Mutual Fund Return Predictability in Partially Segmented Markets*

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Abstract

This paper studies the predictability of European equity mutual fund performance during a period when European stock markets were partially segmented. Specifically, we use macroeconomic variables to predict the performance of European equity funds, 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 10-12%/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.

Key words: European equity markets; mutual fund performance; time-varying investment opportunities. JEL codes: G11, G15, G23.

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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) empirical factors. Avramov and Chordia (2006) extend this literature by showing that substantial alphas are derived from choosing individual stocks based on macroeconomic conditioning variables. These papers, as well as numerous others in the academic literature, indicate that substantial gains in portfolio choice may be obtained from the use of 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 nearby, 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 ties to London financial institutions, 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 specialized knowledge of local telecommunication companies–thus, helping to sort out which firms might recover most quickly. In essence, macroeconomic information may help to indicate when local skills are most needed in a particular market. Hence, a rotation among asset managers 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 these issues, since European stock markets are partially 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. By partial segmentation, we mean that investors across Europe likely have access to many of the funds in our sample, but that the profitability of corporations still are dependent on local (country or regional) conditions, which local asset managers may best understand.

Specifically, we ask under which macroeconomic 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 of 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 further questions which are related to our focus on the segmentation of asset manager skills. 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 *which* country's local equity managers exhibit the best skills at different points in the European business cycle. Our study also has significant real-world economic 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 over 35,000 European-domiciled mutual funds by the end of 2010 (Investment Company Institute, 2011), almost five times 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 partially segmented markets; we illustrate the potential gains from our methodology in European mutual fund markets.[1]

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, another of the objectives of our study is to explore which, if any, macroeconomic state variables are helpful in identifying funds with superior future skills.

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 fully integrated market models, which assume a single common

[1] 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.

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 partially 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.

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 6-8%/year (after fund-level trading costs and fees), when measured with a single-factor model, and from 10-12%/year with a four-factor model that controls for fund exposures to size, book-to-market, and momentum.[2] 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 slightly 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 up to 4.3% per year from using macroeconomic state variables to choose funds, while allowing for segmentation in market risk factors leads to further improvements of about 0.5% 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, which indicates their robustness in locating skilled managers in non-U.S. markets. 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 much of our time series by Fama and Schwert (1981) (inflation), Pesaran and Timmermann (1995) (industrial production), and Welch and Goyal (2008) (volatility).[3]

To better understand the sources of outperformance, we undertake an attribution analysis that

[2] If we assume that our investment strategies must pay full front-end and redemption load fees, the four-factor alphas are reduced to 5-9%/year.

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

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). In addition, we implement a version of our strategies that allow investment in individual European stocks, rather than funds, and the stock-level strategies perform only about half as well as the fund-level strategies. Thus, macroeconomic variables help us to locate fund managers with skills, but they do not indicate that these fund managers are merely using the macrovariables themselves to time their stock purchases.

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,

[4]Although we show that macro variables do not appear to be particularly successful in timing passive country equity market indexes, 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.

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 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 partially 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 in capturing 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 conducts an attribution analysis and Section 6 provides robustness results. Finally, Section 7 concludes. Details on data sources and additional robustness results are provided in a series of appendices.

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, converted to ECU or Euro currency returns, with capital gains and dividend distributions reinvested at the end of the day on which 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 from June 1988 to February 2008, a total of 237 monthly observations. Returns are net of fees and trading costs, i.e., these are returns actually experienced by investors in the funds (ignoring any load charges or broker commissions). 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 period. 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).

The data is limited in some respects. We do not have information on total net assets, nor do we know the exact location of the manager, so we use the fund's legal domicile as a proxy for the manager's location. For a subset of the funds that exist in 2011, we have obtained the domicile of the fund advisor, which is where we would expect the portfolio manager and buy-side analysts to reside. Information about the advisor's location is available for 60% of our universe, and covers mainly regional and country funds. Overall, more than 80% of the country funds with location information have an investment objective that coincides with the advisor's location. In robustness tests that limit our analysis to country funds explicitly identified as having an advisor in that country, our main results prevail. We also have limited data on front-end and redemption loads, as well as total fund expense ratios. We describe the Lipper data more fully in Appendix A1.

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, roughly 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 (including Pan-European) 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 III of Table 1). 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,

[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. 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).

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 for 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 1.7% 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 (increases in median fees are largely due to the large number of small funds that were started later in our sample period).

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 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

[7]This follows the Moskowitz and Grinblatt (1999) 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 Appendix A2.

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 performance models for 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] These augmented models also help to control for persistent fund loadings on unpriced factors, as described by Pastor and Stambaugh (2002a).

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 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 change in stock market volatility (Welch and Goyal,

[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 skills 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 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.

2008), measured as the change in the VDAX index for the German stock market. We also use the inflation rate, 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 the ECU prior to year 2000 and the Euro thereafter, and weighted by each local currency's equity market share, since we measured returns translated to either the ECU or the Euro. 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 A2.

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:

$$\begin{aligned} r_{it} =& \alpha_{i0} + \alpha_{i1}' z_{t-1} + \beta_{i0G}' r_{Gt} + \beta_{i0S}' r_{St} + \beta_{i1}' \left(r_{Bt} \otimes z_{t-1} \right) + \varepsilon_{it} \\ \equiv& \, \theta_i' \begin{bmatrix} x_t \\ r_{Gt} \\ r_{St} \\ r_{Bt} \otimes z_{t-1} \end{bmatrix} + \varepsilon_{it}, \end{aligned} \tag{1}$$

for $\theta_i = (\alpha_{i0} \ \alpha_{i1}' \ \beta_{i0G}' \ \beta_{i0S}' \ \beta_{i1}')'$, $x_t = (1 \ z_{t-1}')'$, and $\varepsilon_{it} \sim N(0, \sigma_i^2)$. Here, r_{it} 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 demeaned 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 on k zero-cost benchmarks, r_{Bt}, into a set of k_G globally integrated benchmarks, denoted r_{Gt}, and k_S locally segmented (country) benchmarks, denoted r_{St}.

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 demeaned 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 the model of Equation (1) (to preserve degrees-of-freedom). Finally, ε_{it} 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.[12]

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

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

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

$$Z_t = \alpha_Z + A_z Z_{t-1} + \varepsilon_{Zt}. \tag{3}$$

[12] In a robustness analysis reported in Section 6 we allow ε_{it} to be correlated across funds and obtain very similar results.

We use de-meaned state variables, $z_t = Z_t - \bar{Z}_t$, in the empirical analysis so that $\alpha_{i1}' z_{t-1}$ captures a zero-mean time-varying alpha component. Finally, the innovations ε_{Bt} and ε_{Zt} are assumed to be independently and normally distributed over time, and mutually independent of fund-specific residuals from Equation (1), ε_{it}.

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 portfolio 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. 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 $1 + m + k + km$ location 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 $\underline{t}$ approaching zero.

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 $p \times (1 + m + k + km)$ matrix, F_I:

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

where $\underline{\Omega}_I$ 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 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 $\underline{f}$, $\underline{\Omega}$:

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

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

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 commutable matrices $\tilde{F}$, $\tilde{F}\theta_i | \sigma_i^2 \sim N\left(\tilde{F}\underline{\theta}, \sigma_i^2 \tilde{F}\underline{V}\tilde{F}'\right)$. To translate the beliefs from equation 6 into a natural conjugate specification, define $(\underline{\theta}_i, \underline{V})$ so that, for any invertible matrix, F,

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

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

This transformation projects our prior beliefs onto the parameter space:

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

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:

$$\begin{aligned}
\theta_i, \sigma_i^{-2}|D &\sim NG\left(\overline{\theta}_i, \overline{V}_i, \overline{s}_i^2, t_i + \underline{t}\right), \\
\overline{\theta}_i &= \left(F\underline{\Omega}^{-1}F' + H_i'H_i\right)^{-1}\left(H_i'H_i\hat{\theta}_i + F\underline{\Omega}^{-1}F'F^{-1}\underline{f}_i\right), \\
\overline{V}_i &= \left(F\underline{\Omega}^{-1}F' + H_i'H_i\right)^{-1}, \\
\left(t_i + \underline{t}\right)\overline{s}_i^2 &= \underline{t}\underline{s}^2 + t_i s^2 + \left(\hat{\theta}_i - F^{-1}\underline{f}_i\right)'\left[F^{-1}\underline{\Omega}F'^{-1} + \left(H_i'H_i\right)^{-1}\right]^{-1}\left(\hat{\theta}_i - F^{-1}\underline{f}_i\right), \\
\underline{\Omega}^{-1} &\equiv \lim_{c\to\infty}\begin{bmatrix} cI_{(d\times d)} & 0 & 0 \\ 0 & \underline{\Omega}_I^{-1} & 0 \\ 0 & 0 & 0_{(1+k+m+km-d)} \end{bmatrix},
\end{aligned} \tag{11}$$

where $D = \{r_{i\tau}, r_{B\tau}, z_{\tau-1}\}_{\tau=1}^{t}$ is the history of the observed data. H_i is the $t_i \times (1 + m + k + km)$ matrix of explanatory variables on 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 $\hat{\theta}_i = (H_i'H_i)^{-1}H_i'r_i$, and $s_i^2 = t_i^{-1}(r_i - H_i'\hat{\theta}_i)'(r_i - H_i'\hat{\theta}_i)$. 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

[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, restricts individual parameters to equal zero. Then the posterior variance and all related covariances for these restricted parameters will be zero.

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:

$$
\begin{aligned}
E\left[r_t|D_{t-1}\right] &= \bar{\alpha}_0 + \bar{\alpha}_1 z_{t-1} + \overline{\beta}_0 \hat{A}_F' x_{t-1} + \overline{\beta}_1 \left(I_K \otimes z_{t-1}\right) \hat{A}_F' x_{t-1} \\
&\equiv \bar{\alpha}_0 + \bar{\alpha}_1 z_{t-1} + \overline{\beta}_{t-1} \hat{A}_F' x_{t-1},
\end{aligned} \tag{12}
$$

$$
V\left[r_t|D_{t-1}\right] = \left(1+\delta_{t-1}\right) \overline{\beta}_{t-1} \hat{\Sigma}_B \overline{\beta}_{t-1}' + \Psi_{t-1}. \tag{13}
$$

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:

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

$$
\hat{\Sigma}_B = \frac{1}{\tau_B} \sum_{\tau=1}^{t-1} \hat{\varepsilon}_{B\tau} \hat{\varepsilon}_{B\tau}'; \;\; \hat{\varepsilon}_{B\tau} = r_{B\tau} - \hat{\alpha}_B - \hat{A}_B z_{\tau-1} \tag{14}
$$

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

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

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

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, $\alpha_{i1}' z_{t-1}$, and excess returns from factor loadings that vary with macroeconomic conditions, $\beta_{i1}' \left(r_B \otimes z_{t-1}\right)$.

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 $\alpha_{i0} =$

$-\exp_i$, $\alpha_{i1} = 0$, $\beta_{i1} = 0$, and $A_B = 0$, where $\exp_i$ is one-twelfth of fund i's annual expense ratio.[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 $\alpha_{i1} = 0$, $\beta_{i1} = 0$, and $A_B = 0$, and introduce the informative prior $\alpha_{i0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$. σ_α^2 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 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 $\alpha_{i,0} + \alpha'_{i,1} z_{t-1} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$.

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: $\alpha_{i,0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$.

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 α_{i1}, and maintains the prior belief

[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 $\delta_{t-1,CAPM} = \frac{1}{t-1}$.

[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.

$\alpha_{i0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$.

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	$\alpha_{i0} = -\exp_i$; $\alpha_{i1} = 0$; $\beta_{i1} = 0$; $A_B = 0$
BCAPM	Not Predictable	Constant	Not Predictable	$\alpha_{i0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$; $\alpha_{i1} = 0$; $\beta_{i1} = 0$; $A_B = 0$
BSMA	Predictable	Constant	Predictable	$\alpha_{i0} + \alpha_{i1}' z_{t-1} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$; $\beta_{i1} = 0$
BAMA	Predictable	Constant	Predictable	$\alpha_{i0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$; $\beta_{i1} = 0$
BAMAP	Predictable	Predictable Market Loading	Predictable	$\alpha_{i0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$ $\beta_{i,j,1} = 0$ if $\beta_{i,j,1}$ does not correspond to the market factor

In short, going from the orthodox CAPM investor-type to the BCAPM investor-type means allowing managers to have constant skills. Moving from BCAPM to BSMA through 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. In unreported robustness tests, we allow non-market risk factors to also be country-specific and obtain very similar results.

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 under-performed the benchmark by 400-500 basis points per annum, while they out-performed the index by 200-400 basis points per annum during the 10-year period that followed.

These numbers refer to raw return performance. It is more informative 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. 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 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. Further evidence that mitigates the concern over survival bias is discussed in Appendix A1.

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.

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

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) among U.S. domestic equity managers. 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:

$$U(W_t, R_{p,t+1}, a_t, b_t) = a_t + W_t R_{p,t+1} - \frac{b_t}{2} W_t^2 R_{p,t+1}^2, \tag{15}$$

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

$$\omega_t^* = \arg\max_{\omega_t} \left\{ \omega_t' \mu_t - ((1 - b_t W_t)/b_t W_t - r_{ft})^{-1} \omega_t' [\Sigma_t + \mu_t \mu_t'] \omega_t / 2 \right\}, \tag{16}$$

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 Appendix A2. Thus, we first provide a large-scale test of the robustness of these macroeconomic variables in locating skilled fund managers, relative to Avramov and Wermers (2006), 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]

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 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 0.30.

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. Bootstrap tests suggest that the null that the Sharpe ratio of the benchmark equals those of the Bayesian investors cannot be rejected at conventional critical levels, with p-values in the range of 10-20% for the BSMA, BAMA and BAMAP investors who allow for time-varying skill. Interestingly, however, compared with the CAPM model, the same three Bayesian strategies obtain significantly higher Sharpe ratios. While the average realized return for the CAPM investor is 2.2% lower than that

[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.

of the benchmark, the Bayesian strategies that allow for time-varying skill achieve average realized utility that are between 2.5% and 4.3% higher than the benchmark. Bootstrap tests of the null that the macro models deliver average realized utility equal to the benchmark allow the null to be rejected at or below the 10% confidence level, indicating that these tests have slightly more power than the tests based on the Sharpe ratio.

4.2.1 Alphas of the Baseline Strategies

We also compute estimates of out-of-sample alphas for the strategies, using models that allow for parameters that vary with macroeconomic variables. In particular, we use the same macroeconomic indicators used by our strategies to evaluate the performance of the strategies–these indicators are used to model both time-varying alphas and betas. In the case of the four-factor model, we fix the exposures to the non-market factors to evaluate the out-of-sample performance, although (in a robustness test) we find that allowing these parameters to be time-varying does not change the alphas by much (but, makes them much noisier, due to the loss of substantial degrees-of-freedom). We report, in Table 3, the total out-of-sample alphas of the strategies, $\alpha_{i0} + \alpha'_{i1} z_{t-1}$, averaged over all out-of-sample periods.

Consistent with the raw return figures, the dogmatic CAPM investor generates a negative single-factor alpha estimate of -1.9% 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 alphas centered on the negative expense ratio) 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 ratio (1.5%/year) that we observe in Table 1, likely because this investor type (who ignores any evidence of underperformance in the data) chooses unskilled specialty funds to help diversify, which tend to have higher trading costs than their unskilled Pan-European counterparts.

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 2.6% 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 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 $-\exp_i$, the single-factor alpha grows by over 5%, to 7.7%/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, 7.5%/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 about 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 BAMA 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 -1.6%/year, does not change much, the estimated alphas from the four active investor types range from 7.8% to 12.1%/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_{i1}) with diffuse priors results in over 4%/year additional alpha. Once again, allowing for predictable market factor loadings does not generate higher alpha estimates, and 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

[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

four-factor alpha is driven by some fund managers' ability to deliver positive returns despite this 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 sub-periods, 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 alpha estimates are very similar during the first and second subsamples, the four-factor alphas are far greater than the single factor alphas during the first 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 in the first subsample 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

type with the highest alpha, namely the BSMA investor, has a single-factor beta which is indistinguishable from one.

persistent, but temporarily high returns.[20]

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 partially 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 partially 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−at most, 1.7%/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 investor type, whose one-factor alpha increases by 1.8%/year (increasing this investor's ability to locate constant skill funds). 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 partially segmented models indicate that controlling for temporary, country-specific shocks (not related to macrofactor shocks) can help to more precisely identify

[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 theme based on persistent, unpriced factors.

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 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 and consider the performance of portfolios invested in individual European stocks as a way to gauge whether managers themselves use macroeconomic variables to time their stock selection.

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, and again in 2003, but reduces that weight in 1998 and 2007.

[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.

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) 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 partially 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 segmented models (BSMA-S, BAMA-S, and BAMAP-S) lower their exposure to Scandinavian funds, relative to the respective integrated market models, 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.

[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 one and the coefficients are non-negative. The results of these estimations are available upon request from the authors.

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 for the three macro strategies (BSMA, BAMA, and BAMAP) shows that they clearly pursue very active strategies to exploit macroeconomic information in picking managers. In the final section of this paper, we explore the robustness of these results to the existence of front-end and redemption load fees.

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. Note, also, that the CAPM investor tends to hold passive funds holding large capitalization stocks, in order to minimize expenses and fund-level trading costs.

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, alternatively, might be exploited through the macroeconomic variables applied to passive country market indexes, as explored in Table 4). 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 6) to effect changes in industry allocations.

[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.

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:

$$r_P = w_{Euro,P} r_{Euro,P} + w_{Sect,P} r_{Sect,P} + \sum_{i=1}^{C} w_{Ctry_i,P} r_{Ctry_i,P}, \tag{17}$$

where, for example, $w_{Euro,P}$ is the investor's portfolio allocation to pan-European funds, and $r_{Euro,P}$ is the return realized on the Pan-European funds chosen by the strategy. We compare this return to the return on the MSCI Europe Benchmark, which is decomposed into C country-specific components as:[25]

$$\begin{aligned} r_B =& w_{Euro,P} r_B + w_{Sect,P} r_B \\ &+ (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} * r_{Ctry_i,B} \\ &+ (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} \left(r_B - r_{Ctry_i,B} \right). \end{aligned} \tag{18}$$

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

[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.

of Equations (17) and (18), respectively. These components reflect the ability of the portfolio to select funds that outperform the benchmark and are computed as:

$$r_{European\ Selection} = w_{Euro,P} * (r_{Euro,P} - r_B) \tag{19}$$

$$r_{Sector\ Selection} = w_{Sect,P} * (r_{Sect,P} - r_B)\,. \tag{20}$$

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

$$r_{Country\ Select} = (1 - w_{Euro,P} - w_{Sect,P}) \sum_{i=1}^{C} w_{Ctry_i,B} * (r_{Ctry_i,P} - r_{Ctry_i,B})\,. \tag{21}$$

While this decomposition is suggested by Brinson, et al. (1986), we also use an alternative definition of country selection that uses the country weights of the active investor strategy, rather than the country weights in the benchmark:[27]

$$r_{Country\ Select} = \sum_{i=1}^{C} w_{Ctry_i,P} * (r_{Ctry_i,P} - r_{Ctry_i,B})\,. \tag{22}$$

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

$$r_{Country\ Time} = \sum_{i=1}^{C} (w_{Ctry_i,P} - (1 - w_{Euro,P} - w_{Sect,P})\, w_{Ctry_i,B})\, r_{Ctry_i,B}. \tag{23}$$

Finally, the residual for the abnormal portfolio performance is given by the "interaction effect" of country allocation with country stock-selection, since (as noted by Brinson, et al. (1986)), it is

[27] This alternative definition of country selection assumes that any overweighting of a country in conjunction with the outperformance of the stocks selected in that country is purely a selection effect. The prior definition given by Equation (21) makes no such assumption.

not clear whether the manager overweighted the country to time the country return or to emphasize the manager's selection ability in that country:[28]

$$r_{resid} = \sum_{i=1}^{C} \left(w_{Ctry_i,P} - \left(1 - w_{Euro,P} - w_{Sect,P}\right) w_{Ctry_i,B} \right) \left(r_{Ctry_i,P} - r_{Ctry_i,B} \right) \tag{24}$$
$$- \left(1 - w_{Euro,P} - w_{Sect,P}\right) \sum_{i=1}^{C} w_{Ctry_i,B} \left(r_B - r_{Ctry_i,B} \right).$$

Panel A of Table 7 presents the results of this decomposition for each of the investor types. We see that portfolio outperformance, for investors allowing for active manager skills (BCAPM, BSMA, BAMA, and BAMAP), 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, compared to the BCAPM investor. 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. 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 most promising 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

[28] Under the alternative definition of country selection given by Equation (22), the only residual is due to the (small) difference between market capitalization weights of countries (which we use) and the actual weights of countries in the MSCI Europe index (which are not available to us): $r_{resid} = - \left(1 - w_{Euro,P} - w_{Sect,P}\right) \sum_{i=1}^{C} w_{Ctry_i,B} \left(r_B - r_{Ctry_i,B} \right)$.

managers with the best skills in those industries during a particular macroeconomic phase.[29] Finally, note that the alternative definition of the country selection attribution component (Panel C) suggests a slightly bigger contribution from country fund selection for the BSMA, BAMA, and BAMAP investors but does not change our qualitative conclusions about manager skill in that area.

5.4 A Stock-Level Strategy

The success of our conditional strategies support the presence of significant time-varying fund manager skills. However, perhaps these managers are, themselves, merely using innovations in macroeconomic indicators to time their choice of stocks. In such a case, we would not need to invest in the funds, as long as individual stock trade costs are competitive with fund-level trade costs and fees. In this section, we examine our strategies applied to a database of European stock returns during the January 1, 1988 to December 31, 2008 time period.

Specifically, we obtained stock returns (capital gains plus cash dividends) on stocks in 15 developed Europe equity markets. The universe of stocks comprises both listed and delisted stocks, and cash dividends are reinvested on the ex-dividend date. We focus on strategies that invest in the top 30% of stocks each month, ranked by market capitalization, in order to assure that the strategies are reasonably implementable at an institutional scale. The smallest stock that we include in our consideration set has an equity market capitalization of \$182.6 million on December 1, 1993, while the smallest stock on December 1, 2007 has a capitalization of \$438.1 million. (However, our results remain qualitatively similar when we allow the strategies to choose from all but the bottom 10% of stocks, ranked by market capitalization–results available upon request). Further details on this stock dataset are available in Appendix A3.

We implement our baseline strategies of Table 3, and show results in Table 8. To further constrain our strategies to reflect an implementable portfolio, we limit positions in individual stocks to, at most, 5% of the portfolio. In addition, to control estimation error in betas, we exclude stocks with an estimated market exposure below 0.6.

Note that all Bayesian strategies achieve relatively small and statistically insignificant single

[29] 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.

factor alpha estimates below 3.6%. In the case of the four-factor alphas, only the BSMA investor achieves a sizable (but statistically insignificant) alpha of 5.4% while the other alpha estimates fall below 2.1%.

These stock-level results are an interesting contrast to our fund-level strategies, which generate somewhat larger four-factor alphas. For instance, the BCAPM investor, who does not use macroeconomic information, finds fund managers with constant skills that generate a four-factor alpha of 7.8%/year (see Table 3), while this investor only manages to assemble stock portfolios with an alpha of 1.1%/year. This result supports that some managers have constant skills over time, rather than that certain stocks are persistently mispriced by the model.

Particularly notable are the results for the BAMA and BAMAP investors, who allow the data to completely inform them about the predictability in stock returns using macroeconomic innovations. The stock-level strategies of these two investors generate four-factor alphas of 0% and 2.1%, while their fund-level strategies generate alphas of 11.7 and 10.1%/year, respectively. Therefore, at least 8%/year, and hence the major part of the total fund-level four-factor performance, is generated by fund manager skills that are correlated to macroeconomic innovations, but that are not directly based on their (potential) use of macroeconomic variables to predict stock returns.

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 investment strategies (allowing short sales or basing portfolios on equal-weighted, ranked funds), presence of load and redemption fees, constraints on the portfolio weights, macroeconomic variables used, the universe of funds considered, construction of the momentum factor, rebalancing frequency, and investors' prior beliefs.

6.1 Alternative Investment Strategies

We first consider the performance of investment strategies that allow for short-selling, apply leverage, or use ranking information to form equal-weighted portfolios.

6.1.1 Mutual Fund Short-Sale Strategies

Table 9 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 perform well. 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 9, 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 investors form 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 9-12%/year.

6.1.2 Individual Stock Short-Sale Strategies

As a benchmark for the results of these long-short fund-level strategies, we return to our European stock database described in Appendix A3. When we allow short-selling of stocks, our stock-level strategies generate much higher four-factor alphas. Appendix Table B1 shows these results.

Specifically, in Panel A, we find that allowing for short-selling of individual stocks (with a maximum short position of -5%) achieves high four-factor alphas between 7.8% and 16.5%/year. Comparing the results across Panels A-C, most of the alphas are attributable to the short-side, which is consistent with most academic papers (Stambaugh, Yu, and Yuan (2011)). However, as opposed to our market neutral strategy based on mutual funds of Table 9, where we allow short-sales of market indexes, it would be quite difficult to actually implement the large short positions of the long-short pure stock strategy.

6.1.3 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 10, we report the out-of-sample 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 monotonically declining mean return (or alpha) as we move from the highest-ranked to the lowest-ranked funds. 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 10 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,

[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.

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.

In unreported results, we evaluate 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 find 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.

6.2 Front End Loads and Redemption Fees

All of our analysis to this point assumes that no front-end or redemption loads are charged by the funds. Although institutions, such as pension funds or endowments, may be able to receive waivers or significant reductions in these fees, small retail investors usually pay something much closer to the quoted loads. In order to assess the drag of these loads on our fund-selection strategies, we generate results that are net of load fees–our data on quoted loads is described in Appendix A1.

Our analysis that includes loads is twofold. First, we subtract the implied (full quoted) load fees of each portfolio weight change of our strategies from their realized out-of-sample performance. And, second, we implement a model that includes load fees in the fund selection algorithms, allowing the investment strategies to take account of loads when they assess funds.

The results, shown in Table 11, show that loads substantially reduce, but do not eliminate, the profitability of our macroeconomic strategies. For example, the four-factor alphas of the BSMA, BAMA, and BAMAP investors lie in the range 5.7%-8.5% (previously 10.1% to 12.1%). The fee-based utility model substantially reduces the turnover, loads and fees but does not systematically improve risk-adjusted return performance.

6.3 Portfolio Optimization Under Alternative Utility Specifications

So far we have focused the performance measurement on alphas, although we also report Sharpe ratios and average realized utility. For some investors other performance measures might be relevant - for example, some investors might want to limit their exposures to risk factors or put a cap on portfolio volatility. One way to get at this is to consider portfolio performance subject to constraints on the extent of exposure to risk factors, constrain the expected return or the volatility of the portfolio.

First, we implement a version of our strategies that constrained (expected) exposure to the market risk factor to one and exposures to non-market risk factors (SMB, HML, and UMD) to zero, all within a range of plus or minus 0.2. Although some residual out-of-sample exposures remained, they were small. Second, we implement a version of the strategies with constrained factor exposures that maximizes the expected return subject to the expected total standard deviation being less than the benchmark volatility of 16.28%. Third, we implement a version that fixes the desired expected portfolio return to be at least 11.4%/year, matching or exceeding that of the benchmark MSCI Europe, while minimizing expected portfolio standard deviation.

The results, shown in Table 12, show Sharpe ratios similar to our baseline results of Table 3. While the alphas of the strategies using these three versions are lower than their counterparts in Table 3, four-factor alphas exceed 5%/year for all strategies that allow for fund manager skills (BCAPM, BSMA, BAMA, and BAMAP).

6.4 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, Appendix Table B2 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.

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. Appendix A2 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.

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.[31] 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.

We also added 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 Appendix A2. 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 most currencies in developed Europe were closely fixed together during our sample period.

6.5 Additional Robustness Checks

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 relax these assumptions, first on the pre-screened size of the universe, then, on the positions the investor can take, and, finally, on the structure imposed on estimation through the estimation model and investor beliefs.

6.5.1 Number of Funds

In Appendix Table B3, we try selecting smaller or larger counts of funds in the optimization procedure, ranging from a universe size of 25 selected funds to 250 selected funds, as well as the

[31] 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.

full set of all mutual funds existing at the end of a particular quarter. Here, we find that greater numbers of funds actually reduces the alpha somewhat for the strategies, although 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).

6.5.2 Portfolio Weight and Trading Constraints

Appendix Table B4 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 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 Appendix Table B4 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 place no constraints on portfolio turnover. Panel C of Appendix Table B4 shows that limiting the portfolio weight change 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 B.

6.5.3 Covariance Estimation

Our analysis assumes that the residuals from models of performance, across funds, are uncorrelated. We also implemented a version of the strategies that estimated these covariances from the data, in case funds may exhibit similar industry or stock tilts. The results, shown in Appendix Table B5 are very similar to those of our baseline tests of Table 3.

6.5.4 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.

Appendix Table B6 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.

6.5.5 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 European countries over the previous 12-month period.[32] 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 Appendix Table B7, 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.

6.5.6 Agnostic Investor for All Parameters

Finally, we analyzed the performance of an investor type with diffuse priors on all parameters, where alpha and all four risk-factor loadings were allowed to vary over time. We call this strategy BAMAPPS (Bayesian Agnostic Macro Alpha with Predictable Style). Here, we find a four-factor out-of-sample alpha of 7.7%/year for the general model and 8%/year for the country-segmented model, using time-varying parameters for alpha and all risk-factor loadings to evaluate out-of-sample performance. These results are statistically significant, but somewhat lower than the results for BSMA, BAMA, and BAMAP in Tables 3 and 4. However, this model has 25 free parameters used on 60 months of fund returns, so it is likely that this model suffers from overfitting.

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

[32]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.

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.

Appendix A1: Description of Lipper Mutual Fund Data

We obtained, from Lipper (a subsidiary of Thomson Reuters), several datasets on developed European-domiciled (including the UK) mutual funds having a focus on equities (either Pan-European or country/region/sector specific) in developed Europe (including the UK) during the March 1988 to February 2008 period. We do not have information on the exact location of the portfolio manager or the manager's buy-side analysts, so we use the fund's country of investment objective as a proxy for the location of these key fund employees. For a subset of the funds that exist in 2011, we have obtained the domicile of the fund advisor, which is where we would expect the portfolio manager and buy-side analysts to reside. Information about the advisor's location is available for 60% of our universe, and covers mainly regional and country funds. Overall, more than 80% of the country funds with location information have an investment objective that coincides with the advisor's location. The sample includes funds that were alive at the end of the sample, as well as non-surviving funds; about 15% of the funds dropped out of our sample prior to the end of the sample period. We include actively managed funds, index funds, and both active and passive sector funds, although European index funds are less prevalent in Europe than in the U.S. These data include monthly net returns, total expense ratios, and load fees. Summary statistics for these data are provided in Table 1. In this appendix, we describe, in more detail, the characteristics and limitations of the data.

A1.1 Inclusion of Funds

Lipper actively examines registration lists for mutual funds from regulatory authorities across Europe in an attempt to create a complete database, and contacts management companies to follow up on funds for which the companies have not proactively supplied data. Although all mutual fund datasets contain an "incubation bias," as per Evans (2010), this bias should be minimal in our paper as we require a minimum of 36 months of return history to be available for a fund to be included in the strategies at the end of a particular calendar quarter.

A1.2 Net Returns

Our returns dataset contains monthly net returns (with fund distributions reinvested at the end of the day that they are paid) on each shareclass of all European equity mutual funds with a European investment focus. Returns are net of fees and fund-level trading costs, i.e., these are returns actually experienced by investors in the funds (ignoring load charges or investor-level broker commissions).

Since we do not have complete information on total net assets (TNA) of the individual shareclasses of the funds, we select the earliest-existing shareclass to represent that fund's returns. When a monthly return is missing for that shareclass, we check the other shareclasses to see if they have a return during that month to proxy for the missing return. Generally, shareclasses have very close returns, so this should not be a problem. We continue this process until we reach the last available return for that shareclass, then we continue to search for any further returns from any shareclass. In general, the shareclass with the first available return exists as long as all of the other shareclasses, so we continue using returns from that shareclass to represent the fund.

A1.3 Expense Ratios

Lipper provided historical total annual expense ratios (TERs), including fund management,administration, and distribution fees for a subset of the funds that existed in 2008. No TER data is available for funds that did not exist in 2008.

Table A1 shows the number of funds, existing during each given month, with TER information. Note that, in the early years of our sample, Lipper did not have TER data for all but a few funds.

Table A1: Fund Universe TER Coverage

Date	Number TERs	Total Number Funds	% with TER
December 2007	1,377	4,206	32.7
December 2002	952	3,186	29.9
December 1997	191	1,377	13.9
December 1992	10	700	1.4
March 1988	4	228	1.8

To handle missing TER data at the end of a given calendar quarter, we use, for a given fund, the cross-sectional average TER of all funds with available annual expense ratio data at the end of that quarter.

A1.4 Load Fees

We retrieved front-end and redemption load fees from Morningstar Direct, though these were only available for funds existing at the time of data extraction. Due to a lack of historical data availability, this information is only available as of the date of data extraction, 2011, and not for earlier years. Therefore, over all prior years, for a given fund that exists at 2011, we use its 2011 load fee level. For funds not surviving until 2011, we use, at the end of each calendar quarter, the cross-sectional average front-end (or redemption) load during 2011 as a proxy.

Appendix A2: 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
Currency factor	Weighted average (using country market capitalizations) of the squared monthly change in exchange rates (adjusted for the interest rate spread) measured against the Ecu or the Euro.	Federal Reserve System
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 A2: Descriptive Statistics for Benchmark and Macroeconomic Factors

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.

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

Appendix A3: Description of Datastream European Stock Data

We obtained, from Thomson Datastream, end-of-month prices and monthly returns on European stocks during the January 1, 1988 to December 31, 2008 time period, where cash dividends are reinvested at the ex-dividend date. Also, all stock returns and prices are U.S. dollar denominated. The universe of stocks comprises both listed and delisted stocks, and covers 15 European equity markets. In particular, our sample includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Switzerland, and the UK. Table RRR.1 presents a snapshot of the evolution of our universe of stocks over time.

To identify stock delisting events, we use price data for individual stocks. In Datastream, when a company is delisted, the stock price remains constant until the end of the sample, while there is no evidence of the delisting date on the return index data. We match both datasets, identifying the delisting date in the return series as that of the second observation of constant prices.

To eliminate illiquid stocks from consideration for the strategies, we exclude the bottom 70% of stocks, ranked by equity market capitalization, each month. The smallest stock in the top 30% is still fairly small, as shown by the table below:

Table A3: Stock Universe Capitalization Filter Thresholds

Date	Market Capitalization of Smallest Stock ($ Millions)
December 1, 2007	438.1
December 1, 2002	222.1
December 1, 1997	190.2
December 1, 1993	182.6

To eliminate stocks with potentially erroneous return data, we also exclude stock returns at the 0.1% level (we keep returns ranked between 0.1 and 99.9% during each month). A count of the remaining stocks is shown below.

Table A4: Stock Universe Asset Count

	1988	1993	1998	2003	2008
Universe	3,932	4,656	5,663	5,637	6,331
Austria	70	120	112	116	105
Belgium	190	187	185	203	217
Denmark	204	276	265	197	201
Finland	35	68	148	157	145
France	180	567	891	944	955
Germany	296	379	524	826	1,149
Greece	97	182	278	346	296
Ireland	67	63	64	52	58
Italy	250	295	313	308	328
Netherlands	164	179	223	165	138
Norway	57	108	232	168	253
Portugal	77	133	139	79	62
Spain	50	115	158	158	146
Switzerland	351	344	298	282	273
UK	1,844	1,640	1,833	1,636	2,005

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Figures and Tables

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

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.

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

Average			1.38	1.74	1.61
Median			1.38	1.69	1.61
Standard Deviation			0.58	0.51	0.51
No of Expense Obs			275	1016	1378

Table 2: Fund Universe Sample Performance

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.

	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

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

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. The annualized measures of alpha control for macrovariables and time-varying market risk factor loadings. 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.

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
	Panel A: Full Sample Results					
Geometric mean	10.06%	7.50%	11.76%	16.68%	16.47%	15.52%
Arithmetic mean	11.40%	8.62%	13.61%	18.79%	18.59%	17.52%
Volatility	16.28%	14.89%	19.39%	21.18%	21.26%	20.48%
Sharpe ratio	0.449	0.303	0.491	0.693	0.682	0.655
(p-Value for SR > Bmk SR)		93%	48%	12%	14%	15%
Realized Utility	7.48%	5.26%	7.85%	11.75%	11.51%	10.97%
(p-Val for RU > Benchmark)		95%	43%	7%	8%	10%
Outperformance Frequency		36%	55%	53%	52%	50%
Single-Factor Alpha		-1.94%	2.61%	7.79%	7.55%	6.28%
Single-Factor Alpha t-Stat		(1.671)	0.834	2.101	2.038	1.905
Single-Factor Beta		0.868	0.906	0.973	0.980	0.998
Four-Factor Alpha		-1.62%	7.78%	12.08%	11.67%	10.13%
Four-Factor Alpha t-Stat		(1.414)	2.868	3.557	3.429	3.419
Beta - Market		0.826	0.946	1.027	1.039	1.041
Beta - SMB		(0.011)	0.644	0.554	0.541	0.489
Beta - HML		0.133	(0.379)	(0.360)	(0.370)	(0.292)
Beta - Momentum		0.011	0.144	0.242	0.234	0.268
	Panel B: Sub-Sample Results - 1993-2000					
Geometric mean	18.33%	15.34%	17.72%	23.49%	23.60%	22.14%
Arithmetic mean	19.49%	16.33%	19.71%	26.00%	26.11%	24.44%
Volatility	15.31%	14.16%	20.44%	23.55%	23.58%	22.35%
Sharpe ratio	0.941	0.795	0.716	0.888	0.892	0.867
(p-Value for SR > Bmk SR)		83%	80%	71%	70%	72%
Certainty Equivalent Utility	16.02%	14.49%	16.03%	19.29%	19.35%	18.77%
(p-Val for RU > Benchmark)		94%	62%	36%	36%	40%
Outperformance Frequency		43%	48%	45%	45%	43%
Single-Factor Alpha		-0.65%	1.04%	6.24%	6.34%	3.78%
Single-Factor Alpha		(0.330)	0.191	0.927	0.941	0.656
Single-Factor Beta		0.843	0.929	1.034	1.035	1.099
Four-Factor Alpha		-2.22%	18.00%	24.98%	25.08%	19.86%
Four-Factor Alpha t-Stat		(1.107)	4.230	4.625	4.629	4.224
Beta - Market		0.817	0.801	0.895	0.895	0.990
Beta - SMB		(0.085)	0.852	0.894	0.893	0.785
Beta - HML		0.172	(0.414)	(0.544)	(0.542)	(0.478)
Beta - Momentum		(0.041)	0.477	0.666	0.667	0.523
	Panel C: Sub-Sample Results - 2001-2008					
Geometric mean	1.17%	-0.94%	5.34%	9.35%	8.80%	8.40%
Arithmetic mean	2.65%	0.26%	7.01%	10.98%	10.45%	10.03%
Volatility	16.99%	15.36%	18.11%	18.14%	18.27%	18.13%
Sharpe ratio	(0.023)	(0.181)	0.219	0.438	0.405	0.385
(p-Value for SR > Bmk SR)		88%	20%	1%	1%	2%
Certainty Equivalent Utility	-1.62%	-3.26%	0.30%	4.79%	4.27%	3.77%
(p-Val for RU > Benchmark)		77%	26%	1%	2%	4%
Outperformance Frequency		28%	62%	62%	60%	58%
Single-Factor Alpha		-2.88%	4.15%	8.77%	8.21%	7.56%
Single-Factor Alpha		(2.416)	1.376	2.798	2.677	2.330
Single-Factor Beta		0.874	0.846	0.882	0.898	0.882
Four-Factor Alpha		-2.63%	4.53%	10.22%	9.30%	8.58%
Four-Factor Alpha t-Stat		(2.254)	1.627	3.386	3.091	2.794
Beta - Market		0.871	0.865	0.825	0.858	0.859
Beta - SMB		0.085	0.424	0.155	0.123	0.076
Beta - HML		0.002	(0.191)	0.181	0.142	0.222
Beta - Momentum		0.038	0.058	0.116	0.111	0.244

Table 4: Segmented versus Integrated Pricing Models

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 $\sigma_\alpha = 10\%/\text{Month}$.

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
(p-Val for SR > Bmk SR)	13%	13%	48%	22%	36%	28%	56%	35%	12%	9%	27%	20%
Average Realized Utility	8.66%	8.67%	7.85%	9.93%	8.41%	8.87%	7.18%	8.05%	11.75%	12.33%	9.46%	10.03%
(p-Val for ARU > Bmk RU)	17%	17%	43%	18%	33%	27%	54%	33%	7%	5%	22%	16%
Outperf. Frequency	53%	53%	55%	54%	53%	51%	49%	50%	53%	54%	54%	51%
Single-Factor Pricing												
Alpha	1.68%	1.68%	2.61%	4.37%	2.33%	2.82%	0.58%	1.37%	7.79%	8.22%	3.94%	4.45%
Alpha t-Stat	1.379	1.394	0.834	1.514	0.888	1.108	0.352	0.872	2.101	2.245	1.305	1.482
Beta	0.882	0.882	0.906	0.873	0.864	0.844	0.964	0.956	0.973	0.935	0.932	0.911
Four-Factor Pricing												
Alpha	0.92%	0.91%	7.78%	9.31%	6.25%	7.12%	-0.11%	0.90%	12.08%	13.00%	7.74%	9.49%
Alpha t-Stat	0.752	0.748	2.868	3.809	2.714	3.290	(0.070)	0.588	3.557	4.054	2.850	3.852
Beta Market	0.899	0.899	0.946	0.916	0.906	0.884	0.973	0.965	1.027	1.015	0.990	0.979
Beta SMB	(0.071)	(0.074)	0.644	0.623	0.502	0.544	(0.077)	(0.052)	0.554	0.642	0.504	0.661
Beta HML	(0.007)	(0.006)	(0.379)	(0.382)	(0.327)	(0.340)	0.042	0.033	(0.360)	(0.479)	(0.364)	(0.467)
Beta MoM	0.053	0.055	0.144	0.132	0.129	0.113	0.164	0.174	0.242	0.228	0.165	0.154
			Panel C: BAMA						Panel D: BAMAP			
Geometric mean	10.17%	10.98%	16.47%	17.06%	13.34%	13.61%	10.77%	10.15%	15.52%	15.79%	13.21%	11.98%
Arithmetic mean	11.65%	12.41%	18.59%	19.05%	15.11%	15.33%	12.34%	11.66%	17.52%	17.60%	15.16%	13.58%
Volatility	17.09%	16.81%	21.26%	20.58%	19.10%	18.79%	17.60%	17.29%	20.48%	19.34%	20.07%	17.93%
Sharpe ratio	0.441	0.494	0.682	0.727	0.576	0.597	0.468	0.437	0.655	0.698	0.551	0.529
(p-Val for SR > Bmk SR)	56%	35%	14%	8%	27%	23%	48%	59%	15%	10%	34%	33%
Average Realized Utility	7.18%	8.06%	11.51%	12.37%	9.45%	9.84%	7.59%	7.09%	10.97%	11.72%	8.95%	8.62%
(p-Val for ARU > Bmk RU)	54%	33%	8%	4%	21%	18%	44%	56%	10%	6%	27%	29%
Outperf. Frequency	49%	50%	52%	56%	53%	52%	49%	47%	50%	51%	52%	49%
Single-Factor Pricing												
Alpha	0.58%	1.38%	7.55%	8.22%	3.93%	4.30%	1.01%	0.47%	6.28%	6.77%	3.43%	2.33%
Alpha t-Stat	0.353	0.878	2.038	2.265	1.304	1.412	0.613	0.291	1.905	2.178	1.143	0.969
Beta	0.965	0.957	0.980	0.938	0.934	0.910	1.009	0.988	0.998	0.936	1.019	0.949
Four-Factor Pricing												
Alpha	-0.10%	0.91%	11.67%	12.95%	7.64%	9.41%	0.56%	0.14%	10.13%	10.73%	7.22%	6.07%
Alpha t-Stat	(0.064)	0.599	3.429	4.101	2.831	3.776	0.345	0.090	3.419	3.968	2.700	2.919
Beta Market	0.973	0.966	1.039	1.020	0.996	0.981	1.013	0.991	1.041	0.980	1.064	0.968
Beta SMB	(0.076)	(0.050)	0.541	0.638	0.498	0.672	(0.054)	(0.042)	0.489	0.504	0.487	0.453
Beta HML	0.042	0.031	(0.370)	(0.483)	(0.371)	(0.481)	0.047	0.048	(0.292)	(0.301)	(0.308)	(0.227)
Beta MoM	0.164	0.174	0.234	0.234	0.176	0.156	0.159	0.186	0.268	0.274	0.214	0.172

Table 5: Portfolio Country and Sector Rotation

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.

Panel A: Integrated Models

	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%	-	-	-	-	-	-	-	-	-	-	-	2%	-	-	-
Benelux	-	14%	-	-	10%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
France	-	6%	10%	23%	-	-	16%	-	-	40%	-	-	-	40%	-	-	-	10%	-	-
Germany	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	10%	-	-	-	10%
Italy	-	-	-	-	-	-	3%	-	-	20%	-	-	-	20%	-	-	-	41%	-	-
Pan-Europe	10%	-	30%	60%	28%	10%	32%	6%	10%	10%	-	10%	10%	10%	-	10%	21%	20%	-	10%
Scandinavian	-	-	-	-	18%	90%	50%	58%	60%	21%	100%	-	61%	20%	100%	-	37%	29%	89%	-
Spain/Portugal	-	-	-	-	-	-	-	10%	-	9%	-	10%	-	10%	-	10%	-	-	-	10%
Switzerland	-	10%	10%	-	9%	-	-	-	10%	-	-	-	10%	-	-	-	20%	-	-	-
UK	90%	70%	50%	17%	33%	-	-	0%	20%	-	-	-	19%	-	-	-	20%	-	-	-
Sectors	-	-	-	-	-	-	-	26%	-	-	-	70%	-	-	-	70%	-	-	11%	70%

Panel B: Segmented Models

	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%	57%	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%	3%	19%	12%	37%	40%	10%	2%
Scandinavian	-	5%	-	-	16%	70%	45%	65%	20%	19%	52%	-	20%	20%	54%	-	20%	40%	78%	9%
Spain/Portugal	-	-	-	-	-	-	-	-	-	10%	-	-	-	10%	-	-	-	-	-	-
Switzerland	-	20%	10%	10%	-	-	-	-	10%	-	-	-	10%	-	-	-	13%	-	-	-
UK	48%	25%	20%	-	40%	-	-	10%	30%	-	-	10%	30%	-	1%	10%	20%	-	12%	9%
Sectors	-	-	-	-	-	-	-	20%	-	-	9%	80%	-	-	5%	78%	-	-	-	70%

Table 6: Optimal Portfolio Weights (February, 2008)

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 $\sigma_\alpha = 10\%$/Month.

	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 Services ETF	0%	0%	0%	10%	10%	10%	10%	0%	10%
iShares DJ EURO STOXX Telecommunications (DE)	0%	0%	0%	10%	10%	10%	10%	0%	10%
iShares TecDAX (DE)	0%	0%	0%	10%	0%	10%	0%	10%	10%
Etoile Collectivites Europe	0%	0%	0%	0%	10%	0%	10%	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%
Postbank Megatrend	0%	0%	0%	10%	2%	10%	2%	10%	2%
StreetTRACKS MSCI Europe Information TechnologyETF	0%	0%	0%	10%	0%	10%	0%	10%	0%
Fideuram Fund Europe Listed TT Equity	0%	0%	0%	0%	10%	0%	10%	0%	10%
Santander Aggressive Spain, FI	0%	0%	0%	10%	0%	10%	0%	10%	0%
CSIMF Universe F	0%	6%	5%	0%	8%	0%	9%	0%	0%
iShares DJ EURO STOXX Technology (DE)	0%	0%	0%	9%	0%	9%	0%	8%	0%
KBC Multi Track Euro Telecom Acc	0%	0%	0%	10%	0%	10%	0%	4%	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%
Fortis L Equity Telecom Europe Cap	0%	0%	0%	1%	9%	1%	8%	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%
SGAM Index Tech Euro	0%	0%	0%	0%	0%	0%	0%	7%	0%
Aberdeen Global-UK Opportunities A Acc	7%	0%	0%	0%	0%	0%	0%	0%	0%
Oddo Quant France A Cap	3%	0%	0%	0%	0%	0%	0%	0%	0%
iShares DJ STOXX 600 Automobiles (DE)	0%	0%	0%	0%	1%	0%	1%	0%	0%
Storebrand Optima Norge A	0%	1%	0%	0%	0%	0%	0%	0%	0%

Table 7: Out-of-Sample Performance Attribution

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.

Panel A: Integrated Model

	CAPM	BCAPM	BSMA	BAMA	BAMAP
Arithmetic mean	8.62%	13.61%	18.79%	18.59%	17.52%
Return from Pan-Euro Fund Selection	2.21%	0.06%	-0.54%	-0.39%	-0.80%
Return from Country Fund Selection	-0.69%	1.34%	3.13%	3.05%	2.99%
Return from Sector Fund Selection	0.00%	0.55%	2.94%	2.38%	1.96%
Return from Timing Country Weights	-1.62%	1.19%	2.20%	2.27%	3.22%
Residual	-2.68%	-0.94%	-0.34%	-0.12%	-1.25%
Total Outperformance	-2.78%	2.21%	7.39%	7.19%	6.12%

Panel B: Segmented Model

	CAPM-S	BCAPM-S	BSMA-S	BAMA-S	BAMAP-S
Arithmetic mean	8.91%	15.13%	19.03%	19.05%	17.60%
Return from Pan-Euro Fund Selection	1.86%	-1.22%	-0.90%	-0.79%	-0.63%
Return from Country Fund Selection	-0.79%	1.36%	3.19%	3.13%	2.04%
Return from Sector Fund Selection	0.00%	1.45%	3.12%	2.81%	2.49%
Return from Timing Country Weights	-1.41%	1.26%	1.51%	1.41%	1.86%
Residual	-2.15%	0.89%	0.71%	1.09%	0.44%
Total Outperformance	-2.49%	3.73%	7.63%	7.65%	6.20%

Panel C: Alternate Country Selection Definition

	CAPM	BCAPM	BSMA	BAMA	BAMAP
Return from Country Fund Selection	-1.22%	0.57%	4.29%	4.31%	3.34%
Residual	-2.16%	-0.16%	-1.50%	-1.38%	-1.59%

	CAPM-S	BCAPM-S	BSMA-S	BAMA-S	BAMAP-S
Return from Country Fund Selection	-1.06%	1.97%	5.37%	5.52%	4.11%
Residual	-1.89%	0.28%	-1.47%	-1.30%	-1.63%

Table 8: Out of Sample Stock Portfolio Performance (06/1993 - 02/2008)

This table shows the portfolio performance for the different strategies investing in individual stocks 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. The annualized measures of alpha control for macrovariables and time-varying market risk factor loadings. 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 stock to 5%, 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.

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
	Panel A: Full Sample Results					
Geometric mean	10.06%	13.42%	9.80%	12.23%	6.16%	7.06%
Arithmetic mean	11.40%	15.04%	11.92%	13.90%	9.13%	9.77%
Volatility	16.28%	17.84%	20.41%	18.28%	24.47%	23.47%
Sharpe ratio	0.449	0.613	0.383	0.536	0.205	0.242
(p-Val for SR > Bmk SR)		17%	75%	37%	91%	87%
Realized Utility	7.48%	10.08%	5.62%	8.75%	0.21%	1.55%
(p-Val for RU > Benchmark)		13%	71%	33%	94%	90%
Outperformance Frequency		55%	51%	54%	45%	45%
Single-Factor Alpha		4.01%	0.09%	3.53%	-2.23%	-0.85%
Single-Factor Alpha t-Stat		1.655	0.029	1.104	(0.465)	(0.178)
Single-Factor Beta		0.948	1.020	0.847	0.972	0.889
Four-Factor Alpha		4.69%	1.13%	5.42%	0.00%	2.08%
Four-Factor Alpha t-Stat		1.903	0.362	1.675	0.001	0.427
Beta - Market		0.894	1.044	0.793	1.026	0.919
Beta - SMB		0.020	0.155	0.156	0.320	0.374
Beta - HML		0.148	(0.176)	0.111	(0.290)	(0.240)
Beta - Momentum		(0.004)	(0.170)	0.113	0.065	0.091
	Panel B: Sub-Sample Results - 1993-2000					
Geometric mean	18.33%	26.72%	21.40%	19.62%	11.60%	11.12%
Arithmetic mean	19.49%	27.91%	22.64%	20.77%	13.66%	13.01%
Volatility	15.31%	15.45%	15.91%	15.38%	20.59%	19.73%
Sharpe ratio	0.941	1.478	1.104	1.020	0.417	0.402
(p-Val for SR > Bmk SR)		6%	11%	38%	87%	85%
Certainty Equivalent Utility	16.02%	24.35%	21.78%	18.64%	13.14%	13.32%
(p-Val for RU > Benchmark)		1%	10%	38%	80%	79%
Outperformance Frequency		61%	52%	55%	42%	43%
Single-Factor Alpha		10.77%	5.99%	4.78%	-3.03%	-2.77%
Single-Factor Alpha		3.318	1.653	1.291	(0.516)	(0.475)
Single-Factor Beta		0.854	0.803	0.784	0.824	0.754
Four-Factor Alpha		12.14%	11.38%	11.39%	11.31%	11.38%
Four-Factor Alpha t-Stat		3.470	3.166	3.076	2.237	2.158
Beta - Market		0.772	0.740	0.662	0.723	0.630
Beta - SMB		0.033	0.216	0.288	0.675	0.673
Beta - HML		0.177	(0.139)	0.037	(0.452)	(0.344)
Beta - Momentum		0.116	0.303	0.288	0.538	0.502
	Panel C: Sub-Sample Results - 2001-2008					
Geometric mean	1.17%	-0.81%	-2.63%	4.29%	0.29%	2.68%
Arithmetic mean	2.65%	1.11%	0.32%	6.46%	4.22%	6.27%
Volatility	16.99%	19.40%	24.02%	20.85%	28.12%	27.02%
Sharpe ratio	(0.023)	(0.100)	(0.113)	0.164	0.042	0.119
(p-Val for SR > Bmk SR)		50%	76%	26%	64%	56%
Certainty Equivalent Utility	-1.62%	-3.11%	-9.31%	-0.39%	-11.73%	-9.33%
(p-Val for RU > Benchmark)		62%	92%	37%	90%	84%
Outperformance Frequency		48%	51%	53%	47%	46%
Single-Factor Alpha		-2.16%	-4.18%	2.59%	1.67%	3.81%
Single-Factor Alpha		(0.612)	(0.909)	0.503	0.222	0.494
Single-Factor Beta		0.970	1.153	0.828	0.922	0.876
Four-Factor Alpha		-1.41%	-2.90%	4.13%	2.54%	4.63%
Four-Factor Alpha t-Stat		(0.391)	(0.683)	0.797	0.333	0.589
Beta - Market		0.929	1.035	0.748	0.862	0.838
Beta - SMB		0.067	0.247	0.006	(0.010)	0.138
Beta - HML		0.066	(0.188)	0.275	0.116	0.036
Beta - Momentum		(0.020)	(0.498)	0.078	(0.062)	(0.006)

Table 9: Out-of-Sample Short and Long Portfolio Performance

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 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.

	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Panel A: Short Portfolio Performance										
Geometric mean	3.71%	2.29%	-1.06%	-2.17%	-7.66%	-6.91%	-7.18%	-6.82%	-5.63%	-6.19%
Arithmetic mean	5.30%	3.59%	0.28%	-0.59%	-5.09%	-4.47%	-4.69%	-4.38%	-3.48%	-4.27%
Volatility	17.76%	15.99%	16.23%	17.54%	22.14%	21.58%	21.81%	21.61%	20.31%	19.19%
Sharpe ratio	0.067	(0.032)	(0.235)	(0.267)	(0.415)	(0.397)	(0.403)	(0.392)	(0.373)	(0.436)
(p-Val for SR > Bmk SR)	96%	94%	90%	88%	81%	82%	81%	82%	83%	81%
Average Realized Utility	-9.97%	-7.37%	-4.16%	-3.94%	-2.16%	-2.41%	-2.34%	-2.52%	-2.61%	-1.18%
(p-Val for ARU > Bmk ARU)	98%	97%	92%	91%	85%	86%	85%	86%	87%	84%
Outperformance Frequency	37%	37%	29%	34%	33%	33%	34%	32%	31%	28%
Single-Factor Alpha	-5.99%	-7.10%	-10.35%	-11.61%	-17.66%	-16.69%	-17.12%	-16.59%	-15.45%	-15.79%
Single-Factor Alpha t-Stat	(3.073)	(4.464)	(5.417)	(5.545)	(5.567)	(5.364)	(5.490)	(5.299)	(5.640)	(5.923)
Single-Factor Beta	0.990	0.903	0.904	0.972	1.136	1.115	1.120	1.114	1.063	1.001
Four-Factor Alpha	-2.57%	-3.85%	-8.68%	-9.85%	-12.96%	-11.96%	-12.31%	-11.76%	-11.67%	-12.31%
Four-Factor Alpha t-Stat	(1.503)	(2.866)	(4.540)	(4.765)	(4.392)	(4.132)	(4.275)	(4.051)	(4.487)	(4.886)
Beta - Market	0.986	0.895	0.872	0.956	1.104	1.079	1.088	1.076	1.047	0.967
Beta - SMB	0.393	0.370	0.159	0.194	0.521	0.519	0.535	0.528	0.430	0.376
Beta - HML	(0.150)	(0.139)	0.021	(0.072)	(0.187)	(0.166)	(0.192)	(0.165)	(0.180)	(0.111)
Beta - Momentum	0.082	0.022	(0.014)	(0.150)	(0.221)	(0.186)	(0.216)	(0.186)	(0.164)	(0.195)
Panel B: 2:1 Leverage Portfolio Performance										
Geometric mean	3.39%	3.60%	11.77%	14.14%	18.59%	18.56%	18.75%	17.77%	18.86%	18.17%
Arithmetic mean	5.11%	5.39%	15.00%	17.11%	22.27%	22.07%	22.59%	21.37%	22.68%	21.22%
Volatility	18.42%	18.81%	25.86%	24.78%	27.98%	27.22%	28.68%	27.60%	28.64%	25.10%
Sharpe ratio	0.055	0.069	0.422	0.525	0.649	0.660	0.645	0.626	0.649	0.682
(p-Val for SR > Bmk SR)	98%	99%	68%	51%	33%	31%	34%	37%	34%	26%
Average Realized Utility	0.08%	0.15%	4.88%	7.71%	10.14%	10.57%	9.86%	9.59%	9.98%	11.39%
(p-Val for ARU > Bmk ARU)	99%	100%	69%	47%	29%	26%	31%	32%	31%	20%
Outperformance Frequency	39%	43%	52%	53%	54%	57%	53%	55%	56%	56%
Single-Factor Alpha	-5.78%	-6.03%	4.00%	6.39%	10.69%	10.34%	10.85%	9.51%	11.31%	10.28%
Single-Factor Alpha t-Stat	(1.890)	(2.271)	0.748	1.225	1.807	1.790	1.789	1.630	1.831	1.958
Single-Factor Beta	0.861	0.963	0.880	0.832	1.022	0.981	1.045	1.002	1.015	0.934
Four-Factor Alpha	-8.86%	-8.96%	10.15%	12.70%	13.82%	15.16%	14.12%	14.12%	16.21%	15.05%
Four-Factor Alpha t-Stat	(3.095)	(3.522)	2.038	2.664	2.361	2.711	2.364	2.491	2.771	3.052
Beta - Market	0.832	0.964	0.976	0.948	1.092	1.078	1.131	1.106	1.066	0.983
Beta - SMB	(0.385)	(0.337)	0.822	0.862	0.435	0.665	0.468	0.649	0.611	0.597
Beta - HML	0.213	0.122	(0.612)	(0.689)	(0.339)	(0.539)	(0.394)	(0.555)	(0.316)	(0.326)
Beta - Momentum	(0.225)	(0.144)	0.215	0.200	0.326	0.234	0.334	0.221	0.529	0.423
Panel C: Self-Financing Portfolio Performance - Market Factor Neutral										
Geometric mean	4.01%	1.67%	10.39%	8.42%	11.48%	14.21%	11.89%	14.58%	11.01%	12.93%
Arithmetic mean	4.01%	1.87%	10.89%	8.79%	12.34%	14.86%	12.74%	15.22%	11.83%	13.48%
Volatility	0.62%	6.46%	9.96%	8.50%	13.26%	11.62%	13.28%	11.59%	13.09%	10.68%
Sharpe ratio	(0.139)	(0.345)	0.682	0.551	0.621	0.926	0.651	0.959	0.590	0.878
(p-Val for SR > Bmk SR)	0%	83%	18%	23%	27%	5%	25%	4%	30%	7%
Average Realized Utility	3.99%	1.25%	9.28%	7.63%	9.56%	12.60%	9.95%	12.96%	9.13%	11.58%
(p-Val for ARU > Bmk ARU)	78%	89%	34%	47%	33%	15%	31%	14%	36%	20%
Outperformance Frequency	37%	38%	46%	44%	46%	47%	47%	47%	45%	46%
Single-Factor Alpha	-0.11%	-1.89%	6.40%	4.08%	7.86%	10.61%	8.33%	10.86%	7.45%	9.24%
Single-Factor Alpha t-Stat	(1.183)	(1.147)	2.485	1.870	2.257	3.474	2.388	3.575	2.175	3.309
Single-Factor Beta	0.002	(0.075)	0.012	0.028	0.049	0.008	0.041	0.024	0.008	0.005
Four-Factor Alpha	-0.21%	-3.35%	8.10%	5.27%	9.05%	11.89%	9.56%	12.31%	9.43%	10.16%
Four-Factor Alpha t-Stat	(2.268)	(2.024)	3.149	2.375	2.654	3.922	2.800	4.093	2.869	3.637
Beta - Market	0.003	(0.082)	0.038	0.035	0.092	0.032	0.086	0.051	0.073	0.027
Beta - SMB	(0.011)	(0.178)	0.224	0.145	0.179	0.170	0.185	0.193	0.296	0.126
Beta - HML	0.003	0.102	(0.159)	(0.076)	(0.152)	(0.105)	(0.160)	(0.128)	(0.276)	(0.086)
Beta - Momentum	(0.005)	0.012	0.093	0.052	0.269	0.204	0.268	0.197	0.236	0.177

Table 10: Sorted Portfolio Performance

This table presents summary return statistics for equal-weighted portfolios of funds formed each quarter by sorting individual funds into deciles based on their mean returns (Panel A) or their conditional Alpha t-statistic (panel B). The monotonicity test rejects, i.e. yields a low p-value, if the mean returns or alpha-estimates are monotonically declining from the top-ranked through the bottom-ranked decile of funds. The momentum strategy sorts funds based on their trailing 12-month historical returns.

	BCAPM	BCAPM-S	BAMA	BAMA-S	BSMA	BSMA-S	BAMAP	BAMAP-S	Momentum
				Panel A: Annualized Average Return					
1	13.37%	13.08%	13.38%	12.81%	13.37%	12.79%	13.15%	12.64%	14.90%
2	12.52%	12.40%	11.74%	11.89%	11.77%	11.93%	12.27%	11.89%	12.80%
3	11.62%	11.44%	11.40%	11.35%	11.42%	11.34%	11.63%	11.85%	11.30%
4	10.61%	10.67%	11.26%	11.44%	11.14%	11.46%	11.68%	11.18%	10.50%
5	9.64%	11.01%	10.01%	10.72%	10.11%	10.62%	10.12%	11.27%	9.50%
6	10.51%	10.17%	9.99%	10.25%	9.94%	10.41%	9.74%	10.12%	9.80%
7	9.69%	9.95%	9.65%	9.92%	9.67%	9.92%	9.71%	9.88%	9.50%
8	9.57%	9.91%	9.45%	10.04%	9.51%	9.89%	9.32%	9.52%	10.00%
9	9.58%	9.05%	9.83%	9.14%	9.67%	9.22%	9.39%	9.33%	9.80%
10	9.38%	8.79%	9.83%	8.97%	9.94%	8.94%	9.55%	8.84%	8.60%
H-L	3.99%	4.29%	3.55%	3.83%	3.43%	3.85%	3.60%	3.79%	6.40%
				Patton-Timmermann Test p-Values					
H vs L	8%	3%	7%	0%	7%	0%	4%	0%	28%
All	85%	14%	35%	2%	10%	0%	3%	0%	23%
				Panel B: Annualized 4-Factor Alpha					
1	5.87%	5.94%	5.22%	4.91%	5.20%	4.88%	4.86%	4.56%	6.60%
2	3.90%	4.41%	2.37%	2.81%	2.41%	2.83%	3.21%	2.75%	3.90%
3	2.57%	2.60%	1.82%	1.64%	1.86%	1.64%	1.96%	2.54%	2.00%
4	1.44%	1.37%	1.73%	1.94%	1.59%	1.98%	2.22%	1.60%	0.50%
5	-0.10%	1.47%	0.37%	1.02%	0.52%	0.94%	0.52%	1.63%	-0.70%
6	0.88%	0.38%	0.38%	0.55%	0.29%	0.67%	0.15%	0.22%	-0.40%
7	-0.32%	-0.23%	-0.14%	0.17%	-0.09%	0.15%	-0.12%	0.14%	-0.70%
8	-0.53%	-0.57%	-0.17%	0.24%	-0.13%	0.12%	-0.43%	-0.28%	0.30%
9	-0.44%	-1.30%	0.38%	-0.52%	0.17%	-0.45%	-0.14%	-0.48%	0.30%
10	-1.12%	-1.94%	0.16%	-0.61%	0.32%	-0.63%	-0.06%	-0.52%	0.00%
H-L	6.98%	7.87%	5.06%	5.52%	4.88%	5.51%	4.92%	5.08%	6.60%
				Patton-Timmermann 4-Factor Residual Test p-Values					
H vs L	1%	0%	4%	0%	5%	0%	2%	0%	48%
All	69%	1%	69%	1%	25%	1%	8%	0%	36%

Table 11: Accounting for Fees in Portfolio Performance

This table presents the impact on portfolio performance when the investment strategy must pay full Front-End Loads and Redemption Fees. Panel A characterizes the turnover induced costs for the baseline strategies presented in Table 3. Panel B presents results when the immediate turnover costs are deducted from the investor's utility in a myopic utility optimization exercise. Panel C characterizes the turnover induced costs for the strategy in Panel B.

	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Panel A: Turnover and Fees in Baseline Models										
Turnover	58%	65%	113%	96%	227%	221%	231%	229%	221%	215%
Front Loads	1.24	1.62	2.69	2.45	4.36	4.24	4.42	4.39	4.05	3.95
Redemption Fees	0.06	0.07	0.12	0.08	0.29	0.25	0.30	0.26	0.33	0.30
Total Loads and Fees	1.30	1.69	2.81	2.53	4.65	4.49	4.72	4.65	4.38	4.26
Fee-Adjusted Arithmetic mean	7.32%	7.22%	10.80%	12.61%	14.14%	14.54%	13.87%	14.40%	13.14%	13.35%
Fee Adjusted Sharpe Ratio	0.216	0.195	0.345	0.465	0.474	0.506	0.459	0.501	0.442	0.478
Fee Adjusted Single-Factor Alpha	-3.24%	-4.00%	-0.20%	1.85%	3.14%	3.73%	2.82%	3.57%	1.90%	2.51%
t-Stat	(2.79)	(4.00)	(0.06)	0.64	0.85	1.02	0.76	0.98	0.58	0.81
Fee Adjusted Four-Factor Alpha	-2.92%	-3.95%	4.96%	6.79%	7.42%	8.51%	6.95%	8.30%	5.75%	6.48%
t-Stat	(2.55)	(3.85)	1.83	2.78	2.19	2.65	2.04	2.63	1.94	2.39
Panel B: Fee-Adjusted Utility Model Performance										
Geometric mean	8.99%	8.96%	10.92%	11.85%	12.96%	11.57%	13.61%	11.76%	12.38%	9.88%
Arithmetic mean	10.13%	10.21%	12.60%	13.36%	14.69%	13.18%	15.34%	13.37%	14.12%	11.57%
Volatility	15.00%	15.71%	18.35%	17.30%	18.83%	17.99%	18.84%	17.99%	18.88%	18.45%
Sharpe ratio	0.402	0.389	0.463	0.535	0.562	0.505	0.596	0.515	0.530	0.405
p-Val for SR > Bmk SR	62%	78%	53%	29%	26%	39%	19%	36%	34%	70%
Average Realized Utility	6.69%	6.45%	7.45%	8.73%	9.21%	8.21%	9.82%	8.38%	8.63%	6.40%
p-Val for ARU > Bmk ARU	71%	83%	48%	26%	20%	34%	13%	31%	28%	67%
Outperformance Frequency	45%	41%	50%	51%	49%	49%	49%	50%	51%	46%
Single-Factor Alpha	-0.46%	-0.77%	1.44%	2.56%	3.65%	2.18%	4.29%	2.32%	3.02%	0.31%
Single-Factor Alpha	(0.430)	(0.847)	0.617	1.141	1.394	0.952	1.640	1.018	1.188	0.137
Single-Factor Beta	0.882	0.937	0.985	0.922	0.985	0.964	0.987	0.966	1.001	0.995
Four-Factor Alpha	0.83%	0.37%	5.60%	7.19%	7.27%	6.05%	7.99%	6.00%	6.55%	4.12%
Four-Factor Alpha t-Stat	0.814	0.414	2.783	4.004	3.061	3.004	3.357	2.983	2.817	2.048
Beta - Market	0.851	0.926	1.007	0.937	1.016	0.998	1.016	1.002	1.036	1.027
Beta - SMB	0.116	0.120	0.510	0.554	0.455	0.489	0.461	0.470	0.449	0.478
Beta - HML	0.039	(0.019)	(0.284)	(0.275)	(0.272)	(0.313)	(0.270)	(0.309)	(0.287)	(0.295)
Beta - Momentum	0.001	0.004	0.060	0.093	0.123	0.041	0.116	0.045	0.094	0.064
Panel C: Turnover and Fees in Fee-Based Utility Models										
Turnover	9%	10%	28%	28%	45%	39%	44%	40%	45%	41%
Front Loads	0.21	0.23	0.43	0.44	0.54	0.49	0.51	0.52	0.53	0.51
Redemption Fees	0.01	0.02	0.04	0.04	0.09	0.09	0.09	0.09	0.11	0.09
Total Loads and Fees	0.22	0.24	0.46	0.48	0.63	0.57	0.61	0.60	0.64	0.61
Fee-Adjusted Arithmetic mean	9.91%	9.96%	12.14%	12.87%	14.71%	12.79%	14.08%	12.58%	13.47%	10.96%
Fee Adjusted Sharpe Ratio	0.387	0.373	0.438	0.507	0.563	0.483	0.530	0.471	0.496	0.372
Fee Adjusted Single-Factor Alpha	-0.68%	-1.01%	0.98%	2.08%	3.66%	1.74%	3.04%	1.58%	2.38%	-0.29%
t-Stat	(0.64)	(1.11)	0.42	0.93	1.40	0.77	1.16	0.69	0.94	(0.13)
Fee Adjusted Four-Factor Alpha	0.61%	0.12%	5.14%	6.70%	7.36%	5.43%	6.67%	5.44%	5.91%	3.51%
t-Stat	0.60	0.14	2.55	3.73	3.09	2.70	2.81	2.70	2.54	1.75

Table 12: Portfolio Performance under Constrained Utility Specifications

This table shows the portfolio performance for the different strategies during the out-of-sample period 06/1993-02/2008 under alternative objective functions. The out-of-sample portfolio selection exercise 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 $\sigma_\alpha = 10\%/\text{Month}$. Additionally, all models are constrained to have expected Market factor loadings between 0.8 and 1.2 and to have expected SMB, HML, and WML factor loadings between -0.2 and 0.2. Panel A implements the Mean-Variance Utility Objective. Panel B maximizes the portfolio expected return subject to an expected volatility less than or equal to the benchmark volatility of 16.28%. Panel C minimizes the portfolio expected volatility subject to an expected return greater than or equal to the benchmark expected return of 11.40%

Panel A: Mean Variance Utility with Constrained Factor Loading

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
Geometric mean	10.06%	7.61%	13.02%	14.52%	15.33%	14.03%
Arithmetic mean	11.40%	8.72%	14.43%	16.14%	16.95%	15.47%
Volatility	16.28%	14.85%	16.73%	18.13%	18.18%	17.04%
Sharpe ratio	0.449	0.311	0.617	0.664	0.707	0.667
p-Val for SR > Bmk SR		92%	14%	6%	3%	6%
Average Realized Utility		5.38%	10.05%	10.98%	11.73%	10.90%
p-Val for ARU > Bmk ARU		95%	12%	5%	2%	5%
Single-Factor Alpha		-1.82%	3.74%	5.16%	5.95%	4.88%
Single-Factor Alpha		(1.607)	1.664	2.177	2.498	2.153
Four-Factor Alpha		-1.40%	7.02%	8.25%	8.99%	7.72%
Four-Factor Alpha t-Stat		(1.254)	3.483	3.824	4.170	3.638

Panel B: Maximize Expected Return Targeting Benchmark Volatility

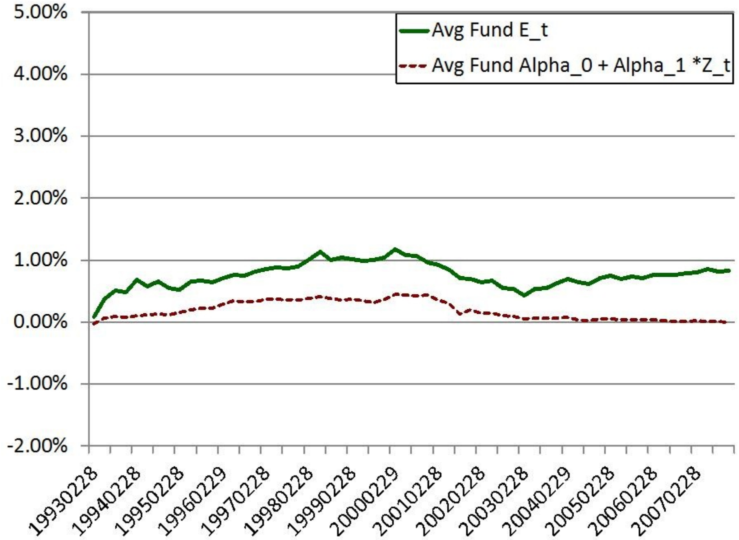
	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
Geometric mean	10.06%	8.08%	13.26%	14.22%	14.69%	13.37%
Arithmetic mean	11.40%	9.25%	14.67%	15.74%	16.22%	14.69%
Volatility	16.28%	15.20%	16.75%	17.63%	17.71%	16.34%
Sharpe ratio	0.449	0.339	0.631	0.661	0.684	0.648
p-Val for SR > Bmk SR		7%	6%	10%	9%	10%
Average Realized Utility		5.75%	10.28%	10.87%	11.28%	10.50%
p-Val for ARU > Bmk ARU		90%	11%	5%	3%	8%
Single-Factor Alpha		-1.48%	3.98%	4.99%	5.45%	4.40%
Single-Factor Alpha		(1.280)	1.729	2.140	2.305	1.983
Four-Factor Alpha		-1.02%	7.28%	8.15%	8.66%	7.42%
Four-Factor Alpha t-Stat		(0.890)	3.542	3.961	4.203	3.701

Panel C: Minimize Volatility Targeting Benchmark Expected Return

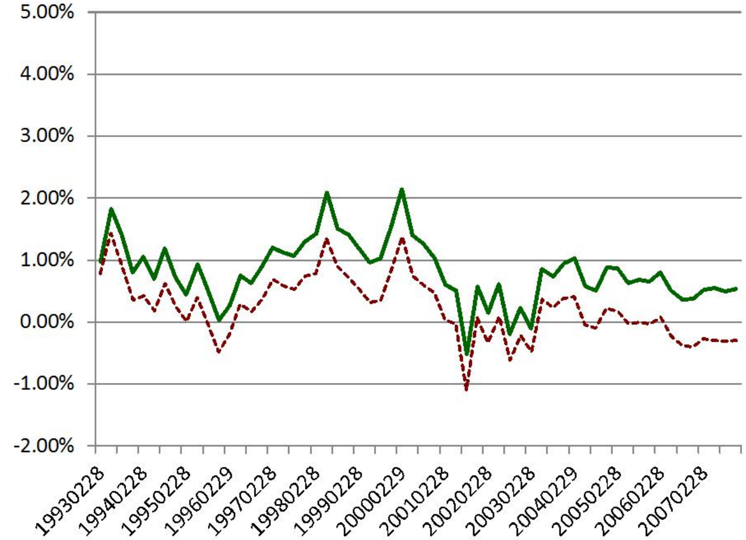
	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
Geometric mean	10.06%	7.12%	12.77%	12.55%	13.33%	11.88%
Arithmetic mean	11.40%	8.41%	14.14%	13.92%	14.70%	13.13%
Volatility	16.28%	16.05%	16.50%	16.64%	16.63%	15.87%
Sharpe ratio	0.449	0.268	0.609	0.590	0.637	0.569
p-Val for SR > Bmk SR		95%	14%	12%	6%	13%
Average Realized Utility		4.53%	9.89%	9.60%	10.36%	9.21%
p-Val for ARU > Bmk ARU		97%	13%	12%	6%	16%
Single-Factor Alpha		-2.35%	3.51%	3.12%	3.92%	2.64%
Single-Factor Alpha		(1.626)	1.591	1.589	1.971	1.408
Four-Factor Alpha		-2.74%	6.84%	5.83%	6.60%	5.34%
Four-Factor Alpha t-Stat		(1.932)	3.487	3.478	3.894	3.162

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

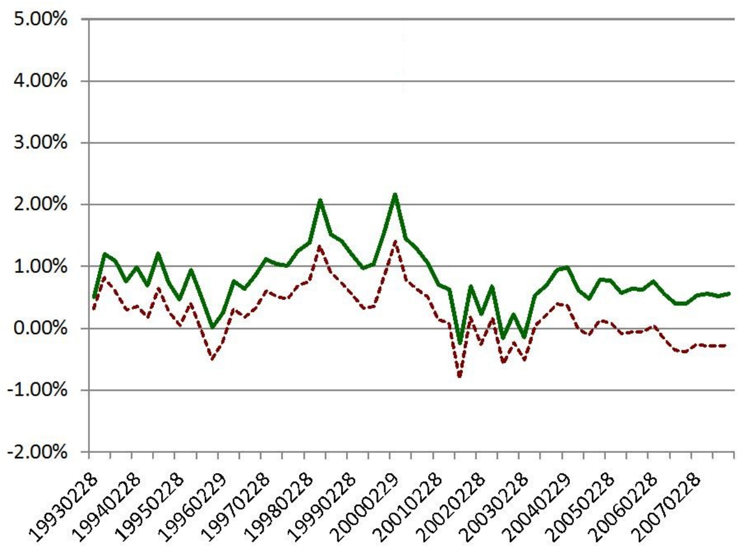
This chart presents the cross-sectional average of estimated expected returns and alphas, estimated with an expanding window, providing an overview of time variation in the investment opportunity set. "Avg Fund E_t" represents the estimated fund total expected return, averaged across all funds, which 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.



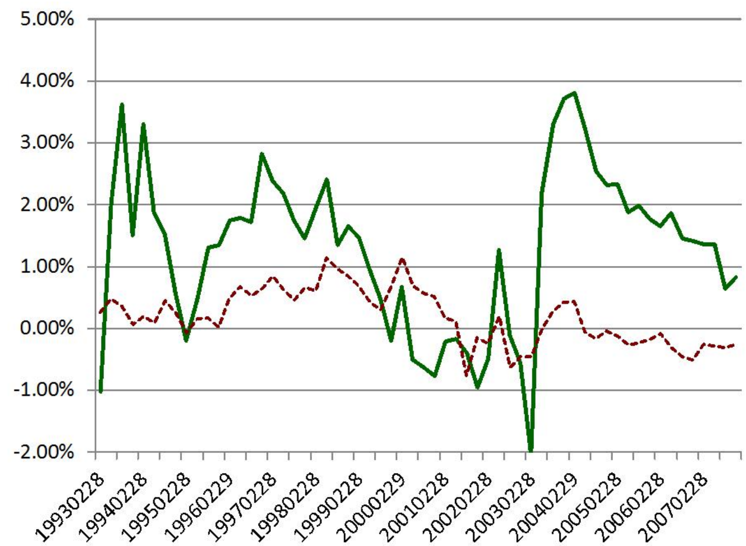
(a) Bayesian CAPM (BCAPM)



(b) Bayesian Skeptic Macro Alpha (BSMA)



(c) Bayesian Agnostic Macro Alpha (BAMA)



(d) BAMA with Predictable Market Loadings (BAMAP)

Appendix B: Tables Reporting Additional Robustness Results

Table B1: Out-of-Sample Short and Long Stock Portfolio Performance

This table presents performance statistics for portfolios that allow short- selling of Individual Stocks. 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 stocks financed by using a 100% short position in benchmark and country indices. Panel C reports the performance of a self-financing portfolio that takes a long position in stocks financed by using a short position in benchmark and country indices with the objective of maintaining zero exposure to the market risk factor.

	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Panel A: Short Portfolio Performance										
Geometric mean	-4.17%	-5.26%	-9.69%	-9.72%	-6.52%	-7.74%	-15.87%	-13.77%	-13.73%	-16.60%
Arithmetic mean	-1.98%	-3.46%	-6.83%	-6.82%	-4.05%	-5.42%	-11.97%	-10.06%	-9.82%	-12.88%
Volatility	21.18%	19.09%	24.41%	24.64%	22.35%	21.64%	28.21%	27.49%	28.44%	27.51%
Sharpe ratio	(0.287)	(0.396)	(0.448)	(0.443)	(0.365)	(0.440)	(0.570)	(0.515)	(0.490)	(0.617)
Outperformance Frequency	39%	37%	34%	36%	35%	35%	33%	34%	32%	34%
Single-Factor Alpha	-11.99%	-13.10%	-15.61%	-15.81%	-13.37%	-14.78%	-22.46%	-20.58%	-20.06%	-22.68%
Single-Factor Alpha t-Stat	(2.849)	(3.470)	(2.795)	(2.840)	(2.793)	(3.252)	(3.478)	(3.339)	(3.080)	(3.592)
Single-Factor Beta	0.812	0.742	0.715	0.735	0.756	0.756	0.813	0.848	0.807	0.777
Four-Factor Alpha	-8.05%	-8.85%	-11.10%	-10.66%	-7.84%	-9.77%	-15.32%	-14.58%	-13.62%	-16.55%
Four-Factor Alpha t-Stat	(1.939)	(2.383)	(1.978)	(1.925)	(1.688)	(2.216)	(2.462)	(2.439)	(2.123)	(2.666)
Beta - Market	0.810	0.718	0.615	0.628	0.670	0.679	0.709	0.743	0.698	0.677
Beta - SMB	0.454	0.468	0.415	0.483	0.557	0.508	0.733	0.599	0.640	0.614
Beta - HML	(0.167)	(0.136)	0.106	0.091	(0.039)	(0.056)	(0.112)	(0.049)	(0.024)	(0.044)
Beta - Momentum	0.160	0.020	(0.001)	(0.036)	(0.201)	(0.248)	(0.423)	(0.422)	(0.270)	(0.310)
Panel B: 2:1 Leverage Portfolio Performance										
Geometric mean	17.46%	30.19%	22.30%	31.38%	24.05%	26.22%	22.47%	17.42%	27.37%	37.80%
Arithmetic mean	26.00%	37.37%	29.54%	41.71%	30.94%	32.19%	32.12%	25.96%	36.74%	47.21%
Volatility	40.46%	36.97%	36.97%	44.39%	37.16%	34.98%	44.61%	41.37%	44.71%	44.39%
Sharpe ratio	0.541	0.900	0.688	0.847	0.722	0.803	0.628	0.528	0.730	0.971
Outperformance Frequency	56%	64%	60%	62%	57%	60%	55%	54%	58%	59%
Single-Factor Alpha	15.32%	25.12%	15.24%	27.05%	19.36%	21.37%	18.14%	15.91%	24.14%	34.77%
Single-Factor Alpha t-Stat	1.568	3.203	1.948	2.788	2.316	2.686	1.850	1.624	2.349	3.361
Single-Factor Beta	0.894	1.219	1.344	1.510	1.158	1.082	1.414	0.999	1.296	1.284
Four-Factor Alpha	13.70%	21.05%	13.37%	23.05%	18.71%	21.83%	21.69%	16.57%	27.41%	36.44%
Four-Factor Alpha t-Stat	1.356	2.646	1.666	2.347	2.232	2.745	2.184	1.661	2.633	3.499
Beta - Market	0.864	1.310	1.470	1.695	1.261	1.194	1.543	1.120	1.397	1.392
Beta - SMB	(0.218)	(0.386)	(0.070)	(0.270)	0.021	0.162	0.550	0.200	0.481	0.297
Beta - HML	0.160	(0.026)	(0.382)	(0.363)	(0.200)	(0.301)	(0.569)	(0.367)	(0.425)	(0.330)
Beta - Momentum	(0.127)	0.330	(0.202)	0.295	0.549	0.503	0.296	0.396	0.427	0.600
Panel C: Self-Financing Portfolio Performance - Market Factor Neutral										
Geometric mean	4.85%	6.58%	17.21%	13.75%	19.39%	11.74%	2.42%	12.40%	19.68%	25.86%
Arithmetic mean	4.91%	7.13%	20.79%	16.78%	22.36%	14.07%	9.39%	18.87%	25.38%	32.37%
Volatility	3.34%	10.53%	25.71%	23.41%	24.25%	21.51%	35.79%	34.60%	33.36%	36.41%
Sharpe ratio	0.241	0.287	0.649	0.541	0.753	0.463	0.148	0.427	0.638	0.776
Outperformance Frequency	38%	42%	58%	54%	54%	50%	49%	55%	55%	59%
Single-Factor Alpha	0.74%	2.47%	14.29%	11.07%	16.89%	9.10%	5.30%	15.24%	21.73%	28.32%
Single-Factor Alpha t-Stat	0.842	0.909	2.171	1.844	2.762	1.635	0.579	1.708	2.511	3.097
Single-Factor Beta	0.011	0.079	0.375	0.307	0.300	0.175	0.191	0.147	0.092	0.241
Four-Factor Alpha	0.95%	1.95%	13.03%	10.74%	15.91%	7.88%	3.96%	13.11%	19.57%	27.55%
Four-Factor Alpha t-Stat	1.062	0.696	1.961	1.764	2.520	1.402	0.426	1.438	2.219	3.008
Beta - Market	0.020	0.103	0.541	0.459	0.320	0.292	0.384	0.292	0.226	0.390
Beta - SMB	0.035	(0.032)	0.051	0.139	(0.097)	(0.015)	0.054	(0.092)	(0.111)	0.058
Beta - HML	(0.038)	(0.069)	(0.576)	(0.553)	0.016	(0.304)	(0.555)	(0.348)	(0.288)	(0.354)
Beta - Momentum	0.018	(0.064)	(0.319)	(0.218)	0.152	0.177	0.198	0.192	0.273	0.542

Table B2: Predictability Generated by Individual and Local Macro Variables

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 shows 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.

Panel A - Skeptic Macro Alpha (Segmented)

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Single-Factor Alpha	Single-Factor Alpha t-Statistic	Beta
Local Macro Variables	15.43%	17.40%	20.40%	0.652	7.21%	2.251	0.852
1 - Short Rate Yield	15.22%	17.24%	20.42%	0.644	6.07%	1.740	0.962
2 - Term Spread	14.39%	15.96%	17.93%	0.661	4.92%	1.838	0.916
3 - Dividend Yield	13.52%	15.24%	18.71%	0.595	4.72%	1.471	0.872
4 - Default Spread	14.69%	16.42%	18.88%	0.652	5.54%	1.837	0.915
5 - Volatility	14.54%	16.29%	18.76%	0.650	4.84%	1.758	0.959
6 - Inflation	15.48%	17.08%	18.08%	0.718	6.41%	2.165	0.872
7 - Industrial Production	15.92%	17.76%	19.66%	0.695	7.02%	2.022	0.895
8 - Economic Sentiment	15.67%	17.54%	19.73%	0.681	6.65%	1.906	0.898
9 - Currency Factor	12.02%	13.55%	17.70%	0.534	2.94%	0.989	0.849

Panel B - Agnostic Macro Alpha (Segmented)

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Single-Factor Alpha	Single-Factor Alpha t-Statistic	Beta
Local Macro Variables	14.94%	16.90%	20.36%	0.629	6.34%	2.016	0.905
1 - Short Rate Yield	15.20%	17.21%	20.38%	0.643	6.05%	1.739	0.960
2 - Term Spread	14.37%	15.95%	17.94%	0.661	4.91%	1.831	0.916
3 - Dividend Yield	13.38%	15.11%	18.76%	0.587	4.58%	1.418	0.872
4 - Default Spread	14.69%	16.42%	18.90%	0.652	5.54%	1.834	0.915
5 - Volatility	14.63%	16.36%	18.73%	0.655	4.93%	1.793	0.956
6 - Inflation	15.42%	17.03%	18.07%	0.715	6.36%	2.150	0.872
7 - Industrial Production	15.91%	17.76%	19.68%	0.694	7.01%	2.017	0.895
8 - Economic Sentiment	15.71%	17.58%	19.78%	0.681	6.69%	1.908	0.897
9 - Currency Factor	12.13%	13.67%	17.75%	0.539	3.04%	1.019	0.852

Panel C - Agnostic Macro Alpha with Predictability (Segmented)

	Geometric mean	Arithmetic mean	Volatility	Sharpe ratio	Single-Factor Alpha	Single-Factor Alpha t-Statistic	Beta
1 - Short Rate Yield	16.16%	18.19%	20.60%	0.684	7.02%	2.001	0.973
2 - Term Spread	14.08%	15.68%	18.13%	0.639	4.86%	1.677	0.895
3 - Dividend Yield	13.28%	15.22%	19.95%	0.557	4.13%	1.223	0.940
4 - Default Spread	14.81%	16.57%	19.09%	0.653	5.76%	1.849	0.911
5 - Volatility	13.32%	15.16%	19.31%	0.572	3.69%	1.232	0.961
6 - Inflation	15.44%	17.34%	19.73%	0.671	6.32%	1.883	0.930
7 - Industrial Production	15.74%	17.55%	19.44%	0.692	6.65%	2.012	0.908
8 - Economic Sentiment	13.85%	15.49%	18.31%	0.622	4.76%	1.612	0.887
9 - Currency Factor	10.63%	11.90%	15.94%	0.489	1.63%	0.649	0.796

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 (Segmented)	13.48%	15.13%	18.29%	0.603	4.26%	1.451	0.889

Table B3: Robustness to Fund Universe Size

This table shows the effect of imposing different 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. Panels A & B test the portfolio performance when the initial sort selects the 25 funds and 250 funds, respectively, with the highest conditional alphas. Panel C tests the portfolio performance when there is no initial sort based on a funds conditional alpha.

Panel A: Portfolios of 25 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%	9.42%	9.49%	12.72%	13.12%	16.33%	17.11%	16.02%	17.25%	15.28%	15.71%
Arithmetic mean	11.40%	10.55%	10.87%	14.70%	14.90%	18.46%	19.14%	18.17%	19.26%	17.31%	17.49%
Volatility	16.28%	14.96%	16.51%	20.14%	18.93%	21.25%	20.73%	21.37%	20.65%	20.65%	19.15%
Sharpe ratio	0.449	0.431	0.410	0.526	0.570	0.676	0.725	0.659	0.734	0.640	0.699
Outperformance Frequency		50%	47%	54%	53%	53%	54%	52%	56%	48%	51%
Single-Factor Alpha		-0.05%	-0.51%	3.75%	4.10%	7.45%	8.24%	7.11%	8.36%	6.01%	6.64%
Single-Factor Alpha t-Stat		(0.041)	(0.492)	1.090	1.303	2.000	2.242	1.906	2.297	1.812	2.198
Single-Factor Beta		0.873	0.982	0.905	0.879	0.974	0.941	0.982	0.941	1.009	0.938
Four-Factor Alpha		0.86%	0.46%	9.46%	9.82%	11.74%	13.03%	11.29%	13.11%	9.95%	10.66%
Four-Factor Alpha t-Stat		0.758	0.439	3.231	3.792	3.431	4.058	3.282	4.140	3.344	4.052
Beta - Market		0.838	0.981	0.950	0.922	1.028	1.022	1.040	1.023	1.058	0.986
Beta - SMB		0.067	0.113	0.713	0.713	0.555	0.644	0.548	0.641	0.507	0.517
Beta - HML		0.068	(0.050)	(0.415)	(0.417)	(0.362)	(0.482)	(0.374)	(0.486)	(0.321)	(0.328)
Beta - Momentum		(0.022)	(0.008)	0.187	0.156	0.233	0.233	0.223	0.233	0.255	0.236

Panel B: 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%	14.37%	13.69%	14.46%	13.53%	14.21%
Arithmetic mean	11.40%	9.25%	9.40%	14.04%	14.51%	15.04%	15.74%	15.16%	15.85%	15.02%	15.56%
Volatility	16.28%	14.61%	15.35%	17.21%	16.40%	17.21%	16.74%	17.35%	16.79%	17.45%	16.55%
Sharpe ratio	0.449	0.353	0.345	0.577	0.635	0.636	0.695	0.637	0.699	0.625	0.693
Outperformance Frequency		39%	37%	51%	53%	51%	55%	51%	55%	51%	55%
Single-Factor Alpha		-1.10%	-1.58%	3.00%	3.72%	4.33%	5.03%	4.40%	5.12%	4.10%	4.83%
Single-Factor Alpha t-Stat		(0.806)	(1.734)	1.366	1.856	1.903	2.325	1.914	2.349	1.837	2.423
Single-Factor Beta		0.833	0.914	0.909	0.881	0.910	0.894	0.916	0.896	0.938	0.903
Four-Factor Alpha		-0.70%	-1.19%	6.70%	7.40%	7.59%	8.79%	7.69%	8.91%	7.32%	8.06%
Four-Factor Alpha t-Stat		(0.528)	(1.316)	3.593	4.421	3.786	4.967	3.817	5.022	3.741	4.912
Beta - Market		0.782	0.883	0.935	0.902	0.931	0.920	0.941	0.924	0.958	0.914
Beta - SMB		(0.011)	0.012	0.459	0.450	0.400	0.464	0.407	0.469	0.393	0.384
Beta - HML		0.152	0.084	(0.261)	(0.245)	(0.211)	(0.255)	(0.223)	(0.264)	(0.201)	(0.168)
Beta - Momentum		(0.023)	(0.010)	0.120	0.090	0.161	0.155	0.165	0.160	0.168	0.187

Panel C: 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%	10.23%	10.20%	10.13%	10.15%
Arithmetic mean	11.40%	9.66%	10.36%	11.35%	11.48%	11.46%	11.43%	11.47%	11.44%	11.37%	11.39%
Volatility	16.28%	15.21%	15.61%	15.76%	15.79%	15.68%	15.69%	15.67%	15.69%	15.69%	15.72%
Sharpe ratio	0.449	0.366	0.401	0.460	0.467	0.469	0.467	0.470	0.468	0.463	0.464
Outperformance Frequency		42%	47%	53%	50%	50%	51%	50%	51%	51%	51%
Single-Factor Alpha		-1.26%	-0.73%	0.24%	0.36%	0.46%	0.41%	0.46%	0.42%	0.36%	0.36%
Single-Factor Alpha t-Stat		(1.603)	(0.891)	0.244	0.363	0.440	0.399	0.447	0.407	0.350	0.357
Single-Factor Beta		0.913	0.938	0.939	0.942	0.933	0.934	0.932	0.934	0.934	0.937
Four-Factor Alpha		-0.50%	0.41%	1.86%	2.04%	2.03%	2.13%	2.04%	2.14%	1.92%	2.03%
Four-Factor Alpha t-Stat		(0.645)	0.530	2.079	2.273	2.162	2.287	2.173	2.299	2.059	2.194
Beta - Market		0.891	0.926	0.933	0.935	0.930	0.930	0.930	0.930	0.930	0.932
Beta - SMB		0.066	0.120	0.181	0.189	0.179	0.196	0.179	0.196	0.177	0.188
Beta - HML		0.032	(0.018)	(0.057)	(0.061)	(0.060)	(0.070)	(0.060)	(0.070)	(0.057)	(0.064)
Beta - Momentum		(0.014)	(0.003)	0.036	0.025	0.059	0.039	0.059	0.039	0.047	0.036

Table B4: Robustness to Investor Trading Strategy Restrictions

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.

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

Table B5: Portfolio Performance with Unrestricted Covariance Matrix

This table shows the portfolio performance for the different strategies with an unrestricted covariance matrix for return residuals. 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. The annualized measures of alpha control for macrovariables and time-varying market risk factor loadings. 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 $\sigma_\alpha = 10\%/\text{Month}$.

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
Panel A: Full Sample Results						
Geometric mean	10.06%	8.53%	13.40%	16.45%	16.27%	16.18%
Arithmetic mean	11.40%	9.63%	14.97%	18.48%	18.33%	18.19%
Volatility	16.28%	14.74%	17.75%	20.81%	20.93%	20.51%
Sharpe ratio	0.449	0.375	0.612	0.691	0.680	0.687
Average Realized Utility	7.48%	6.32%	10.06%	11.69%	11.47%	11.60%
(p-Val for ARU > Bmk ARU)		80%	15%	7%	8%	7%
Outperformance Frequency		40%	56%	51%	51%	49%
Single-Factor Alpha		-0.93%	4.23%	7.59%	7.37%	7.13%
Single-Factor Alpha t-Stat		(0.856)	1.586	2.098	2.041	2.113
Single-Factor Beta		0.865	0.871	0.957	0.967	0.986
Four-Factor Alpha		-0.39%	8.79%	11.81%	11.48%	10.99%
Four-Factor Alpha t-Stat		(0.360)	3.865	3.608	3.509	3.622
Beta - Market		0.831	0.893	1.018	1.034	1.029
Beta - SMB		0.023	0.552	0.554	0.548	0.489
Beta - HML		0.097	(0.282)	(0.379)	(0.396)	(0.289)
Beta - Momentum		0.029	0.155	0.246	0.235	0.283
Panel B: Sub-Sample Results - 1993-2000						
Geometric mean	18.33%	16.56%	17.38%	23.46%	23.70%	22.95%
Arithmetic mean	19.49%	17.56%	19.02%	25.90%	26.17%	25.28%
Volatility	15.31%	14.19%	18.43%	23.26%	23.36%	22.42%
Sharpe ratio	0.941	0.880	0.757	0.896	0.903	0.901
Average Realized Utility	16.02%	15.64%	16.26%	19.36%	19.63%	19.61%
(p-Val for ARU > Bmk ARU)		87%	61%	35%	34%	33%
Outperformance Frequency		46%	48%	43%	43%	42%
Single-Factor Alpha		0.26%	1.41%	6.22%	6.46%	5.04%
Single-Factor Alpha		0.152	0.305	0.940	0.970	0.853
Single-Factor Beta		0.866	0.870	1.029	1.031	1.075
Four-Factor Alpha		-0.76%	15.49%	24.63%	24.97%	21.84%
Four-Factor Alpha t-Stat		(0.420)	4.163	4.687	4.722	4.647
Beta - Market		0.845	0.745	0.892	0.893	0.938
Beta - SMB		(0.054)	0.695	0.873	0.878	0.797
Beta - HML		0.130	(0.295)	(0.543)	(0.545)	(0.450)
Beta - Momentum		(0.033)	0.426	0.668	0.672	0.605
Panel C: Sub-Sample Results - 2001-2008						
Geometric mean	1.17%	-0.09%	9.12%	8.90%	8.27%	8.89%
Arithmetic mean	2.65%	1.06%	10.59%	10.45%	9.84%	10.52%
Volatility	16.99%	15.02%	17.01%	17.62%	17.74%	18.09%
Sharpe ratio	(0.023)	(0.132)	0.443	0.420	0.383	0.413
Average Realized Utility	-1.62%	-2.29%	4.32%	4.60%	3.93%	4.19%
(p-Val for ARU > Bmk ARU)		53%	1%	1%	2%	3%
Outperformance Frequency		33%	66%	60%	60%	56%
Single-Factor Alpha		-2.15%	7.34%	8.15%	7.51%	8.14%
Single-Factor Alpha		(1.660)	2.841	2.779	2.670	2.470
Single-Factor Beta		0.847	0.862	0.862	0.882	0.877
Four-Factor Alpha		-1.88%	7.78%	9.38%	8.42%	9.03%
Four-Factor Alpha t-Stat		(1.571)	3.334	3.326	3.060	2.831
Beta - Market		0.850	0.876	0.819	0.854	0.857
Beta - SMB		0.157	0.374	0.192	0.179	0.068
Beta - HML		(0.040)	(0.140)	0.114	0.063	0.191
Beta - Momentum		0.046	0.076	0.100	0.084	0.209

Table B6: Robustness to Investor Beliefs

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.

	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	11.79%	13.78%	13.48%	13.48%	13.49%	13.49%	15.50%	15.43%	16.48%	17.06%	17.02%	16.87%
Arithmetic mean	13.06%	15.32%	15.13%	15.14%	15.15%	15.15%	17.55%	17.47%	18.48%	19.05%	19.03%	18.88%
Volatility	15.92%	17.57%	18.25%	18.29%	18.30%	18.30%	20.86%	20.78%	20.60%	20.58%	20.64%	20.67%
Sharpe ratio	0.563	0.638	0.604	0.603	0.604	0.604	0.645	0.644	0.698	0.727	0.723	0.715
Outperformance Frequency	51%	55%	54%	54%	54%	54%	55%	53%	54%	56%	55%	54%
Single-Factor Alpha	2.57%	4.67%	4.38%	4.37%	4.39%	4.39%	6.61%	6.46%	7.58%	8.22%	8.22%	8.07%
Single-Factor Alpha t-Stat	1.321	1.752	1.521	1.514	1.516	1.516	1.814	1.792	2.100	2.265	2.240	2.194
Single-Factor Beta	0.859	0.859	0.872	0.873	0.873	0.873	0.967	0.965	0.946	0.938	0.935	0.935
Four-Factor Alpha	6.32%	9.55%	9.31%	9.31%	9.32%	9.32%	11.35%	11.23%	12.24%	12.95%	13.05%	12.90%
Four-Factor Alpha t-Stat	4.217	4.306	3.822	3.809	3.806	3.806	3.588	3.611	3.905	4.101	4.071	4.002
Beta - Market	0.890	0.882	0.915	0.916	0.917	0.917	1.055	1.054	1.033	1.020	1.016	1.015
Beta - SMB	0.469	0.593	0.621	0.623	0.622	0.622	0.647	0.651	0.635	0.638	0.649	0.648
Beta - HML	(0.275)	(0.309)	(0.380)	(0.382)	(0.383)	(0.383)	(0.507)	(0.510)	(0.495)	(0.483)	(0.484)	(0.482)
Beta - Momentum	0.127	0.137	0.132	0.132	0.132	0.132	0.227	0.224	0.230	0.234	0.227	0.222
	Panel C: BAMA-S						Panel D: BAMAP-S					
Geometric mean	8.24%	15.12%	17.38%	17.03%	16.84%	16.84%	13.54%	15.15%	15.75%	15.79%	15.58%	15.57%
Arithmetic mean	9.51%	16.71%	19.39%	19.03%	18.85%	18.85%	15.36%	17.00%	17.56%	17.60%	17.38%	17.37%
Volatility	15.80%	18.10%	20.66%	20.62%	20.66%	20.67%	19.26%	19.50%	19.30%	19.34%	19.26%	19.26%
Sharpe ratio	0.342	0.697	0.740	0.724	0.714	0.714	0.584	0.661	0.697	0.698	0.689	0.689
Outperformance Frequency	44%	55%	58%	54%	54%	54%	49%	51%	51%	51%	51%	51%
Single-Factor Alpha	-1.34%	6.13%	8.53%	8.22%	8.04%	8.04%	4.36%	6.10%	6.74%	6.77%	6.56%	6.54%
Single-Factor Alpha t-Stat	(0.946)	2.129	2.341	2.245	2.186	2.186	1.460	1.951	2.170	2.178	2.122	2.118
Single-Factor Beta	0.909	0.884	0.944	0.935	0.935	0.935	0.955	0.946	0.934	0.936	0.934	0.934
Four-Factor Alpha	-0.07%	10.54%	13.23%	13.00%	12.88%	12.88%	8.44%	10.17%	10.69%	10.73%	10.51%	10.49%
Four-Factor Alpha t-Stat	(0.053)	4.328	4.150	4.054	3.991	3.991	3.295	3.733	3.953	3.968	3.900	3.895
Beta - Market	0.875	0.924	1.025	1.015	1.014	1.014	1.004	0.991	0.978	0.980	0.976	0.976
Beta - SMB	0.110	0.553	0.634	0.642	0.648	0.648	0.525	0.519	0.502	0.504	0.500	0.500
Beta - HML	0.044	(0.323)	(0.477)	(0.479)	(0.481)	(0.481)	(0.332)	(0.316)	(0.299)	(0.301)	(0.294)	(0.294)
Beta - Momentum	(0.041)	0.220	0.231	0.228	0.222	0.222	0.241	0.258	0.273	0.274	0.272	0.271

Table B7: Robustness to using Country Momentum Factor

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

Panel A: Integrated Models

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
Geometric mean	10.06%	7.52%	12.65%	15.94%	14.47%	14.06%
Arithmetic mean	11.40%	8.68%	14.45%	18.06%	16.59%	16.14%
Volatility	16.28%	15.16%	19.09%	21.19%	21.21%	20.88%
Sharpe ratio	0.449	0.302	0.542	0.659	0.589	0.576
Average Realized Utility		5.21%	8.82%	11.06%	9.63%	9.40%
(p-Val for ARU > Benchmark)		96%	31%	11%	22%	22%
Outperformance Frequency		37%	57%	49%	50%	51%
Single-Factor Alpha		-2.00%	3.60%	7.15%	5.57%	4.57%
Single-Factor Alpha t-Stat		(1.751)	1.124	1.963	1.516	1.394
Single-Factor Beta		0.888	0.870	0.986	0.981	1.037
Four-Factor Alpha		-1.72%	8.94%	11.46%	9.71%	8.79%
Four-Factor Alpha t-Stat		(1.491)	3.201	3.377	2.806	2.938
Beta - Market		0.855	0.912	1.053	1.051	1.088
Beta - SMB		(0.006)	0.660	0.564	0.548	0.533
Beta - HML		0.093	(0.450)	(0.482)	(0.478)	(0.427)
Beta - Momentum		0.013	0.075	0.088	0.076	0.108

Panel B: Segmented Models

	Benchmark	CAPM-S	BCAPM-S	BSMA-S	BAMA-S	BAMAP-S
Geometric mean	10.06%	7.58%	14.19%	16.24%	15.41%	14.75%
Arithmetic mean	11.40%	8.92%	15.86%	18.28%	17.38%	16.63%
Volatility	16.28%	16.28%	18.41%	20.77%	20.41%	19.70%
Sharpe ratio	0.449	0.296	0.639	0.683	0.651	0.636
Average Realized Utility		4.92%	10.56%	11.52%	10.88%	10.58%
(p-Val for ARU > Benchmark)		99%	14%	8%	11%	12%
Outperformance Frequency		38%	55%	52%	51%	51%
Single-Factor Alpha		-2.37%	5.14%	7.49%	6.62%	5.61%
Single-Factor Alpha t-Stat		(2.301)	1.671	2.044	1.847	1.844
Single-Factor Beta		0.970	0.850	0.947	0.936	0.978
Four-Factor Alpha		-2.07%	10.39%	12.64%	11.49%	9.94%
Four-Factor Alpha t-Stat		(1.958)	3.961	3.886	3.587	3.656
Beta - Market		0.957	0.911	1.043	1.033	1.034
Beta - SMB		0.019	0.671	0.701	0.670	0.554
Beta - HML		0.026	(0.504)	(0.617)	(0.604)	(0.445)
Beta - Momentum		0.007	0.061	0.054	0.049	0.087