The Cross-section of Conditional Mutual Fund Performance in European Stock Markets*

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Abstract

This paper implements strategies that use macroeconomic variables to select European equity mutual funds, including Pan-European, country, and sector funds. We find that several 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 that exploit time-varying predictability provide four-factor alphas of 12-13%/year over the 1993-2008 period. Our study provides new evidence on the skills of local versus Pan-European asset managers, as well as how macroeconomic information can be used to locate and time these local fund manager skills.

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 returns on 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 can 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 equities of corporations 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 can 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.

Together, these two seemingly unrelated bodies of research suggest that professional asset managers could 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 can 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 could outperform strategies involving either local expertise or macro indicators alone to choose active managers.

This paper brings these issues to a unique data set 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. If such a strategy does result in outperformance, we wish to know *which* country's local equity managers exhibit the best skills during a particular phase of the European business cycle. To address these points, we explore whether, under some macroeconomic conditions, a multi-country fund (i.e., a Pan-European fund) should be chosen due to its ability to time various countries and sectors (perhaps itself using macroeconomic information) or to provide lower-cost diversification; conversely, we ask whether a country or regional fund should sometimes be chosen due to its greater knowledge of industries or stocks in its local geographic area.

Our study 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, the European industry 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 Pan-European vs. individual country funds.[1]

[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 20 years. This gap is an important omission, since investors in any European country 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.

We focus on the dynamics of active management skills, and how an investor might optimally choose active funds during varying business conditions. Building on studies such as Avramov and Wermers (2006) and Moskowitz (2000), we allow for the possibility of time-varying mutual fund alphas and betas among 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 in selecting European equities.

We first construct Pan-European size, book-to-market, and momentum risk factors for stocks. Then, we report on 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 -0.90%/year and -0.32%/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, country, and sector funds with persistent performance, relative to our European risk factors, and (if so) to identify how macroeconomic information helps to improve the selection of these funds. Given the modest costs of trading most open-ended mutual funds, such a strategy would be attractive to a large population of 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 (through their selection of funds), or by identifying funds with superior security selection within each of these investment objective categories. Thus, we can determine whether country or sector funds, during certain phases of the business cycle, outperform funds that invest more broadly across countries and sectors in Europe.[2]

Following recent work in the mutual fund literature (e.g., Pastor and Stambaugh, 2002a,b), we

[2] An early literature discusses the issue of country versus industry effects in the cross-section of stock returns. 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–as mentioned above–finds that stock analysts who are country specialists benefit from an informational advantage over sector specialists. Our paper also brings fresh evidence to the country vs. industry issue through its exploration of the relative expertise of country- versus sector-specific active asset managers in selecting stocks.

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 (alpha), and (2) whether alphas and betas of funds are predictably time-varying from the point-of-view of an investor using public information variables. The investment performance of these four types is compared with the performance of a dogmatic investor who does not believe that funds can generate alpha, relative to the CAPM.

Our main empirical findings are as follows. 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 out-of-sample alphas from 7-9%/year (after fund-level trading costs and fees), when measured with a single-factor model, and from 12-13%/year with a four-factor model that controls for fund exposures to size, book-to-market, and momentum.[3] Moreover, the results are robust in separate out-of-sample portfolio selection tests conducted over the periods 1993-2000 and 2001-2008.[4]

For the investor types believing that active managers can generate alphas, we find that the ability to identify superior performing funds is further improved, albeit slightly, by augmenting the four-factor model with country indices, even if these indices represent non-priced factors, consistent with Pastor and Stambaugh (2002a). To illustrate, our baseline analysis finds CAPM alpha enhancements of up to 5% per year from using macroeconomic state variables to choose funds, relative to active manager choice using an unconditional CAPM model. Further improvements of up to 1% per year are attained from the tighter predictive distribution for fund alphas obtained using the Pastor-Stambaugh (2002a,b) specification, which, in turn, leads to improved portfolio selection.

These baseline results assume a standard set of macroeconomic state variables previously used

[3] If we assume that our investment strategies must pay full front-end and redemption load fees, the single-factor alphas are reduced to 2-5%/year, while the four-factor alphas are reduced to 8-10%/year. However, as discussed in our paper, we believe that larger institutions may be able to receive waivers for these loads.

[4] Interestingly, the portfolio alpha estimates are somewhat higher in the first subsample. Our investor is assumed to be able to invest in all European funds and the out-of-sample alpha values are computed using a pricing model that only includes Europe-wide risk factors. Hence, it is possible that some market segmentation over the early sample period could help explain the high alphas; i.e., perhaps many investors could not easily invest across borders during the early years.

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 ability to locate skilled managers. Interestingly, we find that some additional variables, such as growth in industrial production, inflation, and a proxy for stock market volatility, are also useful in identifying funds with superior future alphas. 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).[5]

To better understand the sources of outperformance, we undertake an attribution analysis that decomposes investor returns into that from (1) the selection of Pan-European funds, (2) the selection of country funds, (3) the selection of sector funds, and (4) the timing of country weights implied by the selection of country funds. This analysis shows that the superior returns associated with the macroeconomic-driven strategies arise from the last three sources of performance, and not from choosing Pan-European funds. These Pan-European funds, while providing lower-cost diversification, do not exhibit exploitable alphas, either time-varying or unconditional.[6]

In addition, we implement a version of our strategies that allows investment in individual European stocks, rather than funds. Here, we find that the investment strategies that use macroeconomic variables to predict investment alphas significantly outperform when they have access to funds (either with or without access to stocks) relative to when they have access only to stocks. 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.

Since we adopt a Bayesian approach in our paper, the choice of investor priors is an issue. We

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

[6]Although, in other tests, we show that macro variables do not appear to be particularly useful for timing passive country equity 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.

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. While a large part of the 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 alphas, our model proves capable in identifying funds with inferior performance, that is, funds least likely to hold outperforming stocks.

To summarize, our study provides the first evidence of local stock-picking skills of country-focused mutual funds. Further, we show that these skills are time-varying, and are best captured through the use of macroeconomic variables. To return to the issue of industry vs. country in Europe, we find evidence that much more effort is spent on managing and offering country-focused funds, although sector-focused funds are gaining in popularity in Europe. As such, it appears that the industry vs. country debate is not yet resolved in the asset management world. 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 period.

Our paper proceeds as follows. Section 2 reviews our data, and describes the economic state variables and risk factors 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, variable construction, and additional robustness results are provided in a series of appendices available from the web.

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. We focus on European-domiciled equity mutual funds with a European equity investment focus (either Pan-European or country/region/sector specific) over the period from March 31, 1988 through February 2008, a total of 239 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, broker commissions, or taxes). 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).[7]

To mitigate concerns with survival bias, Lipper proactively consults official fund lists as well as contacting new and existing fund companies to obtain data on new funds. Otto Kober, Global Head of Methodology, explained that Lipper "... consults official registration lists to have our database updated. We proactively approach the fund management companies for the data. There are a few instances where we do not get the data–especially for private funds or funds that are restricted exclusively to certain investors." Moreover, "We usually consult the official authorization lists. If we find missing instruments [funds] we proactively contact the fund management companies. We are often also contacted by the companies that are already in our database for registering their new funds in our database. No size or any other criteria [are used for inclusion] only official registration except [for] a few private funds in the database." Thus, we believe any survivorship bias is likely to be limited.

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

[7] Since we do not have complete information on total net assets (TNA) of the individual shareclasses of the funds, which would allow us to value-weight the shareclass monthly returns into a fund-level return, we select the earliest-existing shareclass to represent a fund's returns. When a monthly return is missing for that shareclass, we attempt to obtain that return from one of the other shareclasses to proxy for the missing return. Generally, shareclasses have very close returns, so the above procedures should be a very close approximation to the true fund-level returns. We continue this process until we reach the last available return for that (oldest) shareclass, then we continue to search for any further returns from other shareclasses. 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.

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.[8] 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), particularly 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. Nevertheless, it appears that asset management in Europe has mostly been aligned with countries, rather than sectors, at least until very recently.

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 portfolio manager, so we use the fund's legal domicile as a proxy for the manager's location.[9] We also have limited data on front-end and redemption loads, as well as total fund expense ratios. Moreover, we do not have data on many of the individual funds' expenses and fees, particularly during the early part of the sample (we searched for these data, and none of the major services–e.g., Morningstar–appear to have historical data covering our entire sample period). However, for the last decade or so, we obtained data from Lipper and Morningstar 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

[8]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 (that would imply a particular regional focus, such as telecom stocks in Scandinavia).

[9]For a subset of the funds that exist in 2011, we have obtained the domicile of the fund advisor (from Morningstar), which is where we would expect the portfolio manager and buy-side analysts to reside. Information about the advisor's location is available for about 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 (e.g., Germany equities with an advisor in Frankfurt). In robustness tests that limit our analysis to country funds explicitly identified as having an advisor in that country, our main results prevail.

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

2.2. Risk factors and state variables

We control for risk exposures in measuring the funds' ability to outperform following the four factor approach advocated by Carhart (1997). 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 one-month Euribor short rate; a size factor (small minus big, or SMB) that 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 equal-weighted return difference between the six top and six bottom 12-month lagged return sectors (out of a total of 18 sectors, each of which are value-weighted) from the Dow Jones STOXX 600 Super Sector Indices.[10] For comparison, we also analyze results (but do not construct strategies) using a more conventional single-factor approach that only includes the market factor.

We also 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.[11] These augmented models help to control for persistent fund loadings on unpriced factors, as described by Pastor and Stambaugh (2002a). Adding such factors can help tighten the predictive distribution for fund alphas, which can be beneficial for the construction of portfolios. For example, when the benchmark (global) assets price the non-benchmark (local) assets exactly, in the sense that the alpha of the latter in a regression on the former equals zero, an unbiased estimate of the fund alphas with a lower sampling variance can be achieved by augmenting the model with local non-benchmark asset returns. Empirical work in Pastor and Stambaugh (2002a) suggests that including such seemingly unrelated assets help provide more precise estimates of alphas and

[10] This approach follows the Moskowitz and Grinblatt (1999) evidence in the U.S. that industry momentum is stronger than individual stock momentum.

[11] 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.

Sharpe ratios for the vast majority of mutual funds. This additional precision can in turn be used to construct better portfolios of mutual funds (Pastor and Stambaugh, 2002b).

Recent studies suggest that the ability of funds to generate conditional alpha varies over time, in a way that depends on macroeconomic state variables. Moreover, fund exposures to risk factors can also be state- and time-dependent.[12] 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.[13] Third, we use the bond default spread, calculated as the difference between the yields on German corporate bonds and yields on German 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 could 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, 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 that 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

[12]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.

[13]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.

equity market share, since we measure fund and risk-factor returns translated to either the ECU or the Euro in this paper.[14] 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.

In the baseline analysis, we use European as opposed to country-specific state variables. This specification is dictated by our desire to keep the number of state variables limited. However, in a subsequent analysis, we also consider country-specific macro state variables. Data sources, variable construction, and a brief characterization of the properties of the key state variables used in the study are provided in a data appendix available on the authors' web site.

3. Methodology

This section presents the model for capturing skills among mutual fund managers and describes the different investor types characterized by their prior beliefs concerning manager skills.

3.1. Dynamic Return Generating Process

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

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

for $\theta_i = (\alpha_{i0}\ \alpha_{i1}'\ \beta_{i0B}'\ \beta_{i1}')'$, $x_t = (1\ z_{t-1}')'$, 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. Note that r_{Bt} can consist of both priced and unpriced factors, following the logic of Pastor and Stambaugh (2002a). Specifically, we split the vector denoting the k zero-cost excess returns, $r_{Bt} = (r_{Gt}'$

[14] Specifically, we use the weighted average of the squared monthly change in the exchange rates (adjusted for the interest rate spread) measured against the ECU or the Euro, respectively. Using each currency's equity market share as weights means that the factor captures the currency risk of an investor holding a value-weighted portfolio of European stocks.

$r'_{Lt})'$, into a set of k_G global (common) benchmarks, denoted r_{Gt}, and k_L local (country) unpriced benchmarks, denoted r_{Lt}.

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}. Similarly, β_{i0} measures the constant part of the risk factor loadings, while 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 in which 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.[15]

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

$$r_{B,t} = \alpha_B + A_B z_{t-1} + \varepsilon_{Bt}. \tag{2}$$

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

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

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.

[15] We also implement a version of the strategies that estimate covariances from the data, in case funds exhibit similar industry or stock tilts. The results are very similar to those of our baseline tests.

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 could 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:

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

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

For cases in which 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. These cases can be addressed using 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. Effectively, we construct 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 characterize 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 covariance matrix for prior beliefs. This prior can be constructed from the representation of beliefs in Equation (6) by observing that, for commutable matrices $\tilde{F}$, $\tilde{F}\theta_i|\sigma_i^2 \sim N\left(\tilde{F}\underline{\theta}_i, \sigma_i^2\tilde{F}\underline{V}\tilde{F}'\right)$. 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:

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

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

$$\overline{V}_i = \left(F\underline{\Omega}^{-1}F' + H_i'H_i\right)^{-1}, \tag{11}$$

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

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

where $D_t = \{r_{i\tau}, r_{B\tau}, z_{\tau-1}\}_{\tau=1}^{t}$ 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. 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 $\underline{t} = 0$.[16]

3.4. Predictive Moments for Portfolio Selection

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

$$E\left[r_t|D_{t-1}\right] = \bar{\alpha}_0 + \bar{\alpha}_1 z_{t-1} + \overline{\beta}_0\hat{A}_F' x_{t-1} + \overline{\beta}_1\left(I_K \otimes z_{t-1}\right)\hat{A}_F' x_{t-1}$$

$$\equiv \bar{\alpha}_0 + \bar{\alpha}_1 z_{t-1} + \overline{\beta}_{t-1}\hat{A}_F' x_{t-1}, \tag{12}$$

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

Denoting the time-series average of the macro-variables in D_{t-1} by $\overline{z}$, the remaining variables are defined as:

$$\delta_{t-1} = \frac{1}{t-1}\left\{1 + \left(z_{t-1} - \bar{z}\right)\hat{V}_z^{-1}\left(z_{t-1} - \bar{z}\right)\right\},$$

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

[16] 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.

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

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

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

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

3.5. Investor Models for Manager Skill

Five investor types are considered throughout the paper. 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.[17] 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 $\alpha_{i0} + \alpha'_{i1}z_{t-1} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$.

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

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 $\beta_{i1} = 0$, but, in addition to allowing A_B to be unrestricted, the BAMA investor brings diffuse priors to α_{i1}, 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: $\alpha_{i0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$.

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 β_{i1} corresponding to the interactions between the macro factors and the non-market benchmark entries are restricted to be zero.[18] As with the BAMA investor, the BAMAP investor places no restrictions on α_{i1}, and maintains the prior belief $\alpha_{i0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$.

We summarize our five investor types in Table 2. 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 market factor loadings.

3.6. Model Augmented with Country Factors

Each of the five investor models discussed above assumes that only a Europe-wide market factor contributes to individual fund returns, and so restricts $\beta_{i0L} = 0$. However, as discussed by Pastor and Stambaugh (2002a), inference on alphas may be sharpened by augmenting the model to include other unpriced benchmarks, such as local country index returns. For example, following the setup in Bekaert and Harvey (1995), a German-focused fund return would be benchmarked using the MSCI Europe factor, the SMB, HML, and UMD factors (for Europe), and a German stock market factor (the MSCI Germany index). In unreported robustness tests, we allow non-market risk factors to also be country-specific, and obtain very similar results to the basic augmented model discussed

[18] 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.

here.

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 describe the effect on portfolio performance of allowing for manager skill and further analyze the importance of considering information on macroeconomic state variables.

4.1. Historic Return Performance

Table 3 reports the raw return performance as well as the risk-adjusted return performance measured for the full sample and for two 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 10.20% per annum, or 118 basis points below the benchmark which returned 11.38% per annum. This negative average return performance conceals variation in the returns from active management across subsamples. Prior to 1998, on average, our sample of mutual funds under-performed the benchmark by about 250 basis points per annum, while they out-performed the index by 35 basis points per annum during the 10-year period that followed. This result reflects the style tilt of the average fund, such as a greater presence in small stocks, relative to the MSCI Europe index.

Accordingly, 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, with median underperformance during the sample period of -90 basis points per annum. Under the four-factor model, the median fund generated an alpha of -32 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 1988-1998 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.[19] While these stocks underperformed in general, the funds apparently were successful in

[19]It is noteworthy that MSCI announced, on December 10, 2000, that it would adjust its equity indices using free

choosing stocks within those categories that outperformed their cohorts.

4.2. Portfolio Performance

We next turn to the portfolio performance of our five investor types that are described in the prior section, CAPM, BCAPM, BSMA, BAMA, and BAMAP. 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, maximizing the expected value of this utility function is equivalent to choosing optimal portfolio weights, ω_t^*, that solve

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

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 4 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 European term spread, dividend yield, default spread and the short-term interest rate. Studying the evidence of skills for European equity mutual fund managers and comparing it with the evidence for their U.S. counterparts is of separate interest since it is by no means clear that the two groups should exhibit the same level of skills. (For instance, it is not clear that European mutual fund managers face the same level of competition for investment flows as their US counterparts.)

float adjusted market capitalization weights.

The parameter σ_α, that 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 the start of any particular quarter; in addition, we assume quarterly rebalancing to constrain the turnover of funds by the strategies.[20] Both of these constraints are imposed to avoid strategies that would be difficult to implement in practice.[21] The investor is assumed to have access to a risk-free asset whose rate is set at the Euribor short rate. We do not allow short positions, since it is typically not possible to short-sell open-end mutual funds, nor do we allow the investor to short-sell the riskless asset.

To measure the out-of-sample 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, realized utility, and the percentage of months in which a particular investor type's portfolio outperformed the benchmark. In addition, we report single- and four-factor alphas (estimated using monthly returns), their t-statistics, and factor risk exposures. In evaluating the out-of-sample performance using the single- and four-factor models, we do not include country-specific factors, but we allow the factor loadings to vary with realizations of macroeconomic variables. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas.

First, consider the raw return performance reported in the first five lines of Table 4. 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 benchmark, the CAPM investor who does not believe in active management skills produced rather smaller mean returns (7.01%), but also lower volatility

[20] 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 to the risk-free security.

[21] 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). Section 6.4.1 explores alternative ways of selecting the number of funds.

(13.6%), for a somewhat lower Sharpe ratio of 0.21.

In contrast, every investor type who allows for the possibility that some managers could be skilled, succeeded in generating raw return performance better than that of the MSCI Europe benchmark.[22] For the four Bayesian investor types, arithmetic mean returns lie between 13.7% and 18.8% per annum, with volatilities close to, or slightly above 20%, and Sharpe ratios between 0.49 and 0.69. While the average realized return for the CAPM investor is over 4% lower than that of the benchmark, the Bayesian strategies that allow for time-varying skill achieve average returns that are between 6.1% and 7.4% higher than the benchmark.

Bootstrap tests find somewhat weak evidence that the three Bayesian strategies have out-of-sample Sharpe ratios that exceed that of the benchmark.[23] Specifically, the null is rejected at p-values in the range of 10-20% for the BSMA, BAMA and BAMAP investors who allow for time-varying skill.[24] However, bootstrap tests more strongly reject the null that these three strategies each deliver average realized *utility* equal to the benchmark with p-values in the range between 5-10%, indicating that these tests have slightly more power than the tests based on the Sharpe ratio. (While we would expect the two tests to have the same asymptotic properties, their performance

[22]In this and in subsequent tables, each column shows portfolio results based on the individual Bayesian updating models identified in the corresponding column header and defined in Table 2. Posterior predictive distributions are based on a recursively expanding estimation window, using data from March 31, 1988 (or the date of inception for funds that come into existence at a later date) up to the end of quarter $t-1$ to generate forecasts for quarter t. Since our data ends in February, 2008 and we use quarterly rebalancing, the out-of-sample period runs from June 1993 (the first quarterly rebalancing point with at least five years of data available) through February 2008.

[23]We use a bootstrap procedure to test whether the Sharpe ratio realized by the mutual fund portfolio strategy of a particular investor type equals that of the European benchmark by, first, jointly sampling returns (i.e., drawing from the same calendar months) with replacement from each empirical return distribution (the fund strategy and the benchmark) for 61 quarters (the length of our time-series of actual out-of-sample returns). For each of these bootstrapped time-series, we compute the difference between the Sharpe ratios of the mutual fund portfolio strategy and that of the benchmark, and compare this difference with the corresponding difference (mutual fund strategy return minus benchmark return) in the original out of sample return series. This procedure is repeated to give 1,000 comparisons of actual to bootstrapped results; the p-value for the one-sided bootstrap hypothesis test is the frequency with which the bootstrapped difference (fund strategy minus benchmark) exceeds the difference in the original sample. The bootstrap test for Average Realized Utility is performed analogously.

[24]Interestingly, bootstrap results based on a model augmented with local country factors along the lines of Pastor and Stambaugh (2002a), allow us to reject the null that the Sharpe ratio of the benchmark equals that of the BSMA, BAMA, and BAMAP investors at the 10% significance level.

in small samples is different).

Table 4 also reports 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 -2.7% 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 that tend to have higher trading costs than their unskilled Pan-European counterparts to help diversify.

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 can have (constant) skills generates a single-factor alpha of 3.7% per annum. This level of performance is quite remarkable, since the BCAPM does not allow for any time variation in manager skills.

Moving to the skeptic macro alpha (BSMA) investor who believes that managers' ability to generate alpha can be state-dependent and time-varying, but whose prior centers the total (net of expense) alpha contribution on $-\exp_i$, the single-factor alpha grows by almost 5%, to 8.6%/year. For the macro-alpha investor type who puts weaker constraints on the time-varying portion of the alphas (but conversely constrains more tightly the fixed portion of the alpha compared with the BSMA investor), the single-factor alpha is similar, 8.5%/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–more than doubling 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 market factor loadings, as is done in the BAMAP model, does not lead to better performance than the otherwise similar BAMA model. It is likely 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 period).

Even larger alpha performance is observed when the four-factor model is used as the benchmark for risk-adjustment. With the exception of the CAPM alpha, which, at -2.7%/year, does not change much, the estimated alphas from the four active investor types range from 7.8% to 13.1%/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 5%/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 additional factor portfolios (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 4, relative to the MSCI Europe index.[25] As such, much of the four-factor alpha is driven by some fund managers' ability to deliver positive returns during a period that was very difficult for European Small 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. Four of the five 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 result suggests that the ability to identify funds with superior performance does not solely hinge on one type of market environment.

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

The subsample 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.

4.3. Augmented Model with Local Factors

We next turn to the issue of whether including individual country benchmarks in addition to the pan-European benchmark further helps to locate active managers with true skills. This effect can arise in markets with persistent, unpriced factors, as shown by Pastor and Stambaugh (2002a). Specifically, adding unpriced country risk factors leads to a more robust covariance matrix, and can help tighten the alpha estimates. We, therefore, compare the performance results for a model that only includes the Pan-European equity benchmark index against an "augmented model" that, for all of the funds with country-specific investment objectives, includes the Pan-European equity and the relevant country index.

From the full-sample performance results presented in Table 4, the difference in portfolio returns between the CAPM and Bayesian investor types is larger, relative to the baseline model of the prior section, with the augmented model. Specifically, the CAPM investor is not substantially affected by adding local benchmarks, with nearly identical returns in both treatments. Meanwhile, the BCAPM investor benefits most from adding local market benchmarks, increasing her average out-of-sample return by 1.6%/year, while reducing volatility by 1.1%/year. The investors who allow for macroeconomic predictability also benefit from local market benchmark augmentation, which increases average out-of-sample returns by 0.2-0.4%/year while decreasing volatility by 0.5-1.1%/year. While the differences in average returns between the augmented and baseline models are modest, the benefit of the augmented model for these investor types is sufficient to reject the null hypothesis that their Sharpe ratios are equal to the benchmark Sharpe ratio (at the 10% confidence level). Bootstrap tests also show that the average realized utility under the augmented model for investors who allow macroeconomic predictability is statistically significantly higher than the benchmark (at the 5% confidence level).

As with average portfolio returns, augmenting the pan-European benchmark with local market benchmarks enhances the out-of-sample alpha of the Bayesian models, while slightly hindering the CAPM model. The CAPM investor's single factor and four factor alphas drop by 0.2-0.7%/year to -

2.8% and -3.4%/year, respectively. In contrast, the BCAPM investor's alphas increase by 1.2%/year for the single factor model and 0.7%/year for the four-factor model, respectively. The investors who allow for macroeconomic predictability experience alpha increases ranging from negligible, for the BAMAP investor, to almost 1%/year for the BAMA investor, yielding single-factor alphas of 7-9.5%/year and four-factor alphas of 12.3-13.7%/year.

To summarize, the larger alphas from the augmented models indicate that controlling for temporary, country-specific shocks (not related to macroeconomic shocks) allows the investor types to more precisely identify skilled managers. This result is consistent with the framework of Pastor and Stambaugh (2002a,b), who add an unpriced benchmark to improve fund performance evaluation. We should expect this improvement, as many European countries are heavily tilted toward certain industries. We conclude from this analysis that some active European managers have the ability to select stocks that outperform, relative to pricing models that use Europe-wide and country factors.

4.4. Restricting the Fund Universe

We next consider a sample restricted to country funds, for which we might expect to see the strongest gain in the precision of alpha estimation from the inclusion of country benchmark factors. Table 5 shows that, by eliminating Pan-European funds, the CAPM investor's performance improves slightly, with average returns increasing 0.8%/year. However, the performance of the Bayesian investors degrades with the narrower set of investment opportunities, with the BCAPM investor losing 0.7%/year of the full-universe average return performance, and the investors who allow for predictability losing up to 3.8%/year of their average returns. The Sharpe ratio of the predictability investors is also worsened, since these investor types wish to time their investments in Pan-European funds during phases of the business cycle in which they are more likely to generate superior alphas. The result is that, while the four-factor alphas for all Bayesian investors remain significant, the single-factor alphas, while ranging from 3.0% to 4.2%/year do not.

Moreover, 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 as proxies for index-tracking funds. For this universe comprising only indexes, single-factor and four-factor alphas of the strategies are always economically small–at most, 1.0%/year–and statistically insignificant. This performance applies across all four investor types, suggesting that there are only small gains to be made from a pure country rotation 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.

4.5. A Stock-Level Strategy

The success of our conditional strategies supports 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.[26] In this section, we examine our strategies applied to a database of European stock returns during the 1988-2008 period.

Specifically, we obtained, from Thomson Datastream, 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 European stocks each month, ranked by market capitalization, 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 data set are provided in a data appendix available on the authors' web site.

We implement our baseline strategies of Table 4, and show results in Table 6. To further constrain our strategies to reflect an implementable portfolio, we limit positions in individual stocks to at most 5% of the portfolio, consistent with 1940 Act requirements to ensure adequate diversification for U.S. mutual funds.[27] In addition, to control estimation error in betas, we exclude

[26] Also, investing in a much larger number of stocks, relative to funds, gives greater degrees-of-freedom in constructing an optimal portfolio using macroeconomic conditioning variables, providing the stock-level strategy with an advantage over the fund-level strategy.

[27] To ensure adequate diversification, the 1940 Act restricts U.S.-domiciled mutual funds to hold positions no larger than 5% of their portfolio, for 75% of their portfolio value. The other 25% may be invested in a single security, if desired. There is no such limitation for holding mutual funds, so our prior sections placed a slightly less restrictive

stocks with an estimated market exposure below 0.6. Priors for investor types on the alphas are constructed in the same way as for the funds−except that they are centered on zero instead of (minus) the expense ratio that we used for the funds, since stock returns are gross of trading costs.

Note that all Bayesian strategies achieve small and statistically insignificant single factor alphas, with only two strategies attaining non-negative outperformance. The results are similar when considering four-factor alphas, with only the BAMAP investors achieving an alpha over 1%/year, while the other alpha estimates are small and mostly negative. Indeed, the CAPM investor has a rather large negative (albeit statistically insignificant) four-factor alpha below -5%/year, although this underperformance dissipates slightly when the CAPM investor allows for locally augmented benchmarks.

These stock-level results are an interesting contrast to our fund-level strategies that 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 4), while this investor does not manage to assemble stock portfolios with positive alphas. 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 -1.2% and 1.1%, while their fund-level strategies generate alphas of 12.9 and 12.3%/year, respectively. Therefore, over 10%/year, and essentially most of the total fund-level four-factor performance, is generated by fund manager skills that are correlated with macroeconomic innovations, but that are not directly based on their (potential) use of macroeconomic variables to predict stock returns.

To focus our results on the marginal value that mutual fund managers add to European investors, we performed a bootstrap test to evaluate the hypothesis that the investment strategies performed equally well, whether restricted to a universe of stocks only, a universe consisting of

maximum constraint of 10%. Nevertheless, we performed a supplementary analysis evaluating the performance of the stock portfolio under a variety of weight restrictions. The out-of-sample performance of stock portfolios degraded rapidly when weight restrictions were further relaxed, which could reflect the effect of estimation error. If an investor were to choose the constraint based on historical out of sample performance, the investor would prefer a 5% constraint over a 10% constraint.

stocks and mutual funds, or a universe consisting of mutual funds only. Using one-sided tests for the average realized Sharpe ratio, investor utility, single-factor alpha, and four-factor alpha, we report p-values comparing the fund and stock universe vs. the stock-only universe, as well as for the fund-only universe vs. the stock-only universe. The bootstrap tests are performed as described earlier in Section 4.2 for comparing the fund strategy performance with the benchmark, except that the stock-only universe takes the place of the benchmark in the current tests.

The outcome of these tests is reported in Table 7. For all Bayesian investor types, Panel A shows that having access to both the funds and stocks significantly outperforms having access only to the stocks, often with p-values below 1%. A similar finding holds for investors who make no investments at all in individual stocks and only hold mutual funds in their portfolio (results for the BAMAP investor are, in some cases, significant at the 10%, rather than 5% level). Panel B shows these results carry through to cases in which we use the local market augmented benchmark models for investment choice. In contrast, the results are much weaker for the CAPM investor type, for which we generally fail to reject the null that the performance of a stock-only investor is at least as good as that for an investor who only has access to mutual funds. All of these results reassure us that our predictability strategies exploit time-varying fund manager skills, and not time-varying stock-level alphas that are directly exploitable with public (macroeconomic) information variables.

For investors who are not charged front-end or redemption loads, these results provide conservative estimates of the benefits from using a mutual fund strategy over a stock-only strategy, since the mutual fund returns are net of expenses and fund level-trading costs, while stock returns do not adjust for trading costs. If such loads cannot be waived, then the benefits of executing a mutual fund strategy over a stock-only strategy would depend on the relative size of the loads versus individual-stock trading costs. It is important to note, however, that Lipper suggests that institutions commonly receive a waiver of all load fees, mitigating this concern.

4.6. 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. 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 are described in a data appendix available on the authors' web site.

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, essentially treating such fees as a one-time transaction cost.

The results, shown in Table 8, 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 7.9%-9.3%/year (previously 12.3%-13.8%/year). The fee-based utility model substantially reduces the turnover, loads and fees but does not systematically improve risk-adjusted return performance.

5. Portfolio Weights and Attribution Analysis

To understand which variables produce the superior performance of the portfolio of actively managed mutual funds, we next consider the country and sector allocations in the optimized portfolios. We also perform an attribution analysis that explores which components account for the investment performance.

5.1. Country and Sector Allocations

We first consider the portfolio allocation of the various investor types through time. To this end, Table 9 shows snapshots of the portfolio weights by region or country. In all cases, the investor is assumed to have access to a risk-free asset whose rate is set at Euribor short rate. The CAPM investor is the only investor type for whom the no-leverage budget constraint was not always binding, which helps to explain its relatively low volatility and average returns. The strategies generally (but not always) 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.[28]

This result indicates that the biggest opportunity for exploiting time-varying alphas consists

[28] Although Pan-European managers could 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.

of large allocations to country-specific funds.[29] In turn, the nature of this opportunity 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.

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.[30] 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, since industry bets can be made using country allocations. 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.

It is interesting that the strategies tend to place larger allocations in some industries as well as some countries during discrete periods of time. With the relatively recent widespread introduction of sector-focused funds in Europe, further analysis could shed light on the country vs. industry

[29]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.

[30]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.

debate in asset pricing. In our attribution analysis presented two sections hence, we show that returns are achieved both through country fund and sector fund allocations by the predictability investor types. Our data on sector funds does not allow a more detailed analysis of whether higher alphas are achieved when only sector funds are available.

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 baseline models (panel A) versus the models that have been augmented with local unpriced market factors (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 local returns. For instance, during 2003, all three country-augmented models (BSMA-A, BAMA-A, and BAMAP-A) lower their exposure to Scandinavian funds, relative to the respective benchmark models, apparently because the Scandinavian market factor (relative to other country market factors) exhibited temporary outperformance relative to the European risk-factor of Panel A.

Sector funds mainly play a role towards the end of the sample, which is to be expected given that there are very few sector funds prior to 2003. Interestingly, all three macro strategies allocate at least 70% to sector funds in 2007. Our prior-mentioned industry analysis (using Sharpe (1992) regressions) indicates that sector funds are used to focus strategies on combinations of certain industries that are not easy to accomplish through country funds alone.[31]

Overall, the finding that country and sector allocations vary considerably over time, especially for the three macro strategies, shows that they clearly pursue very active strategies to exploit macroeconomic information in picking managers.

5.2. Selection of Individual Funds

Table 9 does not show the identity of the individual funds that were selected by the four investor types. In unreported results available in a web appendix, we find that the allocations vary widely across strategies. However, all strategies seem to hold the maximum 10% of the chosen funds. This

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

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 can be achieved without the holdings constraints, a point we shall return to later. The CAPM investor tends to hold passive funds holding large capitalization stocks 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 benchmark or augmented models are used. Our prior-mentioned industry analysis shows considerable differences in industry allocations between the two models, indicating that different funds are selected to effect changes in industry allocations.

5.3. Decomposition of Returns

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

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

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 decomposed into C country-specific components as:[32]

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

where $w_{Ctry_i,B}$ are the actual weights of countries in the MSCI Europe index and $\hat{w}_{Ctry_i,B}$ are the market capitalization weights of countries (taken from the World Bank's Development Indicators);

[32]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.

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.[33] 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.[34]

The contribution of Pan-European fund selection and sector fund selection to our portfolio's performance is given by the difference of the first two terms in the portfolio return decompositions of Equations (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:

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

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, $w_{Ctry_i,P}$, rather

[33] Of course, as we have discussed previously, these Pan-European funds could actively time countries, but we do not believe that they maintain a long-term active tilt toward countries or sectors.

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

than the country weights in the benchmark:[35]

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

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 and is defined as

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

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 not clear whether the manager overweighted the country to time the country return or to emphasize the manager's selection ability in that country:[36]

$$\begin{aligned} r_{resid} = & \sum_{i=1}^{C} \left(w_{Ctry_i,P} - \left(1 - w_{Euro,P} - w_{Sect,P}\right) \hat{w}_{Ctry_i,B}\right) \left(r_{Ctry_i,P} - r_{Ctry_i,B}\right) \\ & - \left(1 - w_{Euro,P} - w_{Sect,P}\right) \sum_{i=1}^{C} \left(w_{Ctry_i,B} - \hat{w}_{Ctry_i,B}\right) r_{Ctry_i,B}. \end{aligned} \tag{24}$$

Panel A of Table 10 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. Note, also, that

[35] 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.

[36] 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). That is, $r_{resid} = -\left(1 - w_{Euro,P} - w_{Sect,P}\right) \sum_{i=1}^{C} \left(w_{Ctry_i,B} - \hat{w}_{Ctry_i,B}\right) r_{Ctry_i,B}$.

the attribution components do not change much when we move to the models augmented with a local market factor.

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 result is particularly interesting in light of the industry concentration of some of the countries. Certain industries (which are concentrated in certain countries) represent the most fertile territory to search for manager skills, perhaps because of the large degree of asymmetric information in these industries at certain points of the business cycle. For instance, the outlook for technology firms varied substantially during the period surrounding the peak of the technology boom. The allocations of our strategies indicate that the macroeconomic-based investment strategies were able to identify the most promising industries as well as to select the portfolio managers with the best skills in those industries during a particular macroeconomic phase.[37] 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.

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), constraints on the portfolio weights, macroeconomic variables used, the universe of funds considered, construction of the momentum factor, rebalancing frequency, and investors' prior beliefs.[38]

[37] 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.

[38] Additional results for the tests performed in this section are available in a supplemental appendix.

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

The model again seems to perform well when our investors attempt to identify underperformers among the mutual funds. 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 that allows for both long and short positions.[39] Specifically, 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. We also consider 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 7-10%/year and four-factor alphas around 8-13%/year.

6.1.2. Individual Stock Short-Sale Strategies

When we allow short-selling of stocks, our stock-level strategies generate much higher four-factor alphas. Specifically, we find that allowing for short-selling of individual stocks (with a maximum short position of -5%) achieves high four-factor alphas between 6.5% and 19.5%/year. Most of the

[39] European mutual funds cannot directly short stocks, but can implement synthetic short positions. Such short positions are mainly implemented on market indexes and currency positions, rather than on individual securities (since derivatives on individual securities would be much less liquid) as either a hedge or a speculative position on the entire market (or a currency).

alphas are attributable to the short-side, a finding consistent with most academic papers (Stambaugh, Yu, and Yuan (2011)). However, as opposed to our market neutral strategy based on mutual funds in the previous sub-section, in which 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. Lipper has confirmed that, while European equity mutual funds cannot directly take short positions, they can use covered synthetic derivative transactions and, thus, achieve short exposure.

6.1.3. Breadth of Predictability in Fund Manager Performance

One concern is that many of the portfolios appeared to be quite concentrated 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 perform a simple sorting test on the funds after computing their expected performance under each model.

Specifically, we compute 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. 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 consider 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 local market augmented Bayesian models that allow for predictability, 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 weaker for the benchmark Bayesian models, thus, testifying to the advantage of allowing for local benchmarks.

In further 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, letting 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 evidence suggests that the Bayesian alpha models are capable of successfully ranking the funds' risk-adjusted performance.

6.2. 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.

Table 11 presents portfolio performance results using different objective functions while imposing constraints on the risk profile of the portfolio. In Panels A, B, and C, we restrict the portfolio's benchmark risk factor exposure by limiting its market factor loading to be near unity and its style factor loadings to be near zero, with a 0.2 tolerance. Specifically, Panel A assumes the investor's objective is simply to maximize mean-variance expected utility. Panel B maximizes the expected return subject to the portfolio return volatility being less than the recursively estimated historical benchmark volatility. Panel C constrains the expected portfolio return to at least match or exceed that of the benchmark MSCI Europe historical average return, while minimizing portfolio return volatility.[40] Finally, Panel D minimizes portfolio return volatility subject to a given desired expected portfolio return and zero contemporaneous covariances between the portfolio return and the macroeconomic variables. This strategy places no restrictions on benchmark factor exposures. The covariance constraint reflects that investors might want to hedge their exposure to information variables that they are concerned about, perhaps because they track time-varying consumption or investment opportunities, see, e.g., Campbell (1996) and Fama (1996). In such a case, exposures to these information "risk-factors" can generate risk-premia. Setting these covariances to zero reassures us that the superior alphas from our strategies are not due to large exposures to state variable risks.

The results show Sharpe ratios similar to our baseline results of Table 4. While the alphas of the strategies using these risk-constrained versions are mostly lower than their counterparts in Table 4, four-factor alphas continue to exceed 5%/year for all strategies that allow for fund manager skills

[40] Occasionally, this expected return constraint was not attainable by portfolios that satisfied restrictions on the portfolio risk factor loadings. In these periods, the investor minimized portfolio variance subject to maintaining a portfolio expected return of at least half the maximum expected return for portfolios satisfying the constraints.

(BCAPM, BSMA, BAMA, and BAMAP).

6.3. 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, we consider five other predictor variables, namely volatility (VDAX index), inflation, industrial production, economic sentiment and a currency factor. 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.[41] We find, in general, that the alphas from the time-varying strategies are slightly lower using local macro factors. This result suggests no gains from using local macro variables over using Europe-wide measures, perhaps due to the increased potential for measurement error when using country-level macro factors. For instance, default spreads may be more accurately measured across Europe than in a single country.

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. The construction of this currency risk factor along with detailed results are available from a supplemental appendix. The results are qualitatively similar to our baseline results: adding a currency macro variable or risk factor does not substantially alter the alphas attained by our time-varying alpha strategies. This finding is not surprising, since most currencies in developed Europe were closely fixed together during our sample period.

6.4. Additional Robustness Checks

Our baseline results assume the mean-variance investor optimizes the portfolio allocation across the top 50 funds, ranked by their conditional alpha, subject to restrictions that preclude short

[41] 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, which left only a short sample is available for out-of-sample evaluation.

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. In the interest of brevity, we report only summary results below.

6.4.1. Number of Funds

We allow the recursive (out-of-sample) selection of smaller or larger counts of funds in the optimization procedure, with cases ranging from a universe size of 25 selected funds to 250 selected funds. In addition, we also consider a case that chooses from the full universe of all mutual funds existing at the end of a particular quarter. In these two additional cases, we find that greater numbers of funds in the opportunity set actually reduces the alpha somewhat for the strategies, although four-factor alphas remain statistically significant for portfolios based on up to 250 funds. 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 could 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). Our investor types could simply expand their allocation to a greater number of funds to diversify more broadly, instead of seeking alpha.

An alternative way to address the concern about dependence of the portfolio allocation results on portfolio constraints is to select the constraints, ex ante. To this end, we perform an analysis whereby the investor chooses constraints, each quarter, based on prior portfolio performance. Specifically, for the constraint on the number of securities in an investor's portfolio, we allow the investor to choose from a coarse grid of {20, 50, 100, 250, 500, and 1,000} funds. Each quarter, when the investor optimizes the portfolio weights, he chooses the maximum number of funds to hold based on prior portfolio performance. That is, the investor chooses the number of funds that would have maximized the average realized utility in the historical period up to the current date.

Our findings show that the CAPM investor prefers a large asset universe comprising 250-500 funds, while the Bayesian investors generally prefer far smaller universes of 20-50 funds. For the Bayesian investors, single-factor alphas decline by 1-3% per annum, while four-factor alphas drop by 2.5-3.5% per annum, but all remain highly significant.

6.4.2. Portfolio Weight and Trading Constraints

Eliminating the maximum weight constraint for investment in any one fund increases the alpha performance by up to 10% 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.

Tightening the 10% maximum on portfolio holdings of a single fund to only 5% reduces 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 11%/year.[42]

Lastly, beyond quarterly rebalancing, our baseline models place no constraints on portfolio turnover. 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.

We also perform an analysis that allows the investor to recursively choose the constraint on the maximum proportion to invest in any single mutual fund. Specifically, for the maximum fund allocation constraint, we allow the investor to choose from a coarse grid of {2.5%, 5%, 10%, 25%, 50%, and 100%}. Each quarter when the investor optimizes the portfolio weights, he chooses the maximum weight to invest in a single fund based on the choice that would have maximized prior portfolio performance. Here, we find that the BSMA, BAMA and BAMAP investors generally prefer not to cap the maximum weight allocated to a single fund. For these largely unconstrained allocations, there is evidence of a marginal improvement in the Sharpe ratio. We see a somewhat larger effect on the Bayesian investors' single-factor alphas, which increase by 1.5-5%, and on the four-factor alphas, which increase by 1-7% per annum, although their statistical significance remains largely unchanged.

[42]These results are particularly striking in contrast to the effect of removing weight restrictions on investment strategies in the individual stock universe. While the investment strategies in mutual funds perform best with minimal restrictions, the opposite result holds for investment strategies in individual stocks, where tighter restrictions tend to improve performance.

For the portfolios invested only in individual stocks (and not funds), we find that a recursive selection of the weight constraint leaves the Sharpe ratio largely unchanged (from the baseline case that constrains individual stock weights to a maximum of 5%), while the single-factor alphas change by less than 0.5%, and the four-factor alphas change by less than 1.1% per annum for the BSMA, BAMA, and BAMAP investors. For the stock-only portfolio strategies, the recursively selected constraints are very close to the baseline constraints and so performance does not change very much. For the mutual fund strategies, the recursively selected constraints yield more concentrated portfolios that further enhance their performance over the baseline specification.

6.4.3. Effect of Priors

Our baseline results assume 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.

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_{i0} is effectively limited to be $-\exp_i$. When we tighten σ_α for the BSMA investor, we shrink the total α_i $(\alpha_{i0} + \alpha_{i1} z_{t-1})$ toward $-\exp_i$. However, for the BAMA investor, we shrink only α_0, and not $\alpha_1 z_{t-1}$.

6.4.4. Country Momentum Factors

The momentum factor used in the analysis so far is based on spreads in the return performance across sectors. Alternatively, we could make use of a country momentum factor. To explore if this factor can help explain our results, we construct it as follows. We consider the performance of each of the 16 European countries over the previous 12-month period.[43] We then compute the return

[43]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.

differential between the three countries with the highest 12-month lagged returns and the three countries with the lowest 12-month lagged returns.

We find that the performance of our strategies, using country-based momentum factors, are very similar to those in Table 4, so we conclude that our findings are robust to whether momentum is defined along sector or country lines.

6.4.5. Agnostic Investor for All Parameters

Finally, we analyze 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. Here, we find a four-factor out-of-sample alpha of 9.1%/year for the general model and 9.3%/year for the local country-augmented 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 4 and 5. However, this model has 25 free parameters and so is likely to suffer 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 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 can vary with the state of the economy.

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 finding is quite interesting in light of the industry concentration of some of the countries.

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Tables

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

Panel A 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	1,397	3,225	4,200
II. Country & 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	1,491	2,133
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

	1998	2003	2008
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	1,016	1,378

Table 2: Bayesian Investor Types

This table summarizes the priors and restrictions adopted by our five investor types in characterizing the dynamic return generating process for equations (1), (2), and (3) presented in section 3.1. Any parameters that are not explicitly restricted or assigned an informative prior belief by the investor (such as A_B in the BAMA and BAMAP models) are left unconstrained under a diffuse prior specification.

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

Table 3: Fund Universe Sample Performance

This table shows the return performance both for the entire sample period, 1988-2008, as well as during two sub-periods, 1988-1998 and 1999-2008. Panel A reports raw return performance for the equal-weighted universe of funds and the MSCI Europe benchmark. Panels B and C characterize the distribution of annualized unconditional in-sample single-factor (controlling for the MSCI Europe benchmark) and unconditional four-factor alpha values (adding the Size, Value and Momentum factors as controls) for the corresponding sample periods.

	Full Sample	1988-1998	1999-2008
A. Annual Average Return Performance			
Eq Weight Universe	10.20%	13.73%	6.10%
Benchmark	11.38%	16.21%	5.76%
B. Single-Factor Alpha (Annualized)			
Universe Average	-0.46%	-1.73%	-0.21%
5% - Quantile	-6.99%	-10.65%	-6.99%
10% - Quantile	-5.06%	-7.44%	-5.02%
25% - Quantile	-2.88%	-3.92%	-2.90%
50% - Quantile	-0.90%	-1.35%	-0.76%
75% - Quantile	1.62%	1.24%	2.03%
90% - Quantile	5.06%	4.36%	6.02%
95% - Quantile	7.54%	6.62%	8.96%
C. Four-Factor Alpha (Annualized)			
Universe Average	0.50%	3.24%	0.29%
5% - Quantile	-6.33%	-8.28%	-6.45%
10% - Quantile	-4.59%	-5.56%	-4.65%
25% - Quantile	-2.54%	-2.35%	-2.66%
50% - Quantile	-0.32%	2.22%	-0.50%
75% - Quantile	2.89%	7.52%	2.64%
90% - Quantile	7.10%	13.35%	6.98%
95% - Quantile	9.74%	19.15%	9.92%
D. Single-Factor Beta			
Universe Average	0.97	0.87	0.98
5% - Quantile	0.67	0.52	0.68
10% - Quantile	0.76	0.61	0.75
25% - Quantile	0.86	0.77	0.86
50% - Quantile	0.97	0.91	0.99
75% - Quantile	1.08	0.99	1.09
90% - Quantile	1.19	1.09	1.21
95% - Quantile	1.27	1.14	1.29

Table 4: Out of Sample Portfolio Performance (06/1993 - 02/2008)

This table shows the portfolio performance for the different mutual fund portfolio strategies when we use both pan-European and locally augmented benchmark models during the out-of-sample period 06/1993-02/2008 (Panel A) as well as for two sub-samples, 1993-2000 (Panel B) and 2001-2008 (Panel C). The arithmetic and geometric mean returns, the volatility, the Sharpe ratio, and average realized utility are all annualized. Bootstrapped one-sided p-Values test the null hypothesis that mutual fund portfolio and benchmark Sharpe Ratio and Average Realized Utility are equal against the alternative that the mutual fund portfolio dominates the benchmark. 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 risk factor loadings but not local benchmarks. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas. Each column shows portfolio results based on the individual Bayesian updating models, which are summarized in Table 2, identified in the corresponding column header. 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 $\sigma_\alpha = 10\%/\text{Month}$.

Panel A: Full Sample Results - 1993-2008

		Pan-European Benchmark Models					Local Market Augmented Benchmark Models				
	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP	CAPM-A	BCAPM-A	BSMA-A	BAMA-A	BAMAP-A
Geometric mean	10.06%	6.08%	11.84%	16.66%	16.47%	15.49%	6.03%	13.61%	16.96%	17.00%	15.94%
Arithmetic mean	11.40%	7.01%	13.71%	18.78%	18.61%	17.51%	7.06%	15.29%	18.98%	19.02%	17.77%
Volatility	16.28%	13.60%	19.51%	21.26%	21.34%	20.55%	14.21%	18.44%	20.72%	20.67%	19.47%
Sharpe ratio	0.449	0.214	0.493	0.690	0.680	0.652	0.208	0.607	0.718	0.721	0.702
(p-Val for Fund SR $\leq$ Bmk SR)		98%	48%	13%	14%	16%	99%	22%	9%	9%	9%
Realized Utility	7.48%	4.23%	7.88%	11.69%	11.48%	10.91%	4.02%	9.99%	12.22%	12.28%	11.80%
(p-Val for Fund ARU $\leq$ Bmk ARU)		98%	43%	7%	8%	10%	99%	17%	5%	5%	6%
Outperformance Frequency		35%	55%	53%	52%	50%	36%	54%	54%	56%	51%
Single-Factor Alpha		-2.67%	3.67%	8.64%	8.51%	6.94%	-2.82%	4.90%	9.51%	9.49%	6.98%
Single-Factor Alpha t-Stat		(2.237)	1.108	2.209	2.179	2.033	(2.670)	1.586	2.477	2.492	2.132
Single-Factor Beta		0.782	0.875	0.935	0.940	0.963	0.806	0.864	0.880	0.883	0.926
Four-Factor Alpha		-2.68%	7.78%	13.14%	12.91%	12.32%	-3.39%	8.51%	13.76%	13.74%	12.30%
Four-Factor Alpha t-Stat		(2.303)	3.227	4.369	4.338	4.566	(3.039)	3.915	5.079	5.185	4.912
Beta - Market		0.749	0.817	0.857	0.868	0.892	0.782	0.824	0.807	0.816	0.853
Beta - SMB		(0.043)	0.502	0.490	0.473	0.459	(0.051)	0.489	0.560	0.545	0.509
Beta - HML		0.146	(0.200)	(0.207)	(0.212)	(0.157)	0.087	(0.222)	(0.287)	(0.288)	(0.215)
Beta - Momentum		0.034	0.055	0.224	0.221	0.341	0.006	0.044	0.168	0.176	0.350

Table 4: Out of Sample Portfolio Performance (06/1993 - 02/2008), Continued

This table shows the portfolio performance for the different mutual fund portfolio strategies when we use both pan-European and locally augmented benchmark models during the out-of-sample period 06/1993-02/2008 (Panel A) as well as for two sub-samples, 1993-2000 (Panel B) and 2001-2008 (Panel C). The arithmetic and geometric mean returns, the volatility, the Sharpe ratio, and average realized utility are all annualized. Bootstrapped one-sided p-Values test the null hypothesis that mutual fund portfolio and benchmark Sharpe Ratio and Average Realized Utility are equal against the alternative that the mutual fund portfolio dominates the benchmark. 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 risk factor loadings but not local benchmarks. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas. Each column shows portfolio results based on the individual Bayesian updating models, which are summarized in Table 2, identified in the corresponding column header. 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 $\sigma_\alpha = 10\%/\text{Month}$.

Panel B: Sub-Sample Results - 1993-2000

		Pan-European Benchmark Models					Local Market Augmented Benchmark Models				
	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP	CAPM-A	BCAPM-A	BSMA-A	BAMA-A	BAMAP-A
Geometric mean	18.33%	14.04%	18.10%	23.53%	23.63%	22.23%	14.45%	18.90%	22.15%	22.16%	20.68%
Arithmetic mean	19.49%	14.97%	20.14%	26.07%	26.18%	24.56%	15.37%	20.63%	24.59%	24.60%	22.72%
Volatility	15.31%	13.64%	20.74%	23.72%	23.76%	22.48%	13.60%	19.10%	23.20%	23.16%	20.79%
Sharpe ratio	0.941	0.725	0.726	0.885	0.888	0.867	0.757	0.815	0.841	0.843	0.849
(p-Val for Fund SR ≤ Bmk SR)		93%	83%	75%	75%	76%	79%	72%	74%	73%	69%
Realized Utility	16.02%	13.30%	16.23%	19.18%	19.24%	18.74%	14.42%	17.38%	19.11%	19.18%	18.89%
(p-Val for Fund ARU ≤ Bmk ARU)		98%	62%	39%	38%	40%	95%	53%	40%	39%	39%
Outperformance Frequency		43%	48%	45%	45%	43%	38%	46%	46%	46%	42%
Single-Factor Alpha		-1.03%	6.10%	10.41%	10.49%	8.48%	-1.55%	6.49%	10.48%	10.55%	6.91%
Single-Factor Alpha t-Stat		(0.528)	1.112	1.479	1.486	1.465	(1.043)	1.249	1.498	1.512	1.267
Single-Factor Beta		0.802	0.892	0.986	0.987	1.040	0.744	0.842	0.908	0.907	0.963
Four-Factor Alpha		-3.78%	10.91%	19.47%	19.54%	16.65%	-2.60%	10.25%	19.54%	19.70%	15.19%
Four-Factor Alpha t-Stat		(1.874)	3.436	4.412	4.415	4.008	(1.677)	3.552	5.329	5.346	4.461
Beta - Market		0.766	0.704	0.788	0.788	0.885	0.756	0.709	0.734	0.730	0.791
Beta - SMB		(0.132)	0.361	0.349	0.346	0.380	0.034	0.391	0.438	0.442	0.383
Beta - HML		0.233	0.070	0.027	0.031	(0.037)	0.011	(0.035)	(0.119)	(0.118)	(0.068)
Beta - Momentum		(0.025)	0.198	0.484	0.484	0.455	0.024	0.174	0.465	0.465	0.525

Panel C: Sub-Sample Results - 2001-2008

		Pan-European Benchmark Models					Local Market Augmented Benchmark Models				
	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP	CAPM-A	BCAPM-A	BSMA-A	BAMA-A	BAMAP-A
Geometric mean	1.17%	-2.48%	5.11%	9.26%	8.77%	8.24%	-3.01%	7.91%	11.37%	11.45%	10.82%
Arithmetic mean	2.65%	-1.59%	6.76%	10.88%	10.42%	9.87%	-1.94%	9.50%	12.91%	12.98%	12.41%
Volatility	16.99%	13.18%	17.99%	18.10%	18.22%	18.11%	14.48%	17.67%	17.62%	17.57%	17.93%
Sharpe ratio	(0.023)	(0.352)	0.206	0.433	0.405	0.377	(0.344)	0.365	0.559	0.565	0.522
(p-Val for Fund SR ≤ Bmk SR)		99%	21%	1%	1%	3%	100%	5%	0%	0%	2%
Realized Utility	-1.62%	-4.14%	0.17%	4.76%	4.31%	3.68%	-5.58%	3.17%	5.85%	5.90%	5.25%
(p-Val for Fund ARU ≤ Bmk ARU)		83%	26%	1%	1%	3%	96%	6%	0%	0%	2%
Outperformance Frequency		26%	62%	62%	60%	58%	33%	64%	64%	67%	61%
Single-Factor Alpha		-4.65%	2.44%	5.56%	5.09%	2.70%	-4.16%	4.85%	8.03%	7.99%	5.03%
Single-Factor Alpha t-Stat		(3.716)	0.847	1.711	1.607	0.844	(2.927)	1.694	2.676	2.849	1.563
Single-Factor Beta		0.775	0.945	0.989	1.011	1.056	0.817	0.942	0.980	0.992	1.050
Four-Factor Alpha		-3.90%	5.05%	7.73%	7.41%	4.71%	-3.91%	7.02%	10.35%	9.93%	7.76%
Four-Factor Alpha t-Stat		(3.641)	2.116	2.853	2.798	1.778	(2.842)	2.933	4.178	4.254	2.889
Beta - Market		0.775	0.927	0.789	0.836	0.874	0.821	0.917	0.793	0.823	0.885
Beta - SMB		0.027	0.501	0.462	0.422	0.377	(0.035)	0.521	0.492	0.427	0.436
Beta - HML		0.074	(0.270)	(0.079)	(0.117)	(0.017)	0.096	(0.278)	(0.086)	(0.078)	(0.066)
Beta - Momentum		0.010	(0.023)	0.182	0.170	0.287	(0.020)	(0.008)	0.139	0.154	0.301

Table 5: Out of Sample Portfolio Performance in Sub-Universes

This table presents key performance statistics for the different mutual fund portfolio strategies when we use both pan-European and locally augmented benchmark models and we consider two different fund universes: country funds (Panel A) and passive index funds (Panel B). The arithmetic and geometric mean returns, the volatility, the Sharpe ratio, and average realized utility are all annualized. Bootstrapped one-sided p-Values test the null hypothesis that mutual fund portfolio and benchmark Sharpe Ratio and Average Realized Utility are equal against the alternative that the mutual fund portfolio dominates the benchmark. 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 risk factor loadings but not local benchmarks. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas. Each column shows portfolio results based on the individual Bayesian updating models, which are summarized in Table 2, identified in the corresponding column header. Results are reported for the out-of-sample period 06/1993 - 02/2008 and assume the setup from the baseline investment exercise, i.e. no short-selling, individual fund holdings capped at 10% of the total holdings, quarterly rebalancing. The short-term Euribor, the default spread, the term spread and the dividend yield are used as predictive variables, and beliefs are specified so that $\sigma_\alpha = 10\%$/Month.

	Panel A: Country Funds Only				
	CAPM	BCAPM	BSMA	BAMA	BAMAP
Geometric mean	6.94%	11.53%	13.18%	13.18%	12.97%
Arithmetic mean	7.88%	13.04%	14.96%	14.96%	14.91%
Volatility	13.64%	17.53%	19.17%	19.18%	20.05%
Sharpe ratio	0.277	0.510	0.566	0.566	0.539
(p-Val for Fund SR $\leq$ Bmk SR)	88%	40%	33%	33%	40%
Realized Utility	5.07%	8.30%	9.27%	9.28%	8.72%
(p-Val for Fund ARU $\leq$ Bmk ARU)	91%	35%	24%	23%	29%
Outperformance Frequency	37%	53%	54%	52%	53%
Single-Factor Pricing					
Alpha	-1.89%	2.99%	4.23%	4.19%	3.64%
Alpha t-Stat	(1.335)	1.072	1.325	1.317	1.182
Beta	0.769	0.845	0.916	0.919	0.994
Four-Factor Pricing					
Alpha	-2.13%	5.93%	6.12%	6.05%	6.74%
Alpha t-Stat	(1.573)	2.906	2.498	2.501	2.754
Beta Market	0.741	0.820	0.876	0.887	0.938
Beta SMB	(0.007)	0.374	0.454	0.448	0.422
Beta HML	0.129	(0.154)	(0.244)	(0.258)	(0.152)
Beta MoM	0.027	0.085	0.069	0.090	0.130
	Panel B: Passive Indices Only				
	CAPM	BCAPM	BSMA	BAMA	BAMAP
Geometric mean	10.24%	10.59%	10.22%	10.24%	10.51%
Arithmetic mean	11.21%	11.70%	11.67%	11.69%	11.96%
Volatility	13.86%	14.80%	16.93%	16.95%	16.92%
Sharpe ratio	0.513	0.513	0.447	0.448	0.465
(p-Val for Fund SR $\leq$ Bmk SR)	12%	18%	55%	55%	48%
Realized Utility	8.23%	8.31%	7.28%	7.29%	7.57%
(p-Val for Fund ARU $\leq$ Bmk ARU)	27%	26%	52%	52%	45%
Outperformance Frequency	49%	49%	50%	50%	51%
Single-Factor Pricing					
Alpha	0.49%	1.01%	0.17%	0.18%	-0.76%
Alpha t-Stat	0.413	0.826	0.098	0.106	(0.402)
Beta	0.835	0.858	0.973	0.974	0.998
Four-Factor Pricing					
Alpha	0.15%	0.68%	0.76%	0.79%	-0.08%
Alpha t-Stat	0.134	0.536	0.462	0.481	(0.041)
Beta Market	0.802	0.854	0.940	0.941	0.960
Beta SMB	(0.140)	(0.049)	(0.015)	(0.014)	(0.001)
Beta HML	0.152	(0.008)	0.014	0.013	0.029
Beta MoM	0.077	0.077	0.213	0.214	0.153

Table 6: Out of Sample Performance of Portfolios Investing in Individual Stocks

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) and for strategies investing in a universe combining individual stocks and mutual funds (Panel B). The arithmetic and geometric mean returns, the volatility, the Sharpe ratio, and average realized utility are all annualized. Bootstrapped one-sided p-Values test the null hypothesis that portfolio strategy and benchmark Sharpe Ratio and Average Realized Utility are equal against the alternative that the mutual fund portfolio dominates the benchmark. 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 risk factor loadings but not local benchmarks. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas. Each column shows portfolio results based on the individual Bayesian updating models, which are summarized in Table 2, identified in the corresponding column header. 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% or in any one mutual 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 $\sigma_\alpha = 10\%/\text{Month}$.

Panel A: Stock Only Investment Universe

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP	CAPM-A	BCAPM-A	BSMA-A	BAMA-A	BAMAP-A
Geometric mean	10.06%	5.71%	5.37%	7.90%	6.39%	7.07%	7.34%	5.97%	8.71%	7.21%	7.04%
Arithmetic mean	11.40%	8.00%	8.44%	10.79%	9.21%	9.76%	9.53%	8.91%	11.47%	9.89%	9.81%
Volatility	16.28%	21.14%	24.54%	24.16%	23.85%	23.29%	20.72%	24.11%	23.53%	23.17%	23.57%
Sharpe ratio	0.449	0.184	0.177	0.277	0.214	0.243	0.262	0.199	0.313	0.250	0.242
(p-Value for Stock SR $\leq$ Bmk SR)		98%	98%	88%	92%	89%	95%	97%	84%	89%	90%
Realized Utility	7.48%	1.34%	-0.51%	2.06%	0.73%	1.66%	3.10%	0.26%	3.16%	1.86%	1.52%
(p-Val for Stock ARU $\leq$ Bmk ARU)		97%	97%	88%	93%	89%	93%	97%	83%	89%	90%
Outperformance Frequency		46%	49%	44%	46%	44%	49%	49%	48%	44%	45%
Single-Factor Alpha		-4.46%	-3.79%	-0.17%	-0.81%	-0.14%	-2.07%	-3.35%	0.63%	-0.14%	0.12%
Single-Factor Alpha t-Stat		(1.331)	(0.933)	(0.034)	(0.166)	(0.028)	(0.690)	(0.858)	0.133	(0.030)	0.024
Single-Factor Beta		1.085	1.109	0.954	0.893	0.850	1.059	1.110	0.920	0.870	0.866
Four-Factor Alpha		-5.59%	-5.31%	-0.78%	-1.20%	1.06%	-3.17%	-5.01%	0.34%	-0.63%	1.60%
Four-Factor Alpha t-Stat		(1.681)	(1.428)	(0.166)	(0.254)	0.215	(1.059)	(1.383)	0.072	(0.135)	0.326
Beta - Market		0.906	0.989	0.860	0.780	0.721	0.897	1.031	0.844	0.782	0.739
Beta - SMB		0.151	0.331	0.392	0.372	0.382	0.108	0.319	0.309	0.325	0.388
Beta - HML		0.118	(0.286)	(0.381)	(0.318)	(0.273)	0.104	(0.345)	(0.331)	(0.330)	(0.252)
Beta - Momentum		(0.039)	(0.137)	(0.024)	(0.026)	0.012	(0.008)	(0.146)	0.002	(0.037)	0.023

Panel B: Stock and Mutual Fund Investment Universe

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP	CAPM-A	BCAPM-A	BSMA-A	BAMA-A	BAMAP-A
Geometric mean	10.06%	10.11%	9.48%	12.36%	12.82%	11.97%	11.84%	10.01%	13.16%	13.65%	12.15%
Arithmetic mean	11.40%	11.36%	11.53%	14.66%	15.03%	14.23%	13.42%	11.90%	15.23%	15.66%	14.37%
Volatility	16.28%	15.70%	20.15%	21.72%	21.25%	21.51%	17.70%	19.38%	20.54%	20.23%	21.22%
Sharpe ratio	0.449	0.463	0.369	0.486	0.514	0.471	0.527	0.403	0.542	0.571	0.484
(p-Value for Stock SR $\leq$ Bmk SR)		98%	51%	16%	18%	19%	99%	23%	12%	11%	12%
Realized Utility	7.48%	4.23%	7.88%	11.69%	11.48%	10.91%	4.02%	9.99%	12.22%	12.28%	11.80%
(p-Val for Stock ARU $\leq$ Bmk ARU)		98%	43%	7%	8%	10%	99%	17%	4%	4%	6%
Outperformance Frequency		51%	51%	50%	51%	50%	56%	52%	50%	54%	49%
Single-Factor Alpha		1.56%	0.05%	4.05%	4.70%	4.06%	2.64%	0.43%	4.78%	5.53%	3.72%
Single-Factor Alpha t-Stat		1.064	0.018	0.972	1.178	0.961	1.596	0.166	1.241	1.481	0.915
Single-Factor Beta		0.868	1.015	0.941	0.927	0.907	0.995	0.999	0.904	0.893	0.924
Four-Factor Alpha		1.97%	0.85%	5.59%	6.10%	5.86%	3.28%	1.01%	6.59%	7.32%	6.03%
Four-Factor Alpha t-Stat		1.325	0.350	1.472	1.699	1.484	1.963	0.434	1.822	2.121	1.577
Beta - Market		0.789	0.932	0.825	0.822	0.781	0.922	0.949	0.807	0.803	0.796
Beta - SMB		0.019	0.367	0.387	0.402	0.370	0.035	0.352	0.385	0.373	0.348
Beta - HML		0.143	(0.219)	(0.222)	(0.251)	(0.202)	0.094	(0.264)	(0.218)	(0.228)	(0.157)
Beta - Momentum		0.016	(0.046)	0.185	0.130	0.142	0.035	(0.034)	0.149	0.125	0.163

Table 7: Tests of Relative Investor Performance in Different Universes

This table evaluates the relative performance of the strategies investing in different asset universes (i.e., Mutual Fund Only, Stock and Mutual Fund, Stock Only) during the out-of-sample period 06/1993-02/2008. Bootstrapped one-sided p-values test the null hypothesis that portfolio strategies have equal Sharpe Ratio, Average Realized Utility, and Annualized Alpha in each universe against the alternative that the strategy performs better in a universe more concentrated in mutual funds. The annualized measures of alpha control for macrovariables and time-varying risk factor loadings. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas. Each column shows portfolio results based on the individual Bayesian updating models, which are summarized in Table 2, identified in the corresponding column header. 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% or in any one mutual 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: Pan-European Benchmark Models

	CAPM	BCAPM	BSMA	BAMA	BAMAP
Sharpe Ratio Null Hypothesis					
Fund and Stock $\leq$ Stock Only	1%	0%	0%	0%	0%
Fund Only $\leq$ Stock Only	22%	3%	0%	0%	1%
Average Realized Utility Null Hypothesis					
Fund and Stock $\leq$ Stock Only	2%	0%	0%	0%	0%
Fund Only $\leq$ Stock Only	22%	2%	1%	0%	1%
Single-Factor Alpha Null Hypothesis					
Fund and Stock $\leq$ Stock Only	2%	4%	3%	1%	3%
Fund Only $\leq$ Stock Only	31%	4%	3%	2%	7%
Four-Factor Alpha Null Hypothesis					
Fund and Stock $\leq$ Stock Only	1%	0%	0%	0%	1%
Fund Only $\leq$ Stock Only	20%	0%	0%	0%	1%

Panel B: Local Market Augmented Benchmark Models

	CAPM-A	BCAPM-A	BSMA-A	BAMA-A	BAMAP-A
Sharpe Ratio Null Hypothesis					
Fund and Stock $\leq$ Stock Only	1%	0%	0%	0%	0%
Fund Only $\leq$ Stock Only	40%	0%	1%	0%	0%
Average Realized Utility Null Hypothesis					
Fund and Stock $\leq$ Stock Only	1%	0%	0%	0%	0%
Fund Only $\leq$ Stock Only	38%	1%	1%	0%	0%
Single-Factor Alpha Null Hypothesis					
Fund and Stock $\leq$ Stock Only	3%	3%	4%	1%	5%
Fund Only $\leq$ Stock Only	61%	2%	3%	2%	6%
Four-Factor Alpha Null Hypothesis					
Fund and Stock $\leq$ Stock Only	1%	0%	0%	0%	2%
Fund Only $\leq$ Stock Only	52%	0%	0%	0%	1%

Table 8: Accounting for Fees in Portfolio Performance

This table presents the impact on portfolio performance during the out-of-sample period 06/1993-02/2008 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 4. 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. The arithmetic and geometric mean returns, the volatility, the Sharpe ratio, and average realized utility are all annualized. Bootstrapped one-sided p-Values test the null hypothesis that portfolio strategy and benchmark Sharpe Ratio and Average Realized Utility are equal against the alternative that the mutual fund portfolio dominates the benchmark. 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 risk factor loadings but not local benchmarks. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas. Each column shows portfolio results based on the individual Bayesian updating models, which are summarized in Table 2, identified in the corresponding column header.

Panel A: Turnover and Fees in Baseline Models

	CAPM	CAPM-A	BCAPM	BCAPM-A	BSMA	BSMA-A	BAMA	BAMA-A	BAMAP	BAMAP-A
Turnover	68%	63%	113%	96%	227%	221%	232%	229%	221%	215%
Front Loads	1.39	1.46	2.69	2.45	4.36	4.24	4.42	4.40	4.05	3.95
Redemption Fees	0.08	0.08	0.12	0.08	0.29	0.25	0.30	0.26	0.33	0.30
Total Loads and Fees	1.47	1.54	2.81	2.53	4.65	4.49	4.72	4.65	4.38	4.26
Fee Adjusted Performance:										
Arithmetic mean	5.55%	5.52%	10.90%	12.76%	14.13%	14.49%	13.89%	14.36%	13.13%	13.52%
Sharpe Ratio	0.106	0.100	0.349	0.470	0.471	0.501	0.458	0.496	0.439	0.483
Single-Factor Alpha	-4.14%	-4.36%	0.86%	2.38%	3.99%	5.02%	3.79%	4.84%	2.57%	2.72%
Single-Factor Alpha t-Stat	(3.47)	(4.13)	0.26	0.77	1.02	1.31	0.97	1.27	0.75	0.83
Four-Factor Alpha	-4.15%	-4.93%	4.97%	5.98%	8.49%	9.27%	8.18%	9.09%	7.94%	8.04%
Four-Factor Alpha t-Stat	(3.56)	(4.42)	2.06	2.75	2.82	3.42	2.75	3.43	2.94	3.21

Panel B: Fee-Adjusted Utility Model Performance

	CAPM	CAPM-A	BCAPM	BCAPM-A	BSMA	BSMA-A	BAMA	BAMA-A	BAMAP	BAMAP-A
Geometric mean	4.47%	4.26%	10.33%	10.84%	12.96%	12.00%	13.08%	12.30%	12.63%	11.25%
Arithmetic mean	4.48%	4.28%	11.89%	12.18%	14.51%	13.38%	14.66%	13.70%	14.33%	12.89%
Volatility	1.82%	2.18%	17.68%	16.29%	17.87%	16.80%	18.06%	16.86%	18.75%	18.29%
Sharpe ratio	0.211	0.082	0.441	0.496	0.582	0.552	0.585	0.570	0.546	0.480
p-Val for Fund SR $\leq$ Bmk SR	0%	0%	59%	36%	24%	27%	24%	24%	34%	51%
Realized Utility	4.41%	4.19%	7.12%	8.09%	9.55%	9.01%	9.60%	9.29%	8.90%	7.76%
p-Val for Fund ARU $\leq$ Bmk ARU	77%	79%	54%	36%	17%	23%	16%	20%	24%	43%
Outperformance Frequency	37%	37%	50%	54%	51%	48%	49%	48%	51%	49%
Single-Factor Alpha	-0.36%	-0.47%	1.69%	2.16%	4.67%	4.05%	4.66%	4.47%	4.08%	2.69%
Single-Factor Alpha t-Stat	(1.638)	(1.712)	0.724	1.019	1.734	1.665	1.714	1.811	1.444	1.019
Single-Factor Beta	0.092	0.103	0.907	0.853	0.895	0.835	0.908	0.829	0.940	0.922
Four-Factor Alpha	-0.36%	-0.51%	6.00%	6.19%	9.78%	9.15%	9.56%	9.60%	9.52%	8.12%
Four-Factor Alpha t-Stat	(1.638)	(1.819)	3.361	3.879	4.484	4.838	4.260	5.058	3.913	3.933
Beta - Market	0.091	0.101	0.867	0.815	0.855	0.795	0.873	0.797	0.930	0.890
Beta - SMB	0.023	0.013	0.426	0.454	0.479	0.490	0.421	0.499	0.469	0.510
Beta - HML	(0.015)	(0.009)	(0.150)	(0.148)	(0.206)	(0.234)	(0.179)	(0.246)	(0.241)	(0.268)
Beta - Momentum	(0.007)	(0.005)	0.070	0.044	0.271	0.171	0.254	0.173	0.272	0.192

Panel C: Turnover and Fees in Fee-Based Utility Models

	CAPM	CAPM-A	BCAPM	BCAPM-A	BSMA	BSMA-A	BAMA	BAMA-A	BAMAP	BAMAP-A
Turnover	3%	3%	22%	21%	41%	37%	39%	36%	41%	35%
Front Loads	0.05	0.07	0.32	0.34	0.46	0.40	0.45	0.41	0.45	0.37
Redemption Fees	0.01	0.01	0.03	0.02	0.09	0.08	0.08	0.08	0.11	0.08
Total Loads and Fees	0.06	0.08	0.35	0.36	0.55	0.48	0.53	0.48	0.56	0.46
Fee Adjusted Performance:										
Arithmetic mean	4.42%	4.20%	11.55%	11.82%	14.11%	13.22%	13.98%	12.90%	13.77%	12.43%
Sharpe Ratio	0.177	0.047	0.421	0.474	0.554	0.541	0.553	0.524	0.516	0.455
Single-Factor Alpha	-0.42%	-0.55%	1.35%	1.80%	4.11%	3.99%	4.14%	3.57%	3.52%	2.23%
Single-Factor Alpha t-Stat	(1.92)	(1.99)	0.58	0.85	1.51	1.61	1.54	1.47	1.25	0.85
Four-Factor Alpha	-0.42%	-0.59%	5.65%	5.83%	9.01%	9.11%	9.25%	8.67%	8.96%	7.66%
Four-Factor Alpha t-Stat	(1.92)	(2.09)	3.17	3.65	4.01	4.80	4.24	4.58	3.68	3.71

Table 9: Portfolio Country and Sector Rotation

This table presents portfolio weights for the investor types, summarized in Table 2, considered in the analysis when we use both pan-European (Panel A) and locally augmented (Panel B) benchmark models. 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. Since the investor is assumed to have access to a risk-free asset paying the prevailing EURIBOR rate, the portfolio weights need not sum to unity.

Panel A: Pan-European Benchmark Models

		Pan-Europe	Sectors	Austria	Benelux	France	Germany	Italy	Scandinavian	Spain/Portugal	Switzerland	UK
CAPM	1993	10%	0%	0%	0%	0%	0%	0%	0%	0%	0%	46%
	1998	0%	0%	0%	14%	6%	0%	0%	0%	0%	10%	70%
	2003	27%	0%	0%	0%	9%	0%	0%	0%	0%	1%	30%
	2007	60%	0%	0%	0%	20%	0%	0%	0%	0%	0%	6%
BCAPM	1993	28%	0%	2%	10%	0%	0%	0%	18%	0%	9%	33%
	1998	10%	0%	0%	0%	0%	0%	0%	90%	0%	0%	0%
	2003	32%	0%	0%	0%	16%	0%	3%	50%	0%	0%	0%
	2007	6%	26%	0%	0%	0%	0%	0%	58%	10%	0%	0%
BSMA	1993	10%	0%	0%	0%	0%	0%	0%	60%	0%	10%	20%
	1998	10%	0%	0%	0%	40%	0%	20%	21%	9%	0%	0%
	2003	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%
	2007	10%	70%	0%	0%	0%	10%	0%	0%	10%	0%	0%
BAMA	1993	10%	0%	0%	0%	0%	0%	0%	61%	0%	10%	19%
	1998	10%	0%	0%	0%	40%	0%	20%	20%	10%	0%	0%
	2003	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%
	2007	10%	70%	0%	0%	0%	10%	0%	0%	10%	0%	0%
BAMAP	1993	21%	0%	2%	0%	0%	0%	0%	37%	0%	20%	20%
	1998	20%	0%	0%	0%	10%	0%	41%	29%	0%	0%	0%
	2003	0%	11%	0%	0%	0%	0%	0%	89%	0%	0%	0%
	2007	10%	70%	0%	0%	0%	10%	0%	0%	10%	0%	0%

Panel B: Local Market Augmented Benchmark Models

		Pan-Europe	Sectors	Austria	Benelux	France	Germany	Italy	Scandinavian	Spain/Portugal	Switzerland	UK
CAPM-A	1993	10%	0%	0%	0%	10%	0%	0%	0%	0%	0%	13%
	1998	0%	0%	0%	20%	30%	0%	0%	5%	0%	20%	25%
	2003	27%	0%	0%	10%	20%	0%	0%	0%	0%	10%	0%
	2007	51%	0%	0%	0%	29%	0%	0%	0%	0%	10%	0%
BCAPM-A	1993	27%	0%	0%	10%	0%	7%	0%	16%	0%	0%	40%
	1998	10%	0%	0%	0%	20%	0%	0%	70%	0%	0%	0%
	2003	25%	0%	0%	0%	30%	0%	0%	45%	0%	0%	0%
	2007	5%	20%	0%	0%	0%	0%	0%	65%	0%	0%	10%
BSMA-A	1993	30%	0%	0%	0%	10%	0%	0%	20%	0%	10%	30%
	1998	4%	0%	0%	0%	58%	0%	10%	19%	10%	0%	0%
	2003	19%	9%	0%	0%	10%	10%	0%	52%	0%	0%	0%
	2007	10%	80%	0%	0%	0%	0%	0%	0%	0%	0%	10%
BAMA-A	1993	30%	0%	0%	0%	10%	0%	0%	20%	0%	10%	30%
	1998	3%	0%	0%	0%	57%	0%	10%	20%	10%	0%	0%
	2003	19%	5%	0%	0%	10%	10%	0%	54%	0%	0%	1%
	2007	12%	78%	0%	0%	0%	0%	0%	0%	0%	0%	10%
BAMAP-A	1993	37%	0%	0%	0%	10%	0%	0%	20%	0%	13%	20%
	1998	40%	0%	0%	0%	10%	0%	10%	40%	0%	0%	0%
	2003	10%	0%	0%	0%	0%	0%	0%	78%	0%	0%	12%
	2007	2%	70%	0%	0%	0%	10%	0%	9%	0%	0%	9%

Table 10: Out-of-Sample Performance Attribution

This table decomposes the abnormal return performance of our Pan-European and Local Market Augmented Benchmark Models into four components, plus a residual. Each column shows portfolio results based on the individual Bayesian updating models, presented in Table 2, identified in the corresponding column header. The differential return is measured relative to the benchmark MSCI Europe portfolio whose annual 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: Pan-European Benchmark Models

	CAPM	BCAPM	BSMA	BAMA	BAMAP
Arithmetic mean	7.01%	13.71%	18.78%	18.61%	17.51%
Return from Pan-Euro Fund Selection	0.52%	0.02%	-0.14%	-0.10%	-0.20%
Return from Country Fund Selection	-0.77%	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	-3.64%	1.19%	2.20%	2.27%	3.22%
Residual	-0.50%	-0.79%	-0.76%	-0.40%	-1.87%
Total Outperformance	-4.39%	2.31%	7.38%	7.21%	6.11%

Panel B: Local Market Augmented Benchmark Models

	CAPM-A	BCAPM-A	BSMA-A	BAMA-A	BAMAP-A
Arithmetic mean	7.06%	15.29%	18.98%	19.02%	17.77%
Return from Pan-Euro Fund Selection	0.42%	-0.31%	-0.22%	-0.20%	-0.16%
Return from Country Fund Selection	-0.62%	1.36%	3.19%	3.13%	2.04%
Return from Sector Fund Selection	0.00%	1.45%	3.12%	2.82%	2.49%
Return from Timing Country Weights	-4.28%	1.26%	1.51%	1.41%	1.86%
Residual	0.14%	0.13%	-0.02%	0.46%	0.14%
Total Outperformance	-4.34%	3.89%	7.58%	7.62%	6.37%

Panel C: Alternate Country Selection Definition

	CAPM	BCAPM	BSMA	BAMA	BAMAP
Return from Country Fund Selection	-1.23%	0.57%	4.29%	4.30%	3.34%
Residual	-0.03%	-0.01%	-1.92%	-1.65%	-2.21%
	CAPM-S	BCAPM-S	BSMA-S	BAMA-S	BAMAP-S
Return from Country Fund Selection	-0.83%	1.97%	5.37%	5.52%	4.11%
Residual	0.35%	-0.48%	-2.19%	-1.93%	-1.93%

Table 11: Portfolio Performance under Alternate Objectives and Risk Profiles

This table shows the portfolio performance for the different strategies during the out-of-sample period 06/1993-02/2008 under alternative objective functions capturing different constraints on benchmark and macroeconomic factor exposures. 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 $\sigma_\alpha = 10\%$ /Month. Additionally, the models in panels A, B, and C 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 trailing historical benchmark volatility. Panel C minimizes the portfolio expected volatility subject to an expected return greater than or equal to the trailing historical benchmark average return. Panel D similarly minimizes the portfolio expected volatility subject to an expected return greater than or equal to the trailing historical benchmark average return. However, instead of restricting benchmark factor exposures, it constrains portfolio returns to be uncorrelated with the contemporaneous macroeconomic state variables. The arithmetic and geometric mean returns, the volatility, the Sharpe ratio, and average realized utility are all annualized. Bootstrapped one-sided p-Values test the null hypothesis that portfolio strategy and benchmark Sharpe Ratio and Average Realized Utility are equal against the alternative that the mutual fund portfolio dominates the benchmark. 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 risk factor loadings but not local benchmarks. Specifically, when computing the single-factor alphas, we allow the market factor loading of the portfolio return to depend on the (time-varying) macroeconomic variables; similarly all risk loadings are allowed to depend on all macroeconomic variables when calculating the four-factor alphas. Each column shows portfolio results based on the individual Bayesian updating models, which are summarized in Table 2, identified in the corresponding column header.

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP	CAPM	BCAPM	BSMA	BAMA	BAMAP
		Panel A: Maximize Mean Variance Expected Utility					Panel C: Minimize Volatility Targeting Benchmark Average Return				
Geometric mean	10.06%	6.10%	12.20%	13.78%	14.57%	13.80%	5.89%	11.61%	14.13%	14.85%	13.71%
Arithmetic mean	11.40%	6.99%	12.96%	15.16%	15.96%	15.16%	6.75%	12.28%	15.47%	16.22%	15.02%
Volatility	16.28%	13.30%	12.24%	16.68%	16.82%	16.62%	13.04%	11.61%	16.54%	16.69%	16.31%
Sharpe ratio	0.449	0.217	0.723	0.663	0.705	0.665	0.203	0.705	0.688	0.726	0.670
p-Val for SR $\geq$ Bmk SR		98%	2%	8%	4%	8%	99%	3%	5%	3%	7%
Average Realized Utility		4.33%	10.54%	10.78%	11.49%	10.81%	4.19%	10.11%	11.15%	11.80%	10.83%
p-Val for ARU $\geq$ Bmk ARU		98%	11%	6%	3%	6%	98%	14%	4%	2%	6%
Single-Factor Alpha		-2.62%	3.12%	4.34%	4.97%	4.30%	-2.60%	2.80%	4.83%	5.41%	4.18%
Single-Factor Alpha t-Stat		(2.260)	1.755	1.843	2.070	1.792	(2.531)	1.622	2.073	2.276	1.781
Four-Factor Alpha		-2.55%	5.86%	8.15%	8.88%	8.61%	-2.67%	5.49%	8.60%	9.33%	8.41%
Four-Factor Alpha t-Stat		(2.272)	3.949	4.013	4.422	4.020	(2.715)	3.821	4.285	4.705	4.040
		Panel B: Maximize Expected Return Targeting Benchmark Volatility					Panel D: Minimize Volatility Targeting Benchmark Average Return with State Constraints				
Geometric mean	10.06%	7.92%	12.22%	13.95%	14.56%	13.40%	5.93%	11.35%	16.54%	16.25%	15.35%
Arithmetic mean	11.40%	9.09%	13.04%	15.24%	15.89%	14.63%	6.79%	12.94%	18.55%	18.26%	17.14%
Volatility	16.28%	15.22%	12.76%	16.20%	16.46%	15.80%	13.04%	17.91%	20.66%	20.62%	19.33%
Sharpe ratio	0.449	0.328	0.701	0.688	0.716	0.666	0.206	0.494	0.699	0.687	0.675
p-Val for SR $\geq$ Bmk SR		7%	5%	12%	11%	12%	98%	46%	14%	15%	15%
Average Realized Utility		5.58%	10.43%	11.09%	11.59%	10.69%	4.23%	8.02%	11.84%	11.59%	11.28%
p-Val for ARU $\geq$ Bmk ARU		93%	11%	4%	3%	7%	98%	40%	6%	6%	8%
Single-Factor Alpha		-1.77%	2.96%	4.32%	4.87%	3.90%	-2.56%	3.16%	8.52%	8.27%	6.70%
Single-Factor Alpha t-Stat		(1.472)	1.588	1.871	2.043	1.646	(2.496)	1.080	2.241	2.212	2.029
Four-Factor Alpha		-1.73%	5.90%	8.22%	9.06%	8.35%	-2.63%	6.94%	12.75%	12.42%	11.62%
Four-Factor Alpha t-Stat		(1.442)	3.665	4.318	4.782	4.047	(2.682)	3.332	4.498	4.518	4.516