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Essays on Predictability of Emerging Markets Growth and Financial Performance

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DEDICATION

To Catalina and Lucas

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VITA

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ABSTRACT OF THE DISSERTATION

Essays on Predictability of Emerging Markets Growth and Financial Performance

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This dissertation seeks to better understand the underlying factors driving financial performance and economic activity in international markets.

The first chapter *"Predictability of Growth in Emerging Markets: Information in Financial Aggregates"* tests for predictability of output growth in a panel of twenty-two emerging market economies. I use pooled panel data methods that control for endogeneity and persistence in the predictor variables to test the predictive power of a large set of financial aggregates including valuation measures, interest rates, and capital flows. I find empirical evidence that stock returns, portfolio investment flows, the term spread and default spreads help predict output growth in emerging markets. In particular, large capital inflows predict subsequent high GDP growth as do high

term spreads. Conversely, higher default spreads on emerging market government debt signals lower future GDP growth. Results also suggest that the performance of global aggregates such as commodity markets, a cross-sectional firm size factor, and returns on the market portfolio contain information about the future state of the economy. I benchmark my results against the US and find that there are differences in information flows and the role of capital markets in predicting economic growth. My analysis extends previous findings in the macro-finance literature on the links between the real economy and financial market performance.

Within emerging markets, a largely unexplored area of research is related to the study of mutual funds performance. In my second chapter, *"Emerging Market Mutual Fund Performance and the State of the Economy"* I propose a set of asset class specific predictive variables and exploit them in order to identify those funds that outperform the market in different phases of the economic cycle. I employ a comprehensive survivorship-bias free universe of global and regional emerging market funds and use a Bayesian framework that incorporates predictability in manager skills (stock selection and benchmark timing skills), fund risk loadings and benchmark returns by exploiting ex-ante business cycle related state variables. Results provide empirical evidence of return predictability and the economic value of active management in emerging markets.

My final dissertation chapter studies market integration and segmentation and their effects on return predictability. In *"Mutual Fund Return Predictability in Partially Segmented Markets"* (co-authored with B. Gillen, A. Timmermann and R. Wermers) we generalize existing models for Bayesian asset selection by considering both integrated and partially segmented market models. We find that regional state variables can be used to identify a significant time-varying alpha component among a large sample of funds with a pan- European, European country, or European sector focus. Specifically, the default yield spread, term spread, dividend yield, short interest rate and market volatility, as well as macroeconomic variables tracking consumer price inflation and growth in industrial production prove valuable in identifying, ex-ante, funds with superior performance. Our analysis also suggests that allowing for segmentation in market risk factors enhances risk-adjusted performance.

Chapter 1

Predictability of Growth in Emerging Markets: Information in Financial Aggregates

Abstract

This paper tests for predictability of output growth in a panel of twenty-two emerging market economies. We use pooled panel data methods that control for endogeneity and persistence in the predictor variables to test the predictive power of a large set of financial aggregates including valuation measures, interest rates, and capital flows. Empirical evidence suggests that stock returns, portfolio investment flows, the term spread and default spreads help predict output growth in emerging markets. In particular, large capital inflows predict subsequent high GDP growth as do high term spreads. Conversely, higher default spreads on emerging market government debt signals lower future GDP growth. We also find evidence that the performance of aggregates such as global commodity markets, a cross-sectional firm size factor, and returns on the market portfolio contain information about the future state of the economy. We benchmark our results against the US and find that there are differences in information flows and the role of capital markets in predicting economic growth. Our analysis extends previous findings in the macro-finance literature on the links between the real economy and financial market performance.

1.1 Introduction

Emerging markets are becoming a central player in the global economy. Following financial liberalization in the late 80's and early 90's, they have an increasing influence on the prospects of global growth and financial stability. In particular, over the past years we have seen emerging markets outperforming developed economies. Many of these countries have undertaken economic and political reforms resulting in more favorable business conditions and stronger government balance sheets. These reforms included but were not limited to fiscal programs aimed at controlling public deficits, trade agreements, financial system regulations and monetary policy that led to lower inflation rates.[1] While at the end of 1985 emerging markets accounted for 11% of the global GDP, by the end of 2009 their share had more than doubled to 23%. Furthermore, current international conditions indicate these markets will continue growing at higher rates than their developed counterparts. Yet, dynamics of emerging market growth are poorly understood. It is unclear whether GDP growth is predictable, and if so, which factors lead economic growth in these transitional economies.

While much of the empirical research in macro-finance literature focuses on developed countries, not much work studies the link between financial market performance and future output growth in developing economies. In this paper we study the predictive dynamics of economic growth in emerging markets and evaluate the extent to which financial aggregates can be used as leading indicators of economic growth. Specifically, we test whether stock returns, valuation measures, interest rates, flows, commodity prices, and a set of well established risk factors, contain information about the future state of the economy. We compare these results with empirical findings about the role of capital markets in predicting future output growth in the US. Given the specific characteristics of emerging market economic, financial and institutional systems, we might expect the transmission channels between financial markets and the real economy to work differently due to liquidity or credit market frictions specific to emerging markets. Also, the impact of financial aggregates such as capital and portfolio

[1] Brazil, China and Mexico, among other countries, greatly improved their fiscal profiles. This improvement in credit quality, together with favorable growth prospects and attractive risk-adjusted returns, has resulted in massive international inflows into emerging markets' sovereign debt.

inflows on output growth can be expected to be more significant in emerging market economies as they tend to be more dependent and vulnerable to such flows. In this regard, we have seen capital flight from developed countries into emerging markets seeking investment opportunities with higher expected returns. These inflows boosted economic growth, relaxed liquidity constraints, raised asset prices as well as broadened and increased the depth of many of these financial markets. On the negative side, capital outflows have preceded financial and economic crisis in emerging markets. There is a large body of research on sudden stops that models the effects of capital flows on output growth in emerging markets, e.g. Calvo (1998), Reinhart and Calvo (2000), Ferretti and Razin (2000). However, few studies quantify the relationship between output growth and capital inflows in these markets. In this paper we use country level data on net portfolio investment and capital flows to empirically evaluate the predictive power of these aggregates in forecasting GDP growth.

To address our main question we construct a comprehensive dataset for twenty two emerging market countries selected based on Standard and Poor's classification system. Our sample includes a large set of country-specific and global macro and financial variables such as real GDP growth, valuation measures, interest rates, capital flows, and commodity indices, covering the period 1992-2010.[2] To test for predictability of output growth we use pooled panel data methods that control for endogenous and persistent predictor variables. A large literature documents the effects of endogeneity and persistence on time-series predictive regressions. Stambaugh (1999) shows that OLS estimates are biased in the presence of endogenous and persistent regressors, inhibiting normal inference. Hjalmarsson (2010) finds that these econometric issues also apply to panel data forecasting models when fixed effects are included and proposes a robust estimator that corrects for the Stambaugh-bias. Even though Stambaugh-bias has been discussed exclusively in the return predictability literature, we find that it can also arise in the context of output growth predictability. In particular, valuation ratios such as the dividend yield and the price-earnings ratio, as well as the capitalization ratio,

[2]We considered extending the period under analysis backwards in time. However, it is only after financial liberalization that the phenomenon of emerging markets loomed. In earlier decades, many of these countries were closed economies and therefore the study of emerging markets as a whole is not of particular relevance.

prove to be highly persistent and endogenous. For this reason, we follow Hjalmarsson's methodology to correct for these features when testing for output growth predictability. Moreover, as part of our empirical analysis we test for output growth predictability at different forecasting horizons by applying reverse regression methods as proposed by Hodrick (1992) and extended by Wei and Wright (2010).

Our results provide empirical evidence that stock returns, portfolio investment flows, the term spread, default spreads, and commodity prices help predict output growth in emerging market economies. In particular, large capital inflows predict subsequent high GDP growth as does a high term spread. Conversely, higher default spreads on emerging market government debt signals lower future GDP growth. Our findings also suggest that some variables such as the term spread, stock returns, and capital flows contain higher predictive power during the 90's, while the short interest rate and portfolio flows prove more useful during the last decade. Furthermore, for regional level data we find that Latin America provides the strongest evidence of output growth predictability across regions.

We also extend previous findings on the links between output growth and Fama and French (1993) risk factors (i.e. Liew and Vassalou (2000)). In particular, we test whether book-to-market, size, and the market portfolio contain information about the future state of the economy. We find strong evidence of the predictive power of the size factor and returns on the market portfolio.

We benchmark our results to the US and find that there are substantial differences in information flows and the role of capital markets in predicting economic growth. Variables that proved to convey information about the future state of the economy in developing countries, such as returns on commodity markets, the term spread, and stock market returns, lack any predictive power in the context of US growth. On the other hand, despite structural differences, our results suggest that default spreads share similar patterns across markets.

Our paper is related to a vast body of work that studies the performance of financial variables as predictors of future output growth in the US and, to a lesser extent, in international developed markets. These studies focus mainly on well documented financial variables such as the term spread, the default spread and stock market returns.

Estrella and Hardouvelis (1991) find evidence that the slope of the yield curve can predict changes in real output. Harvey (1988) documents that the expected real term structure forecasts consumption growth. Hamilton and Kim (2002) confirm and extend the conclusion of earlier research by decomposing the contribution of the term spread to forecast real GDP growth into the expected changes in interest rates and the term premium.[3] The macro-finance literature has also long studied the forecasting power of default spreads. Stock and Watson (1989) find that the spread between commercial paper and treasury bills is a helpful indicator when forecasting output growth. Also Weber (1998) concludes that the paper-bill spread helps predict consumption spending. Later work by Gilchrist et al. (2009) suggests that corporate bond spreads issued by intermediate risk non-financial firms have predictive power over GDP growth. Evidence on the predictive power of stock returns is mixed. An early study by Harvey (1989) finds that only about 5% of variation in output growth is explained by stock market related variables in the US over the 1953-1989 period. On the other hand, Estrella and Mishkin (1998) find evidence that stock price indexes are good predictors of US recessions. Specific to emerging markets, Mauro (2003) focuses on the correlation of lagged stock returns and output growth and finds this relationship to be positive and significant in several cases. Moreover, his findings suggest that countries with a high market capitalization to GDP ratio exhibit stronger correlations.[4] Although there is no consensus about the empirical success of equity prices and related variables to predict future economic activity, they are widely considered by policy makers and investors. Our analysis validates and extends previous studies in the macro-finance literature that find that stock returns, term spreads and default spreads can be helpful predictors of economic activity.

In summary, the main contributions of the paper are as follows. First, we develop a comprehensive dataset on output growth and a large set of country-specific and global financial aggregates for a panel of twenty two emerging market countries. Second, we

[3] See Stock and Watson (2003) for a literature review.

[4] There is also a relatively new literature that studies stock return predictability in emerging markets. Harvey (1995, 1994) shows that equity returns are predictable in some developing countries when conditioning on country specific and global information variables such as dividend yields, past returns, currency index and earning-price ratio. Bekaert et al. (2007) find that local market liquidity is an important driver of returns in these economies.

apply pooled panel data methods to shed light on the predictive dynamics of emerging market growth. Third, we document empirically that stock returns, flows, the term spread, default spreads and commodity prices, among other aggregates, can be used as leading indicators of economic activity in emerging markets. Our results generalize previous empirical findings in the macro-finance literature on the linkages between the real economy and financial market performance.

The paper is organized as follows. Section 2 describes our data set. Section 3 details the predictive regression methodology. In section 4 we present our empirical findings. Section 5 provides robustness analysis. Finally, we conclude in section 6.

1.2 Data

Our study focuses on twenty-two countries that were classified as emerging market economies by Standard and Poor's as of December of 2009. We develop a comprehensive dataset of country-specific and global macroeconomic and financial variables for the period covering December 1992 to March 2010. We use quarterly series that include real GDP growth rates, inflation, stock returns, valuation measures, interest rates, capital flows, and commodity returns. GDP series are from the IMF's International Financial Statistics (IFS) except in the cases of Mexico, Taiwan, and South Africa where the source is Global Financial database (GFD). We deflated these series using the corresponding GDP deflators from the IFS. We tested and removed seasonality using the X-12-ARIMA Seasonal Adjustment Program from the U.S. Census Bureau. Table 1.1 presents descriptive statistics for the GDP series over the fourth quarter of 1992 to the first quarter of 2010. During the span of our sample all countries report positive average output growth rates. On average, quarterly GDP rates reach 1.13%, with China exhibiting the highest average growth rate (3.05%) and Mexico the lowest (0.61%) within emerging markets.[5] In terms of volatility, Morocco presents the highest average volatility level (4.2%) while Hungary shows the most stable growth pattern (1.05%).

[5]GDP summary statistics for China only start in Q4 1999.

Stock market index returns for our set of countries are from Global Financial Database. They are inflation adjusted, include both changes in price and dividends, and are expressed in local currency terms. With respect to valuation measures, we consider country-specific dividend yields and price-earning ratios from GFD. These aggregates are based on large cap stocks which represent about 75% of the capitalization of the country. We also study the information content of stock market capitalization on subsequent output growth. In doing so, we employ capitalization growth rates and a ratio of capitalization to GDP from GFD. We evaluate different measures of financial flows from the balance of payments in our panel of developing countries. At the broader level, we consider capital and portfolio flows. Capital flows are the net sum of direct investment, portfolio investment, financial derivatives, and other investments from the financial account. Portfolio investment flows are a subset of the capital flow variable and account for transactions with nonresidents in financial securities. We disaggregate this category into debt and equity flows. Debt flows are the net sum of both inflows and outflows of assets and liabilities covering fixed income instruments such as bonds and money market securities. Equity Securities are the sum of assets and liabilities covering stocks, and similar instruments that represent ownership of equity. Within capital flows, we also evaluate the predictive power of direct investment capital flows. This aggregate is the sum of direct investment abroad and direct investment in the reporting country. The source of our flow aggregates is the IFS.

Our interest rate variables are from GFD. We consider the term spread, the real short interest rate, and returns on JPMorgan's Emerging Markets Bond Index Plus country indices (EMBI+). This family of indices reports the spread between local and US government debt instruments. More specifically, they track the spread between the average yield on the securities of the local country against that of US Treasuries. The local debt instruments include US-dollar denominated Brady bonds, Eurobonds, and traded loans issued by sovereign entities. We also test whether US interest rate aggregates lead the business cycle of emerging market countries. In doing so, we consider the US default spread, short interest rate and the term spread. The default spread is measured as the difference between Moody's Corporate BAA and AAA bond yields, the short interest rate is the yield on the 3 months Treasury Bill, and the term spread is the difference between the yields on the 10-year Government Bond and the 3 months Treasury Bill.

We also consider the performance of a set of commodity indices. We use the Goldman Sachs commodity index (GSCI) as a proxy for the performance of commodity markets at the aggregate level. GSCI is a composite index of commodity sector returns weighted by world production. We also drill down to the sector level and include returns covering agricultural, energy, livestock and precious metal commodity markets from the S&P GSCI family indices.

Finally, we build and test the predictive power of proxies for Fama and French risk factors. The size factor is the spread between returns on the MSCI Emerging Markets Small Cap and the MSCI Emerging Markets Large Cap total return indices. The book-to-market factor is represented by the return difference between the MSCI Emerging Markets Standard Growth and the MSCI Emerging Markets Standard Value total return indices. Lastly, we use the MSCI Emerging Markets total return index as a proxy for the market portfolio.

1.3 Estimation

In this section we describe our predictive regression methodology. We use Hjalmarsson's (2010) panel data framework, that can be represented by the following system of equations:

$$y_{i,t} = \alpha_i + \beta' x_{i,t-1} + u_{i,t} \tag{1.1}$$

$$x_{i,t} = A_i x_{i,t-1} + v_{i,t}$$

$$A_i = I + C_i / T$$

where $y_{i,t}$ is real GDP growth for country i at time t, $x_{i,t}$ is a mx1 vector of predictor variables, $u_{i,t}$ are country-specific innovations assumed to be martingale difference sequences with finite fourth moments, A_i is an mxm matrix representing the near unit root assumption and C_i is the local-to-unity parameter. The model allows for endogeneity by letting $u_{i,t}$ and $v_{i,t}$ be contemporaneously correlated and introduces persistency by defining the dependent variable, $x_{i,t}$, as an autoregressive process of order

1 with roots being local to unity. By letting C_i differ across countries we allow for the time series to have different persistence levels. We find this property to be of relevance in our analysis since we are considering a heterogenous panel of countries, and can therefore expect regressors to have different cross-sectional characteristics. [6]

Using panel data methodology results in more precise estimates than the analogous individual time-series regressions. Furthermore, even in the case where the slope coefficients differ across countries, the pooled estimator will provide information about the average slope coefficient. Also, pooling the data allows us to evaluate whether our group of developing countries possesses common characteristics. This could be of particular relevance to investors who consider investing in emerging markets as an asset class.

In our baseline setting we consider three different scenarios for pooled estimation presented in Hjalmarsson's (2010) study. First, the naive case where we estimate a standard pooled estimator. We then allow for the possibility of individual effects by letting α_i differ across countries. Finally, we consider a recursively demeaned estimator that corrects for the bias found in the fixed effects procedure.

The standard pooled estimator does not allow for individual effects and is given by the following equation:

$$\hat{\beta}_{Pool} = \left(\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{x}_{i,t-1}\tilde{x}'_{i,t-1}\right)^{-1}\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{y}_{i,t}\tilde{x}_{i,t-1}\right) \tag{1.2}$$

$$\tilde{y}_{i,t} = y_{i,t} - \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T} y_{i,t}$$

$$\tilde{x}_{i,t} = x_{i,t} - \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T} x_{i,t}$$

Despite the fact that from an economic perspective we might think that country-specific intercepts should be considered, it is worth evaluating this simple

[6]The near unit root assumption is preferred to a unit root set up since it is a less restrictive condition on the regressors when modeling non-stationary series. Also, as Hjalmarsson (2010) points out, under the near unit root assumption the degree of persistence in the predictive regressors will be carried over to the asymptotic distribution. This will allow the small sample distribution to correspond with that predicted by asymptotic distribution theory.

case given the econometric properties of this estimator. In particular, this estimator is asymptotically normally distributed therefore allowing for normal inference.

The fixed effects estimator is defined by the following equation:

$$\hat{\beta}_{FE} = \left(\sum_{i=1}^{n} \sum_{t=1}^{T} \underline{x}_{i,t-1} \underline{x}'_{i,t-1} \right)^{-1} \left(\sum_{i=1}^{n} \sum_{t=1}^{T} \underline{y}_{i,t} \underline{x}_{i,t-1} \right) \tag{1.3}$$

$$\underline{y}_{i,t} = y_{i,t} - \frac{1}{T} \sum_{t=1}^{T} y_{i,t}$$

$$\underline{x}_{i,t} = x_{i,t} - \frac{1}{T} \sum_{t=1}^{T} x_{i,t-1}$$

Although economically more meaningful in the context of emerging markets, this estimator suffers from a second-order bias in the presence of endogenous regressors. The time-series demeaned regressor, $\underline{x}_{i,t-1}$, incorporates information corresponding to periods after $t-1$. As a result the demeaned regressor is correlated with $u_{i,t}$, generating a small sample bias. [7] This bias, also known as the Stambaugh bias (Stambaugh (1999)), can be defined in terms of the limiting bias in the autoregressive root of the predictor variable. As shown in Hjalmarsson (2007), the analogue of the Stambaugh bias in the panel case can be written as:

$$\underset{(T,n\to\infty)_{seq}}{plim} T(\hat{\beta}_{FE} - \beta) = \underset{(T,n\to\infty)_{seq}}{plim} \frac{w_{12}}{w_{22}} T(\hat{\rho}_{FE} - \rho) \tag{1.4}$$

where w_{12} and w_{22} are the average covariance between $u_{i,t}$ and $v_{i,t}$ and variance of $v_{i,t}$ respectively, and $\hat{\rho}_{FE}$ is the fixed effects estimator of the autoregressive root of the predictor variable.[8]

The recursively demeaned estimator that corrects for this bias is given by the following equations:

[7] In the standard pooled estimation, the small sample bias is not an issue since the effects of endogeneity are eliminated when pooling the data.

[8] Note that when the local-to-unity parameters are unknown, direct estimation of the bias is not feasible.

$$\hat{\beta}_{FD} = \left(\sum_{i=1}^{n} \sum_{t=1}^{T} \underline{x}_{i,t-1}^{dd} x'_{i,t-1} \right)^{-1} \left(\sum_{i=1}^{n} \sum_{t=1}^{T} \underline{y}_{i,t}^{dd} x_{i,t-1} \right) \tag{1.5}$$

$$\underline{y}_{i,t}^{dd} = y_{i,t} - \frac{1}{T-t+1} \sum_{s=t}^{T} y_{i,s}$$

$$\underline{x}_{i,t}^{dd} = x_{i,t} - \frac{1}{T-t+1} \sum_{s=t}^{T} x_{i,s}$$

This estimator uses $x_{i,t-1}$ as an instrument and $\underline{u}_{i,t}^{dd}$ only includes data corresponding to periods after t. Therefore, by forward demeaning, $\underline{u}_{i,t}^{dd}$ is independent of $x_{i,t-1}$ and no second-order bias arises.[9]

The literature that studies the effects of and corrections for endogenous and persistent regressors has focused exclusively on return predictability. However, as tables 1.2 and 1.3 show, we find that this issue also arises in the context of output growth predictability. In particular, there is evidence of high persistence and endogeneity when using the capitalization ratio, the dividend yield and, the price earning ratio as regressors. Also, the term spread and short interest rate are highly persistent. However, cross-correlations for these predictors lack statistical significance in most of the countries. These results reinforce our choice of predictive framework.

Many studies have shown that the predictive power of a variable may depend on the forecasting horizon under analysis. Variables that proved to be helpful predictors for short horizons may lack any predictive power when tested over longer horizons, and vice-versa. Hence, as part of our empirical analysis, we test for predictability of our set of financial aggregates using different horizons. In doing so, we use reverse regressions as proposed by Hodrick (1992) who shows that, under the null of no predictability and covariance stationary, in the usual long horizon predictive regression

$$\Delta y_{t:t+k} = \alpha_{k,1} + \beta_{k,1} x_t + u_{t:t+k} \tag{1.6}$$

with k representing the number of periods ahead considered in the forecast, and $\Delta y_{t:t+k} = \Delta log(y_{t+k}/y_t) = \Delta y_{t:t+1} + \Delta y_{t+1:t+2} + ... + \Delta y_{t+k-1:t+k}$ the k-period GDP growth, the

[9] See Hjalmarsson (2010) for theorems and proofs of the properties of the above estimators.

numerator of the slope coefficient estimated by

$$cov[(\Delta y_{t:t+1} + ... + \Delta y_{t+k-1:t+k}); x_t] \tag{1.7}$$

is equivalent to

$$cov[\Delta y_{t:t+1}; (x_t + ... + x_{t-k+1})] \tag{1.8}$$

where (1.8) is the numerator of the slope coefficient in the following predictive regression

$$\Delta y_{t:t+1} = \alpha_{k,1} + \gamma_{k,1} x_{t-k+1:t} + u_{t:t+1} \tag{1.9}$$

with $x_{t-k+1:t} = x_t + ... + x_{t-k+1}$. The coefficient in the forward regression, β_k, can be expressed as a linear function of the coefficient in the reverse regression, γ_k

$$\beta_k = \frac{\tilde{V}_{xx}}{V_{xx}} \gamma_k$$

where $\tilde{V}_{xx}$ and V_{xx} are the covariance matrices of the regressors in the reverse and forward regressions respectively. As a result, testing the null of no predictability $\beta_{k,1} = 0$ is equivalent to testing $\gamma_{k,1} = 0$. However, under the reverse regression setting of equation (1.9), inference will lead to less size distortions. Recent work by Wei and Wright (2010) extends these findings by considering persistency in the predictive regressors. They model the predictors as autoregressive processes of order 1 with near unit roots and find that reverse regression methods can still be performed in the context of nearly non-stationary processes. Furthermore, their results confirm previous findings that inference is more robust in small sample under the reverse regressions than with typical long horizon regression methods (i.e. equation 1.6). We use this methodology to perform inference for long-term horizon growth rates by regressing the one-period ahead return on the sum of the regressors over the past k=4, and k=8 periods.

1.4 Empirical Results

In this section we present the empirical findings for our set of predictive regressions. Table 1.4 introduces our baseline results on the predictive power of country-specific financial aggregates to forecast subsequent, one year, and two years ahead output growth. Following the empirical macro-finance literature (i.e. Stock and Watson (2003)), our regressions include lagged GDP growth and the variable of interest as regressors. However, for convenience, we only report results for our set of financial predictors[10]. We also normalized our series to allow for comparison across variables. Table 1.5 goes one step further in the analysis of flows by testing the predictive power of net inflows related to direct investment capital, debt, and equity securities. In table 1.6 we shift our focus away from country-specific regressors and assess the forecasting ability of a group of global aggregates. This set of variables includes returns on commodity markets and US interest rates. In table 1.7, we examine the information content of Fama and French (1993) risk factors in Emerging Markets. We also evaluate the differences and similarities on the role of capital markets to predict future economic growth in emerging markets and in the US. In doing so we test for output growth predictability in the US over the same sample period, and use analogous predictive regressors of our emerging market analysis. These results are described in table 1.8. Finally, in table 1.9 we report findings at the country level using time series predictive regressions.

1.4.1 Returns and Valuation Measures

Although the goal of this paper is not to establish causality in the traditional economic sense, our results can be related to financial theories that relate stock prices to the present value of future cash-flows. In particular, theories such as the "passive informant" hypothesis suggests that positive news about future output growth will be translated into higher equity market prices, resulting in a positive relationship between stock returns and future GDP growth.[11] In our baseline case, we find strong evidence of the predictive power of stock market returns in emerging markets. As presented in table 1.4, the slope coefficients are both statistically and economically significant across models, suggesting that returns are positively related to future output growth.

[10]Details are available from the author.

[11]See Mauro (2003) for a detailed description on the main theories studying the relationship between stock markets and output growth.

Furthermore, when we look at longer forecasting horizons our results are validated. Both panels B and C show that there is information content in equity market returns at the one and two years horizons. Strongest results are for the one year ahead forecasts. [12] Time series regressions point in the same direction. However, only ten of the countries present statistically significant coefficients. These findings are in line with Mauro (2003) who finds the correlation of lagged stock returns and output growth to be positive and significant in several emerging economies.

We also evaluate the predictive relationship between market capitalization, commonly used as an indicator of stock market development, and GDP growth. In doing so, we consider a ratio that relates capitalization to GDP. Results from our pooled estimations lack statistical significance when forecasting subsequent and two years ahead economic activity. Only the slope coefficient for our capitalization ratio is significant under the fixed effects model at the one year ahead horizon. This result suggest a negative predictive relationship. However, as shown in tables 1.2 and 1.3, this variable is both highly persistent and endogenous. As a result, our fixed effects estimator is biased[13]. Therefore we focus on the forward demeaned estimator that corrects for this small sample bias. Our country level results present no clear pattern about the relationship between capitalization and subsequent output growth. As table 1.9 shows, slope coefficients lack statistical significance in most of the countries. Estimates are significant only in Argentina, Egypt, and Malaysia where we find a positive relationship between capitalization and subsequent output growth.

Two widely tested valuation measures in the return predictability literature are the price-earning ratio and the dividend yield. As shown in tables 1.2 and 1.3 we find that both aggregates suffer from a second order bias. We correct for this bias in our demeaned estimation. As presented in table 1.4, panels A through C, we find no evidence of the predictive power in the price-earning ratio. Only the fixed effects estimator is statistically significant when forecasting two years ahead. However, when we correct for the Stambaugh bias, we fail to reject the null of no predictability [14]. Time

[12] Lagged GDP growth included in these bivariate regressions lack statistical significance at any forecasting horizon and under all model specifications.

[13] Note that since the direction of the bias depends on the sign of the cross-correlations of the innovation processes, and in this case $cov(u_i, v_i) > 0$, the bias is negative and therefore we see $\beta_{FD} > \beta_{FE}$.

[14] Lagged GDP coefficients are positive and statistically significant across model specifications and

series regressions in table 1.9 provide no clear pattern of the predictive power of P/E ratios. Similarly, we find no predictive relationship between lagged dividend yields and future output growth in our robust estimations. Both the standard pooled and the fixed effects coefficients suggest evidence of a negative predictive relationship between these aggregates when forecasting one quarter ahead (see panel A of table 1.4). However, when we allow for individual effects and correct for endogeneity and persistence, signs of predictability disappear. This result is of particular relevance in the context of a highly persistent variable such as the dividend yield, since findings from our fixed effects estimation could result in misleading interpretations[15]. Time series regressions in table 1.9 lack statistical significance in a large number of countries. However, when significant, they suggest a negative predictive relationship between dividend yields and subsequent output growth.

When we compare the results of emerging markets and the US, we find similar patterns for capitalization and the dividend yield. In particular, there is no sign of predictability in these two measures, slope coefficients lack statistical significance. On the other hand, we find that stock market returns, that lead economic growth in emerging markets, have no predictive power in the context of the US. Also, the price-earning ratio, which presents no evidence of predictive power in emerging markets, can be a helpful predictor of future GDP in the US. Finally, it is worth noting that although there are differences in the information content of valuation measures across markets, we find some similarities in the characteristics of the data. Specifically, aggregates that show high levels of persistence and cross-correlations in emerging markets present the same patterns in the US. This is the case for capitalization ratio, the dividend yield, and the price-earning ratio.

1.4.2 Interest Rates

In table 1.4 we present results for the real short interest rate, the term spread and default spread. As panels A through C show, we find strong evidence of predictability in the spreads when predicting future GDP growth. In particular, higher default spreads on

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horizons. These results are available upon request

[15]In this bivariate setting, lagged GDP coefficients are both positive and statistically significant.

emerging market government debt signal lower output growth [16]. This counter-cyclical predictive relationship can be related to the literature on credit channels linking the financial and real side of the economy, where worsening in the quality of government balance sheets are translated into higher default risk, resulting in higher borrowing rates. These tighter financial conditions will negatively impact future economic growth.

Conversely, a high term spread predicts a future increase in GDP growth (i.e. short interest rate declines relative to the longer rate are followed by future rises in economic activity). Estimates are both positive and statistically significant across models when forecasting subsequent and one year ahead output growth. This predictive relationship could be explained in terms of an expectation and a term premium effect. In the first case spreads are expected to convey information about future short rates. The positive predictive relationship is based on the expectations hypothesis of the term spread and the impact of monetary policy. For example, easing of monetary policy is expected to positively impact interest sensitive sectors, boosting economic activity. On the other hand, the term premium effect signals changes in the term premium related to the compensation demanded for holding long bonds, influenced by risk and liquidity premium among other factors [17]. Regarding the real short interest rate, by adding lagged GDP into the regression the information content of this aggregate vanishes. Our estimates lose predictive power across models and horizons.

We also find that for most of our emerging market countries time series regressions lack statistical significance. Nevertheless, when they are significant, the short term rate and default spread signal a negative relationship with future GDP growth. These findings do not extend to the term spread where there is no clear pattern in our country level estimates.

Our empirical results also suggest that there are some differences in the role of interest rates in predicting output growth in the US and emerging markets. In particular, the term spread that proved to be a helpful predictor in emerging markets shows no

[16]Arellano and Mendoza (2002) document that episodes of sudden stops in emerging markets are characterized by sharp and unexpected declines in EMBI+ spread indices (our measure of default spreads) and plummeting equity markets.

[17]Hamilton and Kim (2002) decompose the contribution of the term spread into the expected changes in interest rates and the term premium and find that both factors are relevant for forecasting real GDP growth in the US.

predictive power in the US over our sample period [18]. On the other hand, the default spread and the real short interest rate present similar patterns across markets [19].

1.4.3 Flows

Results for our measures of flows are presented in tables 1.4 and 1.5. Table 1.4 introduces results at the aggregate level, while table 1.5 looks at components of portfolio investment and capital flows. As described in table 1.4, we find evidence of the predictive power of country flows in forecasting economic activity in emerging markets. Both capital and portfolio flow ratios, present economically and statistically significant slope coefficients when we forecast subsequent output growth. Results suggest that periods of capital and portfolio inflows anticipate future output growth and in turn, periods dominated by large outflows are followed by declines in economic activity. Furthermore, these results are confirmed and extended in table 1.5. We find that equity and debt security flows as well as direct investment flows can be useful predictors of future economic growth. Slope coefficients are economically and statistically significant signaling a positive relationship when predicting subsequent growth. Although the causality question is beyond the scope of this paper, the positive predictive relationship of portfolio flows could be related to an information and portfolio optimization effects. As investors become optimistic about opportunities in emerging markets, we see large financial inflows into local debt and equity securities. Overall, results suggest that investors are well informed and have the ability to react to news and expectations about future economic conditions in emerging markets. Net inflows to equity and debt markets predict subsequent output growth. Conversely, net portfolio outflows signal lower GDP growth. Also, direct investment capital flows present evidence of predictability over subsequent and one year-horizon, signaling a positive relationship between flows and output growth. These results could be related to the effect of demand shocks where an exogenous increase in investments will be associated with an increase in demand which

[18] Work by Haubrich and Dombrosky (1996), Dotsey (1998), and Kucko and Chin (2009) examine the evidence of the yield curve as predictor of future economic activity in the US and find that the predictive power of the yield curve has deteriorated in recent years.

[19] Note that in the case of the default spread we can not perform a precise comparison since we consider corporate bond yield spreads in the US, while in emerging markets we track spreads between local government debt instruments and US treasuries.

will be followed by an increase in economic activity.

When we extend our forecasting window to one and two years, we lose predictability in our aggregate measure of portfolio investment flows. Moreover, if we disaggregate further, we find a similar pattern in the case of debt security flows. On the other hand, fixed effects estimates for equity flows are economically and statistically significant when predicting one year ahead GDP growth. Similarly, slope coefficients for direct investment flows are positive and significant over one year horizon. We also find a reversal in the predictive relationship between capital flows and GDP when forecasting two years ahead.

As described in table 1.9, our country level results, when statistically significant, support findings for our pooled models. Both capital and portfolio investment flows present highly economically significant slope coefficients signaling a positive relationship between inflows and subsequent economic activity. [20]

Results for the US are strikingly different in the cases of capital and portfolio investment flow ratios. In particular, while we find a positive relationship between capital and portfolio flow ratios and future output growth in emerging markets, our results suggest that in the US, increases in the ratios of flows to GDP are followed by subsequent declines in output growth. On the other hand, net capital and portfolio outflows signal subsequent increases in GDP growth. This could be interpreted as a flight to quality effect. In periods of global turmoil, investors will move their capital away from riskier investments such as emerging markets, to safer allocations in the US.

1.4.4 Commodities

It is well known that commodity markets are a vital engine for economic growth in many emerging market countries. Periods of higher prices in international commodity markets are expected to be related to higher output growth, while market declines will negatively impact the growth prospects of many emerging economies. In table 1.6, panel A, we investigate the predictive power of commodity market returns at the global and sector level to forecast economic activity. The set of commodity sectors include

[20] The only exception is Turkey that presents a negative relationship between portfolio flows growth rate and subsequent GDP. This however, is economically meaningless.

agriculture, energy, livestock and precious metals. Overall, we find strong evidence of predictability both at the aggregate market level as well as across sectors. In particular, coefficients for commodity markets are economically and statistically significant across models and horizons at the aggregate level. Nevertheless, the predictive power of commodity market returns appears to be strongest when forecasting subsequent output growth. Given the inelastic nature of demand and supply for commodities, these findings could be interpreted in terms of the effect of demand shocks. As demand for commodities increases, commodity prices rise, having a positive impact on the terms of trade and output of the export countries. These results are in line with Chen et al. (2010) who find that commodity prices Granger-cause exchange rates in-sample when regressions are robust to parameter instability[21].

At the sector level, agricultural and precious metal commodities appear as the most economically significant predictors when forecasting subsequent GDP growth. Also results suggest a positive predictive relationship between energy commodities and future output, with economically and statistically significant coefficients across horizons. However, as we extend the forecasting horizon there is evidence of a decrease in the information content of sector commodity prices with regard to future economic growth. Furthermore, in the two-year forecasts, the livestock sector loses predictability across models.

Findings from our time series regressions validate our pooled results. Slope coefficients of commodity markets are statistically significant in twelve of our countries, suggesting a positive relationship between lagged returns on commodities and output growth. The only exception is Morocco that presents a negative slope coefficient. This result does not contradict our findings given the specific characteristics of this country. More than half of their GDP comes from the service sector while the industry sector represents around 30% of their output. All sector level predictive regressions point in the same direction as the aggregate market. Higher commodity prices are followed by higher economic growth in emerging markets. For example, we find a positive and significant relationship between energy prices and output growth for Russia, among other countries.

[21] They also analyze the reverse predictive relationship and find in and out-of-sample evidence that exchange rates are robust predictors of commodity prices.

We compare our results in emerging markets against the US. As shown in table 1.8, we find significant differences in the information content of commodity markets. While the performance of global and sector commodity markets convey information about future business conditions in our panel of developing countries, they show no forecasting ability when predicting output growth in the US. Slope coefficients are neither economically nor statistically significant. These results can be related to structural differences between the US and emerging market countries. While in the latter group, their economies are heavily dependent on commodities exports, growth in the US is mostly related to services (around 77% of its GDP) and the industry sector to a lesser extent (22%). Moreover, there is a large literature that finds evidence of predictability of energy commodities such as oil prices in the US (Hamilton, 2003, 2010). However, their results suggest a nonlinear relationship between oil prices and output growth.

1.4.5 US Interest Rates

A large literature finds that the US economy leads the cycle of many developed economies. Traditionally, trade has been considered the most common transmission channel. Periods of growth in the US would be accompanied by increases in its imports, which in turn would boost economic growth of the trade partner. An extreme example of this direct relationship could be Mexico, whose GDP growth is known to be highly correlated with that of the US. However, as financial markets become more integrated, they can be expected to be more relevant in the transmission of shocks from the US to the rest of the world.

In this section we also test whether expectations regarding the US economy, that are contained in interest rate aggregates, can help predict output growth in emerging countries. We find evidence that the term and default spreads contain information about subsequent GDP growth. In particular, the lagged US term spread has a positive relationship with future growth in emerging markets. Conversely, we find that increases in the US default spread are followed by subsequent declines in output growth. Furthermore, under the pooled and fixed effects settings, the predictive power of the term spread increases as we extend our forecasting horizon to two years. On the other hand, the default spread loses its predictive power as we move to longer term horizons.

The short interest rate, represented by the 3 month US treasury bill, shows no signs of predictability in the short term. However, its predictive power emerges when we look at a two years ahead forecasting horizon, where we find economically and statistically significant negative slope coefficients.

As described in table 1.9, evidence of predictability is limited when we look at individual time series regressions. Results on the term spread lack statistical significance across countries. The US short interest rate helps predict output growth only in the case of China. Finally, the default spread, has a economically and statistically significant negative relationship with growth only in 8 of our 22 countries.

1.4.6 Book-to-Market, Size, and The Market Portfolio

In this section we test whether well known factors such as book-to-market, size, and the market portfolio convey information about the future state of the real economy. As presented in table 1.7, we find strong evidence of the predictive power of the size factor and market portfolio. Slope coefficients for the size factor are economically and statistically significant across models over the one and two-year ahead forecasting horizons. Positive slope coefficients suggest that outperformance of small over large capitalization stocks precede periods of output growth. Conversely, periods in which large capitalization stocks dominate are followed by declines in future economic activity. As described in table 1.7, we also find a positive predictive relationship between returns on the market portfolio and future GDP growth. Slope coefficients are statistically significant across horizons, with one year ahead forecasts presenting the strongest economic significance. On the other hand, the book-to-market factor shows no evidence of predictive power over one quarter and one year horizons. Only when forecasting two years ahead, and in the context of the forward demeaning model, we find a negative relation between book-to-market and future output growth.

These results confirm and extend some previous findings of Liew and Vassalou (2000). Using time-series regression analysis and Fama and French risk factors (Fama and French (1993)), they test for output growth predictability in a group of 10 developed markets. They document that the book-to-market, the size factor, and market portfolio are positively related to future GDP growth. In the context of emerging markets, we find similarities in the cases of the size factor and market portfolio, where both variables contain information about the future state of the real economy. On the other hand, our results differ in the case of the book-to-market ratio, where we find only mild evidence of predictability.

1.5 Robustness Analysis

In this section we perform a series of additional exercises to evaluate the robustness of our results to different scenarios. We first allow for global innovations in our data generating process. Secondly, we split our sample into sub-periods, 1992-1999 and 2000-2010. We then test for output growth predictability at the regional level. We also group our set of countries based on GDP per capita. We then run our analysis in a multivariate setting. Finally, we perform a cross-validation exercise to check the stability of our results.

As in our baseline scenario, we run bivariate regressions including lagged GDP growth and the variable of interest as regressors[22]. We also normalized our series by their standard deviation to allow for comparison across variables.

1.5.1 Accounting for Common Factors

We use Hjalmarsson's (2010) framework that in addition to idiosyncratic factors allows for the effect of common shocks to returns and proposes a set of pooled estimators that are robust to cross-sectional dependence. This could be of particular relevance when considering the phenomenon of emerging markets, since these countries are known to be more vulnerable to external shocks and episodes of contagion. As a result, it is reasonable to consider that there will be shocks to output growth that will impact the asset class as a whole while others will be country-specific.

[22]For convenience we only report results for our set of financial predictors. Results for lagged GDP coefficients are available upon request.

The data generating process accounting for common factors can be described as follows:

$$y_{i,t} = \alpha_i + \beta' x_{i,t-1} + u_{i,t} + \delta_i' f_t \tag{1.10}$$

$$x_{i,t} = A_i x_{i,t-1} + v_{i,t} + \Gamma_i' z_t$$

$$z_t = A_g z_{i,t-1} + g_t$$

$$A_g = I + C_g/T$$

Where f_t represents the common factor in the error term, and z_t is the common term in the predictor $x_{i,t}$. z_t is an AR(1) process with near unit roots defined by A_g[23].

To perform estimation and inference in our panel setting we use the following estimators that account for common factors:

Robust Pooled Estimation:

$$\hat{\beta}_{RP} = \left(\sum_{i=1}^{n} X_{i,-1}' M_{\bar{H}} X_{i,-1} \right)^{-1} \left(\sum_{i=1}^{n} X_{i,-1}' M_{\bar{H}} Y_i \right) \tag{1.11}$$

$$M_{\bar{H}} = I - \bar{H}(\bar{H}'\bar{H})^{-1}$$

where Y_i is T x 1, X_i is T x m and $\bar{H}$ is also T x m with $\bar{H}_t = \frac{1}{n}\sum_{i=1}^{n} x_{i,t-1}$

Robust Fixed Effects Estimation:

$$\hat{\beta}_{RFE} = \left(\sum_{i=1}^{n} \underline{\hat{X}}_{i,-1}' \underline{\hat{X}}_{i,-1} \right)^{-1} \left(\sum_{i=1}^{n} \underline{\hat{X}}_{i,-1} \underline{\hat{Y}}_i \right) \tag{1.12}$$

with $\hat{Y}_i$=$M_{\bar{H}} Y_i$, $\hat{X}_{i,-1}$=$M_{\bar{H}} X_{i,-1}$, and $\underline{\hat{Y}}_i$ and $\underline{\hat{X}}_{i,-1}$ being their demeaned versions.

Robust Recursive Demeaning Estimation:

$$\hat{\beta}_{RRD} = \left(\sum_{i=1}^{n} \hat{X}_{i,-1}'^{dd} \hat{X}_{i,-1} \right)^{-1} \left(\sum_{i=1}^{n} \hat{X}_{i,-1}' \hat{Y}_i^{dd} \right) \tag{1.13}$$

where $\hat{Y}_i^{dd}$ and $\hat{X}_{i,-1}'^{dd}$ are the recursively demeaned versions of $\hat{Y}_i$ and $\hat{X}_{i,-1}$.

Table 1.10 presents results for this new setting. As in our baseline case, we run bivariate regressions including lagged GDP and the variable of interest to forecast

[23] All variables defined in the estimation section remained unchanged.

subsequent GDP growth[24]. Overall, our baseline results are validated when we allow for common factors. In particular, our set of valuation measures, interest rates and flow aggregates present similar patterns as in table 1.4. We find a positive predictive relationship between stock returns and subsequent output growth. On the other hand, our measure of capitalization ratio shows no evidence of predictability. Similarly, the dividend yield and price-earnings ratio do not present any predictive power when we allow for individual effects and correct for endogeneity and persistence. We also find that the term spread and real short interest rate convey information about future economic activity. However, under this new setting the government default spread lose its predictive power. Finally, results for capital and portfolio flows also suggest a strong positive relationship with future economic growth in emerging markets.

1.5.2 Sub-sample Analysis

Our sample encompasses very different market conditions. Starting in the early stages of this new asset class, we cover the financial liberalization process of many developing countries, the Tequila crisis (1995), the Asian crisis (1997), the Ruble crisis (1998), the Tech bubble (1999-2000), the expansion of the European Union (2004), the rise of China as well as the last global financial and economic crisis, among other key episodes. As described in table 1.11, we split our sample into two sub-periods, 1993-1999 and 2000-2010, to test for output growth predictability under different business conditions.

Overall, we find that financial aggregates that lead economic growth in our baseline case are validated when we test for predictability in our subsample analysis. Results for stock returns, the term spread, dividend yield and capital flows ratio, among other variables, present some similar patterns in both subsamples. However, there are differences. For example, the real short interest rate, portfolio investment flows and returns on global commodity markets show evidence of predictability only in the last decade, a period of higher economic growth and stronger stock market performance [25]. At the commodity sector level, results also suggest that energy

[24]For convenience we only present estimates and t-statistics for our set of country-specific variables. Results for lagged GDP are available upon request.

[25]During 2000-2010, emerging markets' annual average GDP growth reached 5.7% while for

and livestock commodities convey information about output growth only during the 2000-2010 period. On the other hand, we also find that the price-earnings ratio, an aggregate that lacks predictive power in our baseline scenario, presents evidence of predictability during the 90's, signaling a positive relationship with GDP growth. However, predictability vanishes in the last decade when correcting for the small sample bias.

The most striking differences between our subsample and baseline results are related to our set of risk factors. In particular, in our baseline setting estimates for the book-to-market factor lack statistical significance when forecasting subsequent GDP growth. However, when we split our sample we find evidence of predictability. Results suggest a negative predictive relationship during the 90's while, in line with previous findings in developed countries (Liew and Vassalou (2000)), it becomes positive during the last decade.

Finally, we also test for output growth predictability excluding the period covering the last global crisis. Overall, we find similar patterns as in our baseline results. However, the dividend yield that lacks any predictive power in our baseline case, now shows evidence of predictability even when correcting for the small sample bias. Results suggest a negative predictive relationship with future GDP growth. Also, although the direction of the relationships remains unchanged, we find slight differences in the predictive power of the term spread and commodity returns. The information content of the term spread decreases when we include the period covering the crisis. On the other hand, the predictive power of returns on commodity markets increases when we consider the full sample in our analysis.

1.5.3 Regional Analysis

To gain further insights on the relationship between financial aggregates and future economic activity we split our panel of countries according to their geographic location. Following standard classifications we define three different regions, Asia,

1993-1999 GDP growth was 3.7%. Also, average annual returns on emerging equity markets represented by the MSCI Emerging Markets index was 17.6% for the last decade versus 14% during the 90's. In terms of stock market volatility, we find similar volatility levels (39.5% and 40.3%) across sub-samples.

Latin America and EMEA (Europe, Middle East and Africa)[26]. We find strong evidence that our set of financial aggregates can be used as leading indicators of economic activity across regions. However, Latin America presents the strongest evidence of output growth predictability overall. As table 1.12 shows, results suggest that return and valuation measures such as stock returns and capitalization ratio have the strongest forecasting ability in Latin America. In particular, slope coefficients are economically more significant in this region than in Asia and EMEA. Also, portfolio investment flows measured as a ratio of flows to GDP, although economically and statistically significant across regions, presents the strongest results in Latin America. As in our baseline case, we find a positive relationship between lagged portfolio flows and GDP growth. Furthermore, interest rate variables such as the short interest rate and the term spread also proved to have higher predictive power in this region than in the rest of the group. On the other hand, we find that the information content about future economic activity of the default spread and capital flows is the strongest in Asia, while returns on global commodity markets appear to play a bigger role in EMEA.

For robustness we also test for predictability in Asia excluding China, a key driver of regional and global growth in the past years. The goal is to analyze whether the predictive relationships in the region are mainly driven by this country. Overall, results present similar predictive relationships in both scenarios. However, we do find a slight decrease in the information content of stock return when we exclude China. Conversely, the predictive power of the default spread and global commodity returns improves under this new scenario.

1.5.4 GDP per Capita

As part of our robustness analysis we split our sample based on GDP per capita. We grouped the countries in our sample into three categories, high, middle and low income [27]. Table 1.13 presents results for this new setting. Overall, results for our set of

[26]Asia includes China, Indonesia, India, South Korea, Malaysia, Philippines, Taiwan and Thailand. Czech Republic, Egypt, Hungary, Israel, Morocco, Poland, Russia, South Africa and Turkey Represent the EMEA region. In Latin America we consider Argentina, Brazil, Chile, Mexico and Peru.

[27]High income is composed by countries with a PPP-adjusted GDP per capita higher than 13,000 USD per year. This group includes Taiwan, South Korea, Israel, Czech Republic, Hungary and Poland. GDP per capita for middle income countries ranges from 13,000 to 9,000 USD per year. Russia, Argentina,

financial aggregates are validated. However, we do find some differences across groups. In particular, stock and commodity returns present the strongest predictive power in our group of middle income countries. Flows prove to be a helpful predictor across groups, with strongest economic significance in low income countries. On the other hand, the set of interest rate variables show evidence of predictability only in the middle and low income countries.

1.5.5 Multivariate Regressions

In this section we test the predictive power of the set of financial aggregates to forecast GDP growth in a multivariate setting. In doing so we group our variables into four categories. Namely, return and valuation measures, interest rates, flows and commodities. We use principal component analysis to reduce the number of predictors while still accounting for most of the variance in the observed variables. As shown in table 1.14, results suggest that our four set of variables can be useful predictors of output growth. In particular, coefficients related to our return and valuation measures are positive and significant when forecasting subsequent and one year ahead GDP. Commodities present similar patterns, with estimates signaling a positive relationship with future output. On the other hand, interest rate variables show a negative predictive relationship with subsequent GDP. Finally, there is a reversal in the predictive relationship of flows and GDP. While results suggest a positive relationship in the short term, coefficients are statistically significant and negative when forecasting two years ahead.

1.5.6 Cross-Validation Analysis

For robustness, we also perform a cross validation exercise to check the stability of our estimates. The goal is to study whether results are driven by a particular country. In a bivariate setting that includes lagged GDP and the variable of interest as the regressors, we randomly exclude three countries from our sample and estimate

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Chile, Malaysia, Mexico, Turkey, Brazil and South Africa fall in this category. GDP per capita for low income countries covers those with less than 9,000 USD per year. In this group we consider Peru, Thailand, China, Egypt, Morocco, Indonesia, Philippines and India.

coefficients and t-statistics. We repeat this exercise twenty times for each variable. Table 1.15 presents results for this analysis[28]. For each variable we report the average estimate, its standard deviation and the number of times (out of the twenty random draws) that the coefficient is statistically significant. Results provide evidence in favor of the stability of our estimates across models and horizons. The predictive ability of the variables that proved helpful in our baseline case are validated by this analysis.

1.6 Conclusion

This paper provides empirical evidence on the predictive dynamics of emerging market growth. We ask whether there is information content in financial aggregates that allows us to predict economic growth in emerging markets. To tackle this question, we develop a comprehensive dataset on output growth, country-specific and global financial aggregates for a large panel of developing economies. We document empirically that financial aggregates can be used as leading indicators of economic activity in emerging markets.

We find evidence that stock returns, flows, the term spread and default spreads, among other aggregates, convey information about the future state of the economy. In particular, our analysis of portfolio flows suggests that investors are well informed about future economic conditions in emerging markets. Large financial inflows into local debt and equity securities precede periods of higher GDP growth. Conversely, net outflows are followed by declines in economic activity. We do not take a stand on whether this is a causal relation or whether it simply reflects information in forward-looking financial aggregates.

Empirical results also suggest that some variables, such as capital flows, stock returns and the term spread, have a stronger predictive power during the 90's. Conversely, portfolio investment flows, proved more useful during the last decade. Furthermore, our regional level analysis shows that Latin America presents the strongest evidence of output growth predictability across our sample of emerging markets.

[28]For convenience, we only present results for financial aggregates. Results for lagged GDP are available upon request.

We argue that a set of global and regional financial aggregates can be useful predictors of GDP growth in these transitional economies. We find evidence of the predictive power of global commodity prices, US interest rates and a set of regional return-based risk factors. Specifically, higher prices in international commodity markets positively impact the growth prospect of developing countries that heavily rely on exports of raw materials. These results are validated at the commodity sector level. Related to our risk factors, results indicate that greater outperformance of small capitalization stocks precedes periods of higher output growth, as do higher returns on the regional market portfolio. Also, our findings suggest that economic developments in the US will impact output growth of these transitional economies. In particular, information about the US business cycle contained in interest rate aggregates, such as the term spread, appear to predict economic activity in our panel of developing countries.

Finally, we compare results for emerging markets and the US and find that there are differences in information flows and the role of capital markets in predicting economic growth. In particular, the term spread, stock market returns, and global commodity prices that conveyed information about future business conditions in emerging markets show no forecasting ability when predicting output growth in the US. Further, while we find a positive relationship between capital and portfolio flow ratios and future output in these transitional economies, results for the US suggest that increases in these ratios are followed by subsequent declines in GDP growth. These findings could be interpreted as a flight to quality effect where in periods of global turmoil investors move their capital away from riskier investments to safer allocations in developed markets.

Overall, by identifying a set of financial aggregates that convey information on future output growth, our analysis sheds light on the relationship between the state of the economy and financial markets in developing economies. These findings could be of great benefit to policy makers and market participants who try to understand and predict the business cycles of emerging markets.

Table 1.1: **Quarterly GDP Growth Summary Statistics**

This table shows descriptive statistics for real seasonally adjusted GDP growth of emerging market countries. AR(1) represents the autocorrelation coefficient. The sample spans from December 1992 to March 2010. GDP series are at the quarterly frequency.

Country	**Dates**	**Obs.**	**Mean**	**StdDev**	**Skewness**	**Kurtosis**	**AR(1)**
Argentina	Q1 1993-Q1 2010	68	0.896	2.940	-0.055	11.379	0.3546
Brazil	Q1 1995-Q1 2010	60	0.859	2.435	0.758	16.564	-0.244
China	Q4 1999-Q4 2009	40	3.047	2.326	4.222	24.328	0.0495
Chile	Q1 1996-Q4 2009	55	0.887	1.226	-1.099	5.078	0.307
Czech Republic	Q1 1994-Q1 2010	64	0.839	1.585	0.999	9.080	0.076
Egypt	Q1 2002-Q4 2009	31	1.312	1.246	1.143	4.890	-0.2657
Hungary	Q1 1995-Q1 2010	60	0.659	1.050	-1.409	6.071	0.5148
Indonesia	Q1 1997-Q1 2010	52	0.862	2.256	-4.002	19.399	0.4188
India	Q1 2004-Q4 2009	50	1.408	1.891	0.212	3.985	0.4869
Israel	Q4 1992-Q1 2010	69	1.005	1.598	0.322	3.546	-0.1459
Korea	Q4 1992-Q4 2009	68	1.220	1.876	-2.862	16.598	0.1797
Malasya	Q4 1992-Q4 2009	68	1.340	1.700	-1.477	5.785	0.5994
Mexico	Q4 1992-Q1 2010	69	0.608	1.698	-2.338	9.797	0.3369
Morocco	Q4 1992-Q4 2009	68	1.099	4.160	0.499	5.463	-0.4559
Peru	Q4 1992-Q4 2009	68	1.283	1.526	-0.626	2.832	0.3127
philippines	Q4 1992-Q1 2010	69	1.284	1.271	3.023	20.185	0.1233
Poland	Q1 1995-Q4 2009	59	1.141	1.525	0.039	6.921	-0.2384
Russia	Q1 1995-Q3 2009	58	0.887	2.551	-2.316	11.466	0.097
South Africa	Q4 1992-Q4 2009	68	1.131	1.689	0.319	6.888	-0.0804
Taiwan	Q4 1992-Q1 2010	69	1.165	1.604	-1.621	8.458	0.3495
Thailand	Q1 1993-Q1 2010	68	1.004	2.067	-0.855	5.238	0.393
Turkey	Q4 1992-Q4 2009	68	0.976	2.870	-1.109	4.377	0.075

Table 1.2: **Autocorrelation Coefficients for Financial Aggregates.**

This table shows country-specific and global autocorrelation coefficients for the set of financial aggregates. Panel A presents coefficients for stock returns and valuation measures, illustrating the high persistence in the Capitalization Ratio, Dividend Yield, and P/E Ratio time series. Panel B describes autocorrelation coefficients for global variables related to commodity markets.

	Panel A: Returns and Valuation Measures			
	Stock Ret.	**Cap.Ratio**	**DY**	**PE Ratio**
Argentina	-0.121	0.726	0.830	0.825
Brazil	-	0.890	0.801	0.284
Chile	0.289	0.863	0.783	0.881
China	0.052	0.862	0.781	0.560
Czech Republic	-	0.867	0.815	0.590
Egypt	-	0.887	0.882	0.688
Hungary	0.068	0.726	0.749	0.274
Indonesia	-0.010	0.798	0.660	0.709
India	0.210	0.744	0.789	0.907
Israel	-0.077	0.912	0.784	0.134
Korea	0.037	0.891	0.718	0.714
Malasya	-0.118	0.867	0.822	0.828
Mexico	0.051	0.879	0.695	0.666
Morocco	0.102	0.919	-	-
Peru	0.059	0.917	0.723	0.726
philippines	0.057	0.861	0.839	0.783
Poland	0.343	0.932	0.845	0.581
Russia	-0.044	0.946	0.661	0.594
South Africa	-0.086	0.897	0.788	0.831
Taiwan	-0.060	-	0.884	0.806
Thailand	-0.104	0.901	0.743	0.670
Turkey	0.029	0.850	0.632	0.254
US	0.117	0.901	0.926	0.793
	Panel B: Global Aggregates			
Commodities	0.032			
Agriculture	0.001			
Energy	-0.052			
Livestock	-0.243			
Precious Metals	0.024			

Table 1.2: Autocorrelation Coefficients for Financial Aggregates (cont.)

This table shows country-specific and global autocorrelation coefficients for the default spread, the term spread and the short interest rate, with the latter two time series illustrating high levels of persistence.

	Panel C: Interest Rates		
	Default Spread	**Term Spread**	**Short Interest Rate**
Argentina	0.185	0.623	0.541
Brazil	0.151	0.571	0.704
Chile	-0.043	-	0.943
China	0.063	0.734	0.619
Czech Republic	-	0.615	0.808
Egypt	0.057	-	0.810
Hungary	0.088	0.642	0.741
Indonesia	0.324	-	0.541
India	-	-	0.755
Israel	-	-	0.816
Korea	0.021	0.767	0.893
Malasya	0.188	0.677	0.684
Mexico	0.168	0.637	-0.081
Morocco	0.001	0.796	0.742
Peru	0.093	0.786	0.727
Philippines	0.063	0.616	0.774
Poland	-0.015	0.930	0.853
Russia	0.130	0.586	0.321
South Africa	0.121	0.824	0.864
Taiwan	-	-	0.726
Thailand	-	0.822	0.713
Turkey	-0.091	0.422	0.595
US	0.082	0.863	0.818

Table 1.2: Autocorrelation Coefficients for Financial Aggregates (cont.)

This table shows country-specific and global autocorrelation coefficients for our measures of portfolio and capital flows.

	Panel D: Flows		
	Portfolio Flows (%)	**Capital Flows Ratio**	**Portfolio Flows Ratio**
Argentina	-0.031	0.756	0.410
Brazil	-0.090	0.323	0.103
China	-	0.064	-
Czech Republic	0.000	0.215	0.279
Hungary	-0.026	0.046	-0.056
Indonesia	-0.002	0.500	0.116
India	0.087	0.542	0.368
Israel	-0.018	0.364	0.160
Korea	-0.034	0.321	0.412
Malasya	0.017	0.199	0.273
Mexico	-0.015	0.339	0.418
Morocco	-0.125	-0.255	0.056
Peru	0.000	0.387	0.030
Philippines	-0.038	0.253	0.191
Poland	-0.042	0.302	0.248
Russia	-0.073	0.372	0.335
South Africa	0.055	0.470	0.208
Thailand	0.012	0.672	0.151
Turkey	-0.015	0.392	0.308
US	-0.018	0.491	0.512

Table 1.3: **Cross-correlation Coefficients for Financial Aggregates**
This table shows correlation coefficients of the error terms in the predictive regression and the predictor's first-order autoregressive process. Panel A presents results for stock returns and valuation measures. Coefficients in bold indicate statistical significance at the 5%.

	Panel A: Returns and Valuation Measures			
	Stock Returns	**Capitalization Ratio**	**Dividend Yield**	**PE Ratio**
Argentina	0.039	0.157	-0.061	0.158
Brazil	-	**0.299**	-0.063	-0.004
Chile	-0.105	-0.026	-0.031	0.059
China	-0.008	0.124	-0.193	0.009
Czech Republic	-	**0.338**	**-0.201**	0.012
Egypt	-	0.040	**0.281**	0.050
Hungary	-0.019	-0.157	0.168	0.015
India	0.003	0.013	0.004	-0.057
Indonesia	0.012	0.073	-0.093	-0.093
Israel	0.005	**0.197**	-0.011	0.037
Korea	-0.004	**0.431**	**-0.246**	**0.262**
Malasya	0.051	0.140	-0.163	-0.117
Mexico	-0.019	**0.445**	-0.127	0.058
Morocco	0.002	-0.020	-	-
Peru	0.000	**0.285**	-0.111	-0.108
philippines	0.005	0.060	0.113	0.055
Poland	0.001	0.019	-0.161	0.012
Russia	0.016	**0.344**	-0.232	0.033
South Africa	0.015	-0.031	-0.128	0.019
Taiwan	0.042	-	**-0.390**	**0.275**
Thailand	0.021	**0.344**	0.013	0.043
Turkey	-0.017	**0.244**	**-0.288**	-0.011
US	-0.049	**0.223**	**-0.373**	**-0.214**

Table 1.3: Cross-correlation Coefficients for Financial Aggregates (cont.)

This table shows correlation coefficients of the error terms in the predictive regression and the predictor's first-order autoregressive process. Panel B presents results for the interest rate variables. Coefficients in bold indicate statistical significance at the 5%.

	Panel B: Interest Rates		
	Default Spread	**Term Spread**	**Short Interest Rate**
Argentina	0.013	-0.176	0.034
Brazil	0.012	**0.304**	-0.215
Chile	-0.001	-	-0.008
China	0.003	-0.191	-0.088
Czech Republic	-	-0.083	-0.069
Egypt	0.153	-	-0.142
Hungary	0.001	0.158	0.036
India	0.067	-	0.157
Indonesia	-	-	0.075
Israel	-	-	0.005
Korea	0.006	-0.037	0.184
Malasya	0.037	0.119	0.013
Mexico	0.048	-0.079	-0.025
Morocco	-0.024	-0.104	0.160
Peru	-0.013	0.018	0.127
philippines	-0.037	-0.086	0.083
Poland	0.017	-0.160	0.160
Russia	0.008	0.097	-0.079
South Africa	0.026	0.166	**-0.268**
Taiwan	-	-	-0.152
Thailand	-	0.003	-0.160
Turkey	-0.008	-0.125	-0.083
US	0.012	-0.125	-0.157

Table 1.3: Cross-correlation Coefficients for Financial Aggregates (cont.)

This table shows correlation coefficients of the error terms in the predictive regression and the predictor's first-order autoregressive process. Panel C presents results for our measures of net flows. Coefficients in bold indicate statistical significance at the 5%.

	Panel C: Flows		
	Portfolio Flows (%)	**Capital Flows Ratio**	**Portfolio Flows Ratio**
Argentina	-0.029	0.124	0.010
Brazil	-0.004	0.072	0.008
China	-	-0.003	-
Czech Republic	-0.004	-0.031	0.001
Hungary	-0.006	-0.025	-0.010
India	-0.003	-0.032	-0.043
Indonesia	-0.011	0.285	-0.064
Israel	0.001	0.013	0.005
Korea	0.000	0.025	0.054
Malasya	0.002	-0.048	-0.099
Mexico	-0.002	0.070	0.083
Morocco	-0.013	-0.079	0.003
Peru	0.016	0.050	-0.007
philippines	-0.002	0.056	0.008
Poland	0.033	0.018	0.060
Russia	0.026	0.061	0.025
South Africa	0.003	0.119	0.013
Thailand	-0.005	-0.025	0.006
Turkey	-0.003	0.001	-0.041
US	-0.001	0.059	0.140

Table 1.4: **Output Growth Predictability: Pooled Estimation Results**

This table shows estimated coefficients and t-statistics for our standard pooled, fixed effects, and forward demeaning output growth estimation. The predictive regressions are estimated variable-by-variable in a bivariate setting that also includes lagged GDP growth. Panel A describes results for one quarter ahead forecasts, while Panel B and C for one and two years ahead forecasting horizons. Coefficients in bold indicate statistical significance at the 5% level or better.

	Panel A One Quarter Ahead			Panel B One Year Ahead			Panel C Two Years Ahead		
	Pooled	FE	FD	Pooled	FE	FD	Pooled	FE	FD
Stock Returns (%)	**0.51**	**0.51**	**0.49**	**0.62**	**0.67**	**0.62**	**0.36**	**0.44**	**0.40**
	7.53	8.08	6.87	5.39	6.23	5.19	3.72	4.39	3.99
Capitalization Ratio	-0.04	0.01	0.22	-0.08	**-0.12**	0.11	-0.07	-0.13	0.11
	-0.67	0.24	0.79	-1.49	-2.66	0.59	-1.56	-1.50	0.86
Dividend Yield	**-0.27**	**-0.30**	-0.30	-0.07	-0.06	0.58	-0.02	0.02	1.40
	-4.51	-3.59	-0.59	-1.24	-0.77	0.43	-0.38	0.30	0.59
PE Ratio	0.05	0.06	0.06	-0.01	0.01	-0.02	0.05	**0.07**	0.01
	1.58	1.89	1.62	-0.27	0.38	-0.60	1.56	2.60	0.21
Short Interest Rate	-0.10	-0.09	-0.12	-0.01	0.04	-0.04	0.01	0.01	-0.12
	-1.30	-1.12	-1.24	-0.06	0.39	-0.36	0.21	0.19	-0.83
Term Spread	**0.28**	**0.47**	**0.33**	**0.22**	**0.47**	0.24	0.10	0.23	0.04
	3.70	4.94	4.41	2.44	2.35	1.94	1.06	1.20	0.22
Default Spread	**-0.43**	**-0.45**	**-0.36**	**-0.42**	**-0.53**	-0.29	**-0.16**	**-0.32**	**0.35**
	-3.98	-4.15	-3.09	-3.80	-5.06	-1.59	-2.29	-4.54	2.14
Capital Flows Ratio	**0.26**	**0.34**	**0.43**	-0.05	-0.04	0.10	**-0.19**	**-0.29**	-0.14
	2.76	3.10	3.47	-1.16	-0.55	1.39	-4.48	-3.56	-1.79
Portfolio Flows Ratio	**0.29**	**0.30**	**0.30**	0.10	0.10	0.11	-0.03	-0.05	-0.01
	3.12	3.21	3.14	1.45	1.30	1.38	-0.68	-0.74	-0.11

Table 1.5: **Portfolio and Direct Investment Capital Flow Ratios**

This table presents slope coefficients and t-statistics for our standard pooled, fixed effects, and forward demeaning models. We test the predictive power of net inflows related to direct investment capital, debt, and equity securities. over subsequent, one-year, and two-years ahead periods. Direct investment capital is the sum of direct investment abroad and direct investment in the reporting economy. Debt Securities is the net sum of both inflows and outflows of assets and liabilities covering fixed income instruments. Equity Securities is the sum of assets and liabilities covering stocks, and similar instruments that represent ownership of equity. We run bivariate regressions that include the variable of interest and lagged GDP growth. Coefficients in bold indicate statistical significance at the 5% level or better.

	One Quarter Ahead			One Year Ahead			Two Years Ahead		
	Pooled	**FE**	**FD**	**Pooled**	**FE**	**FD**	**Pooled**	**FE**	**FD**
Debt Securities	**0.13**	**0.14**	**0.19**	-0.02	-0.05	0.07	-0.09	-0.15	0.03
	2.43	2.61	3.79	-0.38	-0.59	0.67	-1.67	-1.95	0.30
Direct Investment	0.04	0.08	**0.14**	0.02	**0.12**	0.11	-0.04	0.09	0.02
	0.81	1.29	2.33	0.51	2.12	1.80	-1.21	0.88	0.13
Equity Securities	**0.15**	**0.16**	0.06	0.12	**0.15**	-0.07	0.09	0.12	-0.31
	2.30	2.29	0.81	1.81	2.07	-0.73	1.23	1.14	-1.49

Table 1.6: **Global Aggregates**

This table presents slope coefficients and t-statistics for our standard pooled, fixed effects, and forward demeaning output growth estimation when we test the predictive power of global financial aggregates. Panel A tests the predictive power of the performance of commodity markets while Panel B describes results for the set of US interest rates variables. Regressions are estimated variable-by-variable in a bivariate setting that also includes lagged GDP growth.

	One Quarter Ahead			**One Year Ahead**			**Two Years Ahead**		
Panel A: Commodity Markets									
	Pooled	**FE**	**FD**	**Pooled**	**FE**	**FD**	**Pooled**	**FE**	**FD**
Commodity Index (%)	**0.39**	**0.40**	**0.41**	**0.22**	**0.28**	**0.34**	**0.15**	**0.21**	**0.37**
	7.00	7.30	6.71	3.00	4.23	5.00	2.36	3.37	5.21
S&P Agricultural Index (%)	**0.35**	**0.35**	**0.39**	**0.18**	**0.21**	**0.35**	0.01	0.03	**0.38**
	9.00	9.07	10.16	2.36	2.84	6.38	0.21	0.62	12.85
S&P Energy Index (%)	**0.30**	**0.31**	**0.31**	**0.17**	**0.22**	**0.25**	0.11	**0.15**	**0.23**
	5.11	5.40	4.91	2.72	4.07	4.39	1.95	2.84	3.38
S&P Livestock Index (%)	**0.16**	**0.16**	**0.14**	**0.21**	**0.24**	**0.19**	0.06	0.10	0.01
	2.71	2.82	2.51	3.08	3.49	2.80	0.91	1.55	0.18
S&P Metal Index (%)	**0.37**	**0.36**	**0.47**	**0.30**	**0.30**	0.19	**0.20**	**0.20**	0.12
	6.50	6.57	11.66	4.67	4.56	0.65	3.55	3.19	0.31
Panel B: US Interest Rates									
Moody's Default Spread	**-0.23**	**-0.27**	0.09	0.00	-0.07	-0.23	0.10	0.04	-0.40
	-3.36	-4.13	0.33	-0.01	-0.86	-1.55	1.68	0.71	-1.86
US T-bill	-0.03	-0.04	-0.02	-0.05	-0.06	0.02	**-0.14**	**-0.15**	0.07
	-0.60	-0.68	-0.25	-0.91	-1.09	0.37	-2.80	-2.94	1.69
US Term Spread	**0.09**	**0.09**	**0.17**	**0.10**	**0.08**	0.08	**0.21**	**0.20**	0.10
	2.21	2.04	2.08	2.39	2.04	0.85	4.12	3.89	1.26

Table 1.7: **Size, Style and Market Risk Factors**

This table presents slope coefficients and t-statistics for our standard pooled, fixed effects, and forward demeaning models when we test the predictive power of Fama and French factors for Emerging Markets. We test for subsequent, one-year, and two-years ahead output growth predictability. Regressions are estimated variable-by-variable in a bivariate setting that also includes lagged GDP growth. Coefficients in bold indicate statistical significance at the 5% level or better.

	One Quarter Ahead			One Year Ahead			Two Years Ahead		
	Pooled	**FE**	**FD**	**Pooled**	**FE**	**FD**	**Pooled**	**FE**	**FD**
Size	-0.01	-0.03	-0.08	**0.39**	**0.36**	**0.37**	**0.47**	**0.45**	**0.52**
	-0.21	-0.41	-1.23	4.55	4.00	3.64	7.11	6.62	7.91
Book-to-Market	0.10	0.10	0.05	0.05	0.08	-0.05	-0.04	-0.03	**-0.37**
	1.73	1.80	0.79	1.17	1.89	-0.88	-0.89	-0.59	-5.72
Market	**0.55**	**0.56**	**0.55**	**0.59**	**0.65**	**0.67**	**0.28**	**0.37**	**0.47**
	8.38	8.62	8.82	8.49	9.82	9.19	4.03	5.36	6.65

Table 1.8: **Output Growth Predictability in the US**

This table presents estimation results for the US over the period covering December 1992 to March 2010. For each variable we run bivariate regressions that include lagged GDP growth. We report estimates and t-statistics of the variable of interest and lagged GDP growth. Panel A shows results for returns and valuation measures, Panel B for our set of interest rates variables, Panel C for flows, Panel D for performance of global and sector commodity markets and Panel E for Fama and French risk factors.

	Beta	T-stat	Beta GDP	T-stat
Panel A: Return and Valuation Measures				
Stock Returns (%)	0.14	1.80	0.25	2.09
Capitalization Ratio	0.00	-0.01	0.31	2.35
Dividend Yield	-0.04	-0.63	0.30	2.39
PE Ratio	0.03	0.38	0.33	2.04
Panel B: Interest Rates				
Short Interest Rate	0.18	1.90	0.26	2.39
Term Spread	0.00	-0.08	0.31	2.47
Default Spread	**-0.27**	-3.17	0.12	1.14
Panel C: Flows				
Capital Flows Ratio	**-0.16**	-2.04	0.30	2.23
Portfolio Flows Ratio	**-0.13**	-2.12	0.29	2.35
Panel D: Commodity Markets				
Commodity Index (%)	-0.04	-0.46	0.33	2.59
S&P Agricultural Index (%)	-0.02	-0.27	0.32	2.51
S&P Energy Index (%)	-0.05	-0.65	0.33	2.55
S&P Livestock Index (%)	0.05	0.98	0.31	2.48
S&P Metal Index (%)	-0.02	-0.34	0.31	2.48
Panel E: Risk Factors				
Book-to-market	0.06	0.73	0.31	2.24
Size	-0.24	-3.00	0.22	1.77

Table 1.9: **Country Level Estimation**

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels A through E cover returns and valuation measures.

Panel A: Dividend Yield	**Slope**	**T-stat**	**Obs.**	**Panel B: PE ratio**	**Slope**	**T-stat**	**Obs.**
Argentina	**-0.466**	-2.021	68	Argentina	0.104	1.874	68
Brazil	**-0.437**	-2.156	60	Brazil	-0.027	-0.586	60
China	0.841	1.636	40	China	**-0.051**	-2.449	40
Chile	-0.435	-1.443	55	Chile	0.081	0.860	55
Czech Republic	-0.042	-0.555	60	Czech Republic	0.003	0.729	60
Egypt	-0.080	-1.717	28	Egypt	**0.081**	2.262	28
Hungary	**-0.559**	-4.004	60	Hungary	**-0.003**	-3.006	60
Indonesia	-0.058	-0.238	52	Indonesia	0.030	0.656	52
India	0.748	1.220	50	India	-0.028	-0.442	50
Israel	-0.124	-1.169	65	Israel	0.000	0.234	43
South Korea	**-1.861**	-2.959	68	South Korea	**0.108**	2.895	68
Malaysia	**-0.477**	-2.676	68	Malaysia	**0.088**	2.503	68
Mexico	**-1.915**	-2.684	69	Mexico	0.005	0.043	69
Peru	-0.216	-1.735	64	Peru	**0.037**	2.103	67
Philippines	0.439	1.910	69	Philippines	0.003	0.193	69
Poland	-0.090	-0.708	59	Poland	-0.005	-0.181	59
Russian Federation	-1.154	-1.771	51	Russian Federation	**0.061**	3.434	54
South Africa	0.382	1.047	51	South Africa	-0.027	-0.506	68
Taiwan	-0.172	-1.033	69	Taiwan	**0.059**	2.223	69
Thailand	**-0.499**	-2.405	68	Thailand	0.041	1.487	68
Turkey	-0.251	-0.585	68	Turkey	0.001	1.404	68

Table 1.9: Country Level Estimation

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels A through E cover returns and valuation measures.

Panel C: Capitalization	**Slope**	**T-stat**	**Obs.**	**Panel D: Capitalization Ratio**	**Slope**	**T-stat**	**Obs.**
Argentina	**0.085**	3.082	68				
Brazil	**0.040**	2.462	60	Argentina	**18.867**	2.304	68
China	-0.002	-0.143	40	Brazil	0.452	1.572	60
Chile	0.030	1.587	55	China	0.030	0.172	40
Czech Republic	0.008	0.761	60	Chile	0.446	1.283	55
Egypt	0.010	1.016	31	Czech Republic	-0.897	-1.105	60
Hungary	**0.000**	-9.419	60	Egypt	**0.454**	3.861	31
Indonesia	0.010	1.024	52	Hungary	-0.004	-1.867	60
India	0.006	0.400	50	Indonesia	1.072	1.710	52
Israel	**0.021**	2.885	68	India	-1.093	-1.565	24
South Korea	0.029	1.875	67	Israel	0.092	0.749	69
Malaysia	**0.031**	2.617	67	South Korea	0.003	0.894	68
Mexico	**0.061**	3.077	68	Malaysia	**0.244**	3.429	68
Morocco	0.000	-0.002	64	Mexico	0.001	0.441	68
Peru	**0.047**	3.211	67	Morocco	-7.465	-0.490	64
Philippines	0.002	0.430	68	Peru	0.581	0.684	68
Poland	0.007	0.780	59	Philippines	-0.006	-0.408	69
Russian Federation	**0.027**	2.019	58	Poland	-0.327	-0.152	59
South Africa	0.007	0.478	67	Russian Federation	0.012	1.582	58
Taiwan	**0.036**	2.360	68	South Africa	0.000	-0.473	68
Thailand	**0.031**	3.237	68	Thailand	3.789	1.785	68
Turkey	**0.045**	3.996	67	Turkey	32.383	1.099	63

Table 1.9: Country Level Estimation

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels F through H cover interest rates.

Panel E: Stock returns	**Slope**	**T-stat**	**Obs.**	**Panel F: Short Interest Rate**	**Slope**	**T-stat**	**Obs.**
Argentina	**0.047**	2.083	68	Argentina	**-0.075**	-2.679	68
China	0.032	1.723	26	Brazil	**-0.062**	-2.670	59
Chile	0.015	0.705	55	China	-0.181	-1.142	40
Hungary	0.010	0.745	60	Chile	-0.030	-1.306	55
Indonesia	0.014	1.199	52	Czech Republic	-0.218	-1.594	64
India	0.002	0.120	50	Egypt	-0.056	-1.348	31
Israel	**0.038**	3.825	68	Hungary	-0.148	-1.397	60
South Korea	**0.040**	2.368	67	Indonesia	0.018	0.838	52
Malaysia	**0.033**	2.096	67	India	0.042	0.408	50
Mexico	**0.065**	2.956	68	Israel	0.023	0.337	69
Morocco	-0.013	-0.459	59	South Korea	0.077	0.799	68
Peru	**0.034**	2.804	67	Malaysia	0.089	0.384	68
Philippines	**0.002**	0.204	68	Mexico	-0.030	-1.015	69
Poland	0.010	0.977	59	Morocco	0.031	0.238	68
Russian Federation	0.021	1.382	58	Peru	**-0.047**	-2.279	68
South Africa	0.018	1.042	67	Philippines	-0.072	-1.745	69
Taiwan	**0.034**	2.482	68	Poland	-0.070	-1.316	59
Thailand	**0.038**	4.679	68	Russian Federation	-0.003	-0.349	58
Turkey	**0.037**	2.488	67	South Africa	-0.017	-0.163	68
				Taiwan	0.085	0.602	69
				Thailand	-0.066	-0.641	68
				Turkey	0.001	0.297	68

Table 1.9: Country Level Estimation

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels F through H cover interest rates.

Panel G: Default Spread	**Slope**	**T-stat**	**Obs.**	**Panel H: Term Spread**	**Slope**	**T-stat**	**Obs.**
Argentina	**-0.030**	-4.908	64	Argentina	**0.064**	3.315	23
Brazil	-0.012	-1.304	60	Brazil	-0.003	-0.129	29
China	0.004	0.272	40	Chile	**0.341**	2.040	29
Chile	-0.006	-0.581	41	Czech Republic	0.066	0.701	52
Egypt	0.004	0.839	29	Hungary	**-0.227**	-2.113	52
Hungary	-0.006	-0.954	43	South Korea	0.501	1.301	36
Indonesia	**-0.005**	-2.691	22	Malaysia	0.248	1.088	68
South Korea	**-0.025**	-6.941	41	Mexico	0.170	1.127	39
Malaysia	**-0.023**	-3.788	51	Morocco	0.264	1.023	63
Mexico	**-0.031**	-2.015	48	Peru	**0.054**	2.810	38
Morocco	-0.005	-0.677	33	Philippines	0.015	0.148	54
Peru	**-0.017**	-2.515	50	Poland	0.092	1.684	42
Philippines	-0.002	-0.612	48	Russian Federation	0.040	0.572	51
Poland	**-0.002**	-2.671	55	South Africa	**0.285**	2.726	68
Russian Federation	-0.008	-0.796	46	Thailand	**0.539**	3.259	68
South Africa	-0.002	-0.296	59	Turkey	0.373	0.912	19
Turkey	-0.005	-0.362	53				

Table 1.9: Country Level Estimation

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels I through K cover capital and portfolio flows.

Panel I :Portfolio Flows Ratio	**Slope**	**T-stat**	**Obs.**	**Panel J: Portfolio Flows**	**Slope**	**T-stat**	**Obs.**
Argentina	27.696	1.430	68	Argentina	-0.017	-0.522	67
Brazil	25.315	**2.733**	60	Brazil	0.031	0.484	59
Czech Republic	0.465	0.096	64	Czech Republic	0.003	0.914	63
Hungary	3.746	1.243	60	Hungary	0.005	0.497	59
Indonesia	3.746	**2.158**	50	Indonesia	0.005	0.005	48
India	42.571	1.121	21	India	0.005	0.001	42
Israel	4.509	1.054	69	Israel	0.007	**12.022**	68
South Korea	6.816	1.113	68	South Korea	-0.023	-0.292	67
Malaysia	7.136	1.780	40	Malaysia	0.013	**3.258**	39
Mexico	94.476	**2.644**	68	Mexico	0.003	**2.699**	68
Morocco	38.122	1.015	27	Morocco	0.025	**3.202**	26
Peru	18.486	**2.547**	68	Peru	-0.014	-0.676	67
Philippines	7.685	**2.836**	69	Philippines	0.006	1.175	68
Poland	7.685	**4.669**	41	Poland	0.006	0.008	39
Russian Federation	2.903	0.217	58	Russian Federation	-0.040	-1.468	57
South Africa	7.763	0.482	68	South Africa	0.003	0.073	67
Thailand	-0.888	-0.082	68	Thailand	0.028	0.731	67
Turkey	11.198	0.509	68	Turkey	0.000	**-2.266**	67

Table 1.9: Country Level Estimation

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels I through K cover capital and portfolio flows.

Panel K: Capital Flows Ratio	**Slope**	**T-stat**	**Obs.**
Argentina	8.745	0.441	68
Brazil	17.601	**2.204**	60
Chile	-2.088	-0.620	55
Czech Republic	2.995	0.825	64
Hungary	2.662	1.852	60
Indonesia	31.931	**3.466**	52
India	17.379	0.803	21
Israel	-2.479	-1.082	69
South Korea	21.413	**2.426**	68
Malaysia	5.068	1.675	40
Mexico	58.012	1.658	68
Morocco	5.325	1.128	27
Peru	8.655	**2.351**	68
Philippines	-0.974	-0.926	69
Poland	-0.974	-0.949	41
Russian Federation	4.800	0.571	58
South Africa	29.153	1.424	68
Thailand	8.831	**2.089**	68
Turkey	-0.253	-0.044	68

Table 1.9: Country Level Estimation: Global Variables

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels L through P cover returns on commodity markets.

Panel L: Commodities	**Slope**	**T-stat**	**Obs.**	**Panel M: Energy**	**Slope**	**T-stat**	**Obs.**
Argentina	0.032	1.231	68	Argentina	0.010	0.357	68
Brazil	0.050	**2.709**	60	Brazil	0.024	1.257	60
China	0.001	0.049	40	China	-0.007	-0.485	40
Chile	0.033	**3.278**	55	Chile	0.019	**2.218**	55
Czech Republic	0.055	**3.921**	64	Czech Republic	0.035	**2.976**	64
Egypt	0.002	0.100	31	Egypt	-0.002	-0.132	31
Hungary	0.036	**2.275**	60	Hungary	0.024	**2.011**	60
Indonesia	0.039	1.384	52	Indonesia	0.029	1.404	52
India	0.024	1.418	50	India	0.013	0.908	50
Israel	0.028	1.441	68	Israel	0.021	1.361	68
South Korea	0.043	**2.174**	67	South Korea	0.028	1.841	67
Malaysia	0.061	**3.609**	67	Malaysia	0.039	**3.210**	67
Mexico	0.058	**2.118**	68	Mexico	0.037	1.917	68
Morocco	-0.049	**-2.031**	67	Morocco	-0.041	-1.876	67
Peru	0.021	1.139	67	Peru	0.006	0.355	67
Philippines	0.024	**3.206**	68	Philippines	0.014	**2.445**	68
Poland	0.023	**2.602**	59	Poland	0.014	**2.164**	59
Russian Federation	0.097	**2.724**	58	Russian Federation	0.065	**2.373**	58
South Africa	0.019	1.329	67	South Africa	0.003	0.286	67
Taiwan	0.038	1.882	68	Taiwan	0.020	1.314	68
Thailand	0.041	1.887	68	Thailand	0.020	1.122	68
Turkey	0.073	**2.826**	67	Turkey	0.047	**2.281**	67

Table 1.9: Country Level Estimation: Global Variables

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels L through P cover returns on commodity markets.

Panel N: Agriculture	**Slope**	**T-stat**	**Obs.**	**Panel O: Livestock**	**Slope**	**T-stat**	**Obs.**
Argentina	0.055	1.361	68	Argentina	0.030	0.969	68
Brazil	0.079	**3.542**	60	Brazil	0.037	1.376	60
China	0.043	1.529	40	China	0.049	1.435	40
Chile	0.038	1.773	55	Chile	0.013	0.633	55
Czech Republic	0.048	**2.344**	64	Czech Republic	0.024	0.907	64
Egypt	0.031	**2.445**	31	Egypt	0.025	0.804	31
Hungary	0.022	1.014	60	Hungary	0.022	1.499	60
Indonesia	0.012	0.653	52	Indonesia	0.002	0.133	52
India	0.015	0.785	50	India	0.078	**2.268**	50
Israel	0.029	1.563	68	Israel	-0.010	-0.268	68
South Korea	0.041	**2.119**	67	South Korea	0.050	**2.010**	67
Malaysia	0.054	**2.332**	67	Malaysia	0.016	0.682	67
Mexico	0.027	0.996	68	Mexico	0.020	0.692	68
Morocco	-0.003	-0.099	67	Morocco	0.061	1.032	67
Peru	0.050	**2.679**	67	Peru	-0.034	-1.533	67
Philippines	0.012	0.936	68	Philippines	0.057	1.837	68
Poland	0.043	**3.903**	59	Poland	-0.030	-1.112	59
Russian Federation	0.038	1.396	58	Russian Federation	0.080	**2.219**	58
South Africa	0.053	**2.751**	67	South Africa	0.051	1.464	67
Taiwan	0.046	1.587	68	Taiwan	0.013	0.779	68
Thailand	0.063	**2.042**	68	Thailand	-0.024	-0.704	68
Turkey	0.075	**2.418**	67	Turkey	0.003	0.063	67

Table 1.9: Country Level Estimation: Global Variables

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels L through P cover returns on commodity markets and Q through S cover US interest rates.

Panel P: Metal	**Slope**	**T-stat**	**Obs.**	**Panel Q: US Term Spread**	**Slope**	**T-stat**	**Obs.**
Argentina	0.154	**2.287**	68	Argentina	0.188	0.569	68
Brazil	0.083	**3.024**	60	Brazil	0.093	0.541	60
China	0.123	**1.969**	40	China	0.296	0.958	40
Chile	0.035	1.090	55	Chile	0.065	0.384	55
Czech Republic	0.008	0.212	64	Czech Republic	0.014	0.072	64
Egypt	0.038	1.492	31	Egypt	-0.183	-1.895	31
Hungary	0.002	0.110	60	Hungary	-0.082	-0.510	60
Indonesia	0.058	1.285	52	Indonesia	0.276	1.006	52
India	0.001	0.035	50	India	-0.119	-0.401	50
Israel	0.029	1.055	68	Israel	-0.115	-0.952	69
South Korea	0.087	1.674	67	South Korea	0.130	0.680	68
Malaysia	0.072	**2.402**	67	Malaysia	0.344	1.626	68
Mexico	0.024	1.020	68	Mexico	-0.141	-1.236	69
Morocco	0.136	1.661	67	Morocco	-0.113	-0.541	68
Peru	0.077	**3.426**	67	Peru	0.292	1.298	68
Philippines	0.033	1.465	68	Philippines	0.076	0.565	69
Poland	0.033	1.278	59	Poland	-0.177	-1.386	59
Russian Federation	0.071	1.304	58	Russian Federation	0.041	0.145	58
South Africa	0.034	1.519	67	South Africa	-0.049	-0.279	68
Taiwan	0.074	1.947	68	Taiwan	0.186	0.971	69
Thailand	0.101	**2.323**	68	Thailand	0.403	1.766	68
Turkey	0.046	0.680	67	Turkey	0.251	0.764	68

Table 1.9: Country Level Estimation: US Interest Rates

This table presents results for our time series predictive regressions over the entire sample period. We use Newey-West standard errors. Country results are grouped by financial aggregates. Panels Q through S cover US interest rates.

Panel R: US T-bill	**Slope**	**T-stat**	**Obs.**	**Panel S: US Default Spread**	**Slope**	**T-stat**	**Obs.**
Argentina	-0.358	-1.602	68	Argentina	-0.319	-0.665	68
Brazil	0.089	0.616	60	Brazil	-0.377	-0.951	60
China	-0.415	**-2.220**	40	China	-0.237	-0.658	40
Chile	0.052	0.375	55	Chile	-0.724	**-3.199**	55
Czech Republic	0.081	0.642	64	Czech Republic	-1.153	**-3.291**	64
Egypt	0.074	0.598	31	Egypt	-0.358	**-2.243**	31
Hungary	0.114	0.929	60	Hungary	-1.198	**-4.247**	60
Indonesia	-0.318	-1.190	52	Indonesia	0.559	0.895	52
India	-0.240	-1.494	50	India	-1.467	**-3.152**	50
Israel	0.127	1.755	69	Israel	-0.646	**-3.184**	69
South Korea	0.166	0.726	68	South Korea	-0.276	-0.610	68
Malaysia	0.042	0.171	68	Malaysia	-0.656	-1.197	68
Mexico	0.154	1.070	69	Mexico	-1.250	**-2.442**	69
Morocco	-0.098	-0.557	68	Morocco	0.513	1.533	68
Peru	-0.128	-1.011	68	Peru	-0.574	-1.801	68
Philippines	-0.192	-1.937	69	Philippines	0.256	0.711	69
Poland	0.117	1.771	59	Poland	-0.476	**-2.659**	59
Russian Federation	-0.125	-0.585	58	Russian Federation	-1.610	-1.549	58
South Africa	-0.114	-0.809	68	South Africa	-0.757	**-2.869**	68
Taiwan	0.212	0.939	69	Taiwan	-0.455	-0.854	69
Thailand	-0.080	-0.280	68	Thailand	-0.250	-0.380	68
Turkey	0.173	0.620	68	Turkey	-0.764	-1.118	68

Table 1.10: **Common Factors**

This table shows estimated coefficients and t-statistics for our standard pooled fixed effects, and forward demeaning output growth estimation when we account for common factors in the data generating process. Panel A describes results for returns and valuation measures, Panel B covers interest rates variables, and Panel C portfolio and capital flows. The coefficients in bold indicate statistical significance at the 5 % level or better.

	RPooled	**RFE**	**RFD**
Panel A: Return and Valuation Measures			
Stock Returns	**0.33**	**0.26**	**0.24**
	3.03	2.51	2.63
Capitalization Ratio	0.22	0.18	0.42
	1.56	1.21	0.10
Dividend Yield	0.01	**-0.30**	-0.30
	0.07	-2.70	-1.05
PE Ratio	**0.25**	0.09	0.10
	2.03	1.00	0.93
Panel B: Interest Rates			
Short Interest Rate	-0.11	**-0.16**	**-0.22**
	-1.41	-2.05	-2.17
Term Spread	**0.39**	**0.63**	**0.55**
	2.04	4.05	2.32
Default Spread	-0.15	-0.24	-0.24
	-0.66	-1.13	-1.04
Panel C: Flows			
Capital Flows Ratio	**0.30**	**0.31**	**0.39**
	3.31	2.89	2.78
Portfolio Flows Ratio	**0.29**	**0.26**	**0.29**
	2.52	2.21	2.32

Table 1.11: **Sub-Sample Analysis**

This table shows sub-sample results for the periods covering 1993-1999, 2000-2010 and 1993-2007. The coefficients in bold indicate statistical significance at the 5 % level or better.

	Panel A: 1993-1999			Panel B: 2000-2010			Panel C: 1993-2007		
	Pooled	FE	FD	Pooled	FE	FD	Pooled	FE	FD
Stock Returns	**0.55**	**0.59**	**0.50**	**0.47**	**0.47**	**0.44**	**0.46**	**0.46**	**0.43**
	3.80	4.58	3.51	4.86	4.97	4.28	5.74	6.18	5.21
Capitalization Ratio	0.06	0.15	0.01	-0.09	0.03	-13.75	-0.02	0.00	-0.03
	0.68	1.00	0.05	-1.79	0.96	-0.16	-0.30	0.04	-0.29
Dividend Yield	**-0.41**	**-0.80**	-1.18	**-0.20**	**-0.24**	-0.02	**-0.24**	**-0.25**	**-1.12**
	-3.79	-5.69	-0.98	-3.57	-2.77	-0.06	-2.63	-1.97	-2.44
PE Ratio	0.34	0.41	**0.60**	0.02	**0.03**	0.02	0.04	0.05	-0.06
	1.86	1.94	2.45	1.49	2.78	1.12	1.36	1.64	-1.60
Short Interest Rate	-0.09	-0.07	-0.10	**-0.13**	**-0.13**	**-0.29**	-0.15	-0.15	-0.18
	-0.68	-0.49	-0.60	-2.69	-2.10	-5.21	-1.43	-1.39	-1.69
Term Spread	**0.56**	**1.40**	**2.70**	**0.18**	**0.34**	**0.17**	**0.33**	**0.60**	**0.45**
	4.17	2.62	4.08	3.80	7.03	3.88	3.82	6.11	5.34
Default Spread	-0.56	-0.60	**-0.91**	**-0.42**	**-0.43**	**-0.26**	**-0.36**	**-0.38**	**-0.39**
	-1.52	-1.53	-2.57	-2.85	-2.86	-2.01	-2.28	-2.46	-2.67
Capital Flows Ratio	**0.64**	**0.70**	**1.12**	0.09	0.16	**0.27**	0.25	**0.32**	**0.42**
	2.76	2.44	3.60	0.94	1.30	2.60	1.91	2.05	2.52
Portfolio Flows Ratio	0.39	0.39	0.50	**0.26**	**0.27**	**0.27**	0.22	0.23	**0.30**
	1.34	1.39	1.72	4.36	4.63	4.62	1.75	1.76	2.17
Commodities	0.18	0.19	0.04	**0.39**	**0.43**	**0.41**	**0.20**	**0.20**	**0.14**

Table 1.11: **Sub-Sample Analysis (cont.)**

	1.68	1.72	0.25	5.42	6.34	5.91	4.70	4.63	2.66
Book-to-market	**-0.41**	**-0.42**	**-0.47**	**0.19**	**0.19**	**0.13**	0.03	0.04	0.09
	-2.37	-2.41	-2.40	3.12	3.16	2.18	0.59	0.70	1.41
Size	-0.01	-0.03	-0.12	-0.02	-0.02	**-0.11**	-0.05	-0.06	-0.12
	-0.06	-0.16	-0.75	-0.35	-0.37	-2.53	-0.69	-0.92	-1.48
Market	**0.59**	**0.59**	**0.57**	**0.49**	**0.51**	**0.49**	**0.44**	**0.44**	**0.38**
	4.80	4.79	4.23	5.96	6.27	5.77	7.58	7.68	6.55

Table 1.12: **Regional Emerging Markets**

This table shows results at the regional level. Panel A presents results for Asian emerging markets, Panel B for Europe, Middle East and Africa, and Panel C for Latin America. The coefficients in bold indicate statistical significance at the 5 % level or better.

	Panel A: Asia			**Panel B: EMEA**			**Panel C: LATAM**		
	Pooled	**FE**	**FD**	**Pooled**	**FE**	**FD**	**Pooled**	**FE**	**FD**
Stock Returns	**0.41**	**0.41**	**0.41**	**0.52**	**0.54**	**0.52**	**0.66**	**0.66**	**0.62**
	4.23	4.25	4.09	6.01	6.45	5.40	7.96	7.70	6.49
Capitalization Ratio	-0.04	**0.14**	-14.11	0.01	-0.03	0.04	**-0.12**	0.05	**1.09**
	-0.60	3.81	-0.62	0.31	-1.08	0.49	-3.46	0.88	5.67
Dividend Yield	-0.10	-0.09	-0.11	**-0.25**	**-0.29**	0.35	**-0.40**	**-0.58**	-2.53
	-0.99	-0.75	-0.07	-2.84	-2.33	1.48	-3.21	-4.91	-1.55
PE Ratio	**0.20**	0.14	0.04	0.06	**0.08**	0.09	**0.27**	**0.24**	0.15
	2.52	1.11	0.49	1.75	2.08	1.68	2.55	1.99	1.50
Short Interest Rate	-0.04	-0.01	**-0.23**	-0.04	-0.04	-0.03	**-0.40**	**-0.44**	**-0.51**
	-1.20	-0.28	-2.07	-0.93	-0.86	-0.46	-5.39	-5.23	-5.20
Term Spread	0.25	0.44	-0.03	**0.22**	**0.27**	**0.27**	**0.24**	**0.56**	**0.23**
	1.41	1.75	-0.11	2.40	2.64	4.80	3.48	6.47	2.58
Default Spread	**-0.69**	**-0.71**	**-0.65**	**-0.25**	**-0.25**	**-0.11**	**-0.64**	**-0.64**	**-0.62**
	-3.86	-4.23	-4.19	-3.89	-3.63	-2.08	-8.49	-8.29	-5.38
Capital Flows Ratio	**0.56**	**0.60**	**0.55**	0.05	0.13	**0.35**	0.25	0.22	0.28
	2.47	2.51	1.98	0.77	1.70	3.60	1.45	1.23	1.49
Portfolio Flows Ratio	**0.45**	**0.44**	0.40	**0.11**	**0.13**	**0.14**	**0.47**	**0.49**	**0.55**
	2.10	2.10	1.79	3.94	4.38	3.60	4.29	4.19	4.56
Commodities	**0.25**	**0.27**	**0.31**	**0.44**	**0.44**	**0.47**	**0.38**	**0.39**	**0.35**

Table 1.12: **Sub-Sample Analysis (cont.)**

	4.96	6.64	5.78	3.56	3.56	3.61	3.75	3.79	3.10
Book-to-market	0.09	0.10	0.03	**0.20**	**0.20**	0.13	-0.05	-0.05	-0.08
	1.04	1.08	0.35	2.40	2.47	1.49	-0.50	-0.49	-0.85
Size	**0.17**	**0.16**	**0.14**	**-0.18**	**-0.18**	**-0.23**	0.04	0.04	-0.05
	2.43	1.98	1.97	-2.80	-2.89	-3.00	0.54	0.53	-0.51
Market	**0.45**	**0.47**	**0.48**	**0.52**	**0.52**	**0.54**	**0.65**	**0.65**	**0.59**
	5.01	5.19	5.08	4.38	4.34	4.87	6.38	6.43	6.06

Table 1.12: Regional Emerging Markets (cont.)

This table shows results for Asia excluding China. The coefficients in bold indicate statistical significance at the 5 % level or better.

	Panel D: Asia ex-China		
	Pooled	**FE**	**FD**
Stock Returns	**0.38**	**0.38**	**0.35**
	3.86	3.91	3.54
Capitalization Ratio	0.02	**0.12**	-14.34
	0.88	3.38	-0.56
Dividend Yield	-0.14	-0.13	0.20
	-1.46	-1.12	0.25
PE Ratio	**0.24**	**0.26**	0.14
	4.72	4.86	1.42
Short Interest Rate	-0.01	-0.01	**-0.24**
	-0.52	-0.43	-2.10
Term Spread	0.25	0.44	-0.03
	1.41	1.75	-0.11
Default Spread	**-0.79**	**-0.79**	**-0.74**
	-4.17	-4.12	-4.65
Capital Flows Ratio	**0.56**	**0.60**	**0.55**
	2.47	2.51	1.98
Portfolio Flows Ratio	**0.45**	**0.44**	0.40
	2.10	2.10	1.79
Commodities	**0.29**	**0.30**	**0.35**
	7.83	7.87	7.33
Book-to-market	0.05	0.05	-0.02
	0.57	0.56	-0.23
Size	**0.22**	**0.22**	**0.19**
	3.66	3.60	3.55
Market	**0.47**	**0.48**	**0.48**
	4.85	4.88	4.68

Table 1.13: **GDP per Capita**

This table shows results for panels grouped by PPP-adjusted GDP per capita (at constant 2005 USD). Panel A presents results for emerging market countries with a GDP per capita of $13,000 or higher, Panel B for countries ranging between $13,000 and $9,000, and Panel C for those with a GDP per capita lower than $9,000. The coefficients in bold indicate statistical significance at the 5 % level or better.

	Panel A: High Income			**Panel B: Middle Income**			**Panel C: Low Income**		
	Pooled	**FE**	**FD**	**Pooled**	**FE**	**FD**	**Pooled**	**FE**	**FD**
Stock Returns	**0.45**	**0.46**	**0.43**	**0.63**	**0.65**	**0.56**	**0.39**	**0.36**	**0.40**
	4.21	4.57	3.80	5.68	6.02	5.09	3.23	3.27	2.92
Capitalization Ratio	**0.14**	**0.26**	-13.97	-0.06	-0.03	0.07	-0.01	**-0.10**	**-0.46**
	9.11	2.26	-0.63	-1.40	-0.78	0.55	-0.13	-2.60	-2.28
Dividend Yield	**-0.26**	**-0.24**	-2.38	**-0.41**	**-0.62**	-0.57	-0.13	-0.10	-0.31
	-2.80	-2.19	-0.58	-5.75	-6.03	-0.87	-1.43	-0.85	-0.57
PE Ratio	0.02	0.04	0.07	0.09	0.09	0.09	0.19	0.10	-0.01
	0.92	1.19	1.05	1.56	1.56	1.30	2.55	0.67	-0.10
Short Interest Rate	-0.02	-0.05	0.10	-0.07	-0.07	-0.13	**-0.23**	-0.21	**-0.29**
	-0.26	-0.48	1.08	-0.87	-0.82	-1.06	-2.01	-1.92	-2.72
Term Spread	0.03	0.06	0.20	**0.25**	**0.48**	**0.34**	**0.46**	**0.51**	0.34
	0.48	0.52	1.35	3.62	6.80	3.60	2.34	2.05	1.82
Default Spread	-0.64	-0.64	-0.51	**-0.49**	**-0.50**	**-0.41**	-0.12	-0.11	-0.08
	-1.86	-1.87	-1.48	-4.12	-4.25	-2.71	-1.15	-1.08	-0.82
Capital Flows Ratio	0.14	0.27	**0.51**	0.16	**0.22**	0.20	**0.51**	**0.52**	**0.61**
	1.00	1.31	2.45	1.94	2.02	1.89	2.44	2.20	2.40
Portfolio Flows Ratio	**0.12**	**0.13**	**0.15**	**0.30**	**0.31**	**0.27**	0.51	0.51	**0.53**
	3.94	4.46	4.39	3.39	3.37	2.57	1.92	1.91	2.02

Table 1.13: **GDP per Capita (cont.)**

Commodities	**0.41**	**0.41**	**0.48**	**0.56**	**0.56**	**0.56**	**0.19**	**0.20**	**0.17**
	9.42	9.75	10.11	5.12	5.15	4.81	3.35	3.57	2.90
Book-to-market	**0.16**	**0.17**	0.09	0.14	0.14	0.08	0.00	0.01	-0.04
	2.24	2.26	1.05	1.32	1.33	0.78	0.02	0.11	-0.42
Size	0.03	0.03	-0.01	-0.08	-0.08	**-0.17**	0.03	0.01	-0.03
	0.34	0.33	-0.10	-1.11	-1.13	-2.19	0.27	0.08	-0.26
Market	**0.44**	**0.44**	**0.47**	**0.75**	**0.75**	**0.72**	**0.41**	**0.42**	**0.39**
	4.21	4.23	4.61	8.48	8.54	8.67	4.63	4.72	4.77

Table 1.14: **Multivariate Analysis**

This table presents results for our multivariate analysis. We group our variables into four categories, return and valuation measures, interest rates, flows and commodities. The coefficients in bold indicate statistical significance at the 5 % level or better.

	One Quarter Ahead			**One Year Ahead**			**Two Years Ahead**		
	Pooled	**FE**	**FD**	**Pooled**	**FE**	**FD**	**Pooled**	**FE**	**FD**
Return and	**0.40**	**0.43**	**0.40**	**0.32**	**0.34**	**0.30**	**-0.27**	-0.15	1.77
Valuation Measures	3.61	4.40	2.81	3.36	3.43	2.39	-2.61	-0.87	0.62
Interest Rates	**-0.27**	**-0.30**	**-0.32**	-0.16	-0.16	-0.16	-0.17	-0.08	-0.35
	-4.28	-3.60	-4.97	-1.37	-1.18	-1.26	-1.14	-0.29	-0.70
Flows	**0.06**	**0.09**	0.10	-0.01	0.04	0.06	**-0.28**	**-0.37**	**-0.10**
	2.07	2.20	1.27	-0.12	0.27	0.49	-2.27	-2.44	2.15
Commodities	**0.29**	**0.29**	**0.31**	0.07	0.07	**0.22**	0.29	0.29	-0.12
	5.24	5.48	5.26	1.04	0.92	3.04	1.67	1.43	-0.14

Table 1.15: **Cross-Validation**

This table presents results for our cross-validation analysis. For each variable we report the average estimate, its standard deviation and the number of times, out of the twenty random draws, that the coefficient is statistically significant.

	One Quarter Ahead			**One Year Ahead**			**Two Years Ahead**		
	Pooled	**FE**	**FD**	**Pooled**	**FE**	**FD**	**Pooled**	**FE**	**FD**
Stock Returns	0.51	0.52	0.49	0.63	0.67	0.63	0.37	0.44	0.40
Stdv.	0.03	0.03	0.03	0.04	0.04	0.05	0.03	0.03	0.05
No. Sig.	20	20	20	20	20	20	20	20	20
Capitalization Ratio	-0.04	0.02	0.48	-0.08	-0.13	0.30	-0.07	-0.15	3.12
Stdv.	0.03	0.06	0.94	0.03	0.05	0.71	0.03	0.10	10.80
No. Sig.	0	2	0	4	20	0	1	2	0
Dividend Yield	-0.27	-0.30	-0.34	-0.07	-0.06	0.27	-0.02	0.02	1.35
Stdv.	0.03	0.04	0.20	0.02	0.03	2.13	0.02	0.04	1.08
No. Sig.	20	20	0	0	0	0	0	0	0
PE Ratio	0.05	0.06	0.06	-0.01	0.01	-0.03	0.05	0.07	0.01
Stdv.	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
No. Sig.	0	4	0	0	0	0	1	17	0
Short Interest Rate	-0.11	-0.09	-0.12	-0.01	0.03	-0.05	0.01	0.01	-0.12
Stdv.	0.03	0.03	0.03	0.05	0.05	0.05	0.03	0.04	0.05
No. Sig.	0	0	1	0	0	0	0	0	2
Term Spread	0.29	0.48	0.34	0.23	0.50	0.26	0.11	0.27	0.05
Stdv.	0.03	0.06	0.04	0.04	0.12	0.05	0.05	0.10	0.05
No. Sig.	20	20	20	19	19	6	4	4	0
Default Spread	-0.42	-0.44	-0.36	-0.42	-0.53	-0.30	-0.17	-0.33	0.36

Table 1.15: **Cross-Validation (cont.)**

Stdv.	0.05	0.05	0.05	0.04	0.03	0.08	0.03	0.03	0.11
No. Sig.	20	20	20	20	20	4	18	20	12
Capital Flows Ratio	0.26	0.33	0.44	-0.05	-0.05	0.11	-0.19	-0.29	-0.13
Stdv.	0.03	0.04	0.05	0.02	0.03	0.05	0.02	0.03	0.05
No. Sig.	20	20	20	2	0	2	20	20	5
Portfolio Flows Ratio	0.30	0.30	0.31	0.10	0.10	0.12	-0.04	-0.05	-0.01
Stdv.	0.03	0.04	0.03	0.03	0.03	0.04	0.02	0.03	0.04
No. Sig.	20	20	20	0	0	3	0	0	0
Debt securities	0.13	0.14	0.19	-0.02	-0.04	0.07	-0.09	-0.15	0.03
Stdv.	0.03	0.03	0.03	0.04	0.04	0.05	0.03	0.03	0.07
No. Sig.	16	18	20	0	0	1	6	7	0
Direct Inv. flows	0.04	0.08	0.13	0.02	0.11	0.10	-0.04	0.07	0.01
Stdv.	0.02	0.03	0.03	0.01	0.02	0.03	0.02	0.04	0.05
No. Sig.	0	2	11	0	7	4	2	0	0
Equity securities	0.16	0.16	0.07	0.12	0.15	-0.06	0.09	0.11	-0.29
Stdv.	0.03	0.03	0.03	0.03	0.04	0.03	0.04	0.06	0.08
No. Sig.	15	15	0	4	11	0	0	1	0
Size	-0.01	-0.03	-0.08	0.39	0.35	0.37	0.47	0.45	0.51
Stdv.	0.02	0.02	0.03	0.04	0.04	0.05	0.03	0.03	0.03
No. Sig.	0	0	0	20	20	20	20	20	20
HML	0.09	0.10	0.05	0.05	0.08	-0.05	-0.05	-0.04	-0.37
Stdv.	0.02	0.02	0.02	0.01	0.01	0.03	0.02	0.02	0.05
No. Sig.	3	3	0	1	3	0	0	0	20
Market	0.11	0.10	-0.99	-0.08	-0.09	-1.44	-0.16	-0.17	-1.54

Table 1.15: **Cross-Validation (cont.)**

Stdv.	0.02	0.02	0.18	0.02	0.03	0.64	0.02	0.03	0.74
No. Sig.	12	9	20	2	3	3	20	20	0
Commodity Index (%)	0.38	0.39	0.40	0.22	0.27	0.33	0.15	0.21	0.36
Stdv.	0.02	0.02	0.02	0.03	0.03	0.03	0.02	0.02	0.03
No. Sig.	20	20	20	20	20	20	14	20	20
S&P Agricultural Index (%)	0.35	0.35	0.39	0.18	0.21	0.35	0.01	0.04	0.38
Stdv.	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.05
No. Sig.	20	20	20	17	20	20	0	0	20
S&P Energy Index (%)	0.29	0.30	0.30	0.17	0.22	0.25	0.11	0.15	0.22
Stdv.	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
No. Sig.	20	20	20	19	20	20	8	20	20
S&P Livestock Index (%)	0.15	0.16	0.14	0.21	0.24	0.19	0.06	0.10	0.01
Stdv.	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
No. Sig.	18	20	12	20	20	19	0	0	0
S&P Metal Index (%)	0.38	0.37	0.47	0.30	0.30	0.59	0.20	0.21	0.83
Stdv.	0.02	0.02	0.02	0.02	0.02	0.05	0.02	0.02	0.11
No. Sig.	20	20	20	20	20	20	20	20	20

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Chapter 2

Emerging Market Mutual Fund Performance and the State of the Economy

Abstract

Following the financial liberalization of many Asian, European, and Latin American countries emerging markets have become a central player in the global economy. As a result the universe of equity funds investing in these developing economies has been in continuous expansion. In this paper we propose a set of asset class specific predictive variables for emerging markets and exploit them in order to identify those funds that outperform the market in different phases of the economic cycle. We employ a comprehensive survivorship-bias free universe of global and regional emerging market funds and use a Bayesian framework that incorporates predictability in manager skills (stock selection and benchmark timing skills), fund risk loadings and benchmark returns by exploiting ex-ante business cycle related state variables. Our results provide empirical evidence of return predictability and the economic value of active management in emerging markets.

2.1 Introduction

During the last decades the mutual fund industry has been continuously growing and gaining importance in global financial markets. As of end of 2007, total worldwide mutual funds' assets amounted to 26.2 trillion dollar, with the US accounting for 46% of the market. As the industry evolved, mutual funds have been gaining the interest of academics and practitioners for whom central questions have been related to performance measurement and the study of persistence and predictability of mutual fund returns.

Predictability of future returns has been long in the agenda of researchers. During the early 70's, under the efficient markets hypothesis, it was widely accepted among financial economists that returns were unpredictable and prices were close to random walks. Market prices were considered to contain all information about fundamentals and the only possible way to gain larger returns was by undertaking additional risk. In this context, it was believed that active management did not add economic value to the investment process. Over the past years these findings have been extensively revised by academic researchers, showing more optimistic evidence on predictability of returns and the potential benefits of actively managed strategies. Using factor model regressions Grinblatt and Titman (1992), Brown and Goetzmann (1995), Elton, Gruber, and Blake (1996) and Kosowski et. al (2006), find evidence of mutual fund persistence. Moskowitz (2000), Avramov (2004), Avramov and Chordia (2005) and Avramov and Wermers (2006) provide further evidence on the value of active management. This body of work suggests that skillful managers can outperform the market under different stages of the economic cycle through actively managed strategies. However, the literature on return predictability is still mixed, evidence is not conclusive.

In recent years, developments in information technology allowed for new techniques and methodologies that triggered the study of return predictability. Also, better coverage and quality of financial and economic data, have broadened the research possibility set. The opportunity of using new forecasting variables or studying new markets such as emerging markets are clear examples of this process.

In this context, this paper focuses on studying return predictability in emerging markets equity funds from the perspective of US-based investors. This is mainly a largely unexplored area of research. Most academic studies in the mutual fund return predictability literature have been related to US equity markets, but not much has been said on developing markets. Emerging markets funds invest mainly in the stock markets of developing countries in Eastern Europe, Africa, the Middle East, Latin America, the Far East and Asia. They have been gaining special importance since the mid 90's after financial liberalization of many Asian, European, and Latin-American economies and the movement toward integration of their capital markets into the global economy. Since then, the number of funds investing in emerging markets has been rapidly growing. This process was mainly motivated by the increasing demand from both individual and institutional investors who incorporated equity emerging markets to their strategic asset allocation in search for risk diversification and higher returns.

Table 2.1 compares performance of emerging versus a group of developed equity markets over the period covering 1988-2008. Results show that emerging equity markets have been significantly outperforming developed markets, delivering 18.9%, 26.3%, 32.5%, 9.7% and 16.14% annualized returns on a one, three, five, ten and twenty years basis respectively. However, as described by Figure 2.1 these higher returns are associated with higher volatility levels which can be related to the higher economic and political instability that characterizes these developing economies. Risk diversification benefits have also been an important factor in the rapid growth of this asset class. These transitional markets tend not to co-move with developed markets and as a result investors use emerging market securities as an instrument to reduce the overall risk of their portfolios. Table 2.2 provides evidence of the correlations across equity markets over time. In the late 80's, before the opening of many financial markets, correlations of emerging and developed markets were at the 0.2 level, doubling in the mid 90's at the time of financial liberalization and progressively increasing as financial integration consolidated. In general, periods with free capital flows have been associated with larger investment opportunity sets but also with higher correlation levels across markets. Still, emerging markets enjoy diversification benefits, especially with respect to US and Japanese equities. Goetzman et al. (2003) find that although global diversification has been decreasing over the last decade, investors can still benefit from it by investing in marginal markets such as emerging markets.

The literature on return predictability in emerging markets is relatively new. Harvey (1994, 1995) shows that equity returns are predictable in some developing countries when conditioning on country-specific and global information variables such as dividend yields, past returns, currency indices and the earning-price ratio. Bekaert et al. (2007) find that local market liquidity is an important driver of returns in developing economies. However, the study of predictability at the asset class level remains unexplored. Asset pricing theory provides little guidance on the factors driving returns in emerging markets. To the best of our knowledge, this paper is the first to study mutual fund predictability in emerging markets using a comprehensive universe of global and regional funds. The universe includes existing and dead funds resulting in a survivorship bias free dataset. Our sample period starts in the early stages of this new asset class, covering the financial liberalization process of the early 90's, the Tequila crisis of 1995, the Asian crisis of 1997, the Russian crisis of 1998, the Tech bubble of 2000, the expansion of the European Union in 2004, the rise of China, as well as the beginning of the last global financial and economic crisis. Starting in January 1992, these sixteen years of data, combined with an extensive universe of emerging markets funds, allows us to study return predictability of emerging markets funds under changing economic conditions.

Using Avramov and Wermers Bayesian framework (2006) we propose a set of asset class specific predictive variables for emerging markets and exploit them in order to identify those funds that outperform the market in different phases of the economic cycle. We find that a variety of global and regional state variables can be useful in generating economic value. Within these variables inflation, commodities and implied volatility are among the most significant ones. As a robustness check, we evaluate our out-of-sample results under a series of different scenarios (changing rebalancing horizons, restrictions on maximum portfolio weights and sub-periods). Out-of-sample performance for the Bayesian strategies support the idea that incorporating predictability in managerial skills, risk loadings and benchmark returns, can help better predict returns and identify those funds that generate abnormal returns under different market conditions. Furthermore, results provide empirical evidence of the economic value of active management in emerging markets.

The paper is organized as follows. Section 2 introduces the econometric framework. Section 3 describes the data used in the analysis. Section 4 presents empirical results. Section 5 discusses our robustness analysis. Finally, we conclude in Section 6.

2.2 The Model

In this section we present our framework, introduce our Bayesian investors, and discuss the portfolio optimization problem. As in any portfolio choice problem, there are two stages involved. In the first stage we forecast returns and correlations for the different investor types. In doing so, we use Avramov and Wermers (2006) closed-formed Bayesian predictive moments. In the second stage, we calculate optimal portfolio allocations.

2.2.1 Econometric Framework

We study emerging markets return predictability in the context of Avramov and Wermers' framework (2006), hereafter AW. The model incorporates predictability in manager skills (stock selection and benchmark timing skills), fund risk loadings and benchmark returns by exploiting ex-ante business cycle related state variables. This approach is particularly relevant to study emerging markets predictability given the nature of the funds in the universe. The vast majority of funds in our sample are actively managed strategies and therefore we would expect managerial skill to explain a large component of returns as well as the dispersion of performance across funds. Hence the payoff to predicting managerial skills should be large.

The emerging markets fund return generating process can be summarized as follows:

$$r_{it} = \alpha_{i0} + \alpha_{i1}' z_{t-1} + \beta_{i0}' f_t + \beta_{i1}' (f_t \otimes z_{t-1}) + v_{it} \tag{2.1}$$

Where r_{it} is the fund excess return, z_{t-1} is the set of state variables observed at the end of $t-1$, f_t represents the risk factors, and v_{it} is a fund-specific event, normally distributed and uncorrelated across funds and over time. Both the state variables, z_t, and the risk factors, f_t, follow autoregressive processes of order one represented by the following set of equations:

$$f_t = a_f + A_f z_{t-1} + v_{ft} \tag{2.2}$$

$$z_t = a_z + A_z z_{t-1} + v_{zt} \tag{2.3}$$

With v_{ft} and v_{zt} independent and normally distributed. The model captures potential predictability in managerial skills ($\alpha_{i1} \neq 0$), emerging markets fund risk loadings ($\beta_{i1} \neq 0$), and benchmark returns ($A_f \neq 0$).

Following AW and Banegas, Gillen, Timmermann and Wermers (2008) we define four types of Bayesian mean-variance optimizing investors who bring distinct prior beliefs about the potential for managerial skill and differ in the value of the parameters described by equations (1)-(3). Our first investor, the Agnostic, considers that some managers might possess stock selection and benchmark timing skills, but has diffuse priors about the existence and level of skills. In other words, the skill level has unbounded standard deviation allowing the data to determine whether or not managers possess fixed and time-varying managerial skills. This investor allows for the possibility that by exploiting business cycle related variables it is possible to predict alphas, fund risk loadings and benchmark returns.

We also consider two different versions of the Agnostic investor. The first one is the Agnostic Predictable Market Loadings (APML) investor and the second one is the Agnostic Macro Alpha (AMA) investor. The APML investor also allows for predictability in managerial skills and benchmark returns but differs from the Agnostic in that only allows for predictability in the market benchmark factor loading. The remaining time-varying non-market loadings (size, book-to-market and momentum factors) are set to zero. From a model perspective, this restriction limits the interactions between the state variables and the risk factors resulting in a reduction in the number of parameters to be estimated.

The AMA investor also believes that managerial skills and benchmark returns can be predictable. However, she considers that risk loadings are constant and therefore independent of market conditions. In other words, the parameters of the time-varying component of risk loadings are defined to be zero.

Finally, The Skeptic investor believes that some fund managers may possess managerial skills and therefore the ability to outperform the market. However, her prior beliefs are bounded, with prior uncertainty about managerial skills set to 1% per month. We consider a version of AW Skeptic investor that allows for predictability in managerial skills but believes that risk loadings and benchmark returns are not predictable.

Bayesian mean and variance for the four investor types are estimated from the following predictive distribution:

$$p(r_{t+1}|\mathscr{D}_t, \mathscr{I}) = \int_{\Theta} p(r_{t+1}|\mathscr{D}_t, \Theta, \mathscr{I}) p(\Theta|\mathscr{D}_t, \mathscr{I}) d\Theta.$$

where $\mathscr{D}_t$ represents the returns, benchmark and macro variables data, $\mathscr{I}$ identifies the investor type, and Θ denotes the parameters of the return generating model.

Appendix A presents a detailed explanation of the predictive moments for the Agnostic and Skeptic investors.

2.2.2 Optimal Portfolios

In the second stage, assuming that investors have quadratic utility functions, we calculate optimal portfolio weights by maximizing the following equation:

$$w^* = \arg\max_{w_t} \{ w_t' \mu_t - \frac{1}{2(1/\gamma_t - r_{ft})} w_t' \Lambda_t^{-1} w_t \}$$

where $\Lambda_t = [\Sigma_t + \mu_t \mu_t']^{-1}$ and γ is the coefficient of relative risk aversion set to 2.94% in the empirical application. We then replace μ and Σ by the Bayesian mean and variance estimated in the first stage.

2.3 Data

An important factor that adds to the complexity of emerging markets data in this analysis is related to the financial liberalization process that many developing countries underwent during the late 80's and early 90's. As many authors document (Bekeart and Campbell 1995, Edwards et al 2003), these regulatory changes had an effect on the characteristics of asset returns, sources of risk and predictability. As countries moved from segmented to more integrated financial markets, regional and global information became more relevant than country-specific information. Financial liberalization is then an important issue in the present analysis. The conditioning information variables that could help predict returns during the pre-liberalization years might not be relevant in the post-reform period. In the present study, we restrict the period under analysis and focus in the post-liberalization period.

Dating liberalization is not an easy task. Bekaert et al. (2002) show that dates of official financial system reforms tend not to coincide with the true date of financial markets' integration. They search for common endogenous breaks in the data generating process of financial and macroeconomic series and find that, in general, endogenous dates take place after official capital markets reforms. We follow their results to define the period under analysis.

2.3.1 Emerging Market Funds

Our universe of funds consists of 1318 global and regional emerging markets equity funds from Lipper database. Global emerging market funds invest in equity markets across developing countries and regions and account for 39% of the funds in the sample. Regional funds include emerging markets Europe (21%), Far East (6%), Latin America (16%), Middle East and Africa (19%), and invest only in equity markets in their area of interest. Table 2.3 presents a summary of the evolution of our universe, in terms of number of funds and average performance, grouped by investment objective. As described by table 4 the number of emerging markets funds has been consistently growing since inception date, both at the global and regional level. However, it is only in the mid 90's that there is a significant increase in the size of the fund universe. Both individual and institutional investors became eager to incorporate emerging markets into their asset allocation, searching for higher returns and diversification benefits.

The sample includes not only existing funds but also dead funds (funds that disappeared through mergers, liquidation, etc.) resulting in a survivorship bias free dataset. The period under analysis extends from January 1992 to February 2008, covering almost the entire history of this relatively new asset class. Also, these sixteen years of data capture the most important regulatory changes, political, economic and financial shocks these developing economies had experienced in the last two decades. The financial liberalization process of many Asian, European, and Latin-American countries, the Tequila crisis, the Asian crisis, the Russian crisis, the Tech bubble, the expansion of the European Union, and the beginning of the last global financial and economic crisis, are clear examples of the structural changes and crisis we capture in our sample. Our fund returns are on a monthly frequency and denominated in US dollars, assuming that no currency hedges take place.

A relevant issue to mutual fund investing is related to front loads, back-end loads and expense ratios. Front and back-end loads are one-time initial and redemption charges that might apply at the moment of purchase or sale of the fund shares. Expense ratios are ongoing annual fees and expenses and are paid directly from fund assets. Table 2.4 presents descriptive statistics for the costs associated to investing in equity funds from our emerging markets universe. Our fees and expense data has an annual frequency, and expands from March 1994 to March 2008. Expense ratios coverage is limited to about one third of the sample, while front loads (initial charges) coverage is 49% and redemption charges reach 74%. As described by panel A, fees and expenses have been following a downward trend over the last years, and as of end of February 2008 average fees were 1.94% per annum. In part, this cost reductions might be explained by the intense competition and economies of scale experienced by this fast growing industry. Fees and expenses have not only been reduced in absolute terms, also the gap between developing and developed markets has been decreasing over the last years, reducing the relative costs associated to investing in emerging markets.

2.3.2 Risk Factors

To control for risk exposures, we consider proxies for Fama and French (1993) market, size and book-to market factors as well as a country momentum factor. Most research in developing economies rely on the S&P/IFC and MSCI indices, which represent the performance of the most active stocks in emerging equity markets. We use both family indices to build the risk factors in our model. The market benchmark is defined as the return on the MSCI Total Return Emerging Markets index. As a proxy for size we consider the return spread between the S&P Primary Emerging Markets index and the S&P Extended Emerging Markets index. The book-to-market factor is represented by the return difference between the MSCI Value Emerging Markets index and the MSCI Growth Emerging Markets index. Finally, building on Moskowitz and Grinblatt (1999), we create a country momentum factor using equity market index returns for twenty six developing countries from MSCI. By incorporating this factor we intend to capture the country rotation that characterizes this asset class.

Panel A in table 2.5 presents descriptive statistics for the set of risk factors. Our factors have a monthly frequency, range from January 1992 to February 2008 and are denominated in US dollars.

2.3.3 Macroeconomic and Financial Predictive Variables

A central question in this paper is related to the identification of the main forces driving the cross-section and time series of returns in emerging markets. Therefore, the definition of the forecasting variables used to predict future returns is of key relevance in this analysis. The literature is relatively new and asset pricing theory provides little guidance on the relevant state variables when studying emerging markets as an asset class. Fama and French (1989), Keim and Stambaugh (1986) and Chen, Roll, and Ross (1986) show that expected stock returns can be related to business conditions. They identify the dividend yield, the default spread and the term spread as good predictors of US equity returns. Together with the yield on short term interest rates, these three instruments proved to be helpful when predicting mutual fund returns for US equity markets. However, the behavior of developing and developed markets differs dramatically, and so we should also expect the underlying factors driving returns to differ across markets.

Bekaert and Harvey (1997) argue that as capital markets become more integrated, global information will be expected to have a greater impact than local information when studying stock market returns and volatility. In this line, we propose as potential predictive factors the world dividend yield, an exchange rate factor, commodity prices, inflation rate, global interest rate, a market sentiment spread, volatility and short term interest rate.

Previous studies on US markets find that the dividend yield is a useful predictor of future returns. In this paper we consider a measure of the world dividend yield which is based upon large cap stocks of fifty mayor developed and emerging markets. Dividend data are reported for the trailing twelve months with country weights based on market capitalization.

Ferson and Harvey (1994) find that global exchange rates are a good measure to explain fluctuations in the stock markets of a group of developed countries. Building on their findings we investigate the predictive power of this variable in the context of emerging markets. Our exchange rate factor is the return on the Federal Reserve Board Dollar -Major Currencies Index which includes the currencies of a group of major US trading partners (the euro, Canadian dollar, Japanese yen, British pound, Swiss franc, Australian dollar, and Swedish krona). Because these currencies trade in liquid markets, this index can be used to measure financial market pressures on the US dollar. We also tested the Federal Reserve Board Dollar - Other Important Trading Partners Index which tracks the trade-weighted exchange value of the dollar against subsets of currencies from other developed and developing economies. However, the predictive power of this alternative variable was significantly lower than the current exchange rate variable.

We use returns on the Goldman Sachs Commodity Index (GSCI) to track the performance of global commodity markets. GSCI is a composite index of 24 commodities from different sectors (energy products, industrial metals, agricultural products, livestock products and precious metals), representing long-only and unleveraged investments in commodity futures. It is world-production weighted, meaning that weights are based on the average quantity of production of each commodity in the index. We expect that when developed economies dominate world growth, the metals sector will respond more than the agricultural components. Conversely, when emerging markets dominate world growth, petroleum based commodities and agricultural commodities will be more responsive.

Inflation has long been a relevant issue in many developing economies. High inflation is generally related to higher uncertainty levels and therefore weaker future economic conditions. Erb et al. (1995) study the relation between local inflation rates and expected stock return in a group of developed and developing countries. They find that in developing economies periods of low inflation are associated with high stock returns and vice versa. We consider a representative inflation factor for emerging markets. Our aggregate is based on the consumer price index for emerging countries from the International Financial Statistics database developed by the International Monetary Fund.

The global interest rate intends to capture returns on the global bond market. It is represented by the GFD Global Total Return Government Bond index, a composite using returns on 10-year bonds from a group of 18 developed countries (with South Africa being the exception) and with a weighting scheme based on GDP levels.

The market sentiment factor is the spread between developed and emerging equity markets returns. To build this variable we use the MSCI World (which includes stocks on 23 developed countries) and the MSCI Emerging Markets Price Index.

We propose the VIX index as a proxy to capture the expectations of future volatility in the market. Previous studies suggest that we can expect higher volatility levels during recessions as well as right after announcements.

Finally, following the literature on US predictive variables, we include a short risk free rate factor represented by the yield on the three months Treasury bill. Appendix B presents detailed definitions and data sources for our proposed set of predictive variables. Panel B in table 2.5 presents descriptive statistics for the variables over our sample period.

2.4 Empirical Results

In this section we present out-of-sample results for the four Bayesian strategies and assess the economic value of predictability in emerging market funds. We also investigate the predictive power of the proposed set of macroeconomic and financial state variables to generate superior performance under changing economic conditions.

The out-of-sample analysis is based on the creation of optimal portfolios from a universe of 1226 funds as of end of January 2008, and expands from February 1997 to February 2008. Given our entire sample starting in January 1992, we begin considering only the fund data available before the backtest date (February 1997), compute the

Bayesian predictive first and second moments for the different active strategies, and create optimal portfolios of funds using updated data every quarter until the current period. If a fund's return is missing during the holding period, the fund's weight is allocated proportionally to funds in the portfolio until the next rebalancing period. Our mean-variance optimization creates long-only portfolios, ruling out any possibility for short selling. We also apply a twenty five percent cap at the fund level when calculating optimal portfolio weights. The degree of belief about managerial skills, σ_α, is set to 0.10 monthly for the Agnostic, APML and AMA investors; and 0.01 monthly for the Skeptic investor. Following AW, we define the coefficient of risk aversion to be 2.94. Under the baseline case we consider the complete set of risk factors, namely returns on the market portfolio, size, book-to-market and country momentum. While as state variables we include commodities, the short term interest rate, inflation and our proxy for implied volatility.

Table 2.6 presents our baseline results for the four investor types over the entire out-of-sample period. We track results versus the market benchmark, represented by the MSCI Emerging Markets Total Return index, and the CAPM portfolio. The CAPM can be interpreted as a dogmatic investor who believes that benchmark returns and factor loadings are not predictable and managers have no skill to generate alpha.

Overall, the four active strategies outperform the market and the CAPM portfolio over the entire out-of-sample period. The level of outperformance is economically significant both from an absolute and risk adjusted basis. Alpha levels range from 6.88% to 9.35% per annum while sharpe ratios extend from 0.56 to 0.65 (versus 0.38, and 0.31 achieved by the market and the CAPM). Within the Bayesian strategies is the APML investor, the version of the Agnostic that assumes that non-market factor loadings are constant, who produces the highest absolute returns with an annualized arithmetic mean of 19.9%, generates an annualized alpha of 9.35% and a 0.65 sharpe ratio. However, is the AMA investor, the Agnostic that allows for constant factor loadings, who manages to beat the market on a more consistent basis, outperforming the benchmark 61% of the times. Figure 2.3 illustrates the cumulative value of one dollar invested in the active strategies, the CAPM and the market benchmark at the beginning of the out-of-sample period, assuming no transaction costs. By the end of the period the APML investor would have more than double the investment value of the market and CAPM portfolio, delivering 6.22 dollars versus 2.90 dollars by the market benchmark and 2.40 dollars by the CAPM.

We next examine optimal allocations for the Bayesian strategies as of end of February 2008. As described by table 2.10, the APML portfolio is also the most diversified across strategies, while the Agnostic, AMA and Skeptic portfolios are fairly concentrated, holding 75% of their allocation in only three funds. Note that optimal portfolios for the AMA and Skeptic investor have similar composition in terms of selected funds.

To investigate further our results, we perform a sub-sample analysis. Table 2.7 presents performance statistics for the Bayesian strategies considering periods of three, five, seven and ten years as of end of February 2008. Note that over the different sub-periods the four strategies delivered superior ex-post performance. Specially over the five and seven years the strategies generated annualized alphas in the order of 14% to 24.7%. During the three and five year periods the AMA investor outperformed the rest of the active strategies, with an alpha of 12.45% and 24.68% respectively. On the other hand, and as in the full sample case, the APML investor delivered the strongest results during the seven and ten year intervals, with annualized alphas of 16.32% and 9.44%.

Figure 2.2 illustrates one-year rolling annualized returns for the four active strategies, the market benchmark and the CAPM portfolio. Note that the active portfolios outperformed the benchmark and the CAPM under changing market conditions, producing superior performance under both bearish and bullish markets. To further investigate these results, table 2.8 provides performance statistics on a calendar year basis for the four strategies and the market benchmark. Note that with the exception of 1998 Russian financial crisis, where market annualized volatility reached 41%, the strategies manage to outperform the market during downward markets. This is the case for 1997 Asian crisis and aftermath of the Tech bubble burst covering part of 2000, 2001 and 2002. Also under bull markets such as 2003, 2004, 2005 and 2007 the four active strategies deliver strong absolute and risk adjusted performance, with alpha levels ranging from 10% to 71% and sharpe ratios from 1.84 to 3.36.

On the other hand, during 1999 and 2006 the strategies lagged the market benchmark. In the case of 2006, underperformance is mainly driven by poor fund selection across strategies during the months of March and June. While in 1999, during the Tech bubble, the active strategies generated strong annualized mean returns ranging from 32.7% to 49%. However, they were unable to beat the market that reported an annualized mean return of 54.4%, with all the strategies trailing the benchmark between May and August of 1999. In general, we find that both during bear and bull market conditions, the active strategies tend to perform stronger under less volatile market conditions.

2.4.1 Portfolio Rotation

Table 2.9 shows annual snapshots of optimal portfolio allocations for the four Bayesian strategies grouped by investment objective. In this table we intend to capture portfolio rotation across regions during the entire out-of-sample period. As described by table 2.9, the four active strategies have been consistently exposed to Global emerging market funds, with larger allocations during the period covering 1997 to 2000. During these years average allocation to Global emerging markets ranged from 50% to 63% across strategies. Also, with the Agnostic investor being the only exception, allocations to emerging Europe have been fairly consistent during 1997 to 2003, with average weights ranging from 20% to 29%. However, since 2004 portfolio weights have successfully shifted to outperforming regions such as Latin America and funds investing in the Middle East and Africa, mainly in the Arabian Peninsula. Note that exposure to funds investing only in the Far East has been considerably limited across strategies. This investment decision benefited our portfolios' performance as the region consistently lagged Global emerging markets as well as outperforming regions such as Latin America. Results provide evidence of the ability of the active strategies to successfully rotate across emerging market regions as favorable economic conditions and investment opportunities arise.

In summary, out-of-sample results for the four Bayesian strategies suggest that incorporating predictability in managerial skills, risk loadings and benchmark returns by exploiting the proposed set of emerging market macroeconomic variables, can help predict returns and identify those fund managers that generate abnormal returns over different phases of the cycle.

2.4.2 Sensitivity to Predictive Variables

In this section we study the set of potential macroeconomic and financial variables use in the estimation of time-variations in alphas, benchmark returns and factor loadings. Table 2.11 presents out-of-sample performance statistics for the Bayesian strategies when considering a single predictive variable during the forecasting stage of emerging market fund returns. We individually evaluate the short term interest rate, world dividend yield, exchange rate, market sentiment, commodities, global interest rate, inflation and implied volatility. As in our baseline case, the complete set of risk factors is considered. All strategies are long-only, subject to quarterly rebalance and have a twenty five percent cap at the fund level when calculating optimal portfolio weights. Note that all the proposed predictive variables managed to produce superior absolute and risk-adjusted performance across the four Bayesian strategies. Inflation produced the strongest results for the Agnostic and the APML investor, with alphas in the order of 10.82% and 9.54% respectively. In the case of the AMA and the Skeptic portfolio, implied volatility, followed by commodities, performed the best. Annualized alpha reached 9.45% for the AMA and 9.66% for the Skeptic investor.

Results support the idea that a variety of global and regional state variables can be useful in generating economic value through active management strategies, with inflation, commodities and implied volatility delivering the strongest results. It is also worth noting that dividend yield and short term interest rate, widely recognized as useful predictors in the context of US markets, can also be helpful when forecasting fund returns in emerging markets.

2.5 Robustness Analysis

In this section we perform a series of robustness checks by modifying the setting of our baseline case. These changes are related to the rebalancing frequency of the optimal allocations and the restrictions on the maximum weight allowed to individual funds in the creation of our optimal portfolios.

2.5.1 Rebalancing Scheme

In our baseline case we calculate optimal portfolio weights on a quarterly basis. However, given initial charges and potential exit fees investors may face when investing in emerging market funds, it seems reasonable considering longer holding periods.

Table 2.12 compares performance statistics for the Agnostic, APML, AMA and Skeptic investor under a semiannual and annual rebalancing scheme. As described by panel A, when we move from quarterly to semiannual horizons, the strategies still managed to generate economic value by identifying portfolios of outperforming funds. However, there is a reduction in the level of out-performance. The AMA's annualized alpha falls from 7.98% to 6.53% and the Skeptic's decreases from 7.95% to 6.13%. Larger drops are experienced by the APML (from 9.35% to 4.54) and the Agnostic investor (from 6.87% to 0.8%). In terms of risk-adjusted performance, sharpe ratios declined across strategies. Nevertheless, the APML, AMA and Skeptic still delivered sharpe ratios in the range of 0.46 to 0.53, outperforming the 0.38 of the market.

Panel B presents performance statistics when we further move to an annual rebalancing scheme. Note that the strategies' ability to generate alpha is largely reduced with only the AMA and Skeptic investor being able to produce positive levels of alpha (2.3% and 1.5% respectively). Sharpe ratio levels also dropped further, lagging that of the benchmark.

With respect to risk levels, reforming every quarter, six months or twelve months has a small impact on portfolio volatility, with all strategies slightly increasing volatility levels as we move from a more to a less frequent rebalancing scheme.

These findings provide empirical evidence that when we incorporate predictability that exploits business cycle related variables, the frequency in which optimal portfolio weights are calculated has a direct impact on the strategy's ability to generate alpha. The less frequent optimal portfolios are rebalanced, the lower the absolute and risk adjusted returns delivered by the active strategies.

2.5.2 Portfolio Weights

In this section we run the Bayesian strategies considering different scenarios based on restrictions on the maximum portfolio weight allowed during the portfolio creation process. As in the baseline case we rule out short selling. Table 2.13 presents out-of- sample performance statistics for the active strategies when considering an unconstrained setting (panel A), a 50% cap at the fund level (panel B) and a 10% constrain (panel C). Note that the strategies' ability to outperform the market and generate strong alphas remained unaffected under the different constraint levels, adding robustness to our baseline results. Across scenarios, average annualized alphas reach 6.49% for the Agnostic, 9.12% for the APML, 7.85% for the AMA and 7.70% for the Skeptic investor. In terms of portfolio volatility, results show that as we reduce restrictions on optimal portfolio weights there is a slight increase in portfolio volatility. Average volatility across strategies reaches 23.66% under the most restrictive setting (panel C) while under the unconstrained case average level rise to 27.23%. Finally, consistent with our previous results, risk adjusted performance also improves as we impose tighter restrictions on maximum weights, with average sharpe ratio across strategies increasing from 0.53 to 0.62.

2.6 Conclusions

Most of the academic studies in the mutual fund literature have been related to US equity markets, but not much has been said on emerging markets funds. This paper is the first to study mutual fund predictability in emerging markets using a comprehensive universe of global and regional equity funds. Our analysis starts in the early stages of this new asset class, allowing us to study the performance of emerging market funds under different market conditions. Our sample covers the financial liberalization process of many developing countries in the early 90's, the Tequila crisis of 1995, the Asian crisis in 1997, the Russian crisis of 1998, the Tech bubble of 2000, the expansion of the European Union in 2004, as well as the beginning of the last global financial and economic crisis, among other key episodes.

A central question in this paper is related to the identification of the forces driving the cross-section and time series of returns in emerging market funds. To tackle this question we propose a set of macroeconomic and financial variables that proved to add value in the investment decision process of our Bayesian investors. These variables include the short risk free rate, the dividend yield, an exchange rate index, a market sentiment factor, commodities, global interest rate, inflation and implied volatility.

We assess the economic value of predictability in emerging market funds under a series of different scenarios. Our out-of-sample results suggest that incorporating predictability in managerial skills, risk loadings and benchmark returns can help predict returns and identify those funds that generate abnormal returns over different phases of the cycle. Furthermore, results provide empirical evidence of the economic value of active management in emerging markets.

Appendix A: Predictive Moments for Bayesian Investors

This appendix describes the predictive moments for our four Bayesian investors as defined by AW (2006) and BGTW (2008).

The Agnostic Investor

This investor is based on the PA-4 investor in AW (2006). Bayesian predictive mean and variance are defined as follows:

$$E\left\{r_{T+1}|D_T\right\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}_T \tilde{A}_F' x_T, \tag{2.4}$$

$$V\left\{r_{T+1}|D_T\right\} = (1+\delta_T)\,\tilde{\beta}_T \hat{\Sigma}_{ff} \tilde{\beta}_T' + A_T, \tag{2.5}$$

where $\tilde{\alpha}_0$, $\tilde{\alpha}_1$, and $\tilde{\beta}_T$ are the all-fund versions of $\tilde{\alpha}_{i0}$, $\tilde{\alpha}_{i1}$, and $\tilde{\beta}_i(z_T) = \tilde{\beta}_{i0} + (I_K \otimes z_T')\,\tilde{\beta}_{i1}$. $\tilde{\alpha}_{i0}$, $\tilde{\alpha}_{i1}$, $\tilde{\beta}_{i0}$, and $\tilde{\beta}_{i1}$ are the first, the next M, K, and the last $K \times M$ elements in the vector $\tilde{\Gamma}_i = (G_i'G_i + \Upsilon)^{-1}(G_i'r_i + \Upsilon\Gamma_{i0})$. $G_i = \left[G_{t_i}', ..., G_{t_i+T_i-1}'\right]$, with $G_t = \left[1, z_{t-1}', f_t', f_t' \otimes z_{t-1}'\right]'$. Υ is a $(KM+K+M+1)\times(KM+K+M+1)$ matrix of zeros except the $(1,1)$ element, which is s^2/σ_α^2. $\Gamma_{i0} = [\bar{\alpha}_{i,0}, 0, ..., 0]'$, where $\bar{\alpha}_{i,0} = -\frac{1}{12}(expense)$. $\tilde{A}_F = \hat{A}_F = (X'X)^{-1}X'F$, where $X = \left[x_0', ..., x_{T-1}'\right]'$, $x_t = [1, z_t]$, and $F = [f_1', ..., f_T']'$.

Related to the predictive variance, we define A_T as a diagonal matrix with (i,i) element equal to

$$\tilde{\psi}_{i2}\begin{pmatrix} 1 + tr\left[\hat{\Sigma}_{ff}\tilde{\Omega}_i\right](1+\delta_T) + x_T'\Omega_i^{11}x_T \\ +2x_T\left[\Omega_i^{12} + \Omega_i^{13}(I_K \otimes z_T)\right]\tilde{A}_F'x_T + tr\left[\tilde{A}_F'x_T x_T'\tilde{A}_F\tilde{\Omega}_i\right] \end{pmatrix} \tag{2.6}$$

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

We define the covariance of the risk factors as $\hat{\Sigma}_{ff} = F'Q_XF/(T-K-M-2)$ with $Q_X = I_T - X(X'X)^{-1}X$. Finally, $\delta_T = \frac{1}{T}\left[1 + (\bar{z} - z_T)'\hat{V}_z^{-1}(\bar{z} - z_T)\right]$ where $\hat{V}_z = \frac{1}{T}\sum_{t=1}^{T}(z_t - \bar{z})(z_t - \bar{z})'$.

The Agnostic Predictable Market Loadings Investor

This investor assumes constant non-market factor loadings. Bayesian predictive mean and variance only differ from AW Agnostic investor in that the time-varying component of risk loadings, β_{i1}, has M elements. Also, in this setting $G_t = \left[1, z'_{t-1}, f'_t, r_{m,t}z'_{t-1}\right]'$ and r_m is the excess return on the market portfolio. Υ is now a $(M+2K+1)\times(M+2K+1)$ matrix.

The Agnostic Macro-Alpha Investor

This investor sets the time-varying component of risk loadings to zero. Predictive moments are defined as follows:

$$E\left\{r_{T+1}|D_T\right\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}_0 \tilde{A}'_F x_T. \tag{2.7}$$

$$V\left\{r_{T+1}|D_T\right\} = (1+\delta_T)\,\tilde{\beta}_0 \hat{\Sigma}_{ff} \tilde{\beta}'_0 + A_T, \tag{2.8}$$

In this setting, $G_t = \left[1, z'_{t-1}, f'_t\right]'$ and Υ is a $(M+K+1)\times(M+K+1)$ matrix. A_T has (i,i) element defined as follows:

$$\tilde{\psi}_{i2}\left(\begin{array}{c} 1+tr\left[\hat{\Sigma}_{ff}\Omega_i^{22}\right](1+\delta_T)+x'_T\Omega_i^{11}x_T+2x_T\Omega_i^{12}\tilde{A}'_F x_T \\ +tr\left[\tilde{A}'_F x_T x'_T \tilde{A}_F \Omega_i^{22}\right] \end{array}\right). \tag{2.9}$$

The Skeptic Investor

This investor is skeptical about manager skills and believes that benchmark returns and factor loadings are not predictable. First and second moments are defined as follows:

$$E\left\{r_{T+1}|D_T\right\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}\,\bar{f}, \tag{2.10}$$

$$V\left\{r_{T+1}|D_T\right\} = \left(1+\frac{1}{T^*}\right)\tilde{\beta}\tilde{V}_f\tilde{\beta} + A_T, \tag{2.11}$$

The individual fund's $\tilde{\alpha}_{i0}$, $\tilde{\alpha}_{i1}$, and $\tilde{\beta}_i$ are the first, M, and the last K elements in $\tilde{\Gamma}_i = \left(G'_iG_i + G'_{i0}G_{i0}\right)^{-1}\left(G'_ir_i + \left[G'_{i0}G_{i0}\right]\Gamma_{i0}\right)$, where $G_i = \left[G'_{t_i}, \ldots, G'_{t_i+T_i-1}\right]$ and

$G_t = [1, z_{t-1}, f_t']'$.

$$\left[G_{i0}'G_{i0}\right]^{-1} = \frac{1}{T_0}\begin{bmatrix} 1+\bar{z}'\hat{V}_z^{-1}\bar{z}+\bar{f}'\hat{V}_F^{-1}\bar{f} & -\bar{z}'\hat{V}_z^{-1} & -\bar{f}'\hat{V}_F^{-1} \\ -\hat{V}_z^{-1}\bar{z} & \hat{V}_z^{-1} & 0 \\ -\hat{V}_F^{-1}\bar{f} & 0 & \hat{V}_F^{-1} \end{bmatrix}. \tag{2.12}$$

Where $T_0 = \frac{s^2}{\sigma_\alpha^2}\left(1+M+SR_{max}^2\right)$. A_T is a diagonal matrix with the (i,i) element given by:

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

where $T^* = T + T_0$, $T_i^* = T_i + T_0$, and Ω_i^{mn} are based on the partition of $\left(G_i'G_i + G_{i0}'G_{i0}\right)^{-1}$.

$$\tilde{V}_f = \frac{T^*\hat{V}_f}{T^*-K-3}$$

$$\tilde{\psi}_{i3} = \frac{\left(T_i^*/T_i\right)r_i'r_i - \tilde{\Gamma}_i'\left(G_i'G_i+G_{i0}'G_{i0}\right)\tilde{\Gamma}_i}{T_i^*-K-M-2},$$

Figures and Tables

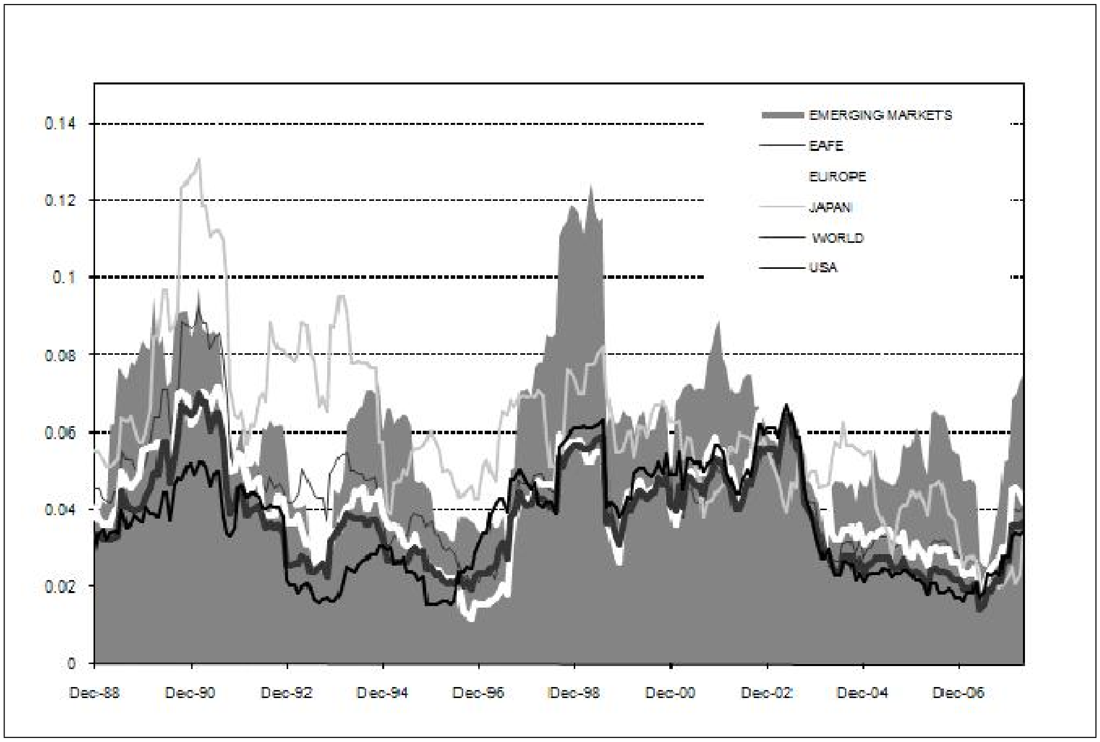

Figure 2.1: **Rolling One-year Volatility**

This figure compares rolling one-year volatilities of emerging equity markets and developed markets. Volatilities are based on monthly returns from MSCI Price indices. Equity indices are from MSCI Barra website.

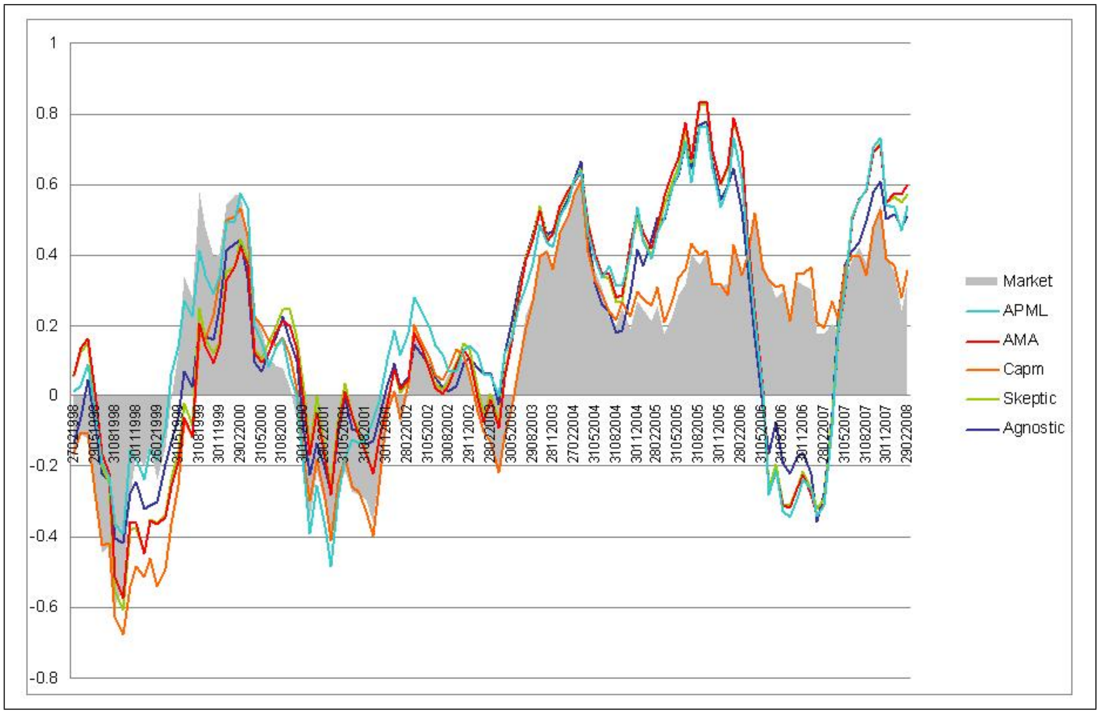

Figure 2.2: **Rolling 1-year returns : Active Strategies vs. Market Benchmark**
This figure presents rolling one-year annualized returns for the four active strategies, the CAPM and the market benchmark over the entire out of sample period. For the active strategies we considered the baseline case as defined in table 2.6.

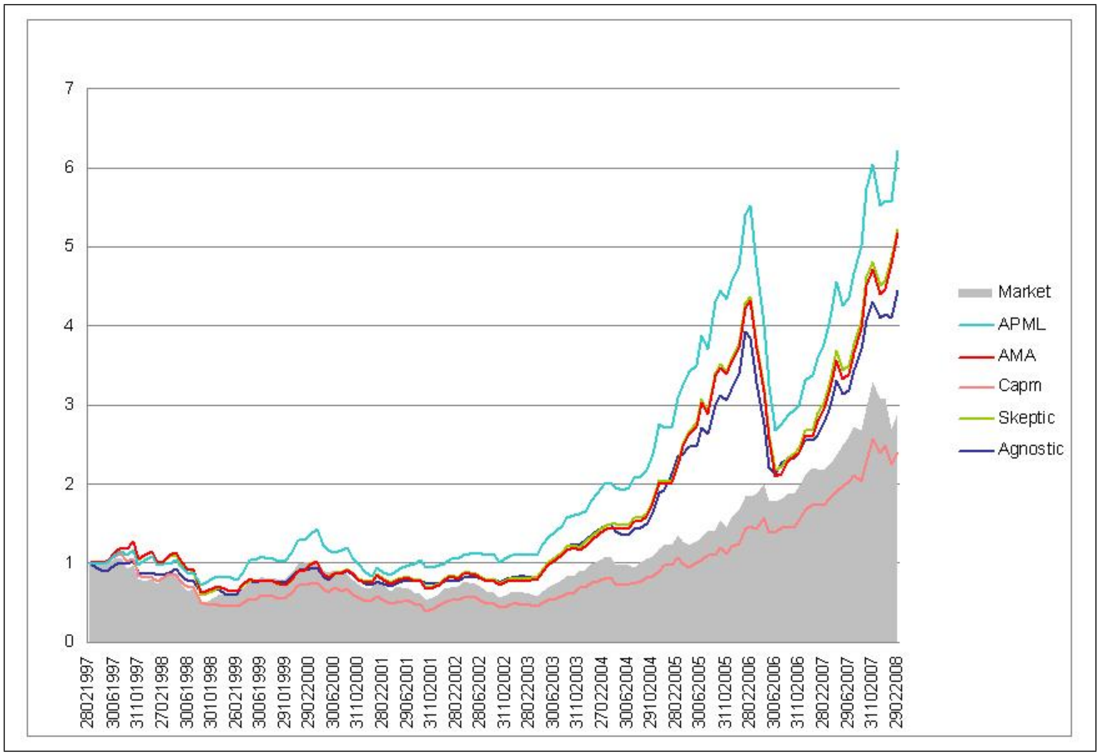

Figure 2.3: **Cumulative Growth of 1 Dollar**

This figure compares the cumulative value of 1 dollar invested in the active strategies, the CAPM and the market benchmark at the beginning of the out of sample period. We assumed no transaction costs.

Table 2.1: **Emerging versus Developed Equity Markets**

This table compares annualized performance of developed and emerging equity markets over a one, three, five, ten and 20 years period. Equity markets are represented by MSCI regional Price Indices. Monthly returns are as of end of March, 2008 denominated in US dollars. Equity indices are from MSCI Barra website.

	1 Yr	**3 Yrs**	**5 Yrs**	**10 Yrs**	**20 Yrs**
Emerging Markets	18.9%	26.3%	32.3%	9.7%	16.14%
USA	-6.6%	4.2%	9.5%	1.7%	12.01%
Europe	-2.5%	11.9%	19.8%	4.3%	11.69%
Japan	-16.1%	5.1%	13.7%	2.5%	-1.51%
Eafe	-5.1%	10.7%	18.6%	4.1%	6.09%
World Developed	-5.1%	7.7%	13.9%	3.0%	8.27%

Table 2.2: **Correlations over time**

This table presents emerging equity markets correlations with developed markets. Correlations are based on monthly returns from MSCI Price indices. Equity indices are from MSCI Barra website.

	1988-1989	**1994-1995**	**1999-2000**	**2004-2005**	**2006-2008**
Eme - USA	0.17	0.46	0.65	0.71	0.63
Eme - Europe	0.08	0.43	0.63	0.78	0.82
Eme - Japan	0.18	0.26	0.65	0.53	0.65
Eme - Eafe	0.17	0.45	0.76	0.86	0.88
Eme - World	0.19	0.51	0.75	0.85	0.81

Table 2.3: **Universe Size and Performance**

Panel A presents the number of funds by investment objective at the beginning of each calendar year. Panel B shows the annualized time series average returns for the different sample categories and the market benchmark (MSCI Emerging Markets Index). Funds' data is from Lipper Mutual Fund Database for the period covering January 1992 to February 2008. Monthly returns are in US dollars. The category Emerging Markets Others is composed by regional funds investing mainly in the Middle East and Africa.

	Total	**Global**	**Europe**	**Far East**	**Latin**	**Others**	**Benchmark**
Panel A. Number of funds							
1992	23	8	7	0	4	4	
1996	124	59	39	6	12	8	
2000	354	153	101	18	52	30	
2004	613	275	158	34	93	53	
2008	1226	466	254	74	191	241	
Entire sample	1318	515	273	77	207	246	
Panel B. Average returns (annualized)							
1992-1993	26.64	23.37	28.19	50.57	19.05	41.30	35.30
1994-1995	-9.37	-7.87	-9.36	-9.84	-9.03	-20.13	-4.91
1996-1997	10.71	7.11	12.52	15.01	9.80	22.21	-1.36
1998-1999	8.86	9.87	9.88	9.53	9.33	1.12	17.06
2000-2001	-12.51	-13.56	-11.69	-12.22	-11.75	-9.31	-16.40
2002-2003	22.59	22.55	24.03	21.89	23.75	19.55	21.15
2004-2005	29.07	28.76	29.73	27.16	27.30	34.72	28.10
2006-2008	27.13	27.27	28.30	27.17	27.46	24.26	27.97
Entire sample	13.04	12.34	14.10	14.21	12.15	14.32	13.52

Table 2.4: **Fees Summary Statistics**

This table presents summary statistics for fees, expenses and related costs. Fees and expenses are ongoing annual expenses and are represented as a percentage of the assets of the fund. Initial charge covers administration costs and commission at the time of purchase of shares of a fund; also known as front end load. Redemption charge refers to the fee charged when assets are withdrawn from a strategy.

	Average	**Median**	**Standard Deviation**
Panel A. Fees and Expenses			
1994-1995	2.26	2.01	0.68
1997-1998	2.08	2.07	0.50
2000-2001	1.99	1.98	0.50
2003-2004	2.22	2.10	0.67
2007-2008	1.94	1.98	0.56
Panel B. Entry and Exit Costs			
Initial Charge	1.68	1.00	1.96
Redemption Charge	0.17	0.00	0.47

Table 2.5: **Descriptive Statistics**

Panel A presents descriptive statistics for the set of risk factors considered in the paper: the market benchmark, size, book-to-market and country momentum. In panel B we show descriptive statistics for the set of proposed state variables. Results are based on monthly series for the period January 1992 to February 2008.

	Mean	**Median**	**Maximum**	**Minimum**	**Standard Deviation**	**Skewness**	**Kurtosis**	**AR**
Panel A. Risk Factors								
Market	1.13	1.32	16.53	-28.91	6.41	-0.78	4.98	0.14
Size	-0.18	-0.19	4.75	-6.81	1.96	-0.36	3.66	0.12
Book-to-market	0.22	0.28	6.75	-9.78	2.02	-0.59	7.54	0.07
Country Momentum	0.81	0.87	41.48	-36.14	11.69	-0.05	4.32	0.04
Panel B. Macro Variables								
Short Term Rate	3.80	4.26	6.19	0.89	1.51	-0.55	2.07	0.98
Commodities	252.51	202.97	679.78	130.83	115.54	1.56	4.49	0.95
Inflation	90.77	98.25	155.82	14.45	38.91	-0.41	2.11	0.98
Volatility	19.74	18.00	48.33	9.82	7.38	1.00	3.86	0.87
Dividend Yield	2.04	2.08	3.00	1.25	0.39	0.11	3.00	0.96
Exchange Rate	91.21	89.25	111.99	72.20	8.93	0.39	2.50	0.97
Market Sensitivity	0.01	0.42	26.04	-18.70	6.14	0.08	4.54	-0.45
Global Interest Rate	248.68	231.23	412.13	132.26	75.04	0.38	1.94	0.98

Table 2.6: **Out of Sample Portfolio Performance - 02/97 to 02/08**

This table presents Out-of- sample performance statistics for the four active strategies and the CAPM during February 1997 to February 2008. We consider commodities, inflation and volatility as the predictive variables. Risk factors are represented by the market benchmark, size, book-to-market and country momentum. We follow a quarterly rebalance scheme and apply a 25% cap at the fund level when calculating optimal portfolio weights. Beliefs are specified at 10% per month. Mean returns, volatility and Sharpe ratio are annualized. Monthly outperformance is the percentage of months during which the strategy outperformed the market benchmark.

	Benchmark	**Agnostic**	**APML**	**AMA**	**Skeptic**	**CAPM**
Geometric mean	9.7%	13.7%	16.7%	15.0%	15.1%	8.0%
Arithmetic mean	12.7%	16.3%	19.9%	18.7%	18.8%	11.0%
Volatility	24.2%	22.7%	25.0%	26.4%	26.8%	24.2%
Sharpe ratio	0.38	0.56	0.65	0.57	0.57	0.31
Beta		0.64	0.71	0.75	0.78	0.95
Alpha		6.88%	9.35%	7.98%	7.95%	-1.42%
Alpha t-Stat		1.36	1.68	1.37	1.37	-0.63
Monthly Outperf.		54%	58%	61%	58%	53%

Table 2.7:

Sub-Sample Results

This table presents out-of- sample performance statistics for the four active strategies and the Capm during 3, 5, 7 and 10 years periods as of end of February 2008. We follow a quarterly rebalance scheme and apply a 25% cap at the fund level when calculating optimal portfolio weights.

	3 years					5 years				
	Market	**Agnostic**	**APML**	**AMA**	**Skeptic**	**Market**	**Agnostic**	**APML**	**AMA**	**Skeptic**
Geometric mean	25.8%	21.5%	23.7%	28.3%	28.0%	31.6%	34.5%	35.1%	38.2%	37.7%
Arithmetic mean	27.8%	25.2%	28.2%	32.9%	32.5%	33.3%	37.5%	38.4%	41.5%	40.9%
Volatility	20.2%	26.9%	30.1%	30.2%	29.7%	18.3%	24.4%	25.9%	25.6%	25.3%
Sharpe ratio		0.79	0.80	0.95	0.96		1.42	1.37	1.50	1.50
Beta		0.58	0.63	0.47	0.49		0.64	0.64	0.45	0.47
Alpha		4.55%	4.01%	12.45%	11.84%		15.07%	15.06%	24.68%	23.66%
Alpha t-Stat		0.31	0.25	0.73	0.71		1.55	1.44	2.22	2.17
Monthly Outperf.		50%	58%	64%	58%		55%	63%	67%	62%
	7 years					10 years				
	Market	**Agnostic**	**APML**	**AMA**	**Skeptic**	**Market**	**Agnostic**	**APML**	**AMA**	**Skeptic**
Geometric mean	20.1%	26.0%	28.1%	27.2%	27.0%	12.8%	16.6%	18.6%	16.4%	16.5%
Arithmetic mean	22.2%	28.4%	30.8%	30.2%	29.9%	15.8%	19.2%	21.8%	20.0%	20.2%
Volatility	20.3%	21.9%	23.2%	24.2%	24.0%	23.9%	23.0%	24.9%	26.3%	26.7%
Sharpe ratio		1.18	1.21	1.13	1.13		0.69	0.74	0.63	0.63
Beta		0.57	0.57	0.57	0.59		0.65	0.70	0.75	0.79
Alpha		14.08%	16.32%	16.24%	15.82%		7.49%	9.44%	6.74%	6.71%
Alpha t-Stat		1.98	2.13	2.00	1.99		1.38	1.60	1.10	1.10
Monthly Outperf.		57%	64%	68%	63%		53%	58%	60%	57%

Table 2.8: **Out of Sample Performance by Calendar Year**

This table presents out-of- sample performance statistics for the four active strategies by calendar year. We considered commodities inflation and volatility as the predictive variables and the market benchmark, size, book-to-market and country momentum as the risk factors.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Agnostic											
Geo. mean	-14.6%	-34.7%	39.1%	-24.8%	8.2%	7.2%	49.9%	35.2%	58.4%	-28.3%	49.8%
Arith. mean	-12.9%	-32.0%	41.2%	-22.3%	9.3%	7.9%	51.5%	36.8%	60.0%	-21.9%	51.4%
Volatility	19.1%	23.3%	22.1%	23.0%	15.3%	12.0%	18.9%	19.3%	19.4%	36.3%	18.6%
Sharpe ratio	-0.94	-1.58	1.65	-1.22	0.39	0.53	2.67	1.84	2.93	-0.73	2.53
Alpha	4.75%	-22.56%	-7.45%	42.28%	2.16%	7.82%	9.97%	18.39%	41.65%	-62.01%	36.14%
Alpha t-Stat	0.32	-2.05	-0.81	4.32	0.24	1.09	0.68	1.39	2.09	-2.03	1.91
APML											
Geo. mean	9.4%	-27.2%	46.0%	-42.0%	16.5%	10.7%	49.7%	42.2%	57.4%	-33.9%	51.3%
Arith. mean	12.9%	-23.8%	49.0%	-39.3%	18.3%	11.6%	50.6%	43.7%	59.3%	-26.6%	53.7%
Volatility	26.8%	26.6%	26.5%	23.6%	19.9%	13.8%	14.7%	18.6%	21.3%	38.9%	22.9%
Sharpe ratio	0.29	-1.07	1.67	-1.92	0.76	0.73	3.36	2.28	2.63	-0.81	2.16
Alpha	39.37%	-7.98%	-8.37%	18.36%	11.38%	8.78%	17.40%	31.83%	58.96%	-69.16%	23.70%
Alpha t-Stat	2.27	-0.82	-0.61	1.18	0.90	1.34	1.60	2.20	2.50	-2.04	1.09
AMA											
Geo. mean	16.8%	-52.5%	30.3%	-19.0%	4.8%	-1.8%	52.7%	44.9%	63.2%	-35.3%	55.3%
Arith. mean	20.3%	-44.9%	32.7%	-16.6%	7.6%	-0.5%	53.9%	46.0%	65.2%	-28.0%	57.6%
Volatility	27.0%	37.6%	23.5%	22.3%	24.7%	17.3%	16.3%	16.0%	21.3%	38.7%	22.3%
Sharpe ratio	0.57	-1.32	1.19	-1.00	0.18	-0.12	3.24	2.78	2.91	-0.85	2.39
Alpha	47.60%	-23.57%	-20.78%	39.64%	-2.72%	-3.78%	31.00%	37.95%	70.98%	-67.29%	32.16%

Table 2.8: **Out of Sample Performance by Calendar Year (cont.)**

Alpha t-Stat	2.69	-1.59	-2.36	3.37	-0.40	-0.46	1.99	2.65	3.02	-1.96	1.43
Skeptic											
Geo. mean	16.4%	-53.1%	32.5%	-18.0%	4.5%	1.0%	51.7%	42.9%	62.7%	-33.2%	54.3%
Arith. mean	20.0%	-44.8%	35.3%	-15.3%	7.6%	2.4%	52.9%	44.0%	64.7%	-26.2%	56.5%
Volatility	27.1%	39.2%	25.4%	24.2%	25.9%	17.6%	16.7%	16.1%	21.2%	38.2%	21.8%
Sharpe ratio	0.55	-1.26	1.20	-0.87	0.17	0.04	3.10	2.65	2.90	-0.81	2.39
Alpha	47.29%	-24.21%	-22.38%	51.93%	-3.28%	-0.85%	28.65%	35.47%	70.23%	-66.14%	30.52%
Alpha t-Stat	2.65	-1.76	-2.58	4.71	-0.49	-0.10	1.85	2.48	2.99	-1.97	1.41
Benchmark											
Geo. mean	-27.4%	-28.9%	52.2%	-36.1%	-2.4%	-6.2%	45.5%	23.3%	30.0%	28.6%	34.0%
Arith. mean	-24.4%	-20.3%	54.5%	-34.8%	2.0%	-4.2%	46.5%	24.4%	31.8%	30.2%	35.5%
Volatility	24.8%	40.7%	23.0%	16.8%	30.8%	20.5%	15.1%	15.7%	19.6%	18.7%	18.4%
Sharpe ratio	-1.19	-0.62	2.17	-2.42	-0.04	-0.28	3.01	1.47	1.46	1.36	1.69

Table 2.9: Portfolio Rotation

This table shows optimal portfolio weights grouped by investment objectives for the different Bayesian strategies. Weights are as of the calendar year with the exception of 2008 which is as of end of January. We follow a quarterly rebalance scheme and apply a 25% of end cap at the fund level.

	1997	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
A. Agnostic												
EM Europe	-	-	11%	-	27%	43%	1%	-	-	25%	31%	50%
EM Far East	-	-	-	-	-	23%	-	-	-	-	-	6%
EM Global	68%	89%	40%	52%	48%	34%	45%	-	25%	24%	40%	44%
EM Latam	32%	-	25%	-	25%	-	3%	25%	25%	37%	11%	-
EM Other	-	11%	24%	48%	-	-	50%	75%	50%	15%	18%	-
B. APML												
EM Europe	12%	25%	23%	20%	26%	20%	15%	-	-	25%	-	12%
EM Far East	-	-	-	-	24%	25%	-	-	-	-	-	-
EM Global	56%	75%	76%	46%	25%	23%	25%	12%	25%	39%	50%	56%
EM Latam	-	-	-	-	25%	32%	25%	10%	25%	20%	25%	31%
EM Other	32%	-	1%	34%	-	-	35%	78%	50%	16%	25%	-
C. AMA												
EM Europe	25%	-	25%	41%	50%	11%	25%	-	-	-	-	6%
EM Far East	-	-	2%	-	-	50%	-	-	-	-	-	-
EM Global	25%	75%	57%	37%	25%	9%	35%	25%	25%	25%	50%	50%
EM Latam	-	25%	-	8%	25%	31%	4%	25%	5%	61%	25%	44%
EM Other	50%	-	16%	15%	-	-	37%	50%	70%	14%	25%	-

Table 2.9: **Portfolio Rotation (cont.)**

D. Skeptic												
EM Europe	25%	-	8%	42%	50%	13%	25%	-	-	-	-	5%
EM Far East	-	-	-	-	-	50%	-	-	-	-	-	-
EM Global	25%	75%	75%	25%	25%	9%	36%	25%	27%	25%	50%	50%
EM Latam	-	25%	15%	14%	25%	28%	1%	25%	-	62%	25%	45%
EM Other	50%	-	2%	19%	-	-	38%	50%	73%	13%	25%	-

Table 2.10: **Optimal Portfolio Weights**

This table shows optimal portfolio weights as of end of February 2008 for the four Bayesian strategies. We considered commodities, inflation and volatility as the predictive variables. Risk factors are represented by the market benchmark, size, book-to-market and country momentum. We apply a 25% cap at the fund level when calculating optimal portfolio weights. Beliefs are specified at 10% per month.

	Agnostic	**APML**	**AMA**	**Skeptic**
As of end of February 2008				
Share Emerging Cap	8.4%	-	-	-
MC Premium - Eastern European Equities	25.0%	3.0%	-	-
AZ Fund 1 EM Asia A AZ FUND	3.9%	-	-	-
ING (L) Invest E Europe P Cap	25.0%	-	-	-
UBI Pramerica Azioni Mercati Emergenti	25.0%	7.0%	-	-
Wellington E M Equity A	10.0%	25.0%	25.0%	25.0%
Swedbank Robur BRICT	0.2%	24.3%	25.0%	25.0%
PXP Fund Ltd	2.5%	-	-	-
Consultatio Growth Fund	-	6.2%	3.2%	3.0%
CMA Criteria Estrategia B	-	5.2%	16.2%	16.7%
RJ Delta Acciones B	-	19.9%	25.0%	25.0%
Prudentis Baltic	-	1.7%	5.6%	5.3%
Sampo New Europe	-	7.6%	-	-

Table 2.11: **Sensitivity to Macro Variables**

This table shows out of sample performance statistics for the different Bayesian strategies when considering a single predictive variable in the forecasting process. Risk factors are the market benchmark, size, book-to-market and country momentum. We follow a quarterly rebalance scheme and apply a 25% cap at the fund level when calculating optimal portfolio weights. Beliefs are specified at 10% per month. No short-selling allowed.

	Geo. Mean	Arith. Mean	Volatility	Sharpe Ratio	Alpha	Alpha t-Stat.	Outperf. %
Agnostic							
Short Rate Yield	11.86%	13.78%	19.64%	0.52	5.18%	1.16	51%
Dividend Yield	11.50%	14.11%	22.38%	0.47	4.97%	0.97	55%
Exchange Rate	15.20%	17.36%	20.68%	0.67	9.80%	1.81	54%
Market Sensitivity	14.69%	16.96%	21.19%	0.63	7.80%	1.72	55%
Commodity index	10.69%	13.87%	25.09%	0.41	3.74%	0.68	54%
Global Interest Rate	15.33%	17.44%	20.44%	0.68	9.75%	1.85	58%
Inflation	15.75%	17.75%	19.90%	0.71	10.82%	1.99	55%
Volatility	12.56%	15.72%	24.93%	0.49	6.74%	1.09	54%
APML							
Short Rate Yield	11.42%	13.19%	18.88%	0.51	4.54%	1.11	53%
Dividend Yield	10.53%	12.91%	21.44%	0.44	4.02%	0.82	55%
Exchange Rate	13.36%	15.56%	20.89%	0.57	7.72%	1.44	54%
Market Sensitivity	14.82%	16.88%	20.28%	0.66	8.32%	1.76	58%
Commodity index	15.59%	18.59%	24.52%	0.61	9.14%	1.59	56%
Global Interest Rate	13.19%	15.47%	21.23%	0.56	7.43%	1.39	57%
Inflation	14.61%	16.62%	20.05%	0.65	9.54%	1.76	55%
Volatility	13.91%	17.21%	25.48%	0.53	8.16%	1.26	56%
AMA							
Short Rate Yield	12.92%	15.03%	20.64%	0.55	6.26%	1.33	55%
Dividend Yield	11.80%	14.51%	22.93%	0.48	5.08%	0.99	55%
Exchange Rate	12.02%	14.30%	21.23%	0.50	5.96%	1.15	55%
Market Sensitivity	14.09%	16.21%	20.47%	0.62	7.64%	1.65	56%
Commodity index	15.69%	18.90%	25.05%	0.61	9.17%	1.65	58%

Table 2.11: **Sensitivity to Macro Variables (cont.)**

Global Interest Rate	10.80%	13.55%	23.03%	0.43	4.55%	0.83	57%
Inflation	11.89%	14.60%	22.99%	0.48	5.62%	1.03	55%
Volatility	15.29%	18.59%	25.35%	0.59	9.45%	1.47	58%
Skeptic							
Short Rate Yield	13.12%	15.27%	20.85%	0.56	6.47%	1.35	55%
Dividend Yield	11.37%	14.08%	22.95%	0.46	4.50%	0.89	54%
Exchange Rate	11.34%	13.97%	22.59%	0.46	4.84%	0.91	52%
Market Sensitivity	14.02%	16.15%	20.48%	0.61	7.52%	1.59	56%
Commodity index	16.02%	19.31%	25.36%	0.62	9.44%	1.68	58%
Global Interest Rate	10.95%	13.70%	23.03%	0.44	4.55%	0.84	55%
Inflation	12.39%	15.05%	22.78%	0.50	6.01%	1.12	55%
Volatility	15.55%	18.85%	25.39%	0.60	9.66%	1.65	58%
Benchmark	9.71%	12.74%	24.17%	0.38			

Table 2.12: **Rebalancing Horizons**

This table presents out-of- sample performance statistics for the four active strategies when considering different rebalancing frequencies. We considered commodities, inflation and volatility as the predictive variables. Risk factors are represented by the market benchmark, size, book-to-market and country momentum. We apply a 25% cap at the fund level when calculating optimal portfolio weights. Beliefs are specified at 10% per month. The out of sample period covers from the end of February 1997 to the end of February 2008.

	Benchmark	**Agnostic**	**APML**	**AMA**	**Skeptic**
Panel A. Semi Annual					
Geometric mean	9.71%	7.80%	11.87%	13.75%	13.44%
Arithmetic mean	12.74%	10.82%	15.10%	17.04%	16.86%
Volatility	24.17%	24.34%	25.20%	25.30%	25.78%
Sharpe ratio	0.38	0.30	0.46	0.53	0.51
Beta		0.71	0.74	0.73	0.76
Alpha		0.8%	4.5%	6.5%	6.1%
Alpha t-Stat		0.16	0.84	1.19	1.11
Monthly Outperf.		51%	55%	56%	55%
Panel B. Annual					
Geometric mean	9.71%	5.27%	6.71%	9.01%	8.60%
Arithmetic mean	12.74%	9.14%	10.41%	12.78%	12.45%
Volatility	24.17%	27.63%	26.94%	27.07%	27.33%
Sharpe ratio	0.38	0.20	0.25	0.34	0.32
Beta		0.78	0.75	0.74	0.77
Alpha		-1.5%	-0.3%	2.3%	1.5%
Alpha t-Stat		-0.24	-0.04	0.37	0.25
Monthly Outperf.		51%	53%	54%	54%

Table 2.13: **Caps on Fund Weights**

This table presents out-of- sample performance statistics for the four active strategies when considering different cap levels on the maximum weight to be allocated to individual funds. Panel A shows results under an unconstrained optimization setting, Panel B applies a 50% cap on individual funds and Panel C a 10%. Results are for the period covering from the end of February 1997 to the end of February 2008. We considered commodities, inflation, volatility and short risk-free rate as the predictive variables. Risk factors are represented by the market benchmark, size, book-to-market and country momentum.

	Benchmark	**Agnostic**	**APML**	**AMA**	**Skeptic**
Panel A. Unconstrained					
Geometric mean	9.71%	11.91%	16.52%	14.44%	14.44%
Arithmetic mean	12.74%	15.04%	20.07%	18.65%	18.70%
Volatility	24.17%	24.87%	26.75%	28.50%	28.80%
Sharpe ratio	0.38	0.46	0.62	0.53	0.52
Beta		0.66	0.70	0.80	0.83
Alpha		5.4%	9.6%	7.6%	7.6%
Alpha t-Stat		0.93	1.52	1.19	1.19
Monthly Outperf.		48%	55%	56%	55%
Panel B. 50%					
Geometric mean	9.71%	12.75%	17.05%	14.61%	14.44%
Arithmetic mean	12.74%	15.62%	20.34%	18.62%	18.56%
Volatility	24.17%	23.81%	25.62%	27.70%	28.12%
Sharpe ratio	0.38	0.51	0.65	0.54	0.53
Beta		0.64	0.68	0.78	0.82
Alpha		6.2%	10.0%	8.0%	7.5%
Alpha t-Stat		1.12	1.67	1.30	1.23
Monthly Outperf.		49%	55%	57%	57%
Panel C. 10%					
Geometric mean	9.71%	15.60%	15.48%	15.07%	15.31%
Arithmetic mean	12.74%	18.14%	18.31%	18.07%	18.40%
Volatility	24.17%	22.49%	23.63%	24.08%	24.45%
Sharpe ratio	0.38	0.65	0.62	0.60	0.61
Beta		0.70	0.72	0.70	0.72
Alpha		7.9%	7.8%	7.9%	8.1%
Alpha t-Stat		1.77	1.59	1.51	1.53
Monthly Outperf.		55%	59%	57%	57%

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Chapter 3

Mutual Fund Return Predictability in Partially Segmented Markets

Abstract

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

3.1 Introduction

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

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

These two seemingly unrelated bodies of research suggest that professional asset managers may be better able to choose local stocks under certain macroeconomic conditions. For instance, during the recent financial crisis, we might expect that active UK asset managers would be valuable because of their ties to London financial institutions, in the face of large asymmetric information on the value of banking stocks.

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

On the other hand, during the technology collapse, we might prefer to invest in active Scandinavian managers, due to their special knowledge of local telecommunication companies–thus, helping to sort out which firms might recover most quickly. In essence, macroeconomic information may help to indicate when local skills are most needed in a particular market. Hence, a rotation among asset managers with local expertise as macroeconomic conditions evolve may outperform strategies involving either local expertise or macro indicators alone to choose active managers.

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

Our paper, in studying the monthly returns of over 4,000 mutual funds having a (developed-market) European equity focus over the 1988 to 2008 period, covers the recent period of market integration across Europe. This market integration brings several further questions which are related to our focus on the segmentation of asset manager skills. For example, it is natural to wonder whether the reduced frictions of investing across Europe have decreased the usefulness of country-specific investing skills. And, we may further wish to know *which* country's local equity managers exhibit the best skills at different points in the European business cycle. Our study also has significant real-world economic implications. European funds grew from a little over \$3 trillion during 2000 to nearly \$9 trillion during 2007; by the end of 2007, this amounted to nearly three-quarters of the size of the U.S. mutual fund industry, which, over the same period, grew from \$7 trillion to \$12 trillion. Further, there were 35,000 European-domiciled funds by the end of 2007 (Investment Company Institute, 2008), far more than the number of U.S.-domiciled funds, indicating that the European market is highly fragmented. Clearly, European investors have a confusing array of decisions to make in choosing their stock portfolio managers, including country allocations, sector allocations, and specialized vs. generalist European stock managers. Our study brings a new method of fund selection to bear to the complex problem of mutual fund manager choice in partially segmented markets; we illustrate the potential gains from our methodology in European mutual fund markets.[2]

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

We focus on the dynamics of active management skills and how an investor might optimally invest in active funds during varying business conditions. Building on

[2]Despite the economic significance and fragmentation of the European mutual fund industry, European-domiciled funds remain very much an under-researched area. Some studies have been conducted at the individual country level—e.g., for funds that invest in the UK, Germany, Italy or France, or some combination of these countries. One such widely known study is Otten and Bams (2002). However, there is no comprehensive study that has simultaneously examined the performance of stock funds that invest across Europe (Pan-European funds), funds that invest in specific countries or regions (e.g., Germany or Scandinavia), and funds that invest in specific sectors (e.g., telecommunications) over a long time period that includes the integration of European financial markets of the past ten years. This is an important omission, since investors in any European state find it increasingly easy and inexpensive to invest in mutual funds incorporated in other countries as a result of this market integration and the adoption (by many developed European countries) of the common Euro currency.

recent papers such as Avramov and Wermers (2006) and Moskowitz (2000), we allow for the possibility of time-varying mutual fund alphas and betas by active managers in Europe. Following Christopherson, et al. (1998) and Ferson and Schadt (1996), we model such time-variation using a publicly available set of conditioning state variables. Thus, another of the objectives of our study is to explore which, if any, macroeconomic state variables are helpful in identifying funds with superior future skills.[3]

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

We first construct European factors to represent the broad stock market within each developed country, and Pan-European size, book-to-market, and momentum risk factors for stocks. Then, we document the average performance of European mutual funds over our time period using these benchmarks. Our findings are similar to those of many studies of U.S. mutual funds (e.g., Carhart, 1997 and Wermers, 2000). Specifically, the median one-factor and four-factor alphas are -0.84%/year and -0.24%/year, respectively. This finding indicates that our benchmarks successfully control for common variation in European equity mutual fund returns.

We next move to our main contribution, which is to determine whether a European investor can actively select Pan-European, regional, and sector funds with persistent performance, relative to our European risk factors, and to identify if and how macroeconomic information helps to improve the selection of these funds in a partially segmented market environment. Given the modest costs of trading most

[3]The vast majority of studies that have considered this question have focused on funds with a U.S. equity objective, but it is clearly important to see if these results generalize to other markets, in part to provide an out-of-sample test relative to the U.S. results, and in part to see if there are differences in how the macroeconomic environment affects the performance of funds in a partially segmented market such as Europe.

open-ended mutual funds, such a strategy would be attractive to many investors in European funds if it is successful. By including funds whose investment objectives focus on a particular region or sector, as well as funds that invest in the entire European region, we allow our strategies to generate abnormal returns by timing countries or sectors, or by identifying funds with superior security selection within each of these investment objective categories. Thus, we can determine whether specialist country or sector funds, during certain phases of the business cycle, outperform generalist funds that invest more broadly across countries and sectors in Europe.

Following recent work in the mutual fund literature (e.g., Pastor and Stambaugh, 2002a,b), we study European mutual fund choice through the lenses of four different types of Bayesian investors. These four types have differing prior views of (1) the ability of mutual funds to generate abnormal returns, and (2) whether alphas and betas of funds are time-varying. The investment performance of these four types are compared with the performance of a dogmatic investor who does not believe that funds can generate abnormal performance (alpha), relative to the CAPM.

Our main empirical findings are as follows. First, we find that a range of financial and macroeconomic variables prove helpful in selecting funds that are capable of generating future alphas. In particular, we find evidence that a number of investment strategies (that use macroeconomic variables to predict fund returns) generate alphas from 4-8%/year (after fund-level trading costs and fees), when measured with a single-factor model, and from 7-12%/year with a four-factor model that controls for fund exposures to size, book-to-market, and momentum. These results are generated by an out-of-sample exercise in which investors use the first five years of our sample (1988-1992) to obtain initial model parameter estimates, then revise their prior beliefs recursively through time as new data arrive, using Bayesian updating rules. Moreover, the results are robust to the choice of sample period, and hold in separate out-of-sample portfolio selection tests conducted over the periods 1993-2000 and 2001-2008.

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

These baseline results assume a standard set of macroeconomic state variables previously used to analyze U.S. mutual fund return predictability by Avramov and Wermers (2006)–the dividend yield, default spread, short-term interest rate, and term spread. We find that these variables prove valuable in selecting funds with superior performance in Europe, giving them important out-of-sample credibility. Interestingly, we find that some additional variables, such as growth in industrial production, inflation, or a proxy for stock market volatility, are useful in identifying funds with superior performance. The predictive success of these additional macro variables is consistent with their documented power in predicting market returns over historical periods prior to much of our time series by Fama and Schwert (1981) (inflation), Pesaran and Timmermann (1995) (industrial production), and Welch and Goyal (2008) (volatility).[4]

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.[5] As such, our study adds weight to the conjecture that European markets have a stronger country segmentation than industry segmentation–similar to the findings for sell-side analysts of Sonney (2009).

[4]Our finding that a different set of macroeconomic variables forecast mutual fund performance in a partially segmented market–Europe–relative to the U.S., presents a new and intriguing question for future research on conditional asset pricing. We also note that results for all macro variables that we considered are included in this paper. We did not selectively include results based on the success of the particular macro variable.

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

We adopt a Bayesian approach in our paper, so the choice of investor priors is an issue. We find that investors do best when they allow the data to largely determine the parameters that they use in their portfolio analysis, that is, when we designate diffuse priors. Further, by evaluating the impact of different beliefs for different investor-types, and different assumptions regarding market integration or segmentation, we show that macroeconomic information and partial segmentation both play important roles in allowing investors to generate significant outperformance.[6] Indeed, while a large part of the improved performance against a CAPM benchmark comes from a fixed (constant) alpha component, modeling time-varying alphas substantially helps to improve performance from country fund selection and from timing country weights.

In addition to identifying funds with superior performance, our model proves capable in identifying funds with inferior performance, that is, funds least likely to hold outperforming stocks. Thus, a self-financing long-short strategy adds further to the performance of a long-only strategy, while controlling the exposure to systematic risk factors. This finding indicates that mimicking the portfolio holdings of European funds, where securities held by inferior funds are shorted, may outperform our basic long-only fund-level strategy (depending on stock trading costs, as well as the impact of the delay in public availability of fund holdings information–which may be longer in Europe than in the U.S.). We leave this issue as a promising avenue for further research.

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

Our paper proceeds as follows. Section 2 reviews our data, and describes the economic state variables used in the study. Section 3 reviews the investor types considered in our study, and provides details on the methodology. Section 4 presents

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

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 are provided in an appendix.

3.2 Data

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

3.2.1 Mutual fund data

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

The data is limited in some respects. We do not have information on total net assets, nor do we know the exact location of the manager, so we use the fund's legal domicile as a proxy for the manager's location. We also do not have any load information, and only have limited expense ratio information. As such, any detailed analysis of pre-expense returns is not possible.

Table 3.1 lists the number of funds at five-year intervals by investment objective. The number of funds in our sample rose sharply from just over 200 in 1988 to 4,200 at the end of the sample, at least doubling during each of the first three five-year periods. A similar, if less pronounced, pattern has been observed in the U.S. fund industry.

Funds with a country or regional investment objective are shown in section II of Table 3.1. In particular, there were 3,936 such funds in 2008, compared with only 264 sector funds. By far, the largest group of regional funds is Pan-European funds−these are funds that are allowed to invest across all the developed European stock markets. The number of Pan-European funds increases faster than any other category, comprising more than half of the total number of funds in our sample by 2008.[7] Important country- or region-specific funds include the UK (625 funds in 2008), Scandinavia (314), and France (275).

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

It is worth noting that the division between sector funds and country funds is less clear-cut than may first seem the case. Indeed, some of the smaller European stock markets are dominated by a few firms and one or two sectors (e.g., Nokia in the Finnish stock market). Thus, investors likely used country funds to invest in certain industries during earlier periods of our time-series.

We do not have data on many of the individual funds' expenses and fees, particularly during the early part of the sample. However, for the last decade or so, we do have this data on a sizeable fraction of the funds. In Panel B of Table 3.1, we show that the average expenses and fees have been quite stable over the period from 1998-2008, and have ranged between 1.4% and 1.6% per annum. Although our sample includes low-fee passive funds, it is still evident that fees on European funds exceed those in the U.S. during the later years, on average.

3.2.2 State variables and risk factors

We control for risk exposures in measuring the funds' ability to outperform following the four factor approach advocated by Carhart (1997). It is something of a challenge to determine the proper benchmarks to use in Europe, as markets have become

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

more integrated over the 20 years that we study. However, we start with a Pan-European four-factor model. The four factors include a market risk factor, measured by the MSCI Europe total return index minus the 1-Month Euribor short rate; a size factor (small minus big, or SMB) which captures the difference between returns on the Europe STOXX Small Cap Return Index and the Europe STOXX Large Cap Return Index; a value factor (high minus low, or HML) computed as the difference between European value and growth portfolios. Finally, our momentum factor is constructed from the following month return difference between the six top and six bottom 12-month lagged return sectors (out of a total of 18 sectors) from the Dow Jones STOXX 600 Super Sector Indices.[8] For comparison, we also analyze results (but do not construct strategies) using a more conventional single-factor approach that only includes the market factor.[9]

Recognizing that European equity markets were somewhat segmented over at least part of our time period, we also employ some augmented models in our analysis. Specifically, we add, to the four-factor model above, country-specific market indexes in some of our analysis to country-focused funds. For instance, when we turn to such models, a UK fund will have, in addition to the Pan-European factors, a UK market index in a five-factor model.[10]

Recent studies suggest that funds' ability to generate alpha varies over time, in a way that can be predicted with macroeconomic state variables. Moreover, fund exposures to risk factors may also be state- and time-dependent.[11] 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.[12] Third, we use the default spread

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

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

[10]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.

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

[12]The monthly dividend yield for Europe, obtained from the Global Financial Database, is based on

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

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

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

large capitalization stocks in each country that represent about 75% of the capitalization of that market. Dividend data are based upon the dividends reported for the trailing twelve months, when the dividends are known by the market. Fourth quarter dividends, for example, are generally not reported until February, and only at this point are fourth quarter dividends included in the dividend yield calculations.

in the appendix.

3.3 Methodology

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

3.3.1 Dynamic Return Generating Process

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

$$\begin{aligned} r_{i,t} =& \alpha_{i0} + \alpha'_{i1} z_{t-1} + \beta'_{i0G} r_{G,t} + \beta'_{i0S} r_{S,t} + \beta'_{i1} \left(r_{B,t} \otimes z_{t-1} \right) + \varepsilon_{i,t} \\ \equiv& \theta'_i \begin{bmatrix} x_t \\ r_{G,t} \\ r_{S,t} \\ r_{B,t} \otimes z_{t-1} \end{bmatrix} + \varepsilon_{i,t}, \end{aligned} \tag{3.1}$$

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

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

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

$$\begin{bmatrix} r_{G,t} \\ r_{S,t} \end{bmatrix} \equiv r_{B,t} = \alpha_B + A_B z_{t-1} + \varepsilon_{B,t}. \tag{3.2}$$

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

$$z_t = \alpha_Z + A_z z_{t-1} + \varepsilon_{z,t} \tag{3.3}$$

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

3.3.2 Incorporating Restrictions and Beliefs from Asset Pricing Models

Given the linear return generating process, (3.1) - (3.3), the Bayesian framework provides a flexible approach to modeling the portfolio implications of asset pricing models either through dogmatic restrictions on parameter values, prior beliefs on those parameter values, or some combination of the two. All of our investor models incorporate informative investor beliefs that some linear combination of the parameters governing the return generating process is centered at a given value. Frequently, these priors relate information solely about an individual parameter, but we can also consider priors that relate information in the form of cross-parameter restrictions. For example, an investor may hold conditional beliefs that the total contribution of macroeconomic predictability to a fund's expected return, $\alpha_{i1}' z_{t-1}$, has mean zero and standard deviation σ_α. By analyzing this general case, we provide a unifying framework for characterizing predictive expected returns, variances, and covariances for portfolio selection.

We often want to explicitly restrict parameters, a priori, on theoretical grounds to limit the effects of estimation error on our posterior moments.[13] 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 (3.1), so we can represent d dogmatic restrictions on these parameters by forming the $d \times (1+m+k+km)$ matrix, F_R. Denoting a $d \times d$ matrix of zeros by $0_{(d\times d)}$, we then express our prior beliefs in the context of the standard Normal-Gamma model:

$$F_R\theta_i|\sigma_i^2 \sim N\left(0, \sigma_i^2 0_{(R\times R)}\right); \;\; \sigma_i^{-2} \sim G\left(\underline{s}^{-1}, \underline{t}\right). \tag{3.4}$$

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

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

$$F_I\theta_i|\sigma_i^2 \sim N\left(f_{I,i}, \sigma_i^2\Omega\right); \;\; \sigma_i^{-2} \sim G\left(\underline{s}^{-1}, \underline{t}\right), \tag{3.5}$$

where Ω reflects the tightness of the prior beliefs. Of particular interest will be investor priors with regard to the components of manager skill, $\alpha_{i0} + \alpha_{i1}' z_{t-1}$, in the return equation, (3.1). 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

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

parameters to span the parameter space. We do this through a set of uninformative priors, F_U, so that the complete set of priors is represented by the following $(1+m+k+km)\times(1+m+k+km)$ matrix, F, and the parameters $\underline{f}$, $\underline{\Phi}$:

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

$$F\theta_i|\sigma_i^2 \sim \lim_{c\to\infty} N\left(\underline{f_i},\sigma_i^2\begin{bmatrix} 0_{(d\times d)} & 0 & 0 \\ 0 & \Omega & 0 \\ 0 & 0 & cI_{(1+m+k+km-d-p)} \end{bmatrix}\right)\equiv N\left(\underline{f_i},\sigma_i^2\underline{\Phi}\right). \quad (3.6)$$

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

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

$$\theta_i|\sigma_i^2 \sim N\left(\underline{\theta}_i,\sigma_i^2\underline{V}\right). \quad (3.7)$$

where $\underline{\theta}_i$ is the prior expectation for θ_i and $\sigma_i^2\underline{V}$ is the variance covariance matrix for prior beliefs. This prior can be constructed from the representation of beliefs in equation (3.6) by observing that, for any non-singular matrix $\tilde{F}$, $\tilde{F}\theta_i|\sigma_i^2 \sim N\left(\tilde{F}\underline{\theta},\sigma_i^2\tilde{F}\underline{V}\tilde{F}'\right)$. Hence, to translate the beliefs from equation 3.6 into a natural conjugate specification, define $(\underline{\theta}_i,\underline{V})$ so that, for any invertible matrix, F,

$$F\underline{\theta}_i=\underline{f}_i \Rightarrow \underline{\theta}_i=F^{-1}\underline{f}_i \quad (3.8)$$

$$\sigma_i^2F\underline{V}F'=\sigma_i^2\underline{\Phi}\Rightarrow \underline{V}=F^{-1}\underline{\Phi}F'^{-1}, \quad (3.9)$$

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

$$\theta_i|\sigma_i^2 \sim N\left(F^{-1}\underline{f}_i,\sigma_i^2F^{-1}\underline{\Phi}F'^{-1}\right);\ \ \sigma_i^{-2}\sim G\left(\underline{s}^{-2},\underline{t}\right). \quad (3.10)$$

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

3.3.3 Posterior Distribution for Fund Return Generating Process

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

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

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

$$\overline{V}_i = \left(F\underline{\Omega}^{-1}F' + G_i'G_i\right)^{-1}, \tag{3.11}$$

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

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

where $D = \{r_{i\tau}, r_{B\tau}, z_{\tau-1}\}_{\tau=1}^{t}$ is the history of the observed data. G_i is the $t_i \times (1+m+k+km)$ matrix of explanatory variables on the right hand side of the return generating process in equation (3.1) corresponding to the t_i periods in which $r_{i,t}$ is observed, in information set D. The vector r_i denotes this sample of returns so that the least squares estimate of $\hat{\theta}_i$ is simply $\hat{\theta}_i = (G_i'G_i)^{-1}G_i'r_i$, and $s_i^2 = t_i^{-1}(r_i - G_i'\hat{\theta}_i)'(r_i - G_i'\hat{\theta}_i)$. We maintain an uninformative prior for σ_i so that, as before, $\underline{s}$ is any constant and $\underline{t} = 0$.[14]

3.3.4 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

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

more compact notation:

$$
\begin{aligned}
E\left[r_t|D_{t-1}\right] &= \bar{\alpha}_0+\bar{\alpha}_1 z_{t-1}+\overline{\beta}_0\hat{A}_F' x_{t-1}+\overline{\beta}_1\left(I_K\otimes z_{t-1}\right)\hat{A}_F' x_{t-1} \\
&\equiv \bar{\alpha}_0+\bar{\alpha}_1 z_{t-1}+\overline{\beta}_{t-1}\hat{A}_F' x_{t-1},
\end{aligned} \tag{3.12}
$$

$$
V\left[r_t|D_{t-1}\right] = \left(1+\delta_{t-1}\right)\overline{\beta}_{t-1}\hat{\Sigma}_B\overline{\beta}_{t-1}'+\Psi_{t-1}. \tag{3.13}
$$

Here, $\hat{A}_F' = [\hat{\alpha}_B \; \hat{A}_B]$ represents least squares estimates of the VAR parameters in equation (3.2). Denoting the time-series average of the macro-variables in D_{t-1} by $\bar{z}$, the remaining variables are defined as:

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

$$
\hat{\Sigma}_B = \frac{1}{\tau_B}\sum_{\tau=1}^{t-1}\hat{\varepsilon}_{B,\tau}\hat{\varepsilon}_{B,\tau}'; \;\; \hat{\varepsilon}_{B,\tau} = r_{B,\tau}-\hat{\alpha}_B-\hat{A}_B z_{\tau-1} \tag{3.14}
$$

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

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

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

3.3.5 Investor Models for Manager Skill and Segmentation

Five investor types are considered throughout the paper. These types differ in their beliefs about the parameters in equation (3.1) of the fund return generating process. Recall that this model allows for constant (non time-varying) manager skills, $\alpha_{i,0}$, excess returns from stock selection based on macroeconomic conditions, $\alpha_{i,1}' z_{t-1}$, and excess returns from factor loadings that vary with macroeconomic conditions, $\beta_{i,1}'\left(r_B\otimes z_{t-1}\right)$.

The most restrictive view is held by the dogmatist CAPM investor, who believes that no fund manager has skill, time-varying or constant, and that neither benchmark returns nor benchmark factor loadings are predictable. This investor type's beliefs can, therefore, be represented as $\alpha_{i,0} = 0$, $\alpha_{i,1} = 0$, $\beta_{i,1} = 0$, and $A_B = 0$.[15] A slightly less restrictive view that allows for non time-varying manager skill, but precludes predictability in the return generating process, is held by our Bayesian CAPM, or BCAPM, investor. This investor's beliefs are modeled after Pastor and Stambaugh (2002a,b), where the investor holds a prior belief that the average actively managed fund underperforms by the level of the expense ratio. This investor type's beliefs maintain the restrictions $\alpha_{i,1} = 0$, $\beta_{i,1} = 0$, and $A_B = 0$, and introduce the informative prior $\alpha_{i,0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$, where $\exp_i$ is one-twelfth of the average fund annual expense ratio (1.3%/year), since we have very little fund-specific expense ratio data. σ_α^2 is the uncertainty of the investor in his prior, which determines the weight the investor will give to this prior, relative to the data.

The Bayesian Skeptical Macro-Alpha, or BSMA, investor-type allows for manager skill and predictability, but is skeptical of the total contribution of skill to a fund's return, and does not believe risk factor loadings vary with macroeconomic conditions. This investor only restricts $\beta_{i,1} = 0$, allows A_B to be unrestricted, and introduces a conditional prior restricting the total manager skill generated either through constant or time-varying (predictable) skill, which can be represented as $\alpha_{i,0} + \alpha_{i,1}' z_{t-1} \sim N\left(0, \sigma_\alpha^2\right)$.

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

Still less restrictive beliefs are held by the Bayesian Agnostic Macro Alpha with predictable market factor loadings (BAMAP) investor. The BAMAP investor allows the fund manager to have predictable market factor loadings, but maintains

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

the belief that the k-1 other benchmark factor loadings are not predictable, so that the entries in $\beta_{i,1}$ corresponding to the interactions between the macro factors and the non-market benchmark entries are restricted to be zero.[16] As with the BAMA investor, the BAMAP investor places no restrictions on $\alpha_{i,1}$, and maintains the prior belief $\alpha_{i,0} \sim N\left(-\exp_i, \sigma_\alpha^2\right)$.

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

3.3.6 Market Segmentation

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

[16]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.

3.4 Empirical Results

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

3.4.1 Historic Return Performance

Table 3.2 reports the raw return performance as well as the risk-adjusted return performance measured for the full sample and for various subsamples. Panel A lists performance results for the equal-weighted universe of funds in our sample and the benchmark MSCI Europe index. Over the full twenty-year sample, 1988-2008, the equal-weighted portfolio of funds returned 10.19% per annum, 86 basis points below the benchmark which returned 11.05% per annum. This negative average return performance conceals substantial variations in the returns from active management across sub-samples. Prior to 1998, on average, our sample of mutual funds under-performed the benchmark by 400-500 basis points per annum, while they out-performed the index by 200-400 basis points per annum in the 10-year period that followed.

These numbers refer to raw return performance. It is more relevant to consider risk-adjusted performance, as measured by the single-factor and four-factor alphas reported in panels B and C. In the case of the single-factor model, we observe underperformance, both on average and for the median fund. The average underperformance during the sample was -36 basis points per annum. This number does not convey the large differences in alpha performance during the five-year subperiods, however. For example, during the five-year period from 1988-1992, the average single-factor alpha was negative, at -4.68%, while, conversely, the mean alpha was positive at 1.20% during the five-year period from 1999-2003.

Turning to the results for the four-factor model, the median fund generated an alpha of -24 basis points per annum. Interestingly, this underperformance is similar to the U.S. equity fund underperformance over the 1980-2006 period, as documented by Barras, Scaillet, and Wermers (2010). Note that the four-factor alpha is unusually high during 1993-1998, relative to the CAPM alpha. During this period, the funds, in aggregate, overweighted small- and mid-cap stocks, relative to the value-weighted MSCI Barra market benchmark.[17] While these stocks underperformed in general, the funds apparently were successful in choosing stocks within those segments that outperformed their cohorts.

The results indicate that survivorship bias is not overly important in our sample. To further explore this point, we also report quantiles for the alpha distribution. If survivorship bias was a key concern, we would expect the mass in the left-tail quantiles of the histogram to be much smaller than those observed in the right tails (as under-performing funds are dropped if there is survival-bias in the sample). This is not what we observe. In fact, the cross-sectional distribution of single-factor alphas, which arguably is the most relevant comparison, is reasonably symmetric in the full sample, and highly left-skewed in the two five-year periods, 1988-1992 and 1993-1998.

We conclude from these historical, in-sample performance results that, although the average fund underperformed both on a raw return basis and also on a risk-adjusted basis, many funds were able, ex-post, to generate large and positive alphas. From the perspective of an active investor, however, the key question is whether such funds could have been identified ex-ante, and selected as part of a portfolio strategy to produce performance superior to that available from passive investment strategies. Based on the dynamic features of performance of the fund universe generally, a conditional framework provides an appealing mechanism with which to investigate this question. We address this issue in the next section.

To get a sense of variations in the average performance of funds in our universe, Figure 3.1 presents the cross-sectional average conditional expectations of excess returns as well as alphas, using the four models discussed in the previous section that allow for fund manager skill. At each point in time, these plots reveal how difficult it is for our model to identify funds with superior performance−the lower the average alpha,

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

the narrower the set of funds with positive alphas will tend to be.

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

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

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

3.4.2 Portfolio Performance

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

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

$$U(W_t, R_{p,t+1}, a_t, b_t) = a_t + W_t R_{p,t+1} - \frac{b_t}{2} W_t^2 R_{p,t+1}^2, \tag{3.15}$$

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

$$\omega_t^* = \arg\max_{\omega_t} \left\{ \omega_t' \mu_t - ((1 - b_t W_t)/b_t W_t - r_{ft})^{-1} \omega_t' [\Sigma_t + \mu_t \mu_t'] \omega_t / 2 \right\}, \tag{3.16}$$

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

Table 3.3 reports performance results for an expected utility maximizing investor with mean-variance preferences and coefficient of risk aversion set equal to 2.94, the value advocated by Avramov and Wermers (2006). The baseline portfolio results shown in this table are based on the following assumptions applied using a four-factor European model. First, we use a set of European macro variables similar to those adopted by Avramov and Wermers (2006) in their study of US funds, namely the term spread, dividend yield, default spread and the short-term interest rate–all defined in the Appendix. Thus, we first provide a large-scale out-of-sample test of the Avramov and Wermers (2006) U.S. equity fund results, which is important, given that Ferson, Simin, and Sarkissian (2003) demonstrate that a highly persistent predictive variable (such as our macroeconomic variables, which vary slowly over time) can spuriously appear to predict a dependent variable (fund returns) if the predictive variable has been "data-mined."

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

We cap our strategies at a maximum of 10% invested in a single fund at any particular month; in addition, we assume quarterly rebalancing to constrain the turnover of funds by the strategies. Both of these constraints are imposed to avoid strategies that would be difficult to implement in practice. In addition, we do not allow short positions, since it is typically not possible to short-sell mutual funds.[18,19]

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

First, consider the raw return performance reported in the first five lines of Table 3.3. The MSCI Europe benchmark index returned 11.4% arithmetic average return, with a volatility of 16.3% and produced a Sharpe ratio of 0.45. Compared with this, the CAPM investor who does not believe in active management skills produced somewhat smaller mean returns (8.6%), but also lower volatility (14.9%), for a somewhat lower Sharpe ratio of 0.3.

In contrast, every investor type who believes that some managers may be skilled, succeeded in generating raw return performance better than that of the MSCI Europe benchmark. For the four Bayesian investor types, arithmetic mean returns lie between

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

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

13.6% and 18.8% per annum, with volatilities close to or slightly above 20%, and Sharpe ratios between 0.49 and 0.69, significantly higher than that of the market index.

Alphas of the Baseline Strategies

Turning to the alpha estimates, consistent with the raw return figures, the dogmatic CAPM investor generates a negative single-factor alpha estimate of -1.97% per annum. This finding is not surprising, since the CAPM investor is not seeking to identify funds with superior performance and is clearly at a disadvantage (if active skills do actually exist) by being constrained to form a portfolio comprising actively managed funds (with zero alphas perceived by this investor) with higher expenses than the passive benchmark. In fact, the dogmatist loses, relative to the benchmark, an amount that is slightly higher than the average expense ratio (1.3%/year) that we observe in Table 3.1, likely because this investor type (who ignores any evidence of underperformance in the data) chooses unskilled specialty funds to diversify, which tend to have higher trading costs than their unskilled Pan-European counterparts.

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

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

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

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

In part because of such level differences, the statistical significance is stronger for the four-factor, relative to the one-factor alpha estimates. Clearly, a comparison of the single-factor and four-factor results tells us that fixed and time-varying skills are better predicted with a more robust model that includes equity characteristics (size, value/growth, and momentum/contrarian), since the funds in our database tend to tilt toward smaller-cap, growth, and momentum stocks, as indicated in the average factor loadings in Table 3.3, relative to the MSCI Europe index.[20] As such, much of the four-factor alpha is driven by some fund managers' ability to deliver positive returns despite this period being very difficult for European Growth and Momentum stocks. Between 1993 and 2000, the SMB benchmark delivered an average annual return of -11.3% while the MOM benchmark returned -1.2%, presenting a significant drag on most of the strategies' gross return performance.

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

Our sample covers very different market conditions, spanning the bull market of the nineties, followed by the market crash in 2000, the recovery from mid-2002 and, more recently, the financial crisis beginning in mid-2007. To test if the performance associated with the various investor types varied across these very different market conditions, Panels B and C split our sample into two sub-periods, namely 1993-2000 and 2001-2008. The four investor types under consideration (BCAPM, BSMA, BAMA, and BAMAP) generate positive alphas in both subsamples, regardless of whether the single-factor or four-factor model is used for benchmarking. This suggests that the ability to identify funds with superior performance does not solely hinge on one type of market environment.

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

3.4.3 Market Segmentation

We next turn to the issue of whether allowing for partial market segmentation−i.e., the inclusion of individual country benchmarks in addition to the pan-European benchmark−further helps to locate active managers with true skills. For an investor who believes that markets are segmented along country borders, adding a country risk-factor will improve the identification of truly skilled managers within that country. For an investor who believes that markets are sufficiently integrated, however, adding a country risk-factor may reduce the profits from tilting toward countries with persistent, but temporarily high returns.[21]

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

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

Table 3.4 shows results from this analysis. First, for the universe comprising only passive index funds, single-factor and four-factor alpha estimates are always economically small−in all cases, falling at or below 1.6%/year–and statistically insignificant. This holds across all four investor types, suggesting that there are no gains to be made from a pure market timing strategy that seeks to vary the weights on the passive country index funds, with or without macroeconomic variables. This result indicates that our pan-European market factor properly captures country market risks, and does not allow alphas from trading passive funds.

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

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

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

3.5 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.

3.5.1 Country and Sector Allocations

We first consider the portfolio allocation of the various investor types through time. To this end, Table 3.5 shows snapshots of the portfolio weights by region or country. The strategies generally allocate low weights to Pan-European funds, with the exception of the CAPM and BCAPM strategies. These two strategies apparently find less costly diversification opportunities in Pan-European funds, since they disregard time-varying skills of country funds.[22]

This result indicates that the biggest opportunity for exploiting time-varying alphas consists of large allocations to country-specific funds.[23] In turn, this indicates that country fund managers have a superior ability to generate alphas, but that their advantage is fleeting over time. This finding is consistent with time-varying opportunities that are out of phase across different countries in finding underpriced

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

[23]The country/regional funds obtain by far the highest weights through time, but it should be recalled from Table 3.1 that there are very few European sector funds prior to 2003.

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

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

There are also some large differences in the country allocations of the integrated models (panel A) versus the partially segmented models (panel B). Note that, in general, the allocations to Pan-European funds increase, since the model attributes some of the time-variation in country fund returns to time-variation in segmentation

[24]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.

effects. For instance, during 2003, all three segmented models (BSMA-S, BAMA-S, and BAMAP-S) lower their exposure to Scandinavian funds, relative to the respective integrated market models, apparently because the Scandinavian market factor (relative to other country market factors) exhibited temporary outperformance relative to the non-segmented risk-factors of Panel A.

Sector funds mainly play a role towards the end of the sample, which is to be expected, given that there are very few sector funds prior to 2003. Interestingly, all three macro strategies allocate at least 70% to sector funds in 2007. Our prior-mentioned industry analysis (using Sharpe (1992) regressions) indicates that sector funds are used to focus strategies on combinations of certain industries, which are not easy to accomplish through country funds alone.[25]

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

3.5.2 Selection of Individual Funds

Table 3.5 does not show the identity of the individual funds that were selected by the four investor types. An example is presented in Table 3.6, using data as of February 2008 (the end of our return sample). As expected, the allocations vary widely across strategies. However, all strategies seem to hold the maximum 10% of the chosen funds. This result indicates that a small subgroup of funds are deemed superior by all investment strategies, although the exact composition of these superior funds is different, depending on the model used by the strategy. These "corner solutions" indicate that even greater performance may be achieved without the holdings constraints, a point we shall return to later.

For each investor type, there is a substantial (but nothing close to perfect) overlap in the funds selected, regardless of whether the integrated or the segmented market

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

models are used. Again, this indicates that some (but not all) of the performance exploited by the strategies is not captured by segmentation in the market risk-premia (which, in turn, might be exploited, for example, through the macroeconomic variables). Our prior-mentioned industry analysis shows considerable differences in industry allocations between the integrated and segmented models, indicating that different funds are selected (in Table 3.5) to effect changes in industry allocations.

3.5.3 Decomposition of Returns

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

$$r_P = w_{Euro,P} r_{Euro,P} + w_{Sect,P} r_{Sect,P} + \sum_{i=1}^{C} w_{Ctry_i,P} r_{Ctry_i,P} + \varepsilon_P, \tag{3.17}$$

where, for example, $w_{Euro,P}$ is the portfolio allocation to pan-European funds by the investor, and $r_{Euro,P}$ is the (value-weighted) return on the Pan-European funds chosen. Note that ε_P captures actual fund weights chosen by the investor, relative to value-weights. We compare this return to the return on the MSCI Europe Benchmark, which is decomposed into C country-specific components as:[26]

$$\begin{aligned} r_B = & w_{Euro,P} r_B + w_{Sect,P} r_B \\ & + \left(1 - w_{Euro,P} - w_{Sect,P}\right) \sum_{i=1}^{C} w_{Ctry_i,B} * r_{Ctry_i,B} \\ & + \left(1 - w_{Euro,P} - w_{Sect,P}\right) \sum_{i=1}^{C} w_{Ctry_i,B} \left(r_B - r_{Ctry_i,B}\right). \end{aligned} \tag{3.18}$$

The weights for each country in the benchmark, $w_{Ctry_i,B}$, were computed using the market capitalizations for each country's equity market (taken from the World Bank's Development Indicators); the benchmark country returns are taken from the MSCI Europe Country Indices. Note that we only decompose the proportion of the

[26]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.

benchmark that the portfolio invests in country funds. This split implicitly assumes that the Pan-European and sector funds do not take active country positions, which seems reasonable in the absence of a detailed analysis of fund constituent data and the relatively small sector fund exposure of the portfolio through most of our sample. The third term in the benchmark decomposition is a residual reflecting the small mismatch between the capitalization weighted Europe index (based on MSCI country indexes) and the MSCI Europe benchmark returns.[27]

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 (3.17) and (3.18), respectively. These components reflect the ability of the portfolio to select funds that outperform the benchmark and are computed as:

$$r_{European\ Selection} = w_{Euro,P} * \left(r_{Euro,P} - r_B\right) \tag{3.19}$$

$$r_{Sector\ Selection} = w_{Sect,P} * \left(r_{Sect,P} - r_B\right). \tag{3.20}$$

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:

$$r_{Country\ Select} = \left(1 - w_{Euro,P} - w_{Sect,P}\right) \sum_{i=1}^{C} w_{Ctry_i,B} * \left(r_{Ctry_i,P} - r_{Ctry_i,B}\right). \tag{3.21}$$

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

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

state variables. This is

$$r_{Country\ Time} = \sum_{i=1}^{C} \left(w_{Ctry_i,P} - \left(1 - w_{Euro,P} - w_{Sect,P} \right) w_{Ctry_i,B} \right) r_{Ctry_i,B}. \tag{3.22}$$

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

$$\begin{aligned} r_{resid} = & \sum_{i=1}^{C} \left(w_{Ctry_i,P} - \left(1 - w_{Euro,P} - w_{Sect,P} \right) w_{Ctry_i,B} \right) \left(r_{Ctry_i,P} - r_{Ctry_i,B} \right) \\ & - \left(1 - w_{Euro,P} - w_{Sect,P} \right) \sum_{i=1}^{C} w_{Ctry_i,B} \left(r_B - r_{Ctry_i,B} \right). \end{aligned} \tag{3.23}$$

Panel A of Table 3.7 presents the results of this decomposition for each of the investor types. We see that portfolio outperformance is driven by a combination of fund selection in country and sector funds, coupled with some skill in timing country allocations. The investors that keep an open mind about time-varying alphas (BSMA, BAMA, and BAMAP) generate more than twice the performance in these three attribution categories compared to the BCAPM investor. Thus, time-varying macroeconomic strategies are successful, in part because they better identify country-specific managers with superior skills at a particular point in the business cycle. This interaction effect of timing coupled with selection is also apparent in the relatively large residuals for the conditional Bayesian investors. Note, also, that the attribution components do not change much when we move to the segmented models. Clearly, the strategies are able to locate skilled managers, controlling for possible time-varying segmentation effects.

Also, the time-varying strategies achieve some performance by timing country weights. Given that our earlier results show that timing passive country funds does not work, this finding indicates that using macroeconomic variables helps to identify the countries with the best active managers at a given point in time. Again, this is quite interesting in light of the industry concentration of some of the countries–certain industries (which are concentrated in certain countries) represent the most fertile territory to search for manager skills, perhaps because of the large degree of asymmetric information in these industries at certain points of the business cycle. For instance, the outlook for technology firms varied substantially during the period surrounding the peak of the technology boom. The allocations of our strategies indicate that the macroeconomic-based investment strategies were able to identify the most promising industries as well as to select the portfolio managers with the best skills in those industries during a particular macroeconomic phase.[28]

3.6 Robustness of the Results

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

3.6.1 Macro Variables

To avoid concerns related to possible data mining, so far we have only considered a single set of macro variables, comprising four standard predictor variables used throughout the finance literature. However, it is interesting to address which types of macrovariables are capable of generating superior performance for the active investor types. To this end, Table 3.8 presents alpha estimates and alpha t-statistics for these four as well as five other predictor variables for the three investor types who believe that macro variables matter in identifying manager skills, namely the BSMA, BAMA and BAMAP investors, concentrating on the segmented market model in the interest of brevity. For comparison, the table also shows results at the bottom for the BCAPM investor who assumes constant alphas.

To measure the marginal effect of each predictor variable, we show results when different predictor variables are included, one by one, in the model. Since these

[28]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.

are univariate results, we would expect some decline in performance relative to the benchmark model that includes four state variables. The appendix describes how each of the variables is measured. Many of the individual macro variables are able to generate superior performance, with the most consistent and largest effects obtained for the short rate yield, industrial production, and inflation. Conversely, the currency factor, volatility and the dividend yield do not show much promise.

In addition to single macro-factor specifications, we also consider models that condition on country-specific macroeconomic factors at the top of each panel. These results show the effect of using the same four macro factors for each country fund in our analysis, namely the term-spread, dividend yield, default spread and short-term interest rate, but using country-specific versions of these four macro factors.[29] We find, in general, that the alphas from the time-varying strategies are slightly lower using local macro factors. This suggests no gains from using local macro variables over using Europe-wide measures, perhaps because of the larger measurement error in these local indicators.

3.6.2 Construction of Momentum Factor

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

Alternatively, we could make use of a country momentum factor. To explore if this can help explain our results, we construct this as follows. Here, we consider the performance of each of the 16 European countries over the previous 12-month period.[30] We then compute the return differential between the three countries with the highest 12-month lagged returns and the three countries with the lowest 12-month

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

[30]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.

lagged returns.

In untabulated results, we find that the performance of our strategies, using country-based momentum factors, are very similar to those in Table 3.3, so we conclude that our findings are robust to whether momentum is defined along sector or country lines.

3.6.3 Constraints on Portfolio Optimization

Our baseline results assumed the mean-variance investor optimizes the portfolio allocation across the top 50 funds, ranked by their conditional alpha, subject to restrictions that preclude short positions and impose a maximum of 10% that the strategy can invest in a single fund. We relax these assumptions, first on the pre-screened size of the universe, and, then, on the positions the investor can take.

In untabulated results we find that expanding the set of funds used in the optimization to include either 250 or the full set of funds, rather than 50, actually reduces the alpha somewhat for the strategies, although four-factor alphas remain statistically significant for most models. This dilution effect in portfolio alpha can be explained by two effects. First, estimation error means that forming portfolios from a larger universe that includes funds with low alphas may lead to worse performance when such funds are assigned non-zero weights due to sampling variation. Second, the objective of our portfolio allocation problem is not to directly maximize the expected alpha, but rather to maximize the expected utility of a mean-variance investor (i.e., maximize Sharpe Ratio). In fact, the investor's average realized utility actually increases as the investable universe grows.

Panel A of Table 3.9 shows that eliminating the maximum weight constraint for investment in any one fund increases the alpha performance by 5-8% per year, depending on the strategy. These findings are encouraging, as they suggest that there is significant value in the signals used to select funds based on their conditional alphas. The greater the signal value, the more one would expect that essentially ad-hoc constraints should reduce the portfolio performance. The findings also suggest that a very small number of fund managers have very sharp (predictable) abilities to generate alpha at varying times during the business cycle.

Panel B of Table 3.9 illustrates the effect of tightening the 10% maximum on portfolio holdings of a single fund to only 5%. As expected, tightening this constraint hinders portfolio performance, further illustrating the signal value of the conditional estimates for a fund's expected returns, standard deviation, and correlations. Nevertheless, these more diversified and balanced portfolios continue to perform well, and generate highly significant four-factor alphas between 7 and 10%/year.

Lastly, beyond quarterly rebalancing, our baseline models placed no constraints on portfolio turnover. Panel C of Table 3.9 shows that limiting the sales and purchases of individual funds to 5% per fund per quarter results in a slight deterioration in the alphas of the strategies that use macroeconomic information (BSMA, BAMA, and BAMAP). These results are qualitatively consistent with those of Panel B.

3.6.4 Effect of Priors

Our baseline results assumed a prior of $\sigma_\alpha = 10\%$ per month. Under this choice the investor types (with the exception of the CAPM investor) are very open-minded about the possibility of abnormal performance. It is clearly important, however, to explore the effect of different priors on portfolio selection (see Baks et al. (2001).) In particular, we investigate to what extent tightening the priors of the investor to $\sigma_\alpha = 0.1\%$ per month or loosening them to effectively represent uninformative priors (e.g. $\sigma_\alpha = 100\%$) affects the returns, as we vary the investor's degree of skepticism about the possibility of finding abnormal performance.

Table 3.10 shows that as σ_α gets smaller and, so, the priors get tighter, the alpha performance declines quite substantially for all investor types, and especially so for the BSMA investor. To interpret these findings, notice that when we tighten σ_α for the BCAPM investor, α_0 is effectively limited to be zero. When we tighten σ_α for the BSMA investor, we shrink the total α $(\alpha_0 + \alpha_1 z_{t-1})$ toward zero. However, for the BAMA investor, we shrink only α_0, and not $\alpha_1 z_{t-1}$. The higher sensitivity of BCAPM and BSMA to increasing the precision of prior beliefs, relative to BAMA, provides further evidence that the time-varying $\alpha_1 z_{t-1}$ component is critical to the model's performance, relative to α_0.

3.6.5 Identifying Underperforming Funds

Table 3.11 considers the performance of two different strategies that involve locating underperforming funds. Panel A shows results when our investors attempt to identify underperformers among the mutual funds. In this regard, the model again seems to be doing well. The alphas are substantially negative for all investor types, and more so for the BSMA, BAMA, and BAMAP macro-strategies, not because these funds are attempting to underperform, but because our models identify funds that are likely to underperform in the current economic climate due to difficulties in successfully implementing their strategies in such a climate.

Encouraged by these findings, we also consider the performance of a self-financing portfolio strategy which allows for both long and short positions. In Panel B of Table 3.11, we allow the investor to form a 2 to 1 leveraged portfolio (long 200%, short 100%) in 50 funds with the highest conditional alpha financed by shorting the benchmark and country index portfolios (in the proportion indicated by the fund loadings and tilts). We find these leveraged portfolios generating exceptional performance, with geometric means of roughly 18%/year (for macroeconomic strategies) and single-factor alphas of roughly 10%/year. Panel C takes a purely self-financing approach, with the addition that investors form their portfolios subject to the constraint that their expected exposure to the benchmark factors be zero. This constraint hinders the portfolio's ability to generate alpha by directing more of the short position toward the market benchmark and away from the style indices. Even so, the models that allow for a time-varying alpha continue to generate single-factor alphas around 8-10%/year and four-factor alphas around 9-11%/year.

3.6.6 Breadth of Predictability in Fund Manager Performance

Our results illustrate that predictability in fund manager performance presents an opportunity to investors in equity mutual funds to aid in global portfolio diversification and enhance performance. However, one concern is that many of the portfolios appeared to be quite concentrated (see Table 3.6), and, so, could be overly sensitive to the availability of individual funds for investment. The fact that such concentrated strategies perform well need not be a concern, of course, since concentrated strategies that differ from common benchmarks have been found to be associated with better performance (see, for example, Cremers and Petajisto, 2009). To address the robustness of our strategies' ability to rank the entire cross-section of funds, we present evidence from a simple sorting test conducted on funds after computing their expected performance under each model.

Specifically, in Table 3.12, we report the out-of-sample performance of equal-weighted portfolios formed by sorting, each quarter, the universe of funds into deciles based on the t-statistic for the conditional alpha.[31] The models that allow for predictability generate spreads in both mean return performance and four-factor alphas of 3-5% per year between top and bottom deciles of funds. We also report the results of a Patton-Timmermann (2010) test for a monotonically decreasing pattern in the four factor alphas as we move from the top to the bottom ranked decile funds. This test rejects, i.e. results in a low p-value, if there is evidence of a monotonically declining mean return (or alpha) as we move from the highest-ranked to the lowest-ranked funds. For all the segmented Bayesian models, we find that the test strongly suggests a monotonic relationship, with the top funds delivering higher alphas than the lower-ranked funds. The evidence is slightly weaker for the Bayesian models that assume integrated markets, thus, testifying to the advantage of allowing for segmentation.

The last column of Table 3.12 compares these results with the performance of a momentum strategy that sorts funds based on their trailing 12-month returns. Note that, while the momentum strategy generates attractive spreads between the high and low deciles, there is little evidence supporting a monotonic relationship between momentum and fund manager performance. Moreover, for the sub-sample from 1993-2000, the momentum strategy generated a negative spread between the winners minus losers portfolio, indicating that this strategy does not deliver consistent abnormal performance.

In unreported results, we evaluate the degree to which predictability in fund manager skill is concentrated in just a few funds by reporting the performance of equal-weighted portfolios formed from the N funds with the highest conditional alpha, where we let N vary from 10 to 500. We find that models allowing for

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

predictability generate the most attractive return properties when they are allowed greater concentration. Again, this suggests that the Bayesian alpha models are capable of successfully ranking the funds' risk-adjusted performance.

3.6.7 Augmenting the Models for Currency

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

3.7 Conclusion

Despite their significant growth in recent years, the performance of European equity mutual funds is a largely unexplored area of research. This paper shows that macroeconomic state variables can be used to identify a significant alpha component among a large sample of Pan-European, European country and sector funds. State variables such as the default yield spread, the term spread, the dividend yield and the short risk-free rate as well as macroeconomic variables tracking growth in industrial production are useful in identifying superior performance among funds.

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

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

Acknowledgements

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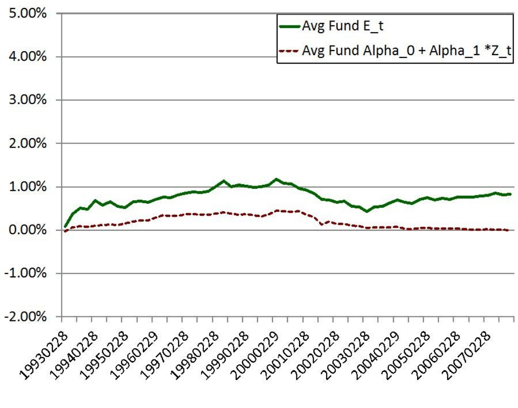
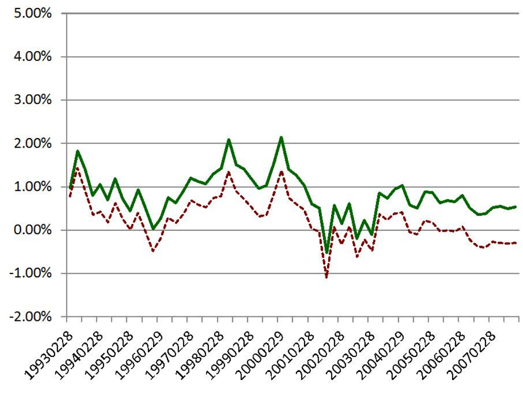
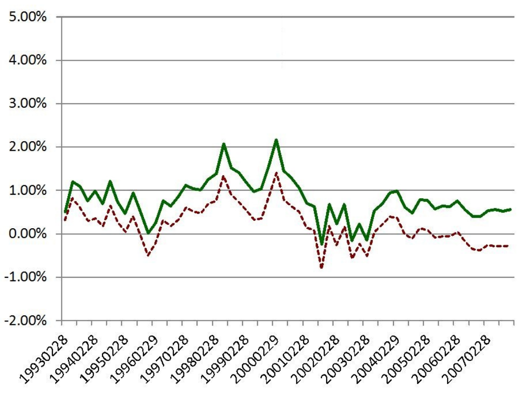
Figures and Tables



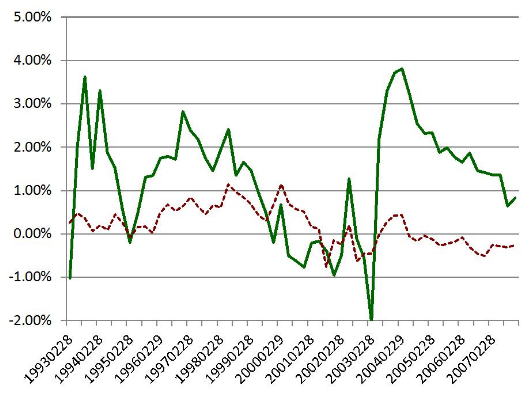
(a) Bayesian CAPM (BCAPM)



(b) Bayesian Skeptic Macro Alpha (BSMA)



(c) Bayesian Agnostic Macro Alpha (BAMA)



(d) BAMA with Predictable Market Loadings (BAMAP)

Figure 3.1: **Time Variation in Mutual Funds' Investment Opportunities**

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

Table 3.1: **Number of Funds over Time, Grouped by Investment Objective**

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

Panel A: Fund Counts					
	1988	1993	1998	2003	2008
I. Universe	228	716	1397	3225	4200
II. Regional Funds					
Austria	1	4	7	12	18
Benelux	3	25	45	73	62
France	2	86	166	277	275
Germany	17	43	77	112	113
Italy	2	19	54	94	96
Pan-Europe	57	228	461	1491	2133
Scandinavian	18	52	140	271	314
Spain/Portugal	0	26	69	113	144
Switzerland	8	24	55	104	156
UK	119	197	299	504	625
III. Sector Funds					
Banks and Financial	0	0	1	24	31
Basic Industries	0	0	0	7	12
Cyclical Goods & Services	0	0	0	10	21
General Industry	0	0	0	7	11
Information Technology	0	0	0	23	20
Natural Resource	0	0	0	8	12
Non Cyclical Con	0	0	0	15	17
Pharma and Health	0	0	0	8	8
Real Estate	1	12	21	46	103
Tech Media and Tele	0	0	1	12	10
Telecom Services	0	0	1	7	7
Utilities	0	0	0	7	12
Panel B: Fund Expenses and Fees					
Average			1.46	1.63	1.49
Median			1.47	1.59	1.61
Standard Deviation			0.55	0.94	0.62
No of Expense Obs			483	1524	925

Table 3.2: **Fund Universe Sample Performance**

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

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

Table 3.3: **Out of Sample Portfolio Performance (06/1993 - 02/2008)**

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

	Benchmark	CAPM	BCAPM	BSMA	BAMA	BAMAP
Panel A: Full Sample Results						
Geometric mean	10.06%	7.50%	11.76%	16.68%	15.28%	14.11%
Arithmetic mean	11.40%	8.62%	13.61%	18.79%	17.39%	16.09%
Volatility	16.28%	14.89%	19.39%	21.18%	21.20%	20.34%
Sharpe ratio	0.449	0.303	0.491	0.693	0.627	0.589
Outperformance Frequency		36%	55%	53%	50%	50%
Single-Factor Alpha		-1.97%	2.47%	7.78%	6.32%	4.77%
Single-Factor Alpha t-Stat		(1.703)	0.771	2.097	1.707	1.496
Single-Factor Beta		0.873	0.927	0.975	0.978	1.005
Four-Factor Alpha		-1.71%	7.47%	12.04%	10.28%	8.44%
Four-Factor Alpha t-Stat		(1.541)	2.803	3.710	3.137	3.021
Beta - Market		0.836	0.978	1.027	1.034	1.045
Beta - SMB		(0.012)	0.641	0.556	0.525	0.470
Beta - HML		0.119	(0.411)	(0.359)	(0.359)	(0.285)
Beta - Momentum		0.005	0.141	0.249	0.235	0.228
Panel B: Sub-Sample Results - 1993-2000						
Geometric mean	18.33%	15.34%	17.72%	23.49%	23.23%	21.65%
Arithmetic mean	19.49%	16.33%	19.71%	26.00%	25.73%	23.93%
Volatility	15.31%	14.16%	20.44%	23.55%	23.51%	22.23%
Sharpe ratio	0.941	0.795	0.716	0.888	0.879	0.848
Outperformance Frequency		43%	48%	45%	43%	43%
Single-Factor Alpha		-0.78%	0.86%	6.47%	6.27%	3.50%
Single-Factor Alpha t-Stat		(0.407)	0.160	0.991	0.956	0.633

Table 3.3: **Out of Sample Portfolio Performance (06/1993 - 02/2008) (cont.)**

Single-Factor Beta		0.852	0.941	1.019	1.009	1.076
Four-Factor Alpha		-2.17%	18.34%	25.35%	25.12%	19.26%
Four-Factor Alpha t-Stat		(1.219)	4.947	5.442	5.368	4.697
Beta - Market		0.831	0.811	0.859	0.851	0.962
Beta - SMB		(0.069)	0.887	0.907	0.906	0.779
Beta - HML		0.153	(0.444)	(0.511)	(0.519)	(0.452)
Beta - Momentum		(0.049)	0.484	0.674	0.674	0.499
Panel C: Sub-Sample Results - 2001-2008						
Geometric mean	1.17%	-0.94%	5.34%	9.35%	6.74%	6.00%
Arithmetic mean	2.65%	0.26%	7.01%	10.98%	8.38%	7.60%
Volatility	16.99%	15.36%	18.11%	18.14%	18.16%	17.88%
Sharpe ratio	(0.023)	(0.181)	0.219	0.437	0.293	0.255
Outperformance Frequency		28%	62%	62%	58%	56%
Single-Factor Alpha		-2.89%	4.12%	8.74%	6.02%	5.13%
Single-Factor Alpha t-Stat		(2.381)	1.246	2.666	1.889	1.730
Single-Factor Beta		0.889	0.914	0.932	0.944	0.941
Four-Factor Alpha		-2.61%	4.62%	10.26%	7.32%	6.37%
Four-Factor Alpha t-Stat		(2.237)	1.539	3.321	2.381	2.296
Beta - Market		0.881	0.912	0.859	0.879	0.891
Beta - SMB		0.081	0.454	0.189	0.109	0.108
Beta - HML		0.004	(0.211)	0.155	0.162	0.193
Beta - Momentum		0.029	0.014	0.071	0.056	0.144

Table 3.4: **Segmented versus Integrated Pricing Models**

This table presents key performance statistics for four investor types when we use both segmented and integrated pricing models and we consider three different fund universes: passive index funds, country funds and our complete sample of funds. Results are reported for the out- of- sample period 06/1993 - 02/2008 and assume the setup from the baseline investment exercise, i.e. no short-selling, individual fund holdings capped at 10% of the total holdings, quarterly rebalancing. The short-term Euribor, the default spread, the term spread and the dividend yield are used as predictive variables, and beliefs are specified so that $\sigma_{\alpha} = 10\%$/Month.

Asset Universe	Passive Index Funds		All Funds		Country Funds Only	
Market Model	Integrated	Segmented	Integrated	Segmented	Integrated	Segmented
			Panel A: BCAPM			
Geo.mean	11.09%	11.11%	11.76%	13.48%	11.59%	11.88%
Arith.mean	12.26%	12.27%	13.61%	15.13%	13.09%	13.31%
Volatility	15.25%	15.23%	19.39%	18.29%	17.43%	16.93%
SR	0.535	0.536	0.491	0.603	0.516	0.544
Outperf.	53%	53%	55%	54%	53%	51%
Single-Factor:						
Alpha	1.60%	1.61%	2.47%	4.26%	2.27%	2.77%
Alpha t-stat	1.311	1.329	0.771	1.451	0.858	1.085
Beta	0.892	0.892	0.927	0.889	0.872	0.851
Four-Factor:						
Alpha	0.85%	0.84%	7.47%	9.09%	6.07%	6.91%
Alpha t-Stat	0.715	0.72	2.803	3.818	2.717	3.293
Beta Market	0.909	0.908	0.978	0.942	0.918	0.893
Beta SMB	-0.071	-0.073	0.641	0.625	0.494	0.528
Beta HML	-0.01	-0.009	-0.411	-0.411	-0.331	-0.335
Beta MoM	0.057	0.059	0.141	0.129	0.135	0.123
			Panel B: BSMA			
Geo.mean	10.17%	10.97%	16.68%	17.03%	13.34%	13.78%
Arith.mean	11.64%	12.39%	18.79%	19.03%	15.11%	15.48%
Volatility	17.08%	16.80%	21.18%	20.62%	19.10%	18.71%
SR	0.441	0.494	0.693	0.724	0.576	0.608
Outperf.	49%	50%	53%	54%	54%	51%
Single-Factor:						

Table 3.4: **Segmented versus Integrated Pricing Models (cont.)**

Alpha	0.49%	1.31%	7.78%	8.20%	3.90%	4.47%
Alpha t-stat	0.299	0.836	2.097	2.239	1.293	1.484
Beta	0.977	0.965	0.975	0.938	0.938	0.907
Four-Factor:						
Alpha	-0.18%	0.89%	12.04%	12.96%	7.54%	9.37%
Alpha t-Stat	-0.114	0.606	3.71	4.236	2.888	3.92
Beta Market	0.987	0.975	1.027	1.017	0.991	0.969
Beta SMB	-0.071	-0.043	0.556	0.648	0.483	0.642
Beta HML	0.026	0.018	-0.359	-0.485	-0.339	-0.44
Beta MoM	0.159	0.169	0.249	0.229	0.184	0.171
			Panel C: BAMA			
Geo.mean	10.08%	11.04%	15.28%	15.64%	13.19%	13.44%
Arith.mean	11.55%	12.46%	17.39%	17.60%	14.98%	15.17%
Volatility	17.05%	16.79%	21.20%	20.41%	19.17%	18.85%
SR	0.437	0.498	0.627	0.661	0.567	0.587
Outperf.	49%	50%	50%	53%	50%	52%
Single-Factor:						
Alpha	0.38%	1.35%	6.32%	6.79%	3.69%	4.09%
Alpha t-stat	0.233	0.868	1.707	1.895	1.235	1.348
Beta	0.974	0.965	0.978	0.936	0.947	0.915
Four-Factor:						
Alpha	-0.32%	0.90%	10.28%	11.12%	7.26%	8.89%
Alpha t-Stat	-0.204	0.619	3.137	3.656	2.816	3.713
Beta Market	0.985	0.975	1.034	1.013	1.002	0.981
Beta SMB	-0.075	-0.047	0.525	0.591	0.476	0.634
Beta HML	0.03	0.019	-0.359	-0.451	-0.342	-0.447
Beta MoM	0.161	0.172	0.235	0.233	0.192	0.188
			Panel D: BAMAP			
Geo.mean	10.75%	10.14%	14.11%	15.63%	12.40%	11.86%
Arith.mean	12.31%	11.65%	16.09%	17.42%	14.33%	13.43%
Volatility	17.59%	17.29%	20.34%	19.25%	19.95%	17.79%
SR	0.467	0.437	0.589	0.692	0.513	0.524
Outperf.	48%	47%	50%	51%	50%	50%
Single-Factor:						

Table 3.4: **Segmented versus Integrated Pricing Models (cont.)**

Alpha	0.95%	0.43%	4.77%	6.57%	2.53%	2.25%
Alpha t-stat	0.581	0.265	1.496	2.118	0.881	0.942
Beta	1.011	0.994	1.005	0.938	1.026	0.939
Four-Factor:						
Alpha	0.56%	0.14%	8.44%	10.48%	5.94%	5.95%
Alpha t-Stat	0.357	0.092	3.021	4.037	2.405	3.023
Beta Market	1.017	0.997	1.045	0.985	1.063	0.962
Beta SMB	-0.045	-0.036	0.47	0.507	0.435	0.455
Beta HML	0.03	0.038	-0.285	-0.319	-0.262	-0.236
Beta MoM	0.151	0.181	0.228	0.261	0.227	0.169

Table 3.5: **Portfolio Country and Sector Rotation**

This table presents portfolio weights for the investor types considered in the analysis. Weights are reported as of end of May, 1993, 1998, 2003 and end of November 2007 and are based on the benchmark out-of-sample portfolio selection exercise that reviews portfolio weights every quarter, limits the maximum holdings in any one fund to 10%, rules out short-selling and uses the short-term Euribor, the default spread, the term spread and the dividend yield to capture time-variations in the conditional alpha and factor loadings with beliefs specified so that $\sigma_\alpha = 10\%$/Month.

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

Table 3.5: **Portfolio Country and Sector Rotation (cont.)**

Germany	-	-	-	10%	-	-	-	10%
Italy	-	13%	-	-	-	18%	-	-
Pan-Europe	10%	10%	-	10%	17%	20%	-	10%
Scandinavian	60%	34%	100%	-	21%	52%	94%	-
Spain/Portugal	-	10%	-	10%	-	-	-	10%
Switzerland	10%	-	-	-	28%	-	-	-
UK	20%	-	-	-	25%	-	-	-
Sectors	-	-	-	70%	-	-	6%	70%

Panel B: Segmented Models

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

Table 3.5: **Portfolio Country and Sector Rotation (cont.)**

	BAMA-S				BAMAP-S			
	1993	1998	2003	2007	1993	1998	2003	2007
Austria	-	-	-	-	-	-	-	-
Benelux	-	-	-	-	-	-	-	-
France	10%	51%	10%	-	10%	10%	-	-
Germany	-	-	10%	-	-	-	-	10%
Italy	-	10%	-	-	-	10%	-	-
Pan-Europe	30%	9%	20%	12%	38%	40%	10%	2%
Scandinavian	30%	20%	48%	1%	20%	40%	78%	9%
Spain/Portugal	-	10%	-	-	-	-	-	-
Switzerland	10%	-	-	-	12%	-	-	-
UK	20%	-	0%	10%	20%	-	12%	9%
Sectors	-	-	11%	78%	-	-	0%	70%

Table 3.6: **Optimal Portfolio Weights (February, 2008)**

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

	CAPM	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Etoile Alimentation Europe	0%	0%	0%	10%	10%	10%	10%	10%	10%
SKARBIEC-RYNKU NIER. FIZ	0%	0%	0%	10%	10%	10%	10%	10%	10%
StreetTRACKS Eur Tel ETF	0%	0%	0%	10%	10%	10%	10%	5%	10%
iShares DJ EURO Tel (DE)	0%	0%	0%	10%	10%	10%	10%	0%	10%
Postbank Megatrend	0%	0%	0%	10%	2%	10%	8%	10%	2%
iShares TecDAXń (DE)	0%	0%	0%	10%	0%	10%	0%	10%	10%
Fideuram Eu Cons Staples	0%	0%	0%	0%	10%	0%	10%	10%	10%
Holly	0%	0%	10%	0%	10%	0%	10%	0%	9%
StreetTRACKS Eur IT ETF	0%	0%	0%	10%	0%	10%	0%	10%	0%
Fideuram Eur TT Equity	0%	0%	0%	0%	10%	0%	10%	0%	10%
Etoile Collectivites Eur	0%	0%	0%	0%	10%	0%	0%	10%	10%
Santander Ag. Spain, FI	0%	0%	0%	10%	0%	10%	0%	10%	0%
iShares DJ EURO Tech (DE)	0%	0%	0%	9%	0%	7%	0%	9%	0%
Fortis L Equ Tel Eur Cap	0%	0%	0%	1%	9%	3%	10%	0%	0%
CSIMF Universe F	0%	6%	5%	0%	8%	0%	4%	0%	0%
KBC Multi Track Eur Tel	0%	0%	0%	10%	0%	10%	0%	2%	0%
Odin Eiendom	0%	10%	10%	0%	0%	0%	0%	0%	0%
FIM Fenno	0%	10%	10%	0%	0%	0%	0%	0%	0%

Table 3.6: **Optimal Portfolio Weights (February, 2008) (cont.)**

Holberg Norge	0%	10%	10%	0%	0%	0%	0%	0%	0%
DnB NOR SMB	0%	10%	10%	0%	0%	0%	0%	0%	0%
Pareto Aksje Norge	0%	10%	10%	0%	0%	0%	0%	0%	0%
WarrenWicklund Norge	0%	10%	10%	0%	0%	0%	0%	0%	0%
Sparinvest Eur Fin. Aktier	0%	6%	10%	0%	0%	0%	0%	0%	0%
Kaupthing - Icelandic Eq	0%	6%	6%	0%	0%	0%	0%	0%	0%
Anima Eur Equity	10%	0%	0%	0%	0%	0%	0%	0%	0%
Eur Equity Index	10%	0%	0%	0%	0%	0%	0%	0%	0%
SGAM Index Euro	10%	0%	0%	0%	0%	0%	0%	0%	0%
Lyxor France Index 1	10%	0%	0%	0%	0%	0%	0%	0%	0%
Andorfons Anglaterra	10%	0%	0%	0%	0%	0%	0%	0%	0%
Andorfons Europa	10%	0%	0%	0%	0%	0%	0%	0%	0%
Andorfons Franca	10%	0%	0%	0%	0%	0%	0%	0%	0%
AXA WF Eu Value Eq	10%	0%	0%	0%	0%	0%	0%	0%	0%
Barclays Eu Blue Chip	10%	0%	0%	0%	0%	0%	0%	0%	0%
Eurovalor Bolsa Esp,	0%	10%	0%	0%	0%	0%	0%	0%	0%
iShares DJ Basic Res. (DE)	0%	10%	0%	0%	0%	0%	0%	0%	0%
Odin Finland	0%	0%	0%	0%	0%	0%	0%	0%	9%
SEBinvest Danske Aktier	0%	0%	9%	0%	0%	0%	0%	0%	0%
iShares DJ Auto (DE)	0%	0%	0%	0%	1%	0%	8%	0%	0%
Aberdeen G-UK Opport.	7%	0%	0%	0%	0%	0%	0%	0%	0%
SGAM Index Tech Euro	0%	0%	0%	0%	0%	0%	0%	4%	0%
Oddo Quant France A Cap	3%	0%	0%	0%	0%	0%	0%	0%	0%
Storebrand Optima Norge	0%	1%	0%	0%	0%	0%	0%	0%	0%

Table 3.6: **Optimal Portfolio Weights (February, 2008) (cont.)**

OP-Delta A	0%	0%	0%	0%	0%	0%	1%	0%	0%

Table 3.7: **Out-of-Sample Performance Attribution**

This table decomposes the abnormal return performance of our integrated and segmented models into four components, plus a residual. The differential return is measured relative to the benchmark MSCI Europe portfolio whose arithmetic mean return was 11.40% over the sample period. It comprises three selectivity components, namely returns from pan-European fund selection, country fund selection and sector fund selection. In addition there are returns from timing the country weights.

Panel A: Integrated Model

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

Panel B: Segmented Model

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

Table 3.8: **Predictability Generated by Individual and Local Macro Variables**

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

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

Table 3.8: **Predictability Generated by Individual Macro Variables (cont.)**

Panel B - BAMA-S

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

Panel C - BAMAP-S

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

Panel D - Reference Portfolios

Benchmark	10.06%	11.40%	16.28%	0.449			
CAPM	7.50%	8.62%	14.89%	0.303	-1.97%	(1.703)	0.873
BCAPM-S	13.48%	15.13%	18.29%	0.603	4.26%	1.451	0.889

Table 3.9: **Robustness to Investor Trading Strategy Restrictions**

This table shows the effect of imposing different constraints on the portfolio weights. All results are based on performance during the out-of-sample period from 06/1993 - 02/2008. The baseline scenario selected the 50 funds with the highest conditional alpha and assumed no restrictions on the changes in the weights, but capped holdings in individual funds to a maximum of 10% of the portfolio. Panel A lifts the constraints on the portfolio weights which are no longer capped at 10%, although short sales are still ruled out. Panel B limits the maximum position in individual funds to 5% of the portfolio. Panel C restricts changes in the portfolio weights so the fund cannot divest more than 5% per quarter. This has the effect of reducing turnover. All other assumptions are identical to those from the baseline scenario.

Panel A: No Maximum Weight Restrictions											
	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geo.mean	10.06%	7.81%	7.26%	16.13%	15.78%	22.53%	22.05%	21.43%	21.26%	17.76%	19.36%
Arith.mean	11.40%	9.07%	8.81%	18.06%	17.65%	25.85%	25.37%	24.76%	24.53%	20.46%	22.29%
Volatility	16.28%	15.74%	17.46%	19.96%	19.66%	27.08%	27.09%	27.12%	26.84%	23.99%	25.08%
SR	0.449	0.315	0.270	0.699	0.689	0.803	0.785	0.762	0.761	0.682	0.725
Outperf.		46%	42%	56%	58%	58%	59%	56%	58%	54%	52%
SF Alpha		-1.02%	-2.96%	7.50%	7.28%	14.43%	14.29%	13.08%	13.55%	8.78%	11.06%
SF Alpha t-stat		(0.653)	(1.803)	1.988	1.948	2.597	2.507	2.392	2.383	1.940	2.203
SF Beta		0.886	0.995	0.851	0.834	1.041	0.999	1.070	0.977	1.026	1.001
4F Alpha		-1.34%	-3.18%	12.77%	12.40%	20.23%	19.72%	18.14%	18.70%	14.04%	16.17%
4F Alpha t-stat		(0.901)	(1.938)	3.874	3.790	4.056	3.926	3.629	3.723	3.572	3.767
Beta - Mkt		0.846	0.982	0.869	0.849	1.046	1.067	1.065	1.052	1.059	1.026
Beta - SMB		(0.081)	(0.040)	0.636	0.615	0.690	0.714	0.588	0.688	0.649	0.621
Beta - HML		0.148	0.061	(0.294)	(0.274)	(0.240)	(0.432)	(0.167)	(0.445)	(0.316)	(0.247)
Beta - Mom		(0.051)	0.008	0.201	0.214	0.424	0.473	0.412	0.474	0.379	0.546

Table 3.9: **Robustness to Investor Trading Strategy Restrictions (cont.)**

Panel B: 5% Maximum Weight

	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geo.mean	10.06%	8.78%	8.49%	11.97%	12.69%	14.71%	14.54%	13.77%	14.49%	13.73%	13.85%
Arith.mean	11.40%	9.93%	9.80%	13.78%	14.25%	16.46%	16.19%	15.52%	16.14%	15.51%	15.43%
Volatility	16.28%	15.12%	16.09%	19.10%	17.72%	19.08%	18.43%	19.13%	18.46%	19.21%	17.91%
SR	0.449	0.386	0.354	0.507	0.573	0.648	0.656	0.597	0.653	0.594	0.633
Outperf.		40%	42%	54%	52%	51%	54%	49%	53%	50%	52%
SF Alpha		-0.85%	-1.47%	2.53%	3.44%	5.58%	5.41%	4.61%	5.36%	4.46%	4.55%
SF Alpha t-Stat		(0.876)	(1.706)	0.846	1.257	1.893	1.906	1.556	1.870	1.579	1.805
SF Beta		0.900	0.968	0.941	0.879	0.953	0.921	0.954	0.918	0.982	0.931
4F Alpha		-0.36%	-0.98%	7.26%	8.26%	9.02%	9.88%	8.16%	9.65%	8.05%	8.32%
4F Alpha t-stat		(0.391)	(1.151)	2.931	3.810	3.516	4.322	3.135	4.115	3.325	4.082
Beta - Mkt		0.871	0.956	0.989	0.929	1.001	0.981	1.002	0.979	1.026	0.977
Beta - SMB		0.024	0.046	0.605	0.618	0.455	0.590	0.467	0.570	0.467	0.489
Beta - HML		0.076	0.013	(0.386)	(0.400)	(0.312)	(0.414)	(0.323)	(0.408)	(0.306)	(0.319)
Beta - Mom		(0.015)	(0.012)	0.140	0.118	0.187	0.150	0.161	0.154	0.186	0.181

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

	Benchmark	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geo.mean	10.06%	8.39%	7.97%	11.93%	12.94%	14.76%	14.31%	13.46%	13.87%	13.57%	13.51%
Arith.mean	11.40%	9.52%	9.21%	13.73%	14.54%	16.52%	15.96%	15.24%	15.56%	15.36%	15.12%
Volatility	16.28%	14.96%	15.66%	19.05%	17.92%	19.14%	18.43%	19.21%	18.62%	19.26%	18.09%
SR	0.449	0.362	0.326	0.505	0.582	0.649	0.643	0.580	0.615	0.584	0.609
Outperf.		42%	45%	54%	54%	49%	54%	47%	53%	47%	47%

Table 3.9: **Robustness to Investor Trading Strategy Restrictions (cont.)**

SF Alpha	-1.11%	-1.83%	2.73%	3.93%	5.63%	5.20%	4.35%	4.68%	4.35%	4.29%
SF Alpha t-stat	(1.076)	(2.054)	0.904	1.398	1.908	1.805	1.459	1.627	1.535	1.658
SF Beta	0.887	0.939	0.937	0.887	0.956	0.914	0.956	0.928	0.984	0.935
4F Alpha	-0.51%	-1.38%	7.46%	8.81%	9.07%	9.61%	7.83%	8.97%	7.92%	7.96%
4F Alpha t-stat	(0.518)	(1.591)	2.973	3.937	3.520	4.142	2.986	3.811	3.244	3.735
Beta - Mkt	0.858	0.919	0.984	0.936	1.003	0.975	1.007	0.991	1.029	0.984
Beta - SMB	0.038	0.030	0.604	0.625	0.453	0.584	0.462	0.571	0.465	0.480
Beta - HML	0.068	0.047	(0.382)	(0.400)	(0.307)	(0.411)	(0.327)	(0.413)	(0.307)	(0.326)
Beta - Mom	(0.016)	(0.007)	0.144	0.128	0.188	0.168	0.164	0.156	0.183	0.179

Table 3.10: **Robustness to Investor Beliefs**

This table shows how the tightness of investor priors affects the portfolio weights. All results are based on performance during the out-of-sample period from 06/1993 - 02/2008. Assumptions are identical to those from the baseline scenario, i.e., portfolio weights are set every quarter, maximum holdings in individual funds is capped at 10%, short-selling is ruled out and the state variables used to capture time-variations in the conditional alpha and factor loadings are the term spread, the dividend yield, the default spread, and the short-term interest rate.

	Sigma Alpha						Sigma Alpha					
	0.10%	1.00%	5.00%	10.00%	50.00%	100.00%	0.10%	1.00%	5.00%	10.00%	50.00%	100.00%
	Panel A: BCAPM-S						Panel B: BSMA-S					
Geo.mean	11.52%	13.78%	13.48%	13.48%	13.49%	13.49%	14.45%	15.15%	17.38%	17.03%	16.84%	16.84%
Arith.mean	12.74%	15.32%	15.13%	15.13%	15.15%	15.15%	15.75%	16.75%	19.39%	19.03%	18.85%	18.85%
Volatility	15.58%	17.57%	18.25%	18.29%	18.30%	18.30%	16.13%	18.11%	20.66%	20.62%	20.66%	20.67%
SR	0.554	0.638	0.604	0.603	0.604	0.604	0.722	0.698	0.740	0.724	0.714	0.714
Outperf.	52%	55%	54%	54%	54%	54%	55%	55%	58%	54%	54%	54%
SF Alpha	2.31%	4.56%	4.26%	4.26%	4.27%	4.27%	5.07%	6.15%	8.52%	8.20%	8.02%	8.02%
SF t-stat	1.220	1.685	1.458	1.451	1.454	1.454	2.483	2.138	2.336	2.239	2.178	2.177
SF Beta	0.849	0.874	0.889	0.889	0.890	0.890	0.866	0.889	0.945	0.938	0.938	0.938
4F Alpha	5.94%	9.35%	9.09%	9.09%	9.10%	9.10%	8.30%	10.45%	13.21%	12.96%	12.84%	12.84%
4F t-Stat	4.232	4.320	3.831	3.818	3.814	3.814	4.916	4.486	4.343	4.236	4.167	4.167
Beta - Mkt	0.879	0.908	0.941	0.942	0.943	0.943	0.881	0.933	1.025	1.017	1.017	1.017
Beta - SMB	0.455	0.598	0.623	0.625	0.625	0.625	0.394	0.550	0.641	0.648	0.654	0.655
Beta - HML	(0.267)	(0.341)	(0.409)	(0.411)	(0.412)	(0.412)	(0.194)	(0.334)	(0.482)	(0.485)	(0.490)	(0.490)
Beta - Mom	0.123	0.131	0.128	0.129	0.129	0.129	0.138	0.218	0.233	0.229	0.223	0.223

Table 3.10: **Robustness to Investor Beliefs (cont.)**

	Panel C: BAMA-S						Panel D: BAMAP-S					
Geo.mean	13.42%	13.85%	15.46%	15.64%	16.93%	16.95%	12.65%	14.45%	15.40%	15.63%	15.56%	15.58%
Arith.mean	15.38%	15.80%	17.44%	17.60%	18.94%	18.96%	14.45%	16.29%	17.22%	17.42%	17.36%	17.38%
Volatility	20.37%	20.34%	20.51%	20.41%	20.63%	20.63%	19.21%	19.43%	19.37%	19.25%	19.26%	19.26%
SR	0.554	0.575	0.651	0.661	0.719	0.720	0.539	0.627	0.677	0.692	0.688	0.689
Outperf.	50%	51%	54%	53%	55%	55%	46%	51%	51%	51%	50%	51%
SF Alpha	4.39%	4.85%	6.52%	6.79%	8.10%	8.13%	3.51%	5.32%	6.30%	6.57%	6.50%	6.52%
SF t-stat	1.227	1.356	1.819	1.895	2.209	2.214	1.147	1.710	2.030	2.118	2.097	2.102
SF Beta	0.933	0.931	0.944	0.936	0.938	0.937	0.942	0.949	0.946	0.938	0.939	0.939
4F Alpha	8.77%	9.26%	10.92%	11.12%	12.88%	12.93%	7.54%	9.39%	10.28%	10.48%	10.46%	10.47%
4F t-stat	2.869	3.024	3.561	3.656	4.213	4.222	2.943	3.615	3.959	4.037	4.043	4.053
Beta - Mkt	1.006	1.003	1.020	1.013	1.019	1.017	0.999	1.001	0.995	0.985	0.987	0.987
Beta - SMB	0.592	0.594	0.600	0.591	0.651	0.653	0.533	0.531	0.517	0.507	0.513	0.514
Beta - HML	(0.443)	(0.440)	(0.457)	(0.451)	(0.489)	(0.490)	(0.372)	(0.348)	(0.330)	(0.319)	(0.323)	(0.324)
Beta - Mom	0.219	0.215	0.204	0.233	0.229	0.228	0.209	0.239	0.250	0.261	0.259	0.259

Table 3.11: **Out-of-Sample Short and Long Portfolio Performance**

This table presents performance statistics for portfolios that allow short-selling of mutual funds. Panel A considers the ability of the stock selection methodology to identify underperformers by studying a portfolio with short-only positions. Panel B reports the performance of a 2:1 leveraged portfolio that takes a 200% long position in mutual funds financed by using a 100% short position in benchmark and country indices. Panel C reports the performance of a self-financing portfolio that takes a long position in mutual funds financed by using a short position in benchmark and country indices with the objective of maintaining zero exposure to the market risk factor.

Panel A: Short Portfolio Performance										
	CAPM	CAPM-S	BCAPM	BCAPM-S	BSMA	BSMA-S	BAMA	BAMA-S	BAMAP	BAMAP-S
Geo.mean	3.71%	2.29%	-1.06%	-2.17%	-7.66%	-6.91%	-6.66%	-5.93%	-4.68%	-6.18%
Arith.mean	5.30%	3.59%	0.28%	-0.59%	-5.09%	-4.47%	-4.15%	-3.55%	-2.58%	-4.24%
Volatility	17.76%	15.99%	16.23%	17.54%	22.15%	21.58%	21.85%	21.33%	20.04%	19.25%
SR	0.067	(0.032)	(0.235)	(0.267)	(0.415)	(0.397)	(0.378)	(0.359)	(0.333)	(0.433)
Outperf.	37%	37%	29%	34%	33%	33%	34%	33%	32%	27%
SF Alpha	-6.01%	-7.14%	-10.24%	-11.52%	-17.69%	-16.69%	-16.56%	-15.74%	-14.52%	-15.79%
SF t-stat	(3.050)	(4.313)	(5.221)	(5.425)	(5.565)	(5.403)	(5.186)	(5.252)	(5.514)	(5.911)
SF Beta	0.993	0.907	0.889	0.959	1.141	1.115	1.117	1.110	1.069	1.006
4F Alpha	-2.49%	-3.73%	-8.31%	-9.64%	-13.09%	-12.15%	-11.40%	-11.13%	-10.70%	-12.35%
4F t-stat	(1.512)	(2.806)	(4.427)	(4.793)	(4.579)	(4.365)	(4.053)	(4.155)	(4.473)	(5.045)
Beta - Mkt	0.993	0.905	0.857	0.944	1.120	1.084	1.094	1.071	1.063	0.978
Beta - SMB	0.410	0.396	0.193	0.211	0.529	0.509	0.590	0.505	0.448	0.383
Beta - HML	(0.165)	(0.162)	0.012	(0.072)	(0.205)	(0.159)	(0.222)	(0.128)	(0.198)	(0.111)
Beta - Mom	0.079	0.017	(0.023)	(0.156)	(0.221)	(0.178)	(0.200)	(0.147)	(0.133)	(0.176)

Table 3.11: **Out-of-Sample Short and Long Portfolio Performance (cont.)**

Panel B: 2:1 Leverage Portfolio Performance

Geo.mean	3.39%	3.60%	11.77%	14.14%	18.59%	18.51%	17.87%	17.99%	18.18%	18.45%
Arith.mean	5.11%	5.39%	15.00%	17.11%	22.27%	22.02%	21.66%	21.60%	21.82%	21.52%
Volatility	18.42%	18.81%	25.86%	24.78%	27.98%	27.21%	28.49%	27.57%	27.90%	25.22%
SR	0.055	0.069	0.422	0.525	0.649	0.659	0.616	0.635	0.635	0.691
Outperf.	39%	43%	52%	53%	54%	57%	51%	55%	56%	54%
SF Alpha	-5.81%	-6.05%	3.67%	6.13%	10.60%	10.22%	10.00%	9.60%	10.53%	10.53%
SF t-stat	(1.908)	(2.282)	0.666	1.149	1.804	1.781	1.656	1.661	1.771	2.000
SF Beta	0.865	0.967	0.927	0.870	1.034	0.991	1.035	1.015	1.006	0.943
4F Alpha	-9.02%	-9.14%	9.50%	12.18%	13.59%	14.89%	13.43%	13.75%	14.74%	15.21%
4F t-stat	(3.283)	(3.741)	1.926	2.609	2.441	2.802	2.353	2.550	2.728	3.226
Beta - Mkt	0.834	0.968	1.044	1.000	1.097	1.084	1.104	1.114	1.066	0.999
Beta - SMB	(0.399)	(0.352)	0.812	0.856	0.419	0.654	0.476	0.599	0.555	0.608
Beta - HML	0.230	0.126	(0.675)	(0.735)	(0.313)	(0.525)	(0.356)	(0.519)	(0.335)	(0.361)
Beta - Mom	(0.214)	(0.144)	0.212	0.202	0.349	0.251	0.346	0.243	0.506	0.424

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

Geo.mean	4.01%	1.67%	10.39%	8.42%	11.49%	14.21%	11.90%	14.17%	11.76%	12.95%
Arith. mean	4.01%	1.87%	10.89%	8.79%	12.34%	14.86%	12.76%	14.81%	12.62%	13.50%
Volatility	0.62%	6.46%	9.96%	8.50%	13.26%	11.62%	13.28%	11.53%	13.34%	10.58%
SR	(0.139)	(0.345)	0.682	0.551	0.621	0.925	0.652	0.929	0.638	0.888
Outperf.	37%	38%	46%	44%	46%	47%	47%	46%	45%	47%
SF Alpha	-0.11%	-1.93%	6.34%	3.94%	7.84%	10.56%	8.37%	10.35%	8.05%	9.25%
SF t-stat	(1.165)	(1.166)	2.433	1.782	2.257	3.461	2.404	3.424	2.304	3.343

Table 3.11: **Out-of-Sample Short and Long Portfolio Performance (cont.)**

SF Beta	0.002	(0.070)	0.021	0.047	0.051	0.014	0.025	0.030	0.037	0.005
4F Alpha	-0.21%	-3.39%	7.84%	5.05%	8.83%	11.60%	9.29%	11.32%	9.18%	9.83%
4F t-stat	(2.339)	(2.120)	3.130	2.335	2.703	3.994	2.835	3.919	2.848	3.697
Beta - Mkt	0.002	(0.082)	0.047	0.060	0.083	0.030	0.061	0.042	0.092	0.020
Beta - SMB	(0.011)	(0.184)	0.204	0.144	0.147	0.138	0.144	0.126	0.189	0.084
Beta - HML	0.004	0.120	(0.150)	(0.092)	(0.111)	(0.067)	(0.122)	(0.051)	(0.197)	(0.049)
Beta - Mom	(0.004)	0.026	0.107	0.057	0.293	0.228	0.288	0.221	0.305	0.192

Table 3.12: **Sorted Portfolio Performance**

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

	BCAPM	BCAPM-S	BAMA	BAMA-S	BSMA	BSMA-S	BAMAP	BAMAP-S	Mom.
Panel A: Annualized Average Return									
1	13.37%	13.08%	13.10%	12.58%	13.38%	12.81%	12.88%	12.62%	14.90%
2	12.52%	12.40%	11.94%	12.05%	11.74%	11.89%	12.45%	11.87%	12.80%
3	11.62%	11.45%	11.49%	11.43%	11.40%	11.35%	11.56%	11.87%	11.30%
4	10.61%	10.67%	10.92%	11.48%	11.26%	11.45%	11.32%	11.20%	10.50%
5	9.64%	11.00%	10.42%	10.63%	10.01%	10.72%	10.69%	11.20%	9.50%
6	10.51%	10.16%	9.88%	10.27%	9.98%	10.23%	9.54%	10.19%	9.80%
7	9.69%	9.95%	9.66%	10.01%	9.65%	9.93%	9.96%	9.86%	9.50%
8	9.56%	9.91%	9.41%	9.76%	9.46%	10.03%	9.01%	9.55%	10.00%
9	9.59%	9.05%	9.73%	9.33%	9.83%	9.14%	9.45%	9.32%	9.80%
10	9.38%	8.79%	10.00%	8.98%	9.83%	8.98%	9.66%	8.84%	8.60%
H-L	3.99%	4.29%	3.10%	3.59%	3.55%	3.83%	3.22%	3.78%	6.40%
Monotonically declining mean return test (p-value)									
H vs L	0.08	0.03	0.10	0.01	0.07	0.00	0.06	0.00	0.28
All	0.86	0.13	0.28	0.00	0.33	0.02	0.19	0.00	0.23

Table 3.12: **Sorted Portfolio Performance (cont.)**

	Panel B: Annualized 4-Factor Alpha								
1	5.71%	5.77%	4.71%	4.42%	5.02%	4.75%	4.37%	4.41%	6.60%
2	3.82%	4.32%	2.56%	2.97%	2.31%	2.76%	3.33%	2.68%	3.90%
3	2.55%	2.58%	1.86%	1.77%	1.80%	1.60%	1.97%	2.54%	2.00%
4	1.42%	1.36%	1.33%	1.95%	1.69%	1.94%	1.80%	1.61%	0.50%
5	-0.09%	1.44%	0.79%	1.01%	0.40%	1.01%	1.07%	1.50%	-0.70%
6	0.87%	0.38%	0.26%	0.46%	0.37%	0.54%	-0.07%	0.32%	-0.40%
7	-0.33%	-0.22%	-0.07%	0.31%	-0.12%	0.19%	0.21%	0.14%	-0.70%
8	-0.54%	-0.57%	-0.21%	-0.09%	-0.14%	0.22%	-0.85%	-0.26%	0.30%
9	-0.43%	-1.26%	0.22%	-0.31%	0.37%	-0.51%	-0.01%	-0.51%	0.30%
10	-1.12%	-1.95%	0.44%	-0.62%	0.17%	-0.63%	0.07%	-0.55%	0.00%
H-L	6.83%	7.72%	4.27%	5.04%	4.85%	5.38%	4.30%	4.96%	6.60%
	Monotonically declining 4-factor residual test (p-value)								
H vs L	0.00	0.00	0.02	0.00	0.01	0.00	0.01	0.00	0.48
All	0.77	0.00	0.33	0.01	0.47	0.03	0.55	0.00	0.36

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