility	15.58%	17.57%	18.25%	18.29%	18.30%	18.30%	16.13%	18.11%	20.66%	20.62%	20.66%	20.67%
Sharpe ratio	0.554	0.638	0.604	0.603	0.604	0.604	0.722	0.698	0.740	0.724	0.714	0.714
Outperformance Frequency	52%	55%	54%	54%	54%	54%	55%	55%	58%	54%	54%	54%
Single-Factor Alpha	2.31%	4.56%	4.26%	4.26%	4.27%	4.27%	5.07%	6.15%	8.52%	8.20%	8.02%	8.02%
Single-Factor Alpha t-Stat	1.220	1.685	1.458	1.451	1.454	1.454	2.483	2.138	2.336	2.239	2.178	2.177
Single-Factor Beta	0.849	0.874	0.889	0.889	0.890	0.890	0.866	0.889	0.945	0.938	0.938	0.938
Four-Factor Alpha	5.94%	9.35%	9.09%	9.09%	9.10%	9.10%	8.30%	10.45%	13.21%	12.96%	12.84%	12.84%
Four-Factor Alpha t-Stat	4.232	4.320	3.831	3.818	3.814	3.814	4.916	4.486	4.343	4.236	4.167	4.167
Beta - Market	0.879	0.908	0.941	0.942	0.943	0.943	0.881	0.933	1.025	1.017	1.017	1.017
Beta - SMB	0.455	0.598	0.623	0.625	0.625	0.625	0.394	0.550	0.641	0.648	0.654	0.655
Beta - HML	(0.267)	(0.341)	(0.409)	(0.411)	(0.412)	(0.412)	(0.194)	(0.334)	(0.482)	(0.485)	(0.490)	(0.490)
Beta - Momentum	0.123	0.131	0.128	0.129	0.129	0.129	0.138	0.218	0.233	0.229	0.223	0.223
	Panel C: BAMA-S						Panel D: BAMAP-S					
Geometric mean	13.42%	13.85%	15.46%	15.64%	16.93%	16.95%	12.65%	14.45%	15.40%	15.63%	15.56%	15.58%
Arithmetic mean	15.38%	15.80%	17.44%	17.60%	18.94%	18.96%	14.45%	16.29%	17.22%	17.42%	17.36%	17.38%
Volatility	20.37%	20.34%	20.51%	20.41%	20.63%	20.63%	19.21%	19.43%	19.37%	19.25%	19.26%	19.26%
Sharpe ratio	0.554	0.575	0.651	0.661	0.719	0.720	0.539	0.627	0.677	0.692	0.688	0.689
Outperformance Frequency	50%	51%	54%	53%	55%	55%	46%	51%	51%	51%	50%	51%
Single-Factor Alpha	4.39%	4.85%	6.52%	6.79%	8.10%	8.13%	3.51%	5.32%	6.30%	6.57%	6.50%	6.52%
Single-Factor Alpha t-Stat	1.227	1.356	1.819	1.895	2.209	2.214	1.147	1.710	2.030	2.118	2.097	2.102
Single-Factor Beta	0.933	0.931	0.944	0.936	0.938	0.937	0.942	0.949	0.946	0.938	0.939	0.939
Four-Factor Alpha	8.77%	9.26%	10.92%	11.12%	12.88%	12.93%	7.54%	9.39%	10.28%	10.48%	10.46%	10.47%
Four-Factor Alpha t-Stat	2.869	3.024	3.561	3.656	4.213	4.222	2.943	3.615	3.959	4.037	4.043	4.053
Beta - Market	1.006	1.003	1.020	1.013	1.019	1.017	0.999	1.001	0.995	0.985	0.987	0.987
Beta - SMB	0.592	0.594	0.600	0.591	0.651	0.653	0.533	0.531	0.517	0.507	0.513	0.514
Beta - HML	(0.443)	(0.440)	(0.457)	(0.451)	(0.489)	(0.490)	(0.372)	(0.348)	(0.330)	(0.319)	(0.323)	(0.324)
Beta - Momentum	0.219	0.215	0.204	0.233	0.229	0.228	0.209	0.239	0.250	0.261	0.259	0.259

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. 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 10%, 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 Short and Long Portfolio Performance

Panel A: Short Portfolio Performance

	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	3.71%	2.29%	-1.06%	-2.17%	-7.66%	-6.91%	-6.66%	-5.93%	-4.68%	-6.18%
Arithmetic mean	5.30%	3.59%	0.28%	-0.59%	-5.09%	-4.47%	-4.15%	-3.55%	-2.58%	-4.24%
Volatility	17.76%	15.99%	16.23%	17.54%	22.15%	21.58%	21.85%	21.33%	20.04%	19.25%
Sharpe ratio	0.067	(0.032)	(0.235)	(0.267)	(0.415)	(0.397)	(0.378)	(0.359)	(0.333)	(0.433)
Outperformance Frequency	37%	37%	29%	34%	33%	33%	34%	33%	32%	27%
Single-Factor Alpha	-6.01%	-7.14%	-10.24%	-11.52%	-17.69%	-16.69%	-16.56%	-15.74%	-14.52%	-15.79%
Single-Factor Alpha t-Stat	(3.050)	(4.313)	(5.221)	(5.425)	(5.565)	(5.403)	(5.186)	(5.252)	(5.514)	(5.911)
Single-Factor Beta	0.993	0.907	0.889	0.959	1.141	1.115	1.117	1.110	1.069	1.006
Four-Factor Alpha	-2.49%	-3.73%	-8.31%	-9.64%	-13.09%	-12.15%	-11.40%	-11.13%	-10.70%	-12.35%
Four-Factor Alpha t-Stat	(1.512)	(2.806)	(4.427)	(4.793)	(4.579)	(4.365)	(4.053)	(4.155)	(4.473)	(5.045)
Beta - Market	0.993	0.905	0.857	0.944	1.120	1.084	1.094	1.071	1.063	0.978
Beta - SMB	0.410	0.396	0.193	0.211	0.529	0.509	0.590	0.505	0.448	0.383
Beta - HML	(0.165)	(0.162)	0.012	(0.072)	(0.205)	(0.159)	(0.222)	(0.128)	(0.198)	(0.111)
Beta - Momentum	0.079	0.017	(0.023)	(0.156)	(0.221)	(0.178)	(0.200)	(0.147)	(0.133)	(0.176)

Panel B: 2:1 Leverage Portfolio Performance

	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	3.39%	3.60%	11.77%	14.14%	18.59%	18.51%	17.87%	17.99%	18.18%	18.45%
Arithmetic mean	5.11%	5.39%	15.00%	17.11%	22.27%	22.02%	21.66%	21.60%	21.82%	21.52%
Volatility	18.42%	18.81%	25.86%	24.78%	27.98%	27.21%	28.49%	27.57%	27.90%	25.22%
Sharpe ratio	0.055	0.069	0.422	0.525	0.649	0.659	0.616	0.635	0.635	0.691
Outperformance Frequency	39%	43%	52%	53%	54%	57%	51%	55%	56%	54%
Single-Factor Alpha	-5.81%	-6.05%	3.67%	6.13%	10.60%	10.22%	10.00%	9.60%	10.53%	10.53%
Single-Factor Alpha t-Stat	(1.908)	(2.282)	0.666	1.149	1.804	1.781	1.656	1.661	1.771	2.000
Single-Factor Beta	0.865	0.967	0.927	0.870	1.034	0.991	1.035	1.015	1.006	0.943
Four-Factor Alpha	-9.02%	-9.14%	9.50%	12.18%	13.59%	14.89%	13.43%	13.75%	14.74%	15.21%
Four-Factor Alpha t-Stat	(3.283)	(3.741)	1.926	2.609	2.441	2.802	2.353	2.550	2.728	3.226
Beta - Market	0.834	0.968	1.044	1.000	1.097	1.084	1.104	1.114	1.066	0.999
Beta - SMB	(0.399)	(0.352)	0.812	0.856	0.419	0.654	0.476	0.599	0.555	0.608
Beta - HML	0.230	0.126	(0.675)	(0.735)	(0.313)	(0.525)	(0.356)	(0.519)	(0.335)	(0.361)
Beta - Momentum	(0.214)	(0.144)	0.212	0.202	0.349	0.251	0.346	0.243	0.506	0.424

Panel C: Self-Financing Portfolio Performance - Market Factor Neutral

	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geometric mean	4.01%	1.67%	10.39%	8.42%	11.49%	14.21%	11.90%	14.17%	11.76%	12.95%
Arithmetic mean	4.01%	1.87%	10.89%	8.79%	12.34%	14.86%	12.76%	14.81%	12.62%	13.50%
Volatility	0.62%	6.46%	9.96%	8.50%	13.26%	11.62%	13.28%	11.53%	13.34%	10.58%
Sharpe ratio	(0.139)	(0.345)	0.682	0.551	0.621	0.925	0.652	0.929	0.638	0.888
Outperformance Frequency	37%	38%	46%	44%	46%	47%	47%	46%	45%	47%
Single-Factor Alpha	-0.11%	-1.93%	6.34%	3.94%	7.84%	10.56%	8.37%	10.35%	8.05%	9.25%
Single-Factor Alpha t-Stat	(1.165)	(1.166)	2.433	1.782	2.257	3.461	2.404	3.424	2.304	3.343
Single-Factor Beta	0.002	(0.070)	0.021	0.047	0.051	0.014	0.025	0.030	0.037	0.005
Four-Factor Alpha	-0.21%	-3.39%	7.84%	5.05%	8.83%	11.60%	9.29%	11.32%	9.18%	9.83%
Four-Factor Alpha t-Stat	(2.339)	(2.120)	3.130	2.335	2.703	3.994	2.835	3.919	2.848	3.697
Beta - Market	0.002	(0.082)	0.047	0.060	0.083	0.030	0.061	0.042	0.092	0.020
Beta - SMB	(0.011)	(0.184)	0.204	0.144	0.147	0.138	0.144	0.126	0.189	0.084
Beta - HML	0.004	0.120	(0.150)	(0.092)	(0.111)	(0.067)	(0.122)	(0.051)	(0.197)	(0.049)
Beta - Momentum	(0.004)	0.026	0.107	0.057	0.293	0.228	0.288	0.221	0.305	0.192

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 2:1 leveraged portfolio that takes a 200% long position in mutual funds financed by using a 100% short position in benchmark and country indices. Panel C reports the performance of a self-financing portfolio that but allows takes a long position in mutual funds financed by using a short position in benchmark and country indices with the objective of maintaining zero exposure to the market risk factor.

Table 13: Sorted Portfolio Performance

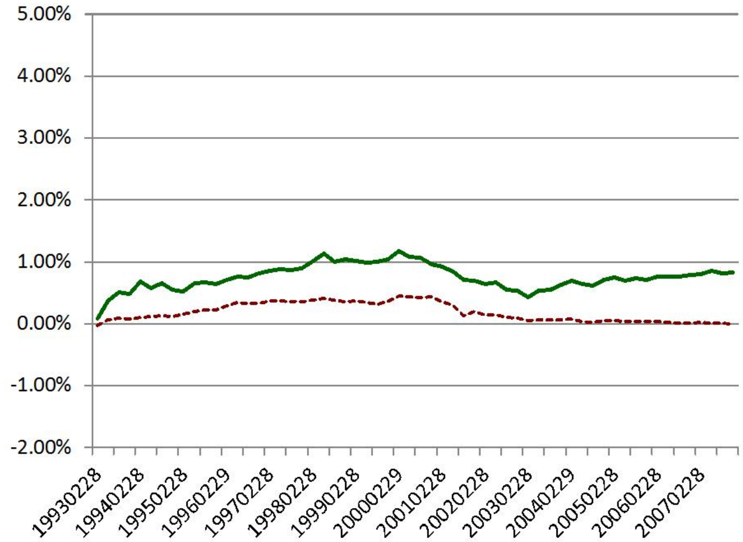
	BCAPM	BCAPM-S	BAMA	BAMA-S	BSMA	BSMA-S	BAMAP	BAMAP-S	Momentum
					Annualized Average Return				
1	13.37%	13.08%	13.10%	12.58%	13.38%	12.81%	12.88%	12.62%	14.90%
2	12.52%	12.40%	11.94%	12.05%	11.74%	11.89%	12.45%	11.87%	12.80%
3	11.62%	11.45%	11.49%	11.43%	11.40%	11.35%	11.56%	11.87%	11.30%
4	10.61%	10.67%	10.92%	11.48%	11.26%	11.45%	11.32%	11.20%	10.50%
5	9.64%	11.00%	10.42%	10.63%	10.01%	10.72%	10.69%	11.20%	9.50%
6	10.51%	10.16%	9.88%	10.27%	9.98%	10.23%	9.54%	10.19%	9.80%
7	9.69%	9.95%	9.66%	10.01%	9.65%	9.93%	9.96%	9.86%	9.50%
8	9.56%	9.91%	9.41%	9.76%	9.46%	10.03%	9.01%	9.55%	10.00%
9	9.59%	9.05%	9.73%	9.33%	9.83%	9.14%	9.45%	9.32%	9.80%
10	9.38%	8.79%	10.00%	8.98%	9.83%	8.98%	9.66%	8.84%	8.60%
H-L	3.99%	4.29%	3.10%	3.59%	3.55%	3.83%	3.22%	3.78%	6.40%
					Patton-Timmermann Test p-Values				
H vs L	8%	3%	10%	1%	7%	0%	6%	0%	28%
All	86%	13%	28%	0%	33%	2%	19%	0%	23%
					Annualized 4-Factor Alpha				
1	5.71%	5.77%	4.71%	4.42%	5.02%	4.75%	4.37%	4.41%	6.60%
2	3.82%	4.32%	2.56%	2.97%	2.31%	2.76%	3.33%	2.68%	3.90%
3	2.55%	2.58%	1.86%	1.77%	1.80%	1.60%	1.97%	2.54%	2.00%
4	1.42%	1.36%	1.33%	1.95%	1.69%	1.94%	1.80%	1.61%	0.50%
5	-0.09%	1.44%	0.79%	1.01%	0.40%	1.01%	1.07%	1.50%	-0.70%
6	0.87%	0.38%	0.26%	0.46%	0.37%	0.54%	-0.07%	0.32%	-0.40%
7	-0.33%	-0.22%	-0.07%	0.31%	-0.12%	0.19%	0.21%	0.14%	-0.70%
8	-0.54%	-0.57%	-0.21%	-0.09%	-0.14%	0.22%	-0.85%	-0.26%	0.30%
9	-0.43%	-1.26%	0.22%	-0.31%	0.37%	-0.51%	-0.01%	-0.51%	0.30%
10	-1.12%	-1.95%	0.44%	-0.62%	0.17%	-0.63%	0.07%	-0.55%	0.00%
H-L	6.83%	7.72%	4.27%	5.04%	4.85%	5.38%	4.30%	4.96%	6.60%
					Patton-Timmermann 4-Factor Residual Test p-Values				
H vs L	0%	0%	2%	0%	1%	0%	1%	0%	48%
All	77%	0%	33%	1%	47%	3%	55%	0%	36%

This table presents summary return statistics for equal weighted portfolios of funds sorted into deciles based their conditional Alpha t-Statistic (Panel B). The Momentum strategy sorts funds based on their trailing 12 Mth historical returns.

Table 14: Equal Weighted Portfolios of N Funds with the Highest Conditional Alpha

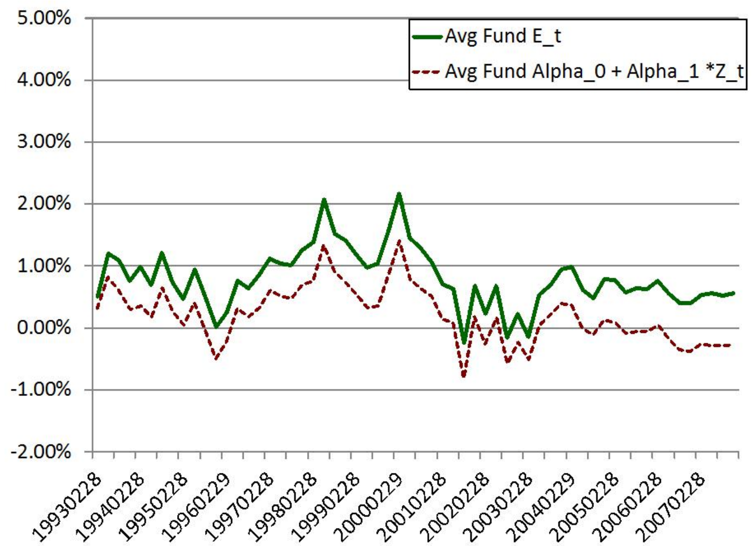
# of Funds	10	25	50	100	150	200	250	500
				Geometric Mean				
CAPM	10.55%	10.56%	9.54%	9.73%	9.69%	9.75%	9.69%	9.59%
BCAPM	11.60%	11.20%	11.02%	11.30%	11.30%	11.26%	11.08%	10.95%
BAMA	14.84%	13.64%	12.63%	11.82%	11.54%	11.52%	11.28%	10.68%
BSMA	17.32%	14.22%	12.87%	12.02%	11.77%	11.63%	11.37%	10.76%
BAMAP	14.42%	13.49%	12.48%	11.76%	11.55%	11.31%	11.29%	10.83%
				Arithmetic Mean				
CAPM	11.88%	11.87%	10.85%	11.00%	10.91%	10.94%	10.85%	10.72%
BCAPM	14.07%	13.34%	12.92%	13.05%	12.96%	12.86%	12.65%	12.39%
BAMA	17.22%	15.52%	14.39%	13.42%	13.06%	12.99%	12.70%	11.99%
BSMA	19.66%	16.09%	14.58%	13.60%	13.27%	13.09%	12.79%	12.07%
BAMAP	16.70%	15.37%	14.17%	13.30%	13.01%	12.72%	12.67%	12.13%
				Volatility				
CAPM	16.21%	16.06%	16.07%	15.84%	15.54%	15.35%	15.16%	15.00%
BCAPM	22.46%	20.77%	19.49%	18.70%	18.23%	17.90%	17.68%	16.88%
BAMA	22.40%	19.71%	18.94%	18.00%	17.51%	17.19%	16.93%	16.22%
BSMA	22.28%	19.70%	18.72%	17.88%	17.41%	17.15%	16.89%	16.20%
BAMAP	21.92%	19.76%	18.61%	17.68%	17.16%	16.84%	16.69%	16.12%
				Sharpe Ratio				
CAPM	0.480	0.483	0.420	0.435	0.438	0.445	0.445	0.441
BCAPM	0.444	0.445	0.452	0.478	0.486	0.489	0.484	0.491
BAMA	0.586	0.579	0.543	0.518	0.511	0.517	0.508	0.487
BSMA	0.699	0.609	0.560	0.531	0.527	0.524	0.515	0.492
BAMAP	0.575	0.571	0.541	0.520	0.519	0.512	0.514	0.498
				Alpha				
CAPM	0.84%	0.61%	-0.41%	-0.13%	-0.08%	0.07%	0.10%	0.04%
BCAPM	2.34%	1.66%	1.18%	1.43%	1.37%	1.29%	1.10%	0.96%
BAMA	5.73%	4.26%	3.00%	2.04%	1.65%	1.62%	1.38%	0.82%
BSMA	8.32%	4.84%	3.29%	2.27%	1.95%	1.78%	1.51%	0.91%
BAMAP	5.17%	4.11%	2.88%	2.06%	1.79%	1.51%	1.46%	1.02%
				Alpha t-Stat				
CAPM	0.62	0.54	(0.42)	(0.13)	(0.07)	0.06	0.09	0.04
BCAPM	0.59	0.50	0.44	0.59	0.62	0.63	0.57	0.62
BAMA	1.47	1.43	1.17	0.95	0.86	0.91	0.83	0.62
BSMA	2.15	1.61	1.30	1.07	1.01	0.99	0.91	0.69
BAMAP	1.39	1.38	1.18	1.01	0.98	0.90	0.91	0.78
				4-Factor Alpha				
CAPM	2.95%	2.39%	0.99%	1.39%	1.51%	1.73%	1.89%	1.85%
BCAPM	8.25%	7.02%	5.77%	5.77%	5.31%	4.96%	4.55%	3.63%
BAMA	9.84%	7.99%	6.63%	5.14%	4.37%	4.19%	3.82%	2.88%
BSMA	12.59%	8.50%	6.88%	5.37%	4.74%	4.39%	3.99%	2.97%
BAMAP	9.39%	7.85%	6.22%	4.96%	4.37%	3.95%	3.82%	3.03%
				4-Factor Alpha t-Stat				
CAPM	2.42	2.39	1.13	1.45	1.52	1.70	1.84	2.12
BCAPM	2.42	2.58	2.62	2.97	3.02	3.03	2.93	2.87
BAMA	2.80	3.05	3.02	2.84	2.71	2.80	2.74	2.59
BSMA	3.69	3.23	3.18	3.03	2.96	2.94	2.87	2.68
BAMAP	2.84	3.04	2.97	2.86	2.85	2.79	2.85	2.73

This table presents performance statistics for equal weighted portfolios that consist of 10 to 500 funds with the highest conditional alphas.

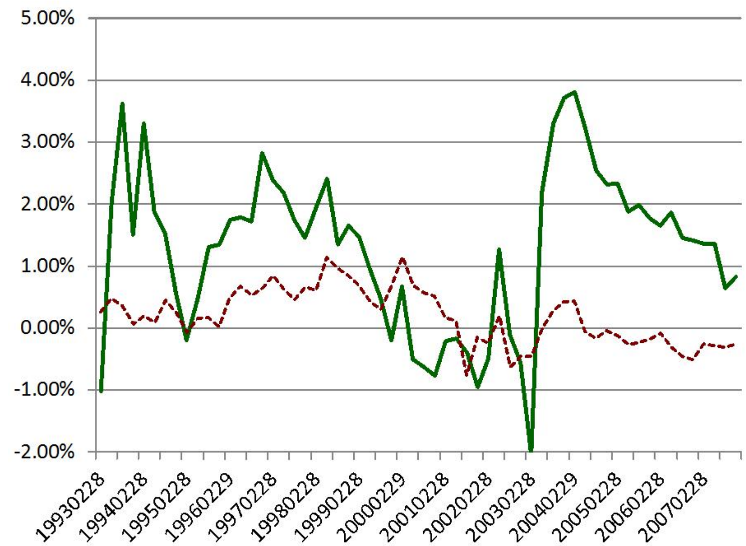


(a) Bayesian CAPM (BCAPM)

(b) Bayesian Skeptic Macro Alpha (BSMA)



(c) Bayesian Agnostic Macro Alpha (BAMA)



(d) BAMA with Predictable Market Loadings (BAMAP)

Figure 1: Time Variation in European Mutual Funds' Investment Opportunities

This chart presents the cross-sectional average of estimated expected returns and alphas over time, providing an overview of the investment opportunity set by characterizing the average expectations and alpha across funds. "Avg Fund E_t" represents the estimated fund total expected return, averaged across all funds, which corresponds to the expected return on an equal weighted portfolio of mutual funds in the universe. The series "Avg Fund Alpha_0 + Alpha_1*Z_t" represents total conditional manager skill, both idiosyncratic and that due to timing macro factors, averaged across all funds.