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Time-Varying Performance of International Mutual Funds

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A B S T R A C T

We examine the ability of one- and two-factor regime switching models to describe US, developed, and emerging market mutual fund returns. We find that a two-factor fixed transition probability model adequately describes the multivariate series of mutual fund returns without the need to model time-varying transition probabilities. Mutual fund performance, as measured by a state dependent Jensen's alpha, varies with economic regimes that are defined according to the global equity market mean. Our primary two-factor fixed transition probability model shows that emerging market mutual fund alphas are often significantly positive in global bull regimes. Consideration of alternative second risk factors suggests that both the foreign exchange factor, or the recently proposed Hou, Karolyi and Kho (2011) value factor can improve series forecasts and out-of-sample portfolio performance.

Keywords:
Mutual fund performance
Regime-switching models
Fixed transition probabilities
Forecasting

1. Introduction

Mutual funds are an important investment alternative for US investors. In 2010, combined assets in US mutual funds exceeded 11.8 trillion US dollars. Approximately 90 million individuals hold mutual funds in the United States, and of these individuals, 65% maintain more than half of their financial assets in mutual funds (Investment Company Institute, 2011).

The performance of mutual funds has been extensively studied by a wide range of authors beginning with the seminal works of Sharpe (1966), and Jensen (1968). Recent studies have examined the persistence in mutual fund winners and losers (Carhart, 1997), the role of luck in observed portfolio performance (Fama and French, 2008, 2010; Kosowski et al., 2006), and the importance of economic information in affecting conditional measures of performance (Ferson and Schadt, 1996; Jha et al., 2009; Kosowski, 2006).[1]

Since Solnik's (1974b) seminal work, the potential benefits to adding international investments to a well-diversified US-based portfolio continue to be actively debated. For example, De Santis and Gerard (1997) estimate that the expected gain from international diversification is more than 2% per year. Li et al. (2003) further show that international diversification benefits remain substantial for US investors even with short selling constraints. In contrast, Lewis (2007) finds that the diversification benefit,

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[1] Kosowski (2006) examines domestic mutual fund performance in the context of a regime-switching model. He finds that risk-adjusted mutual fund alphas are higher in recessions than in expansions with both single and multi-factor models. His model differs from ours in that he assumes a single regime for all risk factors, with fund returns that vary across regimes. Our specification models regime-specific moments for all risk factors and fund excess returns.

either from investing in foreign equities directly, or in American Depository Receipts traded in the US, is diminishing due to the increase of world equity market integration (also see Pukthuanthong and Roll, 2009). In our primary two-factor fixed transition probability model we find that emerging market funds can be used to generate superior out-of-sample Sharpe ratios.

Motivation to study international mutual funds, and especially emerging market funds, continues due to market frictions such as barriers to information flows, costs of information transmission, and cultural, legal and other institutional differences. However, empirical evidence regarding the performance of emerging markets funds is limited. Huij and Post (2009) use the rank portfolio method of Hendricks et al. (1993) to examine persistence in mutual fund performance. They find evidence of strong persistence in emerging market funds that is pervasive even among previous winners.[2] Conover et al. (2002) consider the linkages between developed economies and find that when an exogenously specified measure of monetary policy is tight, emerging market funds outperform domestic funds.

We analyze emerging market, (non-US) developed market, and US mutual funds returns in the context of a multivariate Markov regime-switching model with one or two risk factors, and with either fixed or time-varying transition probabilities. We investigate the significance of regime dependent alphas in an econometric model that admits changes in means and covariances across regimes for all assets and risk factors along with a transition matrix to characterize the likelihood of regime shifts. Transition probabilities between regimes are either fixed or time-varying as a function of the Organization for Economic Co-operation and Development (OECD) composite leading indicator. Both the fixed and time-varying transition probability models produce regime probabilities that evolve over time. Our single factor model includes a global equity market risk factor. Our primary two-factor specification also includes a foreign exchange risk factor supported by Solnik (1974a), Adler and Dumas (1983), Dumas and Solnik (1995), and De Santis and Gerard (1998), among others. We also examine two-factor specifications with a second risk factor given by the value factor of Fama and French (1998), the momentum factor of Hou, Karolyi and Kho (HKK 2011), or the HKK (2011) cash to price value factor.

Our empirical results suggest that a two-factor model with fixed transition probabilities can adequately describe the multivariate series of mutual funds considered. Further in our primary fixed transition probability (FTP) model, the estimated alpha for emerging market funds increases by over 1.3% per month when the environment changes from a global bear to a global bull market. When global equity returns are large, emerging market funds provide a substantially increased Jensen's alpha. Our approach is similar in spirit to Conover et al. (2002) in that we find that the economic environment impacts emerging fund returns. The primary differences are that our regimes are endogenously determined, and are related to global equity bull and bear markets rather than the monetary environment. Our finding that emerging market mutual funds provide superior state dependent alphas in bull markets is consistent with Conover et al. (2002) if tight money policy coincides with global bull markets.

We provide the following contributions to the literature. First, we find that a two-factor fixed transition probability (FTP) model provides a parsimonious description of the multivariate return series according to both the AIC and SBC information criteria. This result is consistent with much of the extant literature in related contexts (cf., Kon and Jen, 1978; Turtle et al., 1994; Hamilton, 1989; Ang and Bekaert, 2002a, 2002b; Guidolin and Timmermann, 2008a, 2008b; or Guidolin and Nicodano, 2009). Information criteria find little evidence that time-varying transition probabilities are particularly helpful in characterizing our sample. Nonetheless, the likelihood of various regimes displays substantial variability over time even in our simpler FTP setup. Second, we find that the single-factor FTP model seems to adequately capture the impact of changes in the OECD leading economic indicator without explicitly requiring transition probabilities to evolve with this variable. The model seems to have a tendency to identify bear regimes in equity markets even when the OECD indicator is quite positive and when the NBER does not identify a recession. This puzzle is partially resolved by recognizing that the model identifies global equity market regimes rather than economic regimes per se. That is, we find that global equity markets are noisy predictors of recessions.[3] Plots of the bear regime probability show a close relationship with one-year global equity market returns.

Many of our regime-switching specifications provide good out-of-sample predictability relative to the single regime results, but there is little evidence that time-varying transition probabilities improve out-of-sample forecasts. In general, the world market risk factor substantially improves the prediction for all mutual funds returns. Based on the extant international finance literature we also consider a second risk factor given by a foreign exchange risk factor. Out-of-sample, this factor most improves the predictability of emerging market fund returns. Of the other potential second factors considered, the HKK (2011) value factor improves the out-of-sample forecasts for all mutual funds series.

We also consider out-of-sample Sharpe ratios for various portfolios formed using the Okhrin and Schmid (2006) expected utility maximizing portfolios for various model-specific moment forecasts and risk aversion levels. This analysis offers potentially important differences relative to the simple forecast results in that portfolio choices are impacted by changes in both conditional means and covariances that will impact the resultant weight vectors chosen by our representative investor. In general, we find that FTP models offer superior out-of-sample Sharpe ratios relative to portfolios based on unconditional sample moments.

The remainder of the paper is organized as follows. Section 2 describes the data and their sources. Section 3 presents the regime-switching model and its application in mutual fund performance evaluation. Section 4 presents the primary empirical results of one- or two-factor fixed or time-varying transition probability regime-switching models. In Section 5 we present our primary out-of-sample analyses including a comparison of the various models using 60 one-month forecasts, as well as a related analysis of out-of-sample Sharpe ratios from the various FTP models. The latter is important in that they employ the model-generated covariance matrices in portfolio choice. Section 6 summarizes and concludes.

[2] This finding of persistence contrasts with the lack of persistence found in Carhart (1997) when examining US mutual funds.

[3] As Paul Samuelson famously noted " … the stock market has predicted nine of the previous five recessions."

2. Data

2.1. Mutual fund data

We collect mutual fund data from the Morningstar Principia database. Principia provides detailed information on mutual funds, including manager characteristics and fund performance. We limit our analysis to stock funds that are not closed to all investments, or to new investments, and have an initial minimum purchase amount of less than $20,000.[4] We classify mutual funds into domestic funds if the percentage of US stock holdings is equal to or greater than 80%, developed market funds if the percentage of developed market stock holdings outside the US exceeds 70%, or emerging market funds if the percentage of emerging market stock holdings exceeds 70%. Because many funds offer multiple classes on the same underlying fund, we retain only the largest class as measured by net assets at the end of March 2009 when there are multiple class offerings.[5] Our final sample includes 2190 US domestic funds, 499 developed market funds, and 37 emerging market funds. We extract monthly returns for all funds for the period from April 1989 to March 2009, and form equal-weighted monthly returns for domestic, developed market, and emerging market fund portfolios.[6] Equal weighted portfolios allow us to examine a simple portfolio strategy, albeit with required rebalancing, across US, developed and emerging markets in a manner consistent with much of the extant literature (cf., Ferson and Schadt, 1996; or more recently Jha, et al., 2009).[7]

2.2. Risk factors in international equity

Our world market portfolio is the Morgan Stanley Capital International (MSCI) All Country World Index (ACWI). Much of the related international literature uses a similar measure of global market returns. For example, Cumby and Glen (1990) show that the intercepts are jointly zero from regressions of country index returns on Morgan Stanley World Index returns, providing support for the use of the MSCI World Index as a mean-variance efficient portfolio. Ferson and Harvey (1993), Fama and French (1998), and Harvey et al. (2002) also use the MSCI World Index as their market proxy. The MSCI World Index is a market-capitalization weighted index of 23 developed countries. Given that our interest includes the performance of domestic, developed, and emerging markets, we use the broader market-capitalization weighted MSCI All Country World Index (ACWI) as our world market benchmark. As of April 2010, the ACWI includes 23 developed markets and 22 emerging markets.[8]

Following Harvey et al. (2002), we construct our foreign exchange risk factor as the return on the trade-weighted exchange index from the Federal Reserve Bank of St. Louis less the riskless rate.[9] The existing international asset pricing literature provides strong evidence that foreign exchange risk affects expected equity returns.[10] For example, Dumas and Solnik (1995) find that departures from purchasing power parity induce foreign exchange risk premium for the world's largest equity markets. Ferson and Harvey (1993, 1994), and Harvey et al. (2002) find that the aggregated exchange risk is another significant factor in both unconditional and conditional asset pricing tests. We therefore consider changes in the US dollar against the currencies of a broad group of major US trading partners as the second global risk factor (Harvey, 1995; Harvey et al., 2002). A positive (negative) change indicates appreciation (depreciation) of the US dollar.[11]

The 30-day Eurodollar deposit rate from the Federal Reserve Bank of St. Louis is our proxy for the international risk-free rate.

2.3. State variable

Chen et al. (1986) suggest that macroeconomic variables may serve as useful leading indicators of stock returns. We hypothesize that fund managers make portfolio decisions using macroeconomic information that affects state transition probabilities. In a related setting of business cycle phases and dynamics, Filardo (1994) uses the US Composite Leading Indicator (CLI) as his

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[4] The screen applied here is similar to Del Guercio and Tkac (2002).

[5] In a similar context, Chen et al. (2004) and Gaspar et al. (2006) also choose to retain the largest mutual fund class when collecting data from the CRSP US Mutual Fund database to avoid multiple counting of returns for the same managed fund. Multiple share classes in the same management family have the same pool of securities, and thus the same returns before expenses and loads. This restriction helps to retain important variability across the underlying mutual funds without including a wide number of funds with very highly correlated returns.

[6] Measured monthly returns from Principia do not adjust total returns for any brokerage costs or loads, but do account for management, administrative, and 12b-1 fees. In our later robustness analysis, we consider total returns adjusted by management expense ratios available as of March 2009 for individual mutual funds. We acknowledge the helpful suggestions of two anonymous referees that motivated this analysis.

[7] Unfortunately, Morningstar Principia does not provide fund values over time to allow the creation of value weighted portfolios.

[8] The developed market country indices include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States. The emerging market country indices include Brazil, Chile, China, Colombia, the Czech Republic, Egypt, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey.

[9] The trade-weighted exchange index (broad) is a trade-weighted average of the foreign exchange value of the US dollar against the currencies of a broad group of major US trading partners. The broad currency index includes the Euro Area, Canada, Japan, Mexico, China, United Kingdom, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Switzerland, Thailand, Philippines, Australia, Indonesia, India, Israel, Saudi Arabia, Russia, Sweden, Argentina, Venezuela, Chile and Colombia.

[10] See Solnik (1974a), Karolyi and Stulz (2003) for detailed discussion of foreign exchange risk pricing.

[11] Although this foreign exchange risk factor may be an excellent asset pricing risk factor, it is does not represent an investable security. For this reason and to meaningfully compare across other potential second risk factors in our later analysis, we form portfolios only from the three equal weighted portfolios of mutual fund returns and the world market portfolio. Different modeling specifications may nonetheless improve measurement of asset moments.

economic information variable. Similarly, both Perez-Quiros and Timmermann (2000) in their research of cyclical variations in stock returns, and Kosowski (2006) in his state-dependent domestic mutual fund performance paper use the CLI as their economic information variable. Given our international focus, we adopt the global CLI as our state variable in determining time-varying transition probabilities. The global CLI measure is constructed from the Organization for Economic Co-operation and Development (OECD) based on composite leading indicators for its member countries. The measure reflects business-cycle variation in each country and provides an aggregate leading indicator to capture business-cycle variation in the world economy.[12,13]

Table 1 provides a brief description of the monthly excess returns on the US domestic fund portfolio (r_{US}), the developed market fund portfolio (r_{DE}), the emerging market fund portfolio (r_{EM}), the world market portfolio (r_m), and the foreign exchange portfolio (r_{FX}). We also report summary statistics for the one-month Eurodollar deposit rate (R_f) and for the log growth rates of the OECD global composite leading indicator (g_{CLI}). All values are expressed in percent per month format. We observe that the US domestic fund, developed market fund, and world market benchmark have comparable sample minimums, maximums, and standard deviations. The emerging market fund excess returns, however, display considerably greater times series volatility. The average monthly excess returns of the US domestic fund portfolio and the developed fund portfolio are 0.40% and 0.17%, with a standard deviation of 4.42% and 4.47%, respectively. The monthly excess return of the world market portfolio is 0.19% with a standard deviation of 4.30%. The emerging market portfolio has a considerably greater mean excess return of 0.55% but is also much more volatile. Reported p-values indicate that excess returns to emerging, developed, and US mutual funds are not significantly different from the risk-free rate over this sample period using preliminary univariate tests.

3. Regime-switching models

Following Kon and Jen (1978), and Hamilton (1989), regime-switching models have been successfully applied to business cycles (Filardo, 1994), asset allocation (Ang and Bekaert, 2002a; Guidolin and Timmermann, 2008a), stock returns (Guidolin and Timmermann, 2005; Kim et al., 2001; Perez-Quiros and Timmermann, 2000), interest rates (Ang and Bekaert, 2002b), international mean-variance frontiers (Guidolin and Ria, 2010), and to consider the impact of higher return moments on optimal portfolio holdings in a regime context (Guidolin and Timmermann, 2008b). We apply the Markov regime-switching model to a sample of international mutual funds with both fixed and time-varying transition probabilities to examine regime specific performance.

We assume two states of the economy and use a latent variable S_t to denote the state as equal to either one or two. The states of the market switch from one regime to the other based on a transition matrix,

$$T_t \equiv \begin{bmatrix} p_t^{11} & p_t^{21} \\ p_t^{12} & p_t^{22} \end{bmatrix} \equiv \begin{bmatrix} p(\varphi_{t-1}) & 1-q(\varphi_{t-1}) \\ 1-p(\varphi_{t-1}) & q(\varphi_{t-1}) \end{bmatrix} \tag{1}$$

where $p(\varphi_{t-1}) \equiv p_t^{11} \equiv prob(S_t = 1|S_{t-1} = 1; \varphi_{t-1})$ is the probability of staying in state one if the previous state is one, $q(\varphi_{t-1}) \equiv p_t^{22} \equiv prob(S_t = 2|S_{t-1} = 2; \varphi_{t-1})$ is the probability of staying in state two if the previous state is two, and φ_{t-1} is the information set available to investors at time $t-1$. To guarantee well defined transition probabilities, we follow Perez-Quiros and Timmermann (2000), and Kosowski (2006) by using the logistic transformation to map the state variable into the interval (0,1) such that $p(\varphi_{t-1}) = \frac{\exp(a_0 + a_1\ \varphi_{t-1})}{1+\exp(a_0+a_1\ \varphi_{t-1})}$, and $q(\varphi_{t-1}) = \frac{\exp(b_0+b_1\varphi_{t-1})}{1+\exp(b_0+b_1\varphi_{t-1})}$, where a_0, a_1, b_0, and $b_1$are constants to be estimated along with the other model parameters.[14] We define the general model above as our time-varying transition probability (TVTP) model. Models with $a_1 = b_1 = 0$ are defined as fixed transition probability (FTP) models.

Our specification for equity portfolio expected returns and volatilities is similar to Turtle et al. (1994), Ang and Bekaert (2002a), and Tu (2010), among others. For any given model considered, we initially define the risk factors from one of two regimes, where each factor has a regime specific mean, variance, and covariance with all other assets under consideration. For the two-factor model including the market and foreign exchange factor, we can write,

$$r_{mt} = \mu_{m,S_t} + \varepsilon_{m,S_t}, \tag{2}$$

and

$$r_{FXt} = \mu_{FX,S_t} + \varepsilon_{FX,S_t}. \tag{3}$$

To facilitate discussion of our results we characterize the regime defined by the smallest estimated world market excess return mean, $\mu_{m,\ S_t}$, as the bear regime and we identify this as regime one. For any particular mutual fund or set of mutual funds we also have the equivalent specification,

$$r_{jt} = \mu_{j,S_t} + \varepsilon_{j,S_t} \tag{4}$$

[12] The OECD-Total covers 29 countries including Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

[13] We recognize that the global CLI variable will only imprecisely measure changes in emerging markets; however, given the economic importance of the 29 countries covered in the OECD measure, this proxy should effectively capture much of the world economic environment over time.

[14] Kosowski (2006) chooses a more restrictive form for time-varying transition probabilities that excludes the constant terms a_0 and b_0. Our modeling preference is to include a constant and slope term within the exponent to allow a comparison between fixed and time-varying transition probability models.

Table 1
Descriptive statistics for mutual fund excess returns, risk factors and the state variable.

Variable	Minimum	25th percentile	Median	75th percentile	Maximum	Mean (p-value)	Standard deviation
r_{US}	−19.467	−2.149	1.058	3.270	10.268	0.404 (0.176)	4.420
r_{DE}	−21.894	−2.554	0.612	2.934	10.934	0.171 (0.570)	4.473
r_{EM}	−32.424	−2.949	2.115	4.758	21.684	0.554 (0.244)	7.050
r_m	−20.193	−2.323	0.770	2.753	8.877	0.194 (0.503)	4.300
r_{FX}	−3.363	−0.948	−0.177	0.585	6.300	−0.116 (0.170)	1.250
R_f	0.064	0.248	0.393	0.447	0.668	0.343 (0.000)	0.139
g_{CLI}	−1.696	−0.229	−0.003	0.180	0.598	−0.040 (0.107)	0.371

We report summary statistics for monthly excess returns on the domestic equal weighted fund portfolio (r_{US}), the developed market equal weighted fund portfolio (r_{DE}), the emerging market equal weighted fund portfolio (r_{EM}), the world market portfolio (r_m), and the foreign exchange portfolio (r_{FX}) for the period from April 1989 to March 2009. We also report summary statistics for the one-month Eurodollar deposit rate (R_f), and for the growth rates of the OECD global composite leading indicator (g_{CLI}). Reported p-values test if the mean is significantly different from zero in a two-sided t-test.

for j = 1, 2, …, N_2. In general, the covariance matrix for all variates in any given system may be written in terms of the stacked disturbance vector for all variates in the system as,

$$\varepsilon_{S_t} = \begin{bmatrix} \varepsilon_{m,S_t} \\ \varepsilon_{FX,S_t} \\ \varepsilon_{1,S_t} \\ \vdots \\ \varepsilon_{N_2 S_t} \end{bmatrix} \sim N\left(0, \Sigma_{S_t}\right), \Sigma_{S_t} = \left[\sigma_{ij,S_t}\right] \quad (5)$$

assuming a system of N_2 mutual fund excess returns. Consistent with Elton (1999), this specification of means and covariances that vary by regime may be helpful in admitting potentially long periods of time where realized values deviate from expected returns. We report results for standard deviations and correlations using $\sigma_{ij,\ S_t} = \sigma_{i,\ S_t}\sigma_{j,\ S_t}\rho_{ij,\ S_t}$. All parameters are jointly estimated by maximum likelihood, where all terms subscripted with S_t are understood to have unique values in each regime.

The regime specific regression coefficients may be written as

$$\beta_{jm,S_t} = \frac{\sigma_{j,S_t}\left(\rho_{jm,S_t} - \rho_{jFX,S_t}\rho_{mFX,S_t}\right)}{\sigma_{m,S_t}\left(1 - \rho^2_{mFX,S_t}\right)}, \quad (6)$$

$$\beta_{jFX,S_t} = \frac{\sigma_{j,S_t}\left(\rho_{jFX,S_t} - \rho_{jm,S_t}\rho_{mFX,S_t}\right)}{\sigma_{FX,S_t}\left(1 - \rho^2_{mFX,S_t}\right)}, \quad (7)$$

and

$$\alpha_{j,S_t} = \mu_{j,S_t} - \beta_{jm,S_t}\mu_{m,S_t} - \beta_{jFX,S_t}\mu_{FX,S_t}. \quad (8)$$

In the simplified single factor model, we have,

$$\beta_{jm,S_t} = \frac{\sigma_{jm,S_t}}{\sigma^2_{m,S_t}}, \quad (9)$$

and

$$\alpha_{j,S_t} = \mu_{j,S_t} - \beta_{jm,S_t}\mu_{m,S_t}. \quad (10)$$

Our primary empirical model examines a system comprised of equal weighted portfolio excess returns to mutual funds in the US, developed markets, and emerging markets within the one- and two-factor models described above, with either fixed or time-varying transition probabilities.[15] If only the market risk factor is included, we denote the model as a one-factor model. We analyze the empirical performance of the various models with the Akiake information criterion (AIC) and Schwarz Bayesian Criterion (SBC). We also consider the implied behavior of bear market regime predictions graphically in relation to both the OECD leading indicator state variable and previous global equity market returns.

[15] In Section 5, we consider a variety of other alternatives to the foreign exchange risk factor. Our empirical design presents an out-of-sample comparison of predictability, and portfolio choice for various models and risk factors.

Table 2
Multivariate one-factor regime-switching model with fixed transition probabilities.

	Factor		U.S. funds (U.S.)		Developed funds (DE)		Emerging funds (EM)	
Parameters	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Excess	−0.9918	0.9750	−0.5833	1.0535	−1.0602	0.9825	−1.1750	1.6921
return	(0.036)	(0.000)	(0.248)	(0.000)	(0.031)	(0.001)	(0.138)	(0.000)
			0.4058	0.3763	−0.0901	0.0150	0.2039	0.6558
$\alpha_{j,\,S_t}$			(0.461)	(0.472)	(0.857)	(0.954)	(0.801)	(0.302)
			0.9974	0.6946	0.9781	0.9923	1.3904	1.0629
$\beta_{jm,\,S_t}$			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Correlations/volatilities								
	Regime1				Regime2			
	US	DE	EM	Market	US	DE	EM	Market
	5.8219				2.9780			
US	(0.000)				(0.000)			
	0.8880	5.6893			0.5854	3.1732		
DE	(0.000)	(0.000)			(0.000)	(0.000)		
	0.8329	0.8730	8.9623		0.5081	0.7268	5.0894	
EM	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	
	0.9434	0.9467	0.8543	5.5069	0.7008	0.9396	0.6275	3.0048
Market	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Transition Probability Parameters, Log Likelihood and Information Criterion								
		$a0$	$b0$		Log Likelihood	AIC	SBC	
		(p-value)	(p-value)					
		3.9811	4.3127					
		(0.000)	(0.000)		−2058.01	4176.02	4277.96	

This table reports parameter estimates for the multivariate two-state FTP regime-switching model

$$\begin{bmatrix} r_{US,\,t} \\ r_{DE,\,t} \\ r_{EM,t} \\ r_{mt} \end{bmatrix} = \begin{bmatrix} \mu_{US,S_t} \\ \mu_{DE,S_t} \\ \mu_{EM,S_t} \\ \mu_{m,S_t} \end{bmatrix} + \varepsilon_{S_t},\ \varepsilon_{S_t} \tilde{} N\left(0, \Sigma_{S_t}\right)$$

where $r_{US,\,t}$, $r_{DE,\,t}$ and $r_{EM,\,t}$ are the equal weighted monthly excess returns to the US domestic, developed market, and emerging market mutual funds, respectively; r_{mt} is the monthly excess return of the world market portfolio. Alpha and beta estimates are determined from $\beta_{jm,S_t} = \frac{\sigma_{jm,S_t}}{\sigma^2_{m,S_t}}$, and $\alpha_{j,\,S_t} = \mu_{j,\,S_t} - \beta_{jm,\,S_t}\mu_{m,\,S_t}$, where $j = US$, DE or EM and S_t is the latent variable taking a value of 1, or 2, when the system is in regime 1, or 2, respectively. The lower triangular volatility/correlation matrix reports volatilities (in percent) on the diagonal and correlations for off-diagonal elements. The fixed transition probabilities in the two-state model are defined as $p_{11} = prob(S_t = 1|S_{t-1} = 1) = \frac{e^{a0}}{1+e^{a0}}$, and $p_{22} = prob(S_t = 2|S_{t-1} = 2) = \frac{e^{b0}}{1+e^{b0}}$. Parameter estimates are reported with p-values below each estimate in parentheses. The log likelihood, Akaike Information criterion (AIC), and Schwarz Information criterion (SBC) of the full FTP model are also reported.

4. Primary empirical analysis

4.1. Multivariate regime-switching models

In this section we consider our primary regime-switching specifications using i) either the fixed or time-varying transition probabilities, and ii) with the world market portfolio as a single risk factor, or with both the world market

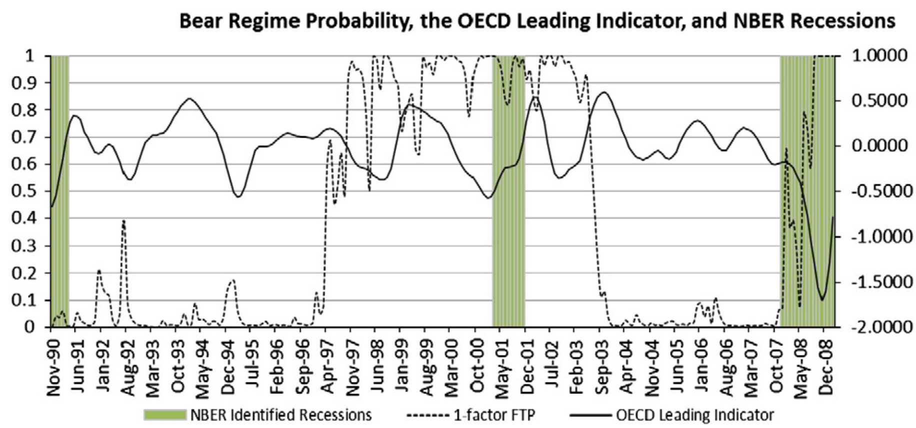

Fig. 1. This figure plots the NBER identified recessions in vertical bars (left vertical scale), the 1-factor fixed transition probability (FTP) model likelihood of a bear regime (left vertical scale), and the OECD leading indicator (right vertical scale).

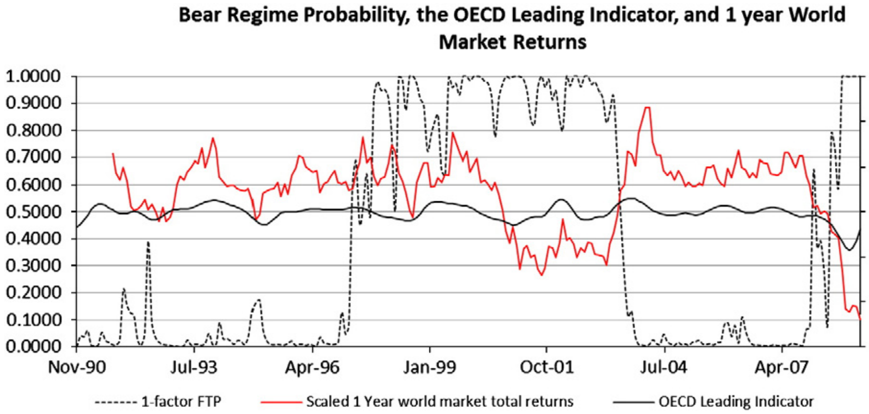

Fig. 2. This figure plots the 1-factor fixed transition probability (FTP) model likelihood of a bear regime (left vertical scale), the scaled 1-year world market total return (right vertical scale), and the OECD leading indicator (right vertical scale).

risk factor and the foreign exchange risk factor. We begin with our fixed transition probability (FTP) models in which there is always a constant transition probability of leaving any given regime. Even within a FTP model, the likelihood of the series being in any given regime over time can still display interesting temporal dynamics. Next we consider the time-varying transition probability (TVTP) models in which the probability of leaving a given regime varies with changes in our leading economic indicator, g_{CLI}.

4.1.1. Fixed transition probability (FTP) models

Table 2 presents estimation results for the one-factor FTP model. As described in Section 3, the model includes four variates given by $r_{US,\,t}$, $r_{DE,\,t}$, $r_{EM,\,t}$, and $r_{m,\,t}$. The FTP model requires two transition probability parameters, as well as four excess return means, four excess return standard deviations, and six correlations per regime. This results in a system with 30 parameters. Alphas and betas are then determined from Eqs. (9) and (10) for all equal weighted mutual funds series, $r_{US,\,t}$, $r_{DE,\,t}$, and $r_{EM,\,t}$.

The initial row of the table reports the estimated mean excess return in each regime for the global market index and each equal weighted portfolio. We observe large differences across regimes with the bear regime (regime 1) demonstrating a dramatically larger negative mean return relative to the bull regime for all series. Interestingly, in the one-factor model, all mean excess returns are of the same sign in each regime. Also, each fund and the market factor have opposite signs across regimes. Both the US and emerging market funds show a much smaller estimated beta in the bull regime than the bear regime, which may be indicative of an asymmetry in betas that is robust across international borders. The developed market fund betas display little difference across regimes.[16] This result regarding bull and bear regimes may be due to larger correlations in returns in bear markets. The estimated transition probability coefficients in the final row are both highly significant providing strong evidence of the existence of two regimes.[17]

To examine the ability of the one-factor FTP model to capture temporal variability in economic aggregates we calculate the implied likelihood of being in a bear regime from the FTP model and consider how this variable evolves. Fig. 1 plots the likelihood of a bear regime from the one-factor FTP model along with the National Bureau of Economic Research (NBER) identified recessions on the left side vertical axis, and the $g_{CLI,\,t-1}$ state variable on the right vertical axis. The NBER identified recessionary periods are determined ex post by the NBER Business Cycle Dating Committee. All of our regime-switching models determine bear and bull regimes as characterized by different excess return and factor moments, rather than by identifying economic periods of growth and decline. Nonetheless, we find that the likelihood of a bear regime is very large in both the mid-sample and latter sample NBER recessionary periods. Similarly, the latter increase in the probability of a bear regime occurs at the same time that the OECD indicator falls. The mid-sample NBER recession follows a large drop in the OECD indicator, but the model bear likelihood is substantively more pessimistic for a much longer temporal period than suggested by either the NBER or OECD variables. The initial NBER recession seems to be largely uncaptured by either the OECD indicator or the model likelihoods.

Fig. 2 adds the scaled one-year prior global market return on the right vertical axis in place of the NBER identified recessions. We now see that previous global market returns may be much more informative in identifying bear regimes than the OECD indicator. In particular, the increase in the likelihood of a bear market in the early 1990's appears to closely follow a period of poor global market returns. Similarly, the large likelihood of a bear regime over the early part of the century is closely related to weak global equity returns. Interestingly, the model bear likelihood appears to extend this period to include the late 1990s, when global returns remain quite positive. The final increase in bear likelihood also matches very well with both the drop in

[16] For brevity, we avoid providing extensive formal tests for differences in all parameters of secondary interest. Unreported tests find significant differences across regimes for correlations, standard deviations, and covariances.

[17] We defer our tests of differences in alphas across regimes and portfolios, so that they may be presented for all models in a single table. Table 5 provides tests for our primary interest in the equality of alphas across regimes, and portfolios for the various FTP and TVTP models.

Table 3
Multivariate two-factor regime-switching model with fixed transition probabilities.

Parameters	Factors		US funds (US.)		Developed funds (DE)		Emerging funds (EM)	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Excess return (Market)	−0.9903	0.9240	−0.5401	0.9851	−1.804	1.0046	−1.7691	1.9854
	(0.279)	(0.002)	(0.570)	(0.002)	(0.210)	(0.001)	(0.240)	(0.000)
Excess return (FX)	0.3213	−0.3853						
	(0.082)	(0.000)						
$\alpha_{j,\,S_t}$			0.2678	0.2686	−0.1898	0.0203	−0.6274	0.7578
			(0.840)	(0.780)	(0.840)	(0.984)	(0.593)	(0.529)
$\beta_{jm,\,S_t}$			0.9030	0.9719	0.9550	0.9944	1.3185	1.1913
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\beta_{jFX,\,S_t}$			0.2686	0.4711	−0.1392	−0.1699	0.5108	−0.3292
			(0.195)	(0.002)	(0.348)	(0.080)	(0.205)	(0.400)

Correlations/volatilities

	Regime 1					Regime 2				
	US	DE	EM	Market	FX	US	DE	EM	Market	FX
US	5.6713					3.2736				
	(0.000)					(0.000)				
DE	0.7886	5.6805				0.8140	3.2388			
	(0.000)	(0.000)				(0.000)	(0.000)			
EM	0.7795	0.8363	8.9179			0.6479	0.7955	5.0567		
	(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)		
Market	0.8646	0.9366	0.7987	5.5243		0.8855	0.9603	0.7423	3.0900	
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
FX	−0.110	−0.230	−0.082	−0.207	1.5292	−0.081	−0.273	−0.233	−0.236	0.9387
	(0.290)	(0.024)	(0.450)	(0.043)	(0.000)	(0.379)	(0.002)	(0.017)	(0.007)	(0.000)
Transition Probability Parameters, Log Likelihood and Information Criterion										
		$a0$	$b0$			Log Likelihood	AIC	SBC		
		(p-value)	(p-value)							
		1.5993	2.0923							
		(0.001)	(0.000)			−2389.17	4858.34	4994.27		

This table reports parameter estimates for the multivariate two-factor FTP regime-switching model

$$\begin{bmatrix} r_{US,\,t} \\ r_{DE,\,t} \\ r_{EM,t} \\ r_{m,t} \\ r_{FX,t} \end{bmatrix} = \begin{bmatrix} \mu_{US,S_t} \\ \mu_{DE,S_t} \\ \mu_{EM,S_t} \\ \mu_{m,S_t} \\ \mu_{FX,S_t} \end{bmatrix} + \varepsilon_{S_t},\ \varepsilon_{S_t} \tilde{} N\left(0, \Sigma_{S_t}\right)$$

where $r_{US,\,t}$, $r_{DE,\,t}$ and $r_{EM,\,t}$ are equal weighted monthly excess returns to the US domestic, developed market, and emerging market mutual funds, respectively; $r_{m,\,t}$ is the monthly excess return of the world market portfolio; r_{FXt} is the monthly excess return from the trade weighted foreign exchange index. Alpha and beta estimates are determined from $\beta_{jm,S_t} = \frac{\sigma_{j,S_t}\left(\rho_{jm,S_t} - \rho_{jFX,S_t}\rho_{mFX,S_t}\right)}{\sigma_{m,S_t}\left(1-\rho^2_{mFX,S_t}\right)}$, $\beta_{jFX,S_t} = \frac{\sigma_{j,S_t}\left(\rho_{jFX,S_t} - \rho_{jm,S_t}\rho_{mFX,S_t}\right)}{\sigma_{FX,S_t}\left(1-\rho^2_{mFX,S_t}\right)}$, and $\alpha_{j,\,S_t} = \mu_{j,\,S_t} - \beta_{jm,\,S_t}\mu_{m,\,S_t} - \beta_{jFX,\,S_t}\mu_{FX,\,S_t}$, where $j = US, DE$ *or* EM and S_t is the latent variable taking a value of 1, or 2, when the system is in regime 1, or 2, respectively. The lower triangular volatility/correlation matrix reports volatilities (in percent) on the diagonal and correlations for off-diagonal elements. The fixed transition probabilities in the two-state model are defined as $p_{11} = prob(S_t = 1|S_{t-1} = 1) = \frac{e^{a0}}{1+e^{a0}}$, and $p_{22} = prob(S_t = 2|S_{t-1} = 2) = \frac{e^{b0}}{1+e^{b0}}$. Parameter estimates are reported with p-values below each estimate in parentheses. The log likelihood, Akaike Information criterion (AIC), and Schwarz Information criterion (SBC) of the full FTP model are also reported.

the OECD variable and the reduction in global equity returns. This graphical representation foreshadows later results that show the FTP model may adequately describe bear regimes without the need for the $g_{CLI,\,t-1}$ variable.

The estimation results from the FTP model with both market and foreign exchange risk factors are presented in Table 3. We again characterize the bear regime as regime 1 where the world market excess return mean is the smallest. The two-factor model provides results similar to those for the one-factor model with respect to the excess return means by regime. Interpreting the foreign exchange factor beta coefficients, we observe that the US funds tend to offer greater excess returns when the US dollar appreciates in either regime, and concomitantly, developed funds offer lower excess returns. These results are only significant in the bull market regime. The foreign exchange risk factor has no significant impact on emerging market excess returns in either regime.

Regime specific alphas are consistently larger in the bull relative to the bear market regime for US, developed market, and emerging market funds. Interestingly, the observed reduction in global bull regime betas is dampened when the foreign exchange factor is included.

Examining the information criteria for the one- and two-factor FTP models, we observe a large increase in both the AIC and SBC, as well as highly significant coefficients on the marginal coefficients in the two-factor model. Given the prevalence of the foreign exchange risk factor in the extant literature, we view the expanded model as superior to the one-factor FTP model.

Table 4
Multivariate regime-switching models with time-varying transition probabilities.

Panel A. One-factor TVTP results

Parameters	Factor		U.S. funds (U.S.)		Developed funds (DE)		Emerging funds (EM)	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Excess return	−0.9905	0.9785	−0.5829	1.0572	−1.0593	0.9864	−1.1716	1.6964
	(0.122)	(0.000)	(0.3888)	(0.000)	(0.108)	(0.001)	(0.266)	(0.000)
$\alpha_{j,\,S_t}$			0.4048	0.3783	−0.0905	0.0156	0.2055	0.6577
			(0.707)	(0.346)	(0.376)	(0.982)	(0.785)	(0.373)
$\beta_{jm,\,S_t}$			0.9972	0.6937	0.9781	0.9921	1.3904	1.0615
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B. Two-factor TVTP results

Parameters	Factors		US funds (US.)		Developed funds (DE)		Emerging funds (EM)	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Excess return (Market)	−1.3190	0.8348	−0.6936	0.8681	−1.6792	0.9550	−2.4770	1.8369
	(0.104)	(0.007)	(0.409)	(0.008)	(0.043)	(0.002)	(0.052)	(0.000)
Excess return (FX)	0.04937	−0.3739						
	(0.028)	(0.000)						
$\alpha_{j,\,S_t}$			0.3902	0.2376	−0.3828	0.0634	−0.9597	0.8273
			(0.618)	(0.817)	(0.271)	(0.961)	(0.155)	(0.000)
$\beta_{jm,\,S_t}$			0.8872	0.9858	0.9778	0.9476	1.3264	1.1967
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\beta_{jFX,\,S_t}$			0.1752	0.5146	−0.0135	−0.2689	0.4705	−0.0282
			(0.476)	(0.000)	(0.935)	(0.08)	(0.313)	(0.932)

This table reports parameter estimates for the multivariate TVTP regime-switching models. The two-factor TVTP model may be written as

$$\begin{bmatrix} r_{US,\,t} \\ r_{DE,\,t} \\ r_{EM,t} \\ r_{m,t} \\ r_{FX,t} \end{bmatrix} = \begin{bmatrix} \mu_{US,S_t} \\ \mu_{DE,S_t} \\ \mu_{EM,S_t} \\ \mu_{m,S_t} \\ \mu_{FX,S_t} \end{bmatrix} + \varepsilon_{S_t},\ \varepsilon_{S_t} \sim N\left(0, \Sigma_{S_t}\right)$$

where $r_{US,\,t}$, $r_{DE,\,t}$ and $r_{EM,\,t}$ are the equal weighted monthly excess returns to US domestic, developed market, and emerging market mutual funds, respectively; $r_{m,\,t}$ is the monthly excess return of the world market portfolio; r_{FXt} is the monthly excess return from the trade weighted foreign exchange index. Alpha and beta estimates are then determined from $\beta_{jm,S_t} = \frac{\sigma_{j,S_t}\left(\rho_{jm,S_t} - \rho_{jFX,S_t}\rho_{mFX,S_t}\right)}{\sigma_{m,S_t}\left(1-\rho^2_{mFX,S_t}\right)}$, $\beta_{jFX,S_t} = \frac{\sigma_{j,S_t}\left(\rho_{jFX,S_t} - \rho_{jm,S_t}\rho_{mFX,S_t}\right)}{\sigma_{FX,S_t}\left(1-\rho^2_{mFX,S_t}\right)}$, and $\alpha_{j,\,S_t} = \mu_{j,\,S_t} - \beta_{jm,\,S_t}\mu_{m,\,S_t} - \beta_{jFX,\,S_t}\mu_{FX,\,S_t}$, where $j = US, DE\ or\ EM$ and S_t is the latent variable taking a value of 1, or 2, when the system is in regime 1, or 2, respectively. We also report the simplified one-factor FTP regime-switching model results when the r_{FXt} is excluded in the related single-factor model and the factor sensitivities are given by the simple regression coefficients as described in Table 3. The time-varying transition probabilities in the two-state model are defined as $p_{11} = prob(S_t = 1|S_{t-1} = 1) = \frac{e^{a0+a1*g_{CLI,t-1}}}{1+e^{a0+a1*g_{CLI,t-1}}}$, and $p_{22} = prob(S_t = 2|S_{t-1} = 2) = \frac{e^{b0+b1*g_{CLI,t-1}}}{1+e^{b0+b1*g_{CLI,t-1}}}$. For brevity we report means and regression coefficients for each model with p-values in parentheses below each estimate. One and two-factor results are reported in Panels A and B, respectively.

4.1.2. Time-varying transition probability (TVTP) models

Filardo (1994) and Diebold et al. (1994) point out that, by allowing the transition probabilities to vary with economic leading factors, the TVTP model can capture more complex temporal persistence in the evolution of the regimes. Table 4 provides empirical results for the TVTP specifications that incorporate the impact of the OECD indicator in our regime-switching transition probabilities. Follow Filardo (1994) and Kosowski (2006), we use the global composite leading indicator (CLI) as a state variable governing time-varying transition probabilities. One-factor TVTP estimation results are presented in Panel A, with two-factor results in Panel B. We find that most of the TVTP parameter estimates are qualitatively comparable to the related FTP model.

Comparing the one-factor FTP and TVTP models in Tables 2 and 4, we find similar coefficient estimates and p-values for most reported coefficients. For brevity we do not report the remainder of the estimates, however we note that both a_1 and b_1 estimates are insignificant suggesting little value in predicting regimes. Further, the information criteria are qualitatively similar.

Table 3 and Panel B of Table 4 reveal a more complicated relationship between the FTP and TVTP specifications for the two-factor model. The estimated excess return and factor moments now appear less stable across model specifications. Many parameter estimates appear economically different. For example, the mean world market excess return in the bear regime from Table 3 is approximately negative 1% – the comparable value from Panel B of Table 4 is less than −1.3%. Large differences across estimates occur throughout the tables. The unreported AIC and SBC values are both reduced relative to the two-factor FTP model, although the unreported a_1 and b_1 estimates for the two-factor TVTP are marginally significant.

Although our evidence is largely unsupportive of the TVTP models, we defer judgment about the value of the relative models until completion of our out-of-sample forecasting and portfolio choice comparisons.

To examine the performance of mutual funds in aggregate, we report a battery of potential Wald tests for various model restrictions related to our estimated alphas in Table 5. Test restrictions are detailed in the initial column for each row of the table. Wald test statistics and associated p-values are then shown in parentheses for each of the one-factor and two-factor models,

Table 5
Wald test of alpha restrictions.

Hypothesis	1-factor FTP	2-factor FTP	1-factor TVTP	2-factor TVTP
$\alpha_{US,1}=\alpha_{US,2}$	0.0008 (0.977)	0.0000 (0.999)	0.0063 (0.937)	0.0416 (0.838)
$\alpha_{DE,1}=\alpha_{DE,2}$	0.0112 (0.916)	0.0884 (0.766)	0.1597 (0.689)	0.5404 (0.462)
$\alpha_{EM,1}=\alpha_{EM,2}$	0.8070 (0.369)	3.8941 (0.048)	9.8196 (0.002)	11.7761 (0.001)
$\alpha_{US,1}=\alpha_{US,2}=0$	1.3037 (0.521)	0.1395 (0.932)	0.6201 (0.733)	0.7182 (0.698)
$\alpha_{DE,1}=\alpha_{DE,2}=0$	0.0268 (0.987)	0.1037 (0.949)	0.6440 (0.725)	0.8360 (0.658)
$\alpha_{EM,1}=\alpha_{EM,2}=0$	1.9371 (0.3780)	3.9018 (0.142)	20.0315 (0.000)	11.7769 (0.003)
$\alpha_{US,1}=\alpha_{DE,1}=\alpha_{EM,1}$	1.5879 (0.452)	4.5535 (0.103)	0.4889 (0.783)	1.0599 (0.589)
$\alpha_{US,1}=\alpha_{DE,1}=\alpha_{EM,1}=0$	1.5889 (0.662)	6.1920 (0.103)	0.5605 (0.905)	3.2023 (0.361)
$\alpha_{US,2}=\alpha_{DE,2}=\alpha_{EM,2}$	0.3406 (0.843)	7.2096 (0.027)	4.6823 (0.096)	34.8161 (0.000)
$\alpha_{US,2}=\alpha_{DE,2}=\alpha_{EM,2}=0$	1.3221 (0.724)	7.7009 (0.053)	11.3960 (0.010)	43.4191 (0.000)
$\alpha_{US,1}=\alpha_{US,2}$, $\alpha_{DE,1}=\alpha_{DE,2}$, $\alpha_{EM,1}=\alpha_{EM,2}$	1.4399 (0.696)	6.9016 (0.075)	20.0765 (0.000)	12.6967 (0.005)
$\alpha_{US,1}=\alpha_{US,2}=0$, $\alpha_{DE,1}=\alpha_{DE,2}=0$, $\alpha_{EM,1}=\alpha_{EM,2}=0$	6.2801 (0.393)	18.4751 (0.005)	29.0490 (0.000)	50.6195 (0.000)

We report Wald test statistics and associated p-values in parentheses for a variety of tests regarding the estimated model regime specific alpha parameters in the 1-factor FTP, 2-factor FTP, 1-factor TVTP, and 2-factor TVTP models.

for both the FTP and TVTP specifications. One- and two-factor FTP results can be found in columns two and three, with one- and two-factor TVTP results in columns four and five, respectively.

The initial panel of the table reports the Wald test results to examine if the alphas are different by regime for each of the US, developed market, and emerging market funds. None of these results are significant for any model for the US or developed market funds. In contrast, for the emerging market funds, we consistently find significantly different alphas across regimes for all but the single-factor FTP model.

The additional panels of Table 5 consider a wide range of restrictions within regimes across funds, as well as across regimes within funds, and across both regimes and funds. Two conclusions are immediately apparent. First, in the one-factor model, we consistently find no evidence of mutual fund mispricing according to our Wald test restrictions. Second, for virtually all other models and all other situations we find that restrictions related to emerging market funds are always binding. In short, emerging market funds appear mispriced. Emerging market alphas are significantly different from zero, significantly different from other funds' alphas within regimes, and significantly different across regimes.[18]

Evidence of regime specific alphas suggests mispricing of emerging market mutual fund excess returns. However, these mispricings may not be economically important if investors are unable to capitalize on them by predicting regimes. To examine the economic importance of non-zero alpha realizations, we graphically plot the weighted average value of our model alphas for the one- and two-factor FTP models in Fig. 3. At each point in time, we use the evolving likelihood of a bear and bull market regime to weight the regime-specific alphas to create a weighted average alpha that we then plot in the figure. The upper panel of the figure plots the one-factor alpha series and the two-factor alpha series is plotted in the lower panel. Both panels show substantial time variability in the model alphas. In the next section, we consider the ability of the models to forecast future returns and also if the models can improve portfolio choice.

5. Out-of-sample analysis

This section presents our out-of-sample forecasting and portfolio choice results.[19] Our goal is to examine the ability of the various regime-switching models to forecast future fund returns and to positively impact portfolio choices. Forecasting results are compared for the single regime model, the one-factor FTP model, the two-factor FTP model, the one-factor TVTP model, and the two-factor TVTP model. To examine the importance of alternative risk factor specifications, we also consider three asset pricing specifications where we replace our primary second foreign exchange risk factor with the value factor of Fama and French (1998), the HKK (2011) momentum factor, or the HKK (2011) value factor.[20]

5.1. Out-of-sample forecasting results

Our out-of-sample forecasting algorithm may be described as follows. Using all available data for each model from October 1990 to March 2004, we initially estimate model parameters for each approach. We then create an out-of-sample one-month forecast for April 2004 for each series and each estimation approach. We then update the estimation sample to include April

[18] As always, tests of this sort are model dependent. In unreported additional tests we find mixed results when we replace our second risk factor, the foreign exchange risk factor, with the HKK value factor. This alternative asset pricing specification suggests strong rejections from nonzero emerging market alphas for the two-factor TVTP model, but little contrary evidence in the FTP context.

[19] We gratefully acknowledge the guidance of two referees in motivating the analysis in this section.

[20] The Fama and French book-to-market value factor is constructed from data provided by Ken French at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We also gratefully acknowledge Andrew Karolyi for providing both the HKK momentum factor and the alternative global cash flow to price HKK value factor.

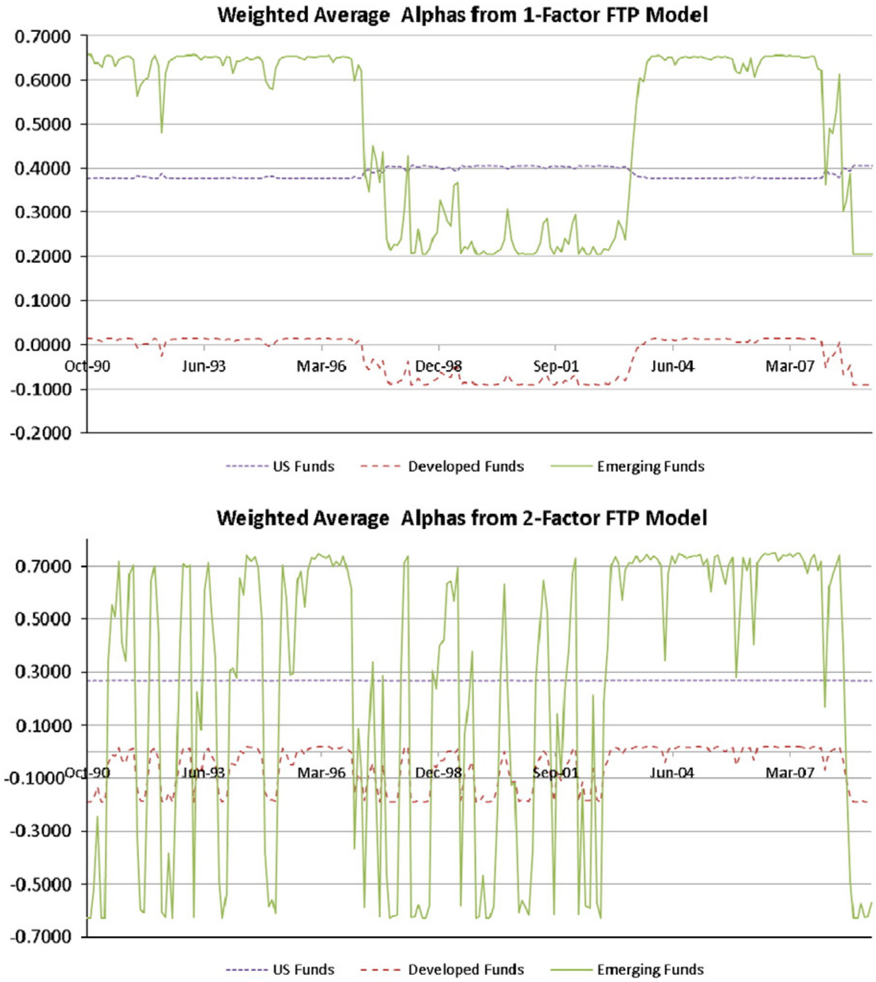

Fig. 3. Each panel plots the weighted average alpha for each equal weighted portfolio of US, Developed market, and Emerging market mutual funds. The weighted average alpha weights each regime-specific alpha by the probability of that regime in any given period. Alphas for the 1-factor fixed transition probability model are reported in upper panel, with 2-factor model results in the lower panel.

2004 and forecast the next month, May 2004. We continue in this manner until we have one-month forecasts for the entire 60-month out-of-sample period from April 2004 to March 2009.

To evaluate the forecasting ability of each model we compare the one-month forecast to the actual return for each of the 60 out-of-sample monthly observations using the mean absolute error (MAE) and the root mean squared error (RMSE),

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}|r_t - \hat{r}_t| \tag{11}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - \hat{r}_t)^2} \tag{12}$$

Table 6 reports the summary results across all specifications considered for the US, developed market portfolios (DE), and the emerging market portfolios (EM). At the top of both left and right panels we report the single regime forecast results based on the updated sample mean for each series. FTP model results are presented on the left side of the table, with TVTP model results presented on the right side of the table. The one-factor models include the world market portfolio (Market) as the sole risk factor. Two factor models then add the foreign exchange risk factor (FX), the Fama and French (1998) value factor (FF value), the HKK (2011) momentum factor (HKK Mom), or the HKK (2011) cash flow to price value factor (HKK value).

In general, we observe a large improvement in all FTP models relative to the single regime results. The single factor FTP model reduces the US MAE from 3.42 to 1.30 and the emerging market portfolio MAE from 5.89 to 2.98. The addition of a second risk factor in the FTP models often yields a forecast benefit for some of the mutual fund series. For example, our primary two-factor FTP model including the market and foreign exchange risk factor produces a good improvement in the MAE (from 2.98 to

Table 6
Rolling one-step forecast results.

Models	Measure	US	DE	EM	Models	Measure	US	DE	EM
Single regime	MAE	3.42	3.82	5.89	Single Regime	MAE	3.42	3.82	5.89
	RMSE	4.86	5.27	7.96		RMSE	4.86	5.27	7.96
1-factor FTP	MAE	1.30	0.87	2.98	1-factor TVTP	MAE	1.33	0.87	3.03
(Market)	RMSE	1.62	1.12	3.65	(Market)	RMSE	1.62	1.14	3.73
2-factor FTP	MAE	1.34	0.86	2.74	2-factor TVTP	MAE	1.41	0.89	2.81
(Market + FX)	RMSE	1.79	1.10	3.41	(Market + FX)	RMSE	2.06	1.10	3.61
2-factor FTP	MAE	1.26	0.97	3.00	2-factor TVTP	MAE	1.23	0.98	3.07
(Market + FF value)	RMSE	1.60	1.27	3.75	(Market + FF value)	RMSE	1.62	1.25	3.82
2-factor FTP	MAE	1.26	0.88	2.85	2-factor TVTP	MAE	1.28	0.89	2.79
(Market + HKK Mom)	RMSE	1.61	1.12	3.64	(Market + HKK Mom)	RMSE	1.61	1.15	3.58
2-factor FTP	MAE	1.25	0.83	2.63	2-factor TVTP	MAE	1.26	0.84	2.69
(Market + HKK Value)	RMSE	1.59	1.08	3.43	(Market + HKK Value)	RMSE	1.59	1.09	3.51

This table reports out-of-sample forecasting errors for various models. The Single Regime model assumes a constant mean vector and covariance matrix determined over the estimation window. The one-factor and two-factor FTP models are described in Tables 2 and 3. The TVTP models are described in Table 4. The single factor is given by the monthly excess return of the world market portfolio, r_{mt}. The two-factor models consider a second factor given by the monthly excess return from the trade weighted foreign exchange index, r_{FXt}, or alternatively, the value factor of Fama and French (1998), the momentum factor of Hou et al. (2011), or the value factor of Hou et al. (2011). For each model, we use data from October 1990 to March 2004 to estimate model parameters, and then generate one-step out-of-sample rolling estimation forecasts for mutual fund returns for the period of April 2004 to March 2009. The mean absolute error (MAE) is defined as $MAE = \frac{1}{T}\sum_{t=1}^{T}|r_t - \hat{r}|$ and the root mean squared error (RMSE) is defined as $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}$, where T is total number of periods in the entire forecasting interval, r_t is the actual return at time t and $\hat{r}_t$ is the one-step-ahead forecasted fund return at time t.

2.74) and RMSE (from 3.65 to 3.41) in the emerging market fund. The FF value and HKK momentum factors yield reductions in the US MAE and RMSE, but have little benefit in forecasting emerging market returns. The market and HKK value factor model offers a good improvement in virtually all measures (except the slightly poorer RMSE when compared with the market and foreign exchange factor model).

The TVTP specifications in the right panel show little benefit in a model by model comparison. For example, the one-factor FTP model yields smaller MAE and RMSE measures for all funds relative to the one-factor TVTP model. Although this strict rank ordering is not preserved in all cases, we find very few instances of improved forecasts using the TVTP model.

In general, we conclude that the one-factor FTP model provides good predictions of next period returns for most series and that the two-factor FTP models, including the world market and either the foreign exchange factor or the HKK value factor, produce good out-of-sample estimates. Based solely on next period return forecasts, the HKK value factor appears to be the most robust second factor in this FTP out-of-sample horse race. Although our work differs relative to Hou et al. (2011) in terms of both underlying assets and methodology, our results provide complementary evidence regarding the potential benefit of the HKK value factor in asset pricing studies.

The behavior of out-of-sample portfolio choices will also be impacted by the ex ante covariance matrix implied by each model over the forecast interval. In the next section we compare out-of-sample Sharpe ratios for various models and for two interesting asset subsets.

5.2. Out-of-sample portfolio choice results

We extend our forecasting algorithm to compute the implied covariance matrix for each model and for each period in our 60-month forecasting interval. This allows us to examine the impact of the time varying expected returns and covariance matrices on investor portfolio choices. There is a burgeoning literature examining the behavior of portfolio weights in the context of regime-switching models. Ang and Bekaert (2002a) consider the differences between single period investment choices and long horizon investment choices to gauge the importance of hedging demands related to the evolution of the underlying investment opportunity set. Their results require a quadrature solution to the first order conditions for the investor's investment problem to determine optimal portfolio weights. To examine the difference between myopic single period choices and longer term intertemporal choices they adopt an innovative stacking of first order conditions. In general they find little reason to focus on intertemporal hedging demands and conclude (p. 1182) that investors " … have little to lose by acting myopically instead of solving more complex dynamic programming problems for horizons greater than one period."

Building from this literature, we consider the sequence of optimal myopic portfolio weights implied by the various beta and regime-switching models. For a given underlying model of multivariate asset returns, our interest is in the ability of the model to improve investment choices.

As is well documented empirically by Frankfurter et al. (1971), more formally by Jobson and Korkie (1983), and later by Britten-Jones (1999) estimated portfolio weights are often poorly behaved. Okhrin and Schmid (2006) provide a number of interesting results related to estimators of various optimal portfolio weight vectors known from the extant literature. In particular, the expected quadratic utility optimal portfolio is

$$w_{EU} = \frac{\Sigma^{-1}e}{e'\Sigma^{-1}e} + \gamma^{-1}M\mu \tag{13}$$

Table 7
Out-of-sample portfolio performance.

Panel A: Expected utility portfolio formed with US, DE, EM and world market portfolios.						
Out-of-sample period	Apr. 04–Mar. 09		Apr. 04–Sept. 06		Oct. 06–Mar. 09	
Models	$\gamma=2$	$\gamma=10$	$\gamma=2$	$\gamma=10$	$\gamma=2$	$\gamma=10$
Base case	−0.134	−0.158	−0.013	0.138	−0.217	−0.320
1-factor FTP (Market)	0.112	0.092	0.318	0.347	0.012	−0.04
2-factor FTP (Market + FX)	0.249	0.230	0.499	0.510	0.203	0.159
2-factor FTP (Market + HKK Value)	0.203	0.182	0.503	0.511	0.136	0.086

Panel B: Expected utility portfolio formed without EM fund portfolio.						
Out-of-sample period	Apr. 04–Mar. 09		Apr. 04–Sept. 06		Oct. 06–Mar. 09	
Models	$\gamma=2$	$\gamma=10$	$\gamma=2$	$\gamma=10$	$\gamma=2$	$\gamma=10$
Base case	−0.201	−0.116	−0.055	0.210	−0.316	−0.29
1-factor FTP (Market)	0.358	0.355	0.450	0.477	0.299	0.257
2-factor FTP (Market + FX)	0.220	0.222	0.553	0.613	0.181	0.158
2-factor FTP (Market + HKK Value)	0.254	0.254	0.603	0.638	0.205	0.177

This table reports out-of-sample sample Sharpe ratios of expected utility portfolios based on various models for the entire out-of-sample period and two sub-periods. The Base Case model assumes an unconditional constant mean vector and covariance matrix determined over the estimation window. The one-factor and two-factor FTP models are described in Tables 2 and 3, where the first factor is given by the monthly excess return of the world market portfolio, r_{mt}. The two-factor models consider a second factor given either by the monthly excess return from the trade weighted foreign exchange index, r_{FXt}, or alternatively, the value factor of Hou et al. (2011). For each model, we use data from October 1990 to March 2004 to estimate model parameters and generate the estimated model-specific mean and covariance matrices for each period for the US, developed market (DE), emerging market (EM), and global benchmark market portfolios for the next period. We then update the sample by one month and generate another one-month forecast to create another mean vector and covariance matrix forecast. For each mean vector and covariance matrix over the forecast interval, we then generate the resultant optimal expected utility portfolios following the Okhrin and Schmid (2006) proposed portfolio weight estimators using

$$\tilde{w}_{EU}=\frac{\hat{\Sigma}^{-1}e}{e'\hat{\Sigma}^{-1}e}+\gamma^{-1}\left(\frac{T-N-1}{T-1}\right)\hat{M}\bar{R}$$

where $\bar{R}$ is the forecast mean vector, $\hat{\Sigma}$ is the next period forecast covariance matrix, e is a conformable $N\times 1$ vector of ones, and $\hat{M}=\hat{\Sigma}^{-1}-\frac{\hat{\Sigma}^{-1}ee'\hat{\Sigma}^{-1}}{e'\hat{\Sigma}^{-1}e}$. We report the mean Sharpe ratio for risk aversion parameters, γ, equal to 2 or 10 for the resultant portfolios created for the 60 forecast intervals for the various models. Panel A shows the results for optimal portfolios formed from total returns on the US, developed market (DE), emerging market (EM), and world market portfolio. Panel B shows results for optimal portfolios formed with the US, developed market (DE), and world market portfolio (excluding the EM portfolio).

where μ is the total return mean vector, Σ is the related covariance matrix of total returns, e is a conformable Nx1 vector of ones, $M=\Sigma^{-1}-\frac{\Sigma^{-1}ee'\Sigma^{-1}}{e'\Sigma^{-1}e}$, and γ is the risk aversion parameter from the objective function $w'\mu-\frac{\gamma}{2}w'\Sigma w$. Okhrin and Schmid (Theorem 1, 2006) show that

$$\tilde{w}_{EU}=\frac{\hat{\Sigma}^{-1}e}{e'\hat{\Sigma}^{-1}e}+\alpha^{-1}\left(\frac{T-N-1}{T-1}\right)\hat{M}\bar{R} \tag{14}$$

is unbiased for w_{EU} where $\bar{R}$ is the sample total return mean vector, $\hat{\Sigma}=\frac{1}{T-1}\sum_{j=1}^{T}(R_t-\bar{R})(R_t-\bar{R})'$, and $\hat{M}=\hat{\Sigma}^{-1}-\frac{\hat{\Sigma}^{-1}ee'\hat{\Sigma}^{-1}}{e'\hat{\Sigma}^{-1}e}$.

We construct out-of-sample Sharpe ratios for portfolios formed according to model forecasts of the mean vector, and covariance matrix. In particular, for each month in the forecast interval we create the optimal expected utility weight vector using Eq. (14). We then apply these weights to the realized returns for all series in the next month to determine the resultant portfolio return. We repeat this process for all forecast months in the single regime case, the one-factor FTP model, and the two-factor models with the world market portfolio and either the foreign exchange factor or the HKK value factor.

Table 7 presents two different asset sets that are available in all models. Panel A reports results for the optimal combination of assets formed from US fund, developed market fund, emerging market fund, and the world market portfolio. In Panel B, we report results where we preclude investments in the emerging market fund. This allows us to gauge the importance of eliminating the emerging market fund as an asset choice out-of-sample.

For each model, we present results for the entire 60-month out-of sample period and for two 30-month intervals that comprise the entire 60-month forecast period. The latter comparison is interesting in that the 60-month forecasting period is characterized by a positive (negative) sample mean for the world market portfolio over the initial (latter) 30-month interval. The initial row of each panel shows results for the base case single regime model. The estimation period sample mean and covariance matrix are used to form the optimal portfolio. The results are poor in both panels. Perhaps not surprisingly, the poor out-of-sample performance of the world market portfolio in the latter portion of the 60-month forecast interval has a large negative impact on the out-of-sample Sharpe ratio.

Panel A shows a marked increase in the out-of-sample Sharpe ratios for both two-factor models and the results appear persistent in both subperiods. In contrast to the simple MAE and RMSE forecasting results in Table 6, the foreign exchange risk factor provides consistently better out-of-sample portfolio performance versus the HKK value factor.

Panel B provides contrasting findings. When the emerging market funds are not included in the asset set, the one-factor FTP model appears to produce the best out-of-sample Sharpe ratios. Further, these values are large relative to those shown in the earlier panel for all models. This general finding is not robust to both forecast subperiods. The two-factor models do better in the first subperiod, but do not perform well in the second subperiod.

In unreported results we also examine individual emerging market funds both with and without consideration of management expenses. This analysis studies a subset of emerging market funds with 12 years of available monthly data and related management expense ratios.[21] We again find substantial variability of means across regimes, with a larger mean in the global bull market at both the means and medians. Evidence regarding the ability of mutual funds to outperform net of management fees is nonetheless very mixed.[22]

6. Conclusions

We evaluate a variety of regime-switching models and find support for a relatively simple two-factor fixed transition probability (FTP) model. A more complicated specification involving time-varying transition probabilities that evolve with a composite leading economic indicator is not recommended by information criteria or out-of-sample comparisons. The FTP models are easy to estimate, produce good out-of-sample forecasts, and provide good out-of-sample portfolio behavior as measured by sample Sharpe ratios.

In the single factor FTP model betas are larger in the global bear regime for both domestic and emerging market funds. When foreign exchange risk is added as a second factor, we find that the foreign exchange factor regime means are inversely related to the world market regime means. We also find significant performance variations in mutual funds across economic states as characterized by statistically different Jensen's alphas. Mispricing is especially prevalent in emerging market mutual funds in a multivariate system of US, developed market, and emerging market mutual funds. Ignoring the presence of economic regimes tends to mitigate significant performance differences that become apparent in the regime-switching models.

We also examine alternative risk factor models that include the Fama and French (1998) value factor, the Hou, Karolyi and Kho (HKK 2011) momentum factor, or the HKK (2011) cash flow to price based value factor. Depending on the goal of the researcher there are situations in which the one-factor FTP model, or the two-factor FTP model may be superior. In our out-of-sample comparisons the foreign exchange risk factor and the HKK (2011) value factor appear to be the best second factors for consideration to improve forecasting and out-of-sample portfolio performance.

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References

Adler, M., Dumas, B., 1983. International portfolio choice and corporation finance: a synthesis. J. Finance 38, 925–984.
Ang, A., Bekaert, G., 2002a. International asset allocation with regime shifts. Rev. Financ. Stud. 15, 1137–1187.
Ang, A., Bekaert, G., 2002b. Regime switches in interest rates. J. Bus. Econ. Stat. 20, 163–182.
Britten-Jones, M., 1999. The sampling error in estimates of mean-variance efficient portfolio weights. J. Finance 54 (2), 655–671.
Carhart, M., 1997. On persistence in mutual fund performance. J. Finance 52, 56–82.
Chen, N., Roll, R., Ross, S.A., 1986. Economic forces and the stock market. J. Bus. 59, 383–403.
Chen, J., Hong, H., Huang, M., Kubik, J.D., 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. Am. Econ. Rev. 94 (5), 1276–1302.
Conover, M., Jensen, G., Johnson, R., 2002. Emerging markets: when are they worth it? Financ. Analysts J. 58, 86–95.
Cumby, R.E., Glen, J.D., 1990. Evaluating the performance of international mutual funds. J. Finance 45, 497–521.
De Santis, G., Gerard, B., 1997. International asset pricing and portfolio diversification with time-varying risk. J. Finance 52, 1881–1912.
De Santis, G., Gerard, B., 1998. How big is the premium for currency risk? J. Financ. Econ. 49, 375–412.
Del Guercio, D., Tkac, P.A., 2002. The determinants of the flow of funds of managed portfolios: mutual funds vs. pension funds. J. Financ. Quant. Anal. 37, 523–557.
Diebold, F.X., Lee, J., Weinbach, G.C., 1994. Regime-switching with time-varying transition probabilities. In: Hargreaves, C. (Ed.), Nonstationary time series analysis and cointegration. Oxford University Press, Oxford, pp. 283–302.
Dumas, B., Solnik, B., 1995. The world price of foreign exchange risk. J. Finance 50, 445–479.
Elton, E.J., 1999. Expected return, realized return, and asset pricing tests. J. Finance 54 (4), 1199–1220.
Fama, E.F., French, K.R., 1998. Value versus growth: the international evidence. J. Finance 53, 1975–1979.
Fama, E.F., French, K.R., 2008. Mutual fund performance. Working Paper. University of Chicago. ds.
Fama, E.F., French, K.R., 2010. Luck versus skill in the cross section of mutual fund alpha estimates. J. Finance 65 (5), 1915–1947.
Ferson, W.E., Harvey, C.R., 1993. The risk and predictability of international equity returns. Rev. Financ. Stud. 6, 527–566.
Ferson, W.E., Harvey, C.R., 1994. Sources of risk and expected returns in global equity markets. J. Bank. Finance 18, 775–803.
Ferson, W., Schadt, R.W., 1996. Measuring fund strategy and performance in changing economic conditions. J. Finance 51, 425–461.
Filardo, A., 1994. Business-cycle phases and their transitional dynamics. J. Bus. Econ. Stat. 12, 299–308.
Frankfurter, G.M., Phillips, H.E., Seagle, J.P., 1971. Portfolio selection: the effects of uncertain means, variances and covariances. J. Financ. Quant. Anal. 6, 1251–1262.
Gaspar, J., Massa, M., Matos, P., 2006. Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization. J. Finance 61, 73–104.

[21] Because expense ratio is available only at the final date of the sample, this analysis is only indicative of performance results and is subject to misspecification if expenses changed substantially over the sample period for individual funds.

[22] We estimate the two-factor FTP model with the world market portfolio and the foreign exchange risk factor in an estimation setup including each of the 30 individual emerging market funds, r_{EMjt}, an equal weighted portfolio of all other 29 emerging market funds, $r_{EM,jt}$, the market risk factor, r_{mt} , and the foreign exchange, r_{FXt}, risk factor as described in Eq. (5).Weaker power may be due to a number of factors including the much larger idiosyncratic noise in the individual emerging market funds.

Guidolin, M., Nicodano, G., 2009. Small caps in international equity portfolios: the effects of variance risk. Ann. Finance 5, 15–48.
Guidolin, M., Ria, F., 2010. Regime shifts in mean-Variance Efficient Frontiers: Some International Evidence. Working paper. Manchester Business School.
Guidolin, M., Timmermann, A., 2005. Economic implications of bull and bear regimes in UK stock and bond returns. Econ. J. 115, 111–143.
Guidolin, M., Timmermann, A., 2008a. International asset allocation under regime-switching, skew and kurtosis preference. Rev. Financ. Stud. 21, 889–935.
Guidolin, M., Timmermann, A., 2008b. Size and value anomalies under regime shifts. J. Financ. Econometrics 6, 1–48.
Hamilton, J.D., 1989. A new approach to the economic analysis of non-stationary time series and the business cycle. Econometrica 57, 357–384.
Harvey, C.R., 1995. Predictable risk and returns in emerging markets. Rev. Financ. Stud. 8, 773–816.
Harvey, C.R., Solnik, B., Zhou, G., 2002. What determines expected international asset returns? Ann. Econ. Finance 3, 249–298.
Hendricks, D., Patel, J., Zeckhauser, R., 1993. Hot hands in mutual funds: short-run persistence of relative performance. J. Finance 48, 93–130.
Hou, K., Karolyi, G.A., Kho, B.C., 2011. What factors drive global stock returns? Rev. Financ. Stud. 24, 2527–2574.
Huij, J., Post, T., 2009. On the performance of emerging market equity mutual funds. Working paper.
Investment Company Institute, 2011. 2011 Investment Company Fact Book, 51st edition.
Jensen, M.C., 1968. The performance of mutual funds in the period 1945–1964. J. Finance 23, 389–416.
Jha, R., Korkie, B., Turtle, H.J., 2009. Measuring performance in a dynamic world: conditional mean-variance fundamentals. J. Bank. Finance 33, 1851–1859.
Jobson, J.D., Korkie, R.M., 1983. Statistical inference in two-parameter portfolio theory with multiple regression software. J. Financ. Quant. Anal. 18 (2), 189–197.
Karolyi, G.A., Stulz, R.M., 2003. In: Constantinides, G.M., Harris, M., Stulz, R.M. (Eds.), Are financial assets priced locally or globally?, Edition 1. : The Handbook of the Economics of Finance, Volume 1. Elsevier, pp. 975–1020.
Kim, C., Morley, J.C., Nelson, C.R., 2001. Does an international tradeoff between risk and return explain mean reversion in stock prices? J. Empir. Finance 8, 403–426.
Kon, S.J., Jen, F.C., 1978. Estimation of time-varying systematic risk and performance for mutual fund portfolios: an application of switching regression. J. Finance 33 (2), 457–475.
Kosowski, R., 2006. Do mutual funds perform when it matters most to investors? Mutual fund performance and risk in recessions and expansions. Working paper. INSEAD.
Kosowski, R., Timmerman, A., Wermers, R., White, H., 2006. Can mutual funds really pick stocks? New evidence from bootstrap analysis. J. Finance 51, 2551–2595.
Lewis, K.K., 2007. Is the international diversification potential diminishing for foreign equity inside the US? Working paper. Wharton School, University of Pennsylvania.
Li, K., Sarkar, A., Wang, Z., 2003. Diversification benefits of emerging markets subject to portfolio constraints. J. Empir. Finance 10, 57–80.
Okhrin, Y., Schmid, W., 2006. Distributional properties of portfolio weights. J. Econ. 134, 235–256.
Perez-Quiros, G., Timmermann, A., 2000. Firm size and cyclical variations in stock returns. J. Finance 55, 1229–1262.
Pukthuanthong, K., Roll, R., 2009. Global market integration: an alternative measure and its application. J. Financ. Econ. 94, 214–232.
Sharpe, W.F., 1966. Mutual fund performance. J. Bus. 1, 119–138.
Solnik, B., 1974a. The international pricing of risk: an empirical investigation of the world capital market structure. J. Finance 29, 365–378.
Solnik, B., 1974b. Why not diversify internationally rather than domestically? Financ. Analysts J. 30, 48–54.
Tu, J., 2010. Is regime switching in stock returns important in portfolio decisions? Manag. Sci. 56 (7), 1198–1215.
Turtle, H.J., Buse, A., Korkie, B., 1994. Tests of conditional asset pricing with time-varying moments and risk prices. J. Financ. Quant. Anal. 29 (1), 15–29.