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# Towards a macroprudential regulatory framework for mutual funds?

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**Abstract**

This paper highlights the procyclical and unstable behaviour of mutual funds, characterized by a varying sensitivity on common asset pricing factors. It proposes a novel factor model that allows for regime changes associated with macroeconomic and financial state variables. Estimated on a panel covering 825 US equity mutual funds over a period of 30 years, it appears that the yield curve, the dividend yield, short term interest rates and the industrial production coincide with regimes switches in the Fama–French factors. Furthermore, the estimated regimes coincide with financial crises and economic downturns, thus confirming the procyclical behaviour of mutual funds' returns. These findings, coupled with the emerging systemic role of mutual funds, promote the consideration for a specific macroprudential regulatory framework targeted at the mutual fund industry.

**KEYWORDS**

financial stability, macroprudential framework, mutual fund industry, regulation

## 1 | INTRODUCTION

Since the Global Financial Crisis (GFC), the assets under management of mutual funds increased by more than twofold, reaching in 2019 the levels of 17.7 trillion USD in the United States, and 14.1 trillion EUR in the EU.[1] The sheer size of the assets under management and the fact that retail and institutional investors fuel the demand for mutual funds qualifies the mutual funds' industry as one of the key components of the financial system. However, despite the growing importance of mutual funds, there is little evidence on their potential to destabilize financial markets. Specifically, concerns have been raised about the procyclical behaviour of the asset managers and, more recently, about its contribution to systemic risk.[2] Nevertheless, as discussed in Bengtsson (2013), the contribution of the asset management sector to financial instability has been ignored until the late 2000s.[3]

In the aftermath of the GFC, the first response to the raising concerns about systemic risk came in the form of the European Directive 2009/65/EC and the Financial Stability Oversight Council (FSOC) under the Dodd-Frank Wall Street Reform and Consumer Protection Act in the United States. These regulatory initiatives focused on the microeconomic dimension and relied on individual funds' reporting. Furthermore, they were imposing restrictions on investment policies, requiring more transparency and more information, especially about financial and climate risks exposure. However, compared to the regulations for the banking and insurance sectors, these attempts are incomplete as they do not take into account macroeconomic risks. This incompleteness has also generated the development of mutual funds directly or indirectly controlled by banks, often labelled as 'shadow banking'. Specifically, Mugerman et al. (2019) show that regulation frameworks do not have a market risk quantification component. To gain an insight into the effects of macroeconomic/financial risk on mutual funds, we need to evaluate the stability of mutual funds' returns under common multifactor models and identify any cyclical dependence on economic activity. To this end, this paper aims to shed light on the relationship between macroeconomic state variables and mutual funds' return dynamics under a non-linear specification of the Fama and French (1993) model. Furthermore, through these relationships, we aim to investigate whether the returns' factor loadings are sensitive to various macroeconomic regimes and appear procyclical, countercyclical or even acyclical.

Within the traditional asset pricing literature, there is evidence of a link between asset pricing factors and macroeconomic factors. For instance, Liew and Vassalou (2000) show that the size and value factors are good predictors of GDP growth, while the momentum factor plays only a minor role in predicting economic growth. Similarly, Vassalou (2003) finds that news related to economic growth coupled with the market factor, can explain returns as well as the Fama and French (1993) model. Petkova (2006) empirically shows that augmenting the market factor with the innovations in the aggregate dividend yield, term spread, default spread and 1-month T-Bill yield leads to a higher explanatory power than the Fama and French (1993) model. Similarly, Aretz et al. (2010) find that macroeconomic fundamentals are indeed priced factors, with pricing performance that is comparable to the Fama and French (1993) factors. Nevertheless, the majority of the relevant empirical studies consider macroeconomic variables as factors per se and not as regime drivers, during which factors affect differently mutual funds' performance. Conditional models can address this issue by introducing the relevant macroeconomic variable as a predictor for the sensitivity of the portfolio's returns to each factor (see, for instance, Ferson (1989), Ferson and Schadt (1996) and Jagannathan and Wang (1996)). However, Ghysels (1998) suggests that misspecification of the relationship between the model parameters and the state variables could lead to severe errors, even against the unconditional counterparts of the models.

To address the limitations mentioned above, we propose a methodology that bridges the gap between the Intertemporal Capital Asset Pricing Model (ICAPM) and conditional CAPM approaches mentioned earlier. Specifically, we propose a Threshold-ICAPM approach where we define regimes of stability for the Fama and French (1993) model driven by a set of economic variables. For our analysis, we estimate the model using a panel approach, aiming to extract information regarding the systemic/common part of risk exposures between mutual funds. Under such specification, it is possible to test for the presence of regimes associating mutual funds' performance with the macroeconomic environment and to evaluate if such regimes evolve simultaneously to economic cycles. It is crucial here to mention that we do not evoke the notion of causality, which is far less trivial.

To anticipate our main results, we find that return sensitivities for a broad set of U.S. equity mutual funds are unstable with respect to the parameters of an unconditionally estimated Fama and French (1993) model. Specifically, we find that the returns' sensitivity to the factors changes with the different regimes set by the term spread, short-term interest rates, dividend yield and economic growth. Depending on the threshold state variable, entering the regime exceeding an estimated threshold would increase or decrease factor sensitivities at time periods that coincide with the macro-environment changes. Such results provide evidence towards a procyclical behaviour of mutual funds returns. We also observe that linearity is rejected for all mutual fund categories except for funds investing in large capitalization stocks. The different behaviour of large-cap mutual funds is consistent with Eun et al.'s (2008) results about international diversification. Indeed, the authors show that large-cap stocks tend to co-move with stock markets, while small-cap stocks enable more effective international diversification than the large-cap ones. Finally, we conclude that due to the unstable and procyclical characteristics of the mutual funds' performance, macroprudential rules could be necessary to define a complete regulatory framework and help minimize their potential destabilizing impact on financial markets.

The remainder of the paper is structured as follows: Section 2 offers a review on the evaluation methodologies for mutual funds performance and introduces our proposed threshold intertemporal CAPM (T-ICAPM) model. Section 3 is devoted to the empirical analysis, whereas Section 4 concludes the paper.

## 2 | MUTUAL FUNDS' PERFORMANCE: METHODOLOGY

In this paper, we evaluate equity mutual funds' performance, following the traditional fund performance literature where asset-pricing models are used to identify skill in terms of abnormal returns, after controlling for various sources of systematic influences. However, in our case, we focus mainly on the sources of risk and not the persistence of alphas as we are interested in the managers' risk taking strategy and not in their skills. Therefore, using the factor loadings of an asset-pricing model, we implicitly quantify the riskiness of mutual funds and their stability across different regimes. The remainder of this section describes the asset pricing approaches and the associated characteristics that contribute towards our proposed specification.

Asset pricing models rely on a basic idea: price equals the expected future discounted payoff. Since the 1960s, a vast literature has grown, deriving and testing more and more sophisticated models stemming from this basic concept. The purpose of both theoretical and empirical work has been to investigate specific market features and pricing anomalies. Among all these models, the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) is a paradigm in financial economics. The underlying idea behind the CAPM is that asset returns can be viewed from an investor's perspective as a reward for market risk exposure. Specifically, for a particular asset $i$, CAPM expresses the expected returns $E(r_i)$ as a function of its exposure to the market return $E(r_m)$ in excess of the return of a risk-free asset as follows:

$$E(r_{i,t}) - r_{f,t} = \alpha + \beta_{im}\left(E(r_{m,t}) - r_{f,t}\right) + \varepsilon_{i,t}, \tag{1}$$

where $\varepsilon_{i,t}$ is a zero-mean residual series and $r_{f,t}$ is the risk-free rate at time $t$. The estimated values of $\beta_{i,m}$ indicate the exposure of asset $i$ (or portfolio $i$) to market risk (i.e. systematic risk). However, empirical tests have challenged the economic motivation related to the investor's utility as well as the simplicity of this model.

## 2.1 | Intertemporal CAPM

As early as the 1980s, pricing anomalies have been identified in the context of the CAPM. Specifically, the most popular anomalies are the size premium (Banz, 1981; Basu, 1983; Schwert, 1983) and the value premium (Rosenberg et al., 1985), leading Fama and French (1992) and Fama and French (1993) to introduce a three-factor model that provides a better description of average returns. In Fama and French (1996), this factor-augmented CAPM is derived in discrete time from the Intertemporal CAPM (ICAPM) of Merton (1973). The size factor (SMB; *Small minus Big*) and the value factor (HML; *High minus Low*) capture risk premia that are not related to market risk exposure. In the ICAPM framework, SMB and HML are portfolios that proxy for the expected return effects of state variables and enable a better empirical estimation of the cross-section of stock returns without any assumption about the nature of these state variables (Fama, 2014). The three-factor model of Fama and French (1993) has the following form:

$$\begin{aligned} E(r_{i,t}) - r_{f,t} = \alpha_i + \beta_{im}\left(E(r_{m,t}) - r_{f,t}\right) + \beta_{i\mathrm{SMB}}\mathrm{SMB}_t \\ + \beta_{i\mathrm{HML}}\mathrm{HML}_t + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

Momentum (MOM) has been identified as another pricing anomaly in the early 1990s (De Bondt & Thaler, 1985; Jegadeesh & Titman, 2001). Carhart (1997) added the momentum factor to the Fama and French (1993) model leading to the emergence of the four-factor model.[4] More recently, Fama and French (2017) proposed a five-factor model, adding RMW (*Robust minus Weak*) and CMA (*Conservative minus Aggressive*) to proxy for the profitability and investment premia, respectively. However, the three-factor model of Fama and French (1993) and the four-factor model of Carhart (1997) remain the standard framework for the majority of the empirical asset pricing studies. Still, the question about underlying risks associated with these factors remains. Indeed, Fama and French (1996) and Lewellen (1999) agree that the economic link between systematic risk and these factors remains weak: Why should investing in small firms' stocks or low book-to-market stocks lead to risk premia that should be rewarded? Why should investing in firms stocks that have a bad momentum lead to a reward? What is the link between these factors and the macroeconomic and financial environment firms operate in?

To answer these questions, one needs to find which economic factors can explain the abnormal returns for anomalies such as size, book-to-market ratio and momentum. Campbell (1996) and more recently Cochrane (2009) uses the framework proposed by Merton (1973), relying on the Consumption CAPM and the Intertemporal CAPM. They propose as validation criteria for the choice of these economic factors, the ability to forecast the stock market return and the ability to explain the cross-sectional pattern of asset returns.[5] In line with these validation measures, several empirical studies have traced the economic roots of risk factors. The first one is Liew and Vassalou (2000) who investigate the link between future economic growth and size (SMB), book-to-market (HML) and momentum (MOM) factors in an international empirical study from 1978 to 1996. The authors show that SMB and HML are good predictors of Gross Domestic Product (GDP) growth, while MOM plays only a minor role in predicting GDP growth. Vassalou (2003) continues this investigation focusing on the

US equity market from 1953 to 1998. The author provides empirical evidence that news related to GDP growth as an additional variable in the CAPM leads to added value. Furthermore, she shows that once this additional factor is included, SMB and HML lose their ability to explain the cross-section of equity returns.

Nevertheless, Cochrane (2001) criticizes these approaches and denotes them as a 'fishing licence' (i.e. choosing multiple factors), suggesting that only factors that forecast future investment opportunities should be included in the CAPM. Following this criticism, Petkova (2006) focuses on innovations in state variables that have forecasting power for future investment opportunities. Specifically, she empirically shows that for the period 1963–2001, a model in which the factors are both the excess market return and innovations in the aggregate dividend yield, term spread, default spread, and 1-month T-Bill yield has a higher explanatory power than the Fama and French (1993) three-factor model. In addition, the author gives evidence that the Fama and French (1993) factors are not significant explanatory variables for the cross section of average returns in the presence of these innovation factors.

## 2.2 | Conditional CAPM

A second stream of the literature has extended the CAPM to allow for time varying $\beta$s as follows:

$$E(r_{i,t}) - r_{f,t} = \alpha_i + \beta_{im,t}\left(E(r_{m,t}) - r_{f,t}\right) + \varepsilon_{i,t}. \tag{3}$$

Ferson (1989), Ferson and Harvey (1991), Ferson and Harvey (2015), Ferson and Korajczyk (1995) and Jagannathan and Wang (1996) empirically show that the conditional CAPM improves dramatically the explanatory power of the cross-section of expected returns. In order to evaluate the economic link between systematic risk and these factors, Ferson (1989) introduced the conditional CAPM and in particular, the impact of the 1-month T-Bill rates on the time-varying betas. The conditional CAPM can be estimated using either Least Square or Generalized Method of Moments (GMM) via the following regression:

$$E(r_{i,t}) - r_{f,t} = \alpha_{0,t} + \beta_{im,t} z_{t-1}\left(E(r_{m,t-1}) - r_{f,t-1}\right) + \varepsilon_{i,t}. \tag{4}$$

where $r_{i,t}$ is the rate of return of asset $i$ between times $t-1$ and $t$, $r_{f,t}$ is the risk-free rate at time $t$ $\beta_{im,t-1}$ is the $i$ asset's sensitivity to the market portfolio, is the conditioning set of variables (information set at time $t-1$) of the market beta, and $\alpha_{0,t}$ is the expected return of all portfolios with a market $\beta$ equal to zero.

Several extensions have been proposed as, for example, by Shanken (1990) or Ferson and Schadt (1996) who modify the model in order to separate the unconditional and conditional part of systematic risk. Still, Ghysels (1998) empirically shows that, due to its fragility, the conditional CAPM performs as poorly as the CAPM despite being a more sophisticated model. Lewellen and Nagel (2006) analytically demonstrate that the conditional CAPM differs from the CAPM via its covariance among betas but that covariance cannot explain CAPM's large pricing errors.

## 2.3 | Threshold ICAPM model

As described earlier, the objective of the present paper consists of testing for the instability and the cyclical behaviour of mutual funds' performance. In this respect, we propose a Threshold-ICAPM (T-ICAPM) model. Similar to the Markov Switching (MS) models, the proposed T-ICAPM model allows us to consider different regimes under which coefficients vary. The difference between both approaches lies in the fact that in T-ICAPM one can control and test for the transition variable, whereas this is not possible for MS models. Specifically, T-ICAPM has the following form:

$$\begin{aligned}
&E(r_{i,t}) - r_{f,t} = \alpha_{i,t} + \beta_{im,t}. \\
&\left(E(r_{m,t}) - r_{f,t}\right) + \beta_{\mathrm{iSMB},t}.\mathrm{SMB}_t + \beta_{\mathrm{iHML},t}.\mathrm{HML}_t \\
&+I(s_t > c).\alpha_{i,t}(s_t) + I(s_t > c).\beta_{im,t}(s_t).\left(E(r_{m,t}) - r_{f,t}\right) \\
&+I(s_t > c).\beta_{\mathrm{iSMB},t}(s_t).\mathrm{SMB}_t + I(s_t > c).\beta_{\mathrm{iHML},t}(s_t). \\
&\quad \mathrm{HML}_t + \varepsilon_{i,t},
\end{aligned} \tag{5}$$

where $s_t$ is a macroeconomic or financial state variable driving the regime change, $I(.)$ is the indicator variable taking the value of one whenever $s_t > c$, which is the estimated threshold, and zero otherwise. The coefficients with the subscript $s_t$ denote the incremental change in the ICAPM parameters, when the threshold is exceeded. Instead of allowing all ICAPM coefficients to vary over time fully, the proposed specification defines regimes of stability where an economic variable drives the transition. Therefore, we consider the changes in $\alpha$ and $\beta$ as well as in the factors and determine which state variable associates them to the regime switch. Our selection of factors is in line with our focus on equity mutual funds and the fact that such factors capture systematic risk that emanates from equity with specific characteristics. In contrast, the momentum factor proposed by Carhart (1997) does not capture specific characteristics rather than prevailing past performance. Hence, since we are not interested in abnormal performances per se, we do not include this factor to our proposed specification.

Model (5) can be estimated for a particular mutual fund ($i$), a cluster of homogeneous mutual funds or more generally in a panel set-up for $i=1,\ldots,N$ and $t=1,\ldots,T$, $N$, $T$ being large and $\Sigma=\varepsilon'_{i,t}\varepsilon_{i,t}$ (Antoch et al., 2019; Westerlund, 2019). The use of a panel instead of the averaging of individual effect as in Fama and MacBeth (1973) approach, provides more efficient estimators (being on a single-step approach) but should lead to careful interpretation. Indeed, the estimator will provide information on the common part between the mutual funds.[6] Following Hansen (1996), Equation (5) can be estimated via Generalized Least Squares (GLS), considering independently or simultaneously several economic variables as transition variables. The threshold estimate is the value that maximizes the log-likelihood. Following Hansen (1996) and Andrews (1993); Andrews et al. (1996), a trimming value 15% of the sample size is imposed. Confidence bounds are obtained via bootstrapping replications, which conserve the cross-sectional structure/dependence. A Wald linearity test described in Appendix A is also available from these bootstrap simulations.

# 3 | EMPIRICAL ANALYSIS

## 3.1 | Data

In this study, we use monthly data from January 1990 to December 2018. For the threshold variable, we follow Petkova (2006) and include six state variables that describe the investment opportunity and macroeconomic environment. Specifically, to describe the investment opportunity environment, we use the 1-month T-Bill, the dividend yield and the term spread calculated as the 10-year government bond yield minus the 10-year treasury yield. For the macroeconomic environment, we use the growth of the consumer price index (CPI) and industrial production index (IPI), and, finally, the level of the three-component economic uncertainty index (*EPU3-Comp*). Table 1 reports the descriptive statistics for the threshold and factor variables. Over the period examined, the average values of the T-Bill, dividend yield and term spread are 0.225%, 2.078% and 1.519%, respectively. On average, inflation and industrial production growth are 2.473% and 1.942% while the EPU index is at 107.246.

Per the specification of the Fama and French (1993) three factor model, we use the U.S. market excess return, SMB and HML variables as factors, for which we observe an average value of 0.619%, 0.124% and 0.170%, respectively.[7]

For mutual fund returns, we use the monthly returns available on the CRSP survivorship bias free mutual fund database.[8] In total, 40,500 funds report as least one return observation within the period of interest. To proceed with our analysis and ensure that there are sufficient observations covering the January 1990–December 2018 period, we select the funds that report at least 300 observations. This exclusion of new and short-lived funds leads to a sample of 3052 funds overall. Each mutual fund is then classified into one of seven categories depending on their investment objective. Specifically, we consider equity funds investing in growth, income and mixed growth-income companies. We also consider funds with primary investment objective being the size of the company (large, medium and small capitalization). Finally, we include a seventh fund category of funds investing in equity and fixed income instruments (mixed). When a mutual fund cannot be precisely classified, it is excluded from our sample. We thus end up with 825 mutual funds. To create a balanced panel and avoid potential survivorship bias, we backfill the missing values according to the four-factor model of Carhart (1997). First, we track every fund existing during our sample period, as in Brown and Goetzmann (1994), Carhart (1997) and Malkiel (1995). Then, following Elton et al. (1996),

**TABLE 1** Descriptive statistics: state and factor variables.

| | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3 comp | Excess returns | SMB | HML |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.225 | 2.078 | 1.519 | 2.473 | 1.942 | 107.246 | 0.619 | 0.124 | 0.170 |
| Standard deviation | 0.191 | 0.590 | 1.033 | 1.279 | 3.937 | 32.899 | 4.238 | 3.192 | 2.967 |
| Skew | 0.294 | 0.829 | −0.004 | −0.022 | −1.894 | 1.009 | −0.638 | 0.751 | 0.232 |
| Kurt | 1.837 | 3.209 | 1.843 | 4.257 | 8.209 | 3.741 | 1.238 | 8.170 | 2.526 |
| $Q_{1\%}$ | 0.000 | 1.140 | −0.360 | −1.232 | −14.787 | 59.316 | −10.256 | −6.125 | −8.402 |
| $Q_{99\%}$ | 0.680 | 3.721 | 3.330 | 6.170 | 8.460 | 194.677 | 9.263 | 7.515 | 8.210 |

*Note*: This table reports the descriptive statistics of the state and factor variables, that is mean, standard deviation, skewness, kurtosis and 1% and 99% quantiles.

we use the risk-adjusted returns and estimate the four-factor (Carhart, 1997) model.

Our approach differs from those of previous studies, as we complete missing returns not only at the end of the sample period but also at the beginning of the sample. This decision is motivated by the fact that we consider a balanced panel framework, and thus, we cannot afford to have missing returns at the end or at the beginning of the sample. Table 2 reports the cross-sectional averages of the descriptive statistics of the mutual fund excess returns, calculated as the difference between the raw returns and the 1-month T-Bill, for both the backfilled and non-backfilled sample. The descriptive statistics are similar in both samples, confirming that the backfilling process has no impact on the distribution of mutual fund returns. Average mutual fund excess returns range from 0.6% (mixed equity – fixed income funds) to 0.9% (large and medium capitalization). The mixed fund category also appears to be the least volatile, while the large capitalization one is the most volatile. With the exception of large capitalization funds, all other categories show negative skewness. Finally, all fund returns appear leptokurtic with the large capitalization funds having the most heavy tailed distribution.

## 3.2 | Preliminary stability tests

Existing ICAPM and conditional CAPM studies have implemented simple stability tests à la Andrews (1993) for known or unknown break dates. For example, Ghysels (1998) (in a conditional CAPM framework) or Vassalou (2003) and Li et al. (2006) (in an ICAPM framework) use the SupLM test of Andrews (1993) to test for the stability of the SMB and HML factors in the Fama–French model for mutual funds extracted from the CRSP database for a relatively long pre-crisis period.[9] Nevertheless, these LM tests have several limitations; they may rely on an incorrect specification of the likelihood function, as they limit the change in the constant and slope coefficients to occur on the same date, despite there being no theoretical justification for this, and have important trimming assumptions, leading to loss of power when the date of the break is located close to the start or the end of the sample. To tackle these issues, we follow Pouliot (2016), who proposed a specific stability test for ICAPM factors in individual funds and we also complement our analysis with a bootstrap-based log likelihood ratio test similar to that proposed by Hansen (1996).[10] It is important to stress that these tests can be implemented simultaneously for all the parameters of Equation (5) or for a restricted subset of them.

We begin our analysis by evaluating the stability of the Fama and French (1993) model parameters according to the testing process proposed by Pouliot (2016). Specifically, for each fund, we regress its excess returns on the three factors proposed by Fama and French (1993). Then, by considering the variation in the sum of squared residuals around a specific datapoint $t$, we estimate a possible

**TABLE 2** Cross-sectional descriptive statistics: mutual fund returns.

| | Aggregate | Growth | Growth-income | Income | Large cap | Medium cap | Small cap | Mixed |
|---|---|---|---|---|---|---|---|---|
| No. Funds | 825 | 233 | 149 | 53 | 22 | 50 | 143 | 175 |
| No Back-filling | | | | | | | | |
| Mean | 0.008 | 0.008 | 0.007 | 0.008 | 0.009 | 0.009 | 0.009 | 0.006 |
| Standard deviation | 0.044 | 0.048 | 0.041 | 0.039 | 0.053 | 0.052 | 0.053 | 0.032 |
| Skew | −0.556 | −0.527 | −0.678 | −0.657 | 0.142 | −0.524 | −0.459 | −0.638 |
| Kurt | 5.739 | 4.911 | 5.329 | 4.920 | 17.723 | 5.157 | 5.200 | 6.537 |
| $Q_{1\%}$ | −0.117 | −0.128 | −0.111 | −0.108 | −0.107 | −0.141 | −0.142 | −0.086 |
| $Q_{99\%}$ | 0.108 | 0.118 | 0.099 | 0.095 | 0.094 | 0.133 | 0.134 | 0.079 |
| Back-filling | | | | | | | | |
| Mean | 0.008 | 0.008 | 0.007 | 0.008 | 0.009 | 0.009 | 0.009 | 0.006 |
| Standard deviation | 0.044 | 0.048 | 0.041 | 0.039 | 0.052 | 0.052 | 0.053 | 0.032 |
| Skew | −0.538 | −0.511 | −0.659 | −0.638 | 0.227 | −0.509 | −0.459 | −0.612 |
| Kurt | 5.730 | 4.862 | 5.270 | 4.858 | 19.080 | 5.070 | 5.116 | 6.554 |
| $Q_{1\%}$ | −0.115 | −0.126 | −0.109 | −0.106 | −0.107 | −0.138 | −0.140 | −0.084 |
| $Q_{99\%}$ | 0.107 | 0.118 | 0.099 | 0.095 | 0.097 | 0.132 | 0.131 | 0.079 |

*Note*: This table reports the descriptive statistics of the mutual funds' returns, i.e., mean, standard deviation, skewness, kurtosis and 1% and 99% quantiles.

point of instability for the parameters. Then, we proceed by testing the joint null hypothesis of no breaks in either alpha or betas (joint test) and the null hypothesis of no breaks in $\beta$s (beta break test). Figure 1 reports the distribution of the estimated timing of the break, the test statistic values for the joint parameters of the model ($\alpha$ and $\beta$) along with the test statistics for the break in the beta coefficients. The blue vertical line (in the last two panels) represents the critical value for each test. The first panel shows that the parameters are not constant over time and exhibit at least one structural break. The timing of the break does not seem to cluster around a specific point in time but rather around the periods 2001–2003 and 2009–2010. Comparing the last two panels of the figure, we conclude that the main reason for the rejection of the joint hypothesis seems to be a break in at least one of the beta coefficient, since for the majority of the individual funds, the null of no breaks in the beta coefficients is rejected.

This preliminary analysis hence supports the idea that the parameters of the three factor Fama French model are not stable over time and are subject to regime changes, in line with Ghysels (1998).

## 3.3 | Testing and estimating the T-ICAPM

In this section, we present our findings for both the standard ICAPM model (Equation 2) and the T-ICAPM (Equation 5) for the full sample (aggregate mutual funds). Table 3 reports the related estimates. Column (2) reports the estimates for the standard ICAPM (Benchmark). Our results confirm the Fama–French findings, that is the three factors (market, HML and SMB) are highly significant. Specifically, the sensitivity to the market risk factor ($\beta_{rm}$) is lower than 1, suggesting that, on average, mutual funds provide a hedge against

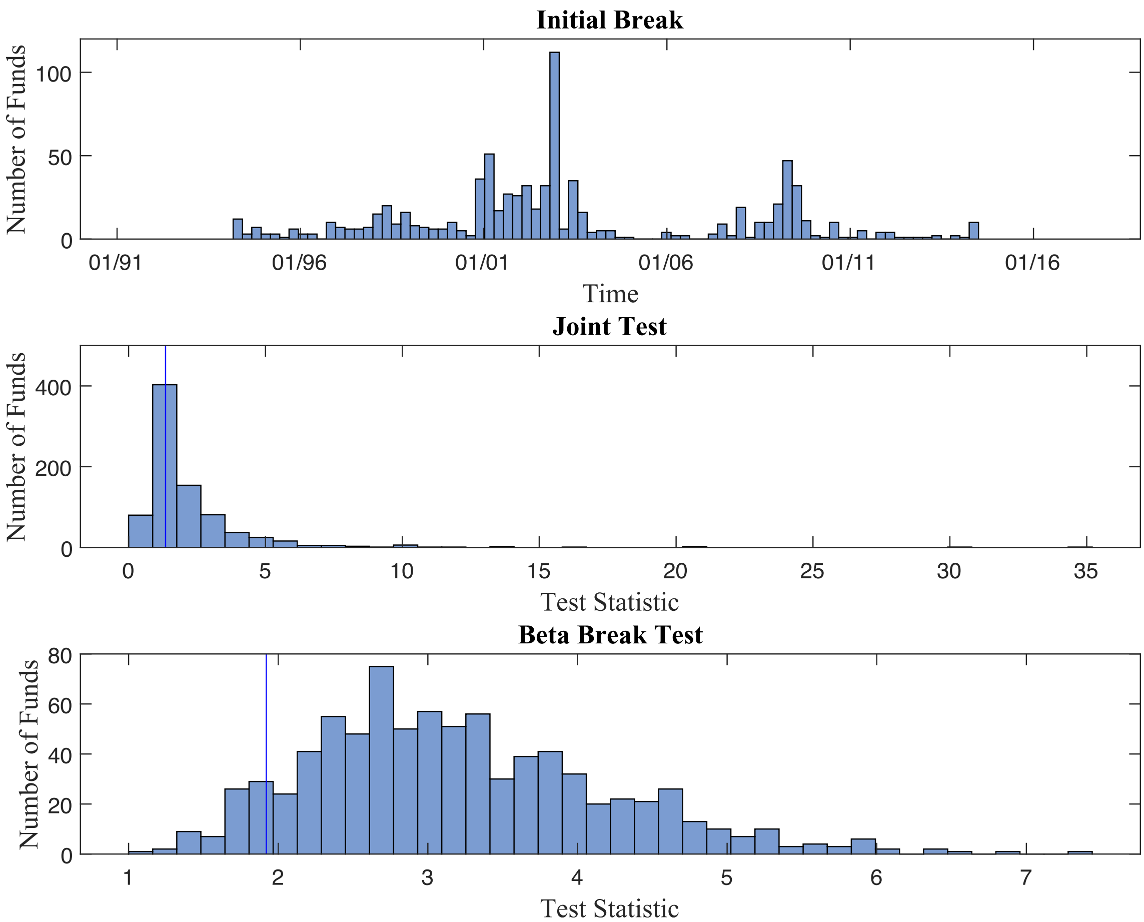


**FIGURE 1** Equity Aggregate Fund Tests for Breaks in the Parameters. The figure reports the aggregate results of the test for breaks in the parameters for all funds. Specifically, the first subplot reports the estimate of the time of the break. The second subplot reports the histogram of the test statistics of the Pouliot (2016) joint test for all funds. The third subplot reports the histogram of the test statistics of the Pouliot (2016) beta break test. For the latter two subplots, the blue vertical lines represent the respective critical values for the 5% significance level. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Equity aggregate funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp | Composite |
|---|---|---|---|---|---|---|---|---|
| $\widehat{\alpha}$ | −0.088 | −0.1 | 0.440*** | −0.006 | −0.117 | −0.086 | −0.093 | 0.074 |
| $\widehat{\beta}_{r^m}$ | 0.893*** | 0.909*** | 0.882*** | 0.902*** | 0.881*** | 0.921*** | 0.884*** | 0.896*** |
| $\widehat{\beta}_{\text{SMB}}$ | 0.114*** | 0.148*** | 0.065* | 0.107*** | 0.170*** | 0.137*** | 0.117*** | 0.112*** |
| $\widehat{\beta}_{\text{HML}}$ | 0.078*** | 0.002 | 0.157 *** | 0.185*** | 0.014 | −0.022 | 0.112*** | 0.196*** |
| $\widehat{\alpha}_s$ | | 0.023 | −0.562*** | −0.113 | 0.057 | −0.003 | −0.065 | −0.136* |
| $\widehat{\beta}_{s,r^m}$ | | −0.008 | 0.014 | −0.001 | 0.044*** | −0.03 | 0.053*** | 0.006 |
| $\widehat{\beta}_{s,\text{SMB}}$ | | −0.023 | 0.094*** | 0.050*** | −0.073*** | −0.018 | 0.004 | 0.044** |
| $\widehat{\beta}_{s,\text{HML}}$ | | 0.164*** | −0.141*** | −0.173*** | 0.112*** | 0.138*** | −0.171*** | −0.197*** |
| Thresholds | | 0.342 | 1.23 | 0.490 | 2.62 | −0.594 | 133.41 | −0.45 |
| CI Up | | 0.372 | 1.28 | 0.614 | 2.83 | 1.023 | 140.01 | −0.429 |
| CI Low | | 0.296 | 1.23 | 0.441 | 2.165 | −1.369 | 125.82 | −0.467 |
| $LR_t$ | | 2618.5 | 4789.4 | 3555.3 | 1965.0 | 1615.9 | 2310.1 | 4525.0 |
| $LR_{CV}$ | | 414.2 | 368.7 | 398.2 | 469.9 | 410.8 | 406.3 | 362.6 |
| $R^2$ | 0.697 | 0.7 | 0.702 | 0.701 | 0.699 | 0.699 | 0.699 | 0.700 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the aggregate sample of mutual funds. Each state variable and a composite index are used as the transition (threshold) variables. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($LR_t$) and 99% critical value $LR_{CV}$ of the linearity test.

market downturns. The magnitudes of the SMB and HML factor loadings are approximately one-tenth of the market loading, albeit positive and highly significant. Moreover, the excess premium ($\alpha$) is not significantly different from zero, showing that on average fund managers do not have a permanent positive effect on the performance of mutual funds. Such a result is in line with almost all studies considering factor models (in particular, Fama & French, 1993). However, this should not be interpreted as fund managers' lack of skill to create extra return. Since our study is a panel one, the $\alpha$ coefficient on average is not significantly positive. Finally, the $R^2$ measuring the fit of the model is approximately 70%, which is in line with those obtained in comparable studies (e.g. Fama and French (2017)).

Columns (3)–(9) provide the estimation results for the T-ICAPM considering each state variable at a time as transition variable. Parameters with a subscript $s$ report the extra sensitivity when the transition/state variable is above the estimated threshold. Depending on the state variable, the regime above the threshold can be characterized as a high growth, high inflation, monetary contraction, high uncertainty one, etc. A positive (negative) sign hence indicates a higher (lower) sensitivity of the mutual fund returns in the above threshold regime, and therefore a procyclical (countercyclical) behaviour. Figure 2 illustrates the estimated thresholds (solid horizontal line) along with the evolution of state variables and graphically dates the regimes.

The first threshold variable considered is the 1-month T-Bill, which reflects the monetary policy stance along with short-term investment opportunities. Since the 2008 crisis and the implementation of quantitative easing (QE) policy by almost all central banks around the world, short-term interest rates have been very low and effectively zero.[11] Observing the periods of the T-Bill exceeding the threshold, we note that these coincide with the periods preceding recessions, such as the dot-com bubble and the global financial crisis. The low interest rate regime is evident in the most recent part of Figure 2.[12]

We also report the estimated threshold value along with 99% confidence intervals and the LR test (Appendix A) for linearity. First, the LR test rejects the linearity hypothesis in favour of our threshold specification and signals that the T-Bill is an important transition variable.[13,14] The estimated threshold is 0.342% (roughly corresponding to an annual rate of 4%) with quite tight confidence intervals. Interestingly, our estimates suggest that in low interest rate periods, the market factor loading along with the SMB factor loading are positive, significant and similar in magnitude to the benchmark linear case. However, the HML loading is insignificant and turns positive and significant (0.164) in the high interest rate periods. This extra positive sensitivity of fund returns

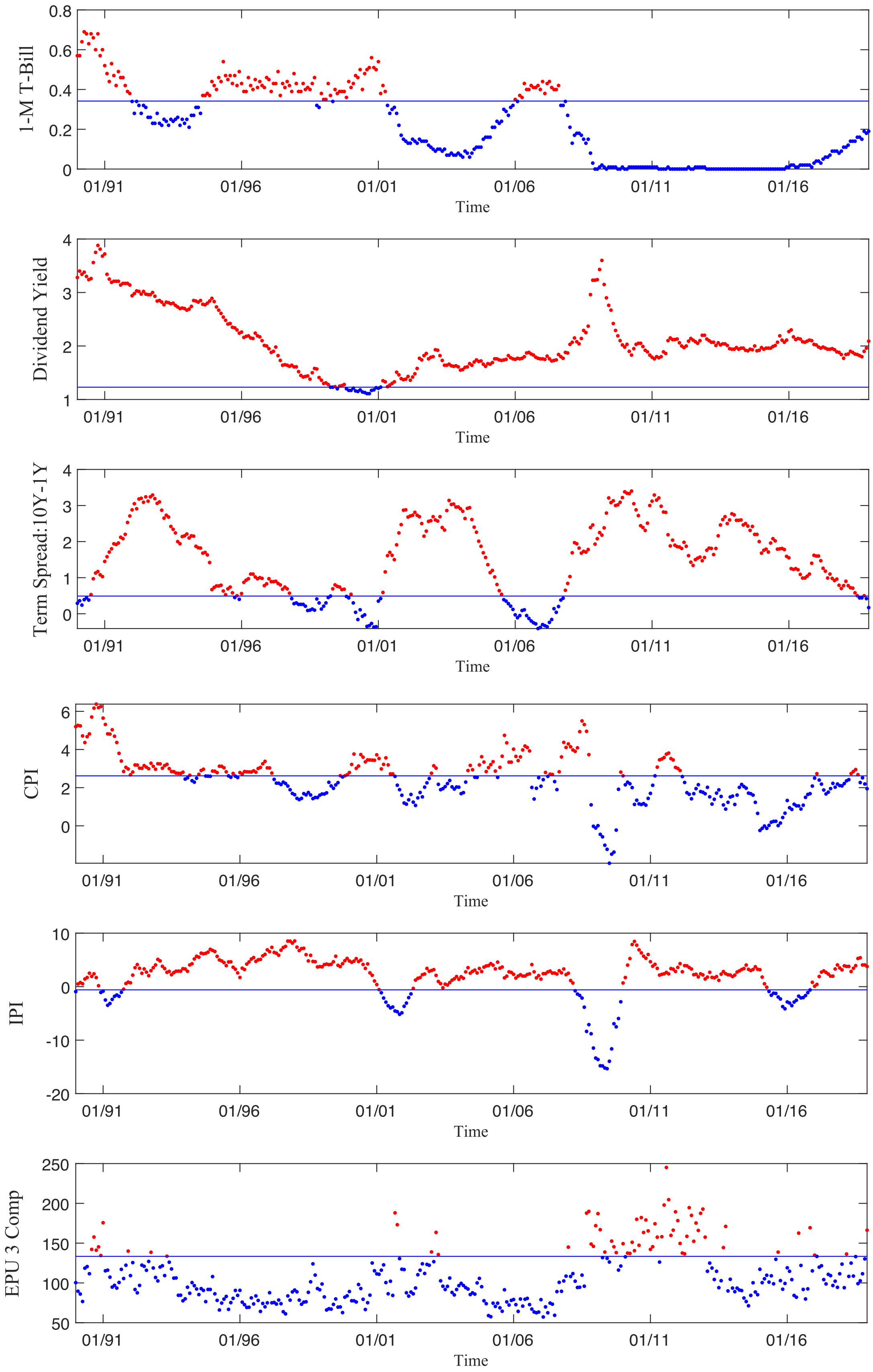


**FIGURE 2** Equity Aggregate Fund Threshold and Regime Estimates. The figure reports the evolution around the estimated threshold of the 1 M T-Bill, Dividend Yield, Term Spread, CPI growth rate, IPI growth rate and EPU variables, respectively. The red colour provides an indication of when each variable's values were over the estimated threshold. [Colour figure can be viewed at wileyonlinelibrary.com]

with respect to the value premium suggests that mutual funds are procyclical under T-Bill regimes.

Looking now at the dividend yield (DY) (Figure 2), we observe a low DY regime covering the period 2001–2002 determined by an estimated threshold of 1.23%. As previously, linearity is rejected in favour of our threshold specification. The sensitivity of mutual fund returns to the market factor is unaffected by the high dividend yield regime. In contrast, in the regime characterized by high DY, we observe positive excess factor sensitivities, that is procyclical for SMB but negative, that is countercyclical, ones for the HML factor. Such a finding regarding factor sensitivity is expected, as periods of high dividend yields are associated with low stock market prices, inducing a negative sensitivity to HML. Similarly, as small firms are often growth stocks and thus more affected than large firms, their returns tend to be positively linked to a high dividend yield. We also observe a change in the sign of the excess premium ($\alpha$) between regimes. In periods of low dividend yields, alpha is positive and statistically significant, while in periods below the threshold, it is negative. This signals that asset managers underperform in a regime of high dividend yields.

The term spread (TS) is now considered as a transition variable. It is well known that TS is a good predictor of future growth (see, inter alia, Estrella and Hardouvelis (1991), Breitung and Candelon (2006) or more recently Chinn and Kucko (2015) and Hasse and Lajaunie (2022)) and thus should impact mutual fund performance. In Figure 2, it is possible to clearly detect the dot-com bubble, the 2008 crisis and the most recent period where the term spread is below the threshold of 0.49 and turns negative, signalling future weak economic growth. When analysing the estimation results, we observe that mutual funds returns are countercyclical with the HML factor, whereas they are procyclical with respect to the SMB factor. The magnitude of the sensitivities of these factors is similar to the one observed for DY. Again, such a result is intuitive. As HML accounts for the spread in returns between value and growth stocks, a decrease in the slope of the yield curve from the deterioration of future economic prospects leads to a reduction in the sensitivity to HML. In contrast, the estimators also support the idea that the yield curve slope primarily affects small firms.

When we consider inflation and the industrial production index (IPI), it is interesting to observe that, as in the case of the term spread, the regimes obtained also closely match business cycle phases [the correlation with the NBER cycle dates is 0.46 (p-value $< 0.01\%$)]. In addition, the estimated threshold for inflation equals 2.62%, which corresponds more or less to the committed target of the Fed. We also find in both cases a higher sensitivity of the HML factor, indicating a procyclical behaviour of mutual fund return in inflation regimes. However, in high inflationary regimes, the extra sensitivity of the market factor is positive and significant, while insignificant in the high growth regime. Moreover, the sensitivity to the SMB factor is reduced by $-0.073$ in the high inflation regimes and remains essentially unchanged in the high growth ones.

Finally, we consider economic policy uncertainty as defined in Baker, Bloom and Davis (2016). It turns out that linearity is also rejected in this case, and the high-uncertainty regimes are located around the 9/11 terrorist attacks, the recent Global Financial Crisis and the Eurozone Crisis. All factor loadings are positive and significant in the low uncertainty periods, while the market factor sensitivity increases by 0.053 and the HML sensitivity decreases by $-0.171$ (similar to the DY and the TS case).

## 3.4 | Testing and estimating the T-ICAPM—A composite transition variable

In the previous section, we verified that all state variables employed are important components of our T-ICAPM model when employed individually. To alleviate uncertainty over the choice of a transition variable, we build the transition variable as a composite index. To estimate the weight of the macroeconomic variables in the transition variable, a grid-search approach is considered. The T-ICAPM is estimated for all the potential combinations of weights[15] and the combination maximizing the log-likelihood is retained. In this way, we are provided with the composite index used in the estimation of the threshold model along with the optimal weights.[16] Table 5 reports the relative weights. When all funds are considered, all variables, with the exception of inflation, are included in the composite index. The highest weights are carried by DY (36%) followed by TS (32%) and T-Bill (24%). These variables appear to adequately summarize the macroeconomic regime. In contrast, the weight for CPI is close to zero. This finding shows that the information content in this variable is subsumed by the remaining state variables. For example, the term spread contains information (according to the expectation hypothesis) on future inflation and economic activity. CPI is thus redundant and provides no additional information.

Figure 3 depicts the estimated threshold and the corresponding regimes. The regimes defined by the composite indicator closely match the business/financial cycle, mimicking the LTCM, dot-com, GFC and recent sovereign debt crises. Not surprisingly, we observe in Table 3 (last column) that mutual funds are exposed to the risk factors in a similar way to the benchmark linear case when the threshold is not exceeded. However, in the periods our composite indicator exceeds the threshold, excess factor loadings are positive for the SMB risk factor, but negative for the HML one. Such a result is also intuitive, as it mimics the results obtained for the state variables participating with a large weight in the composite threshold variable. Finally, fund managers underperform by −0.136% in these cases.

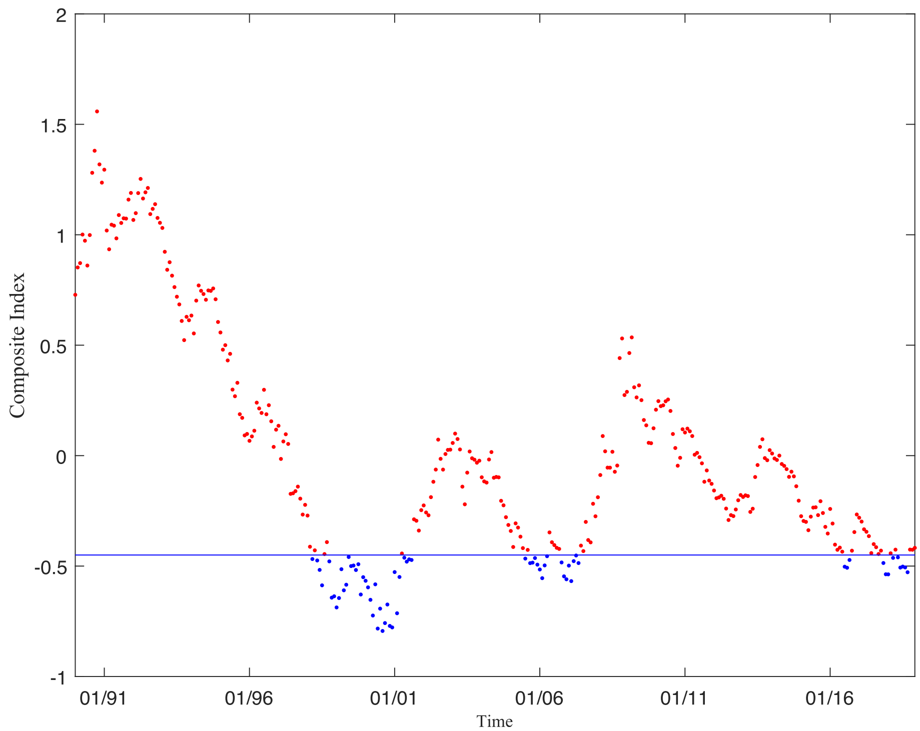


**FIGURE 3** Equity Aggregate Fund Test Threshold—Composite Index. The figure reports the evolution around the estimated threshold of the composite index. The red colour provides an indication of when the index values were over the estimated threshold. [Colour figure can be viewed at wileyonlinelibrary.com]

**TABLE 4** Composite index for sub-groups of funds.

| | Growth funds | Growth income | Income | Large cap | Medium cap | Small cap | Mixed Equity & Fixed Income Funds |
|---|---|---|---|---|---|---|---|
| $\widehat{\alpha}$ | 0.043 | 0.003 | −0.060 | −0.016 | 0.058 | −0.021 | −0.079 |
| $\widehat{\beta}_{r^m}$ | 0.993*** | 0.914*** | 0.832*** | 0.989*** | 1.128*** | 1.023*** | 0.734*** |
| $\widehat{\beta}_{\mathrm{SMB}}$ | −0.016 | −0.092*** | −0.064*** | −0.171*** | 0.147*** | 0.476*** | −0.005 |
| $\widehat{\beta}_{\mathrm{HML}}$ | 0.046*** | 0.316*** | 0.503*** | 0.032*** | 0.125*** | 0.314*** | −0.078*** |
| $\widehat{\alpha}_s$ | −0.127 | −0.111 | −0.017 | 0.625 | −0.112 | −0.063 | 0.081 |
| $\widehat{\beta}_{s,r^m}$ | −0.002 | 0.008 | 0.053 | 0.195 | −0.102** | −0.058 | −0.091*** |
| $\widehat{\beta}_{s,\mathrm{SMB}}$ | 0.113** | 0.073*** | 0.033 | 0.272 | 0.231*** | 0.115*** | 0.035 |
| $\widehat{\beta}_{s,\mathrm{HML}}$ | −0.139*** | −0.221*** | −0.330*** | 0.332 | −0.286*** | −0.252*** | 0.219*** |
| Thresholds | −0.480 | −0.505 | −0.514 | 0.675 | −0.480 | −0.480 | −0.414 |
| CI Up | −0.465 | −0.500 | −0.468 | 0.675 | −0.465 | −0.465 | −0.327 |
| CI Low | −0.480 | −0.505 | −0.514 | −0.625 | −0.480 | −0.480 | −0.475 |
| $\mathrm{LR}_t$ | 1348.6 | 2809.7 | 2158.0 | 31.0 | 1043.4 | 1246.4 | 1500.1 |
| $\mathrm{LR}_{\mathrm{CV}}$ | 153.6 | 136.4 | 109.9 | 251.1 | 113.5 | 166.8 | 168.9 |
| $R^2$ | 0.778 | 0.851 | 0.851 | 0.322 | 0.820 | 0.774 | 0.661 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for each subgroups of mutual funds, where the composite index is used as a transition (threshold) variable. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.

TABLE 5 Composite index composition.

| | Aggregate funds | Growth | Growth income | Income | Large cap | Medium cap | Small cap | Mixed Equity & Fixed Income Funds |
|---|---|---|---|---|---|---|---|---|
| T-Bill | 0.24 | 0.12 | 0.20 | 0.28 | 0.36 | 0.12 | 0.12 | 0.56 |
| DY | 0.36 | 0.20 | 0.28 | 0.50 | 0.28 | 0.20 | 0.20 | 0.08 |
| T-Spread | 0.32 | 0.40 | 0.40 | 0.16 | 0.00 | 0.40 | 0.40 | 0.12 |
| CPI | 0.00 | 0.08 | 0.00 | 0.00 | 0.00 | 0.08 | 0.08 | 0.00 |
| IPI | 0.08 | 0.20 | 0.08 | 0.00 | 0.36 | 0.20 | 0.20 | 0.24 |

*Note*: This table reports the composition of the composite index for the aggregate sample and subgroups of mutual funds.

## 3.5 | A subgroup T-ICAPM estimation

The results reported so far were obtained from a large panel of mutual funds. Nevertheless, it is possible that depending on the ex-ante investment objectives of the mutual fund, the dependence on the state variables may differ. In other words, it would be interesting to analyse whether the behaviour of the funds is heterogeneous with respect to the transition variable. To this end, T-ICAPM is estimated for each of the seven different groups of mutual funds previously defined (growth, growth-income, income, large, medium and small capitalization and mixed). As in the previous subsection, T-ICAPM is tested and estimated for each individual state variable and for the estimated composite index. The results are reported in Table 4 for the composite threshold variable.[17] Several results can be inferred.

It turns out that the linearity hypothesis is rejected for all types of mutual funds in favour of our T-ICAPM specification, except for the funds that invest in large capitalization stocks. This finding indicates that the macroeconomic and financial stance is not associated with the performance of this mutual fund class. Several explanations can justify this result: First, large-cap funds tend to be more stable than their competitors because of their investments in large capitalization stocks. These companies usually have longer-run objectives than the other firms as they have a well-established reputation with investors. Second, Eun et al. (2008) show that as large-cap stocks receive the dominant share of fund allocation, they become more diversified[18] and thus more isolated from macroeconomic regimes. Third, this finding is also related to the low level of the $R^2$ observed for this class of mutual funds. This low explanatory power of the model stresses the heterogeneity between large-cap mutual funds and leads to high estimation uncertainty. The LR test hence fails to reject the null hypothesis of linearity against the different threshold models. Nevertheless, such a result also suggests that this type of mutual funds does not trigger financial instability. Macroprudential regulation would not be necessary for mutual funds oriented towards large-cap stocks. Such a result could also suggest that regulators require other types of mutual funds to hold a part of their holdings in large capitalization assets.

In contrast, our findings for the remaining types of mutual funds (growth, income-growth, income, medium or small cap) suggest that these are more exposed to macroeconomic changes. Specifically, the results of the threshold three-factor Fama–French model broadly point to homogeneity (in terms of signs and magnitude) across mutual fund types and thus similarities to the aggregate findings. However, there is a difference in the composite index and, specifically, in its composition, i.e., the weights of the macroeconomic variables, which are given in Table 5. It appears that the mix of macroeconomic conditions that matter most depends on the type of mutual funds considered. More in detail, the returns of medium-cap, small-cap and growth mutual funds evolve according to a composite index integrating all five state variables. The largest weight (0.40) is taken by the term spread, followed by industrial production growth and dividend yield (0.20). In contrast, the composite index for income mutual funds does not vary with inflation or industrial production but mainly with the dividend yield. Indeed, it is well known that income funds target almost exclusively the dividend yield (0.50) and the T-Bill (0.20). Growth-income funds have a mixed position, as their composite index simultaneously includes all variables but inflation. Finally, the returns of the mixed equity fixed income funds tend to vary mostly with Treasury Bills (0.56) followed by industrial production growth (0.24). Therefore, all these types of mutual funds show dependence on macroeconomic and financial conditions.

Focusing on our parameter estimates (Table 4), we observe that the sensitivity of factor loadings is varying across macroeconomic regimes. Similar to our results for the aggregate funds, the sensitivity to the SMB (in a positive way) and HML (in a negative way) is observed for all mutual fund strategies except for the large cap ones, which can be then viewed as acyclical. However, the positive excess factor loading for the SMB factor is not statistically significant for the income and mixed fund categories. Interestingly only the mixed equity and the medium cap mutual funds exhibit a decrease in their sensitivity to the market return ($\beta_{s,r^m}$) when the composite index exceeds its threshold. They could therefore be considered as the most countercyclical mutual funds. It is also important to notice that the pseudo-$R^2$ for the T-ICAPM exceeds the one of the standard ICAPM when considering all mutual funds irrespective of the state variable considered. Looking at the different fund strategies, it appears that $R^2$ are high (equal of larger than 0.8) for all types of fund except for the mixed equity and the large capitalization mutual funds where the $R^2$ is lower than 0.35. This finding also points to increased heterogeneity among these types of funds. Overall, a macroprudential regulatory framework would thus be able to improve financial stability. Nevertheless, given this heterogeneity, it cannot be uniform but should instead take into account the specificities of types of mutual funds.

## 4 | CONCLUSION

This paper demonstrates that mutual fund performance (as described via factor loadings to typical risk factors) is unstable and mainly procyclical, evolving in line with macroeconomic stances. We consider a novel methodology relying on a factor-augmented CAPM with regimes driven by a set of macroeconomic and financial variables. Using a dataset including the returns of 825 U.S. equity mutual funds over a period of 30 years, we find that linearity in the traditional Fama–French model is rejected for the majority of mutual funds. Furthermore, we show that fund sensitivities to the Fama–French factors are regime dependent and mainly driven by a few variables such as the yield curve, the dividend yield, short-term interest rates and economic growth. Moreover, regime shift dates almost perfectly match financial crises and economic downturns. The only exception is observed for mutual funds investing in large capitalization stocks, which are more diversified and thus less sensitive to reversals in macroeconomic conditions.

Coupled with the systemic role of asset managers, such procyclical and time varying sensitivities of mutual funds constitute a major risk for the whole financial industry. Specifically, this behaviour could lead to extra liquidity risk for mutual funds in periods of economic distress. This risk is not considered by existing regulations. Another issue raised by these findings is the impact on so-called 'shadow banking' activities. Macroprudential rules are now operational in the banking sector via the implementation of capital buffers, cyclically adjusted capital adequacy ratios (see Basel III regulation). Procyclical mutual fund performance constitutes an opportunity for banks to increase their leverage ratios in good economic times. In the aftermath of the GFC, banks massively supported the creation of funds under direct or indirect control to overcome macroprudential-banking regulation. This exposure to risk becomes asset risk for bank balance sheets when economic activity is depressed. Consequently, a regulatory gap exists between the mutual fund industry and commercial banks and insurers (Morley, 2013). Asset managers, bankers and insurers should share common obligations regarding the measurement and management of market risk (Mugerman et al., 2019).

This paper clearly advocates complementing existing mutual fund regulations, which have, to date, been microprudential (van der Veer et al., 2017), by including a macroprudential dimension. Several macro-prudential rules could be considered. First, a limit to the leverage ratio of mutual funds over the business cycle such that the risk exposure reduces, could be proposed. Second, a minimum diversification rule depending on the business cycle could be imposed. Third, asset managers could also been asked to hold a part of their portfolios in large-cap companies, as these investments are not sensitive to economic regime changes because of their diversification abilities. Finally, to reduce the liquidity risk of mutual funds, a counter-cyclical liquidity buffer could be set-up (Ahnert, 2016).

Nevertheless, macroprudential regulation requires a clear and strong mandate by regulators with the power to act. As argued by Aikman et al. (2019), efficient macroprudential regulation is a matter of political choice. In the United States, policymakers have chosen to limit the remit of financial regulation outside the commercial banking system. Without political backing, the FSOC has limited ability to respond to developments in the financial sector. Macroprudential rules also require efficient supervision. A simple way to address this issue would be to include mutual funds in the regular stress tests developed by the European Banking Authorities (ESMA) or Financial Sector Assessment Program (FSAP) of the International Monetary Fund and the World Bank. Such a practice would help to evaluate the impact of macroprudential rules and the links with the other financial sectors, in particular 'shadow banking'.

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Louvain Finance Day (Université Catholique de Louvain, 2019) and the 13th International Conference on Computational and Financial Econometrics—CFE (University of London, 2019). This research was conducted as part of the research program entitled 'Financial and Extra-Financial Risk Modeling' under the aegis of the Europlace Institute of Finance, a joint initiative with Insti7. The usual disclaimer applies.

## DATA AVAILABILITY STATEMENT

The dividend yield, 10-year government bond yield, 1-year treasury yield, CPI and IPI variables are available at the Federal Reserve Economic Data (Fred) Federal Reserve Bank of St. Louis. The EPU index data are available at the Economic Policy Uncertainty domain (https://www.policyuncertainty.com/). Finally, the 1-month T-Bill, U.S. market excess returns, SMB and HML data are available at the Kenneth R. French Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary.html). Crsp Data are the property of Essex business school and therefore are not shared.

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## ENDNOTES

[1] See the 2020 Outlook published by the Securities Industry and Financial Markets Association (SIFMA) and the Annual Asset Management Report (2019) published by the European Fund and Asset Management Association (EFAMA). See also the European Central Bank (ECB) Euro area investment fund statistics quarterly reports.

[2] See Chen et al. (2010), Goldstein et al. (2017) and Morris et al. (2017) about procyclicality and Billio et al. (2012), Cortes et al. (2018), Delpini et al. (2019), Calimani et al. (2019) and Hasse (2022) about systemic risk contribution of the mutual funds industry.

[3] Early papers (Baba et al., 2009; Brunnermeier, 2009; Dwyer & Tkac, 2009) describe developments of the money market funds industry in the United States, but their concerns about financial instability are minimal.

[4] MOM is often denoted as WML (Winners minus Losers) in the literature.

[5] See Novy-Marx (2014) about spurious factors and Fama and French (2018) about the methodology for choosing factors.

[6] Using a balanced panel framework enables the estimation of robust standard errors using the Newey-West procedure modified for use in a panel data set or clustered standard errors. See Petersen (2009) about the comparison of these different approaches in finance panel data sets.

[7] The dividend yield, 10-year government bond yield, 1-year treasury yield, CPI and IPI variables are available at the Federal Reserve Economic Data (Fred) Federal Reserve Bank of St. Louis. The EPU index data are available at the Economic Policy Uncertainty domain (https://www.policyuncertainty.com/). Finally, the 1-month T-Bill, U.S. market excess returns, SMB and HML data are available at the Kenneth R. French Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

[8] Data are the property of Essex business school and therefore are not shared.

[9] See also Guidolin and Timmermann (2008), Chincoli and Guidolin (2017) and Bianchi et al. (2017) about SMB and HML returns instability.

[10] We report the results for this test in the next section and discuss it with our main estimation results.

[11] The U.S. Federal Reserve System began in November 2008 its first QE by purchasing 600 billion USD in mortgage-backed securities. In November 2010, the Fed announced a second round of quantitative easing, buying 600 billion USD of Treasury securities by the end of the second quarter of 2011 (QE2). A third round of quantitative easing, (QE3), was announced in September 2012, which lasted up to nearly the end 2014. Finally, in March 2020, the Fed announced approximately 700 billion USD asset purchases to support U.S. liquidity in response to the COVID-19 pandemic.

[12] It is important here to clarify that we do not provide a causal interpretation but rather consider the coincidence of the regimes.

[13] While, it is possible to test via the LR test (Hansen, 1996) if the T-CAPM model with a specific transition variable is statistically different from the linear model, it is not possible, to the best of our knowledge, to test formally and discriminate between T-ICAPM with different transition variables.

[14] Similar tests have been performed when considering two thresholds and have concluded against rejecting the null hypothesis of a single threshold.

[15] The sum of weights is constrained to be 1.

[16] Please note that we exclude EPU from the composite index construction as this variable is not readily observable.

[17] To save space, we include the detailed tables per fund category and threshold variable in Appendix B (Tables B1–B7). We also do not report the 49 figures associating each type of fund to each transition variable, but they are available from the authors upon request.

[18] Eun et al. (2008) infer that the benefit from international diversification is thus very limited.

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## APPENDIX A: BOOTSTRAP-BASED LIKELIHOOD RATIO TEST FOR LINEARITY

An LR test for linearity can easily be derived from Equation (6) and consists of comparing the log-likelihood of the linear model ($LL_0$), that is without a threshold (under the null hypothesis of linearity [$H_0$]) and the log-likelihood under the alternative ($LL_1$), that is with a threshold (under the alternative of no linearity [$H_1$]). The statistics of the LR test (ST) are, as always, computed as $-2(LL_0 - LL_1)$. Nevertheless, as noted by Hansen (1996), the asymptotic distribution of the test statistic of this linearity is not obvious, as it depends on the threshold estimate, and therefore, a block-bootstrap-based test is recommended. This method follows several steps:

- Estimate (6) regarding the regressors and the threshold as fixed. Save the historical residuals $(\varepsilon_{i,1},\ldots,\varepsilon_{i,n})$ and create a multivariate empirical distribution function, $EF_i(t)$.
- (B1) Draw bootstrapped residuals $\left(\varepsilon^*_{i,1},\ldots,\varepsilon^*_{i,n}\right)$ in $EF_i(t)$. Note that we do not perform wild bootstrap calculations but instead draw blocks (in both dimensions, cross-knit and time) to preserve the cross-sectional dependence of the panel and its dynamic properties. With respect to this last dimension, we consider a block of 2 periods.
- (B2) Build a bootstrapped pseudovariable $y_{i,1} = E(r_{it}) - r_{ft}$, $\left(y^*_{i,1},\ldots,y^*_{i,n}\right)$ under the null of linearity ($H_0$) with the bootstrapped residuals.
- (B3) Under the bootstrapped pseudovariable, estimate the null (linear) and alternative (with threshold) model. Calculate the LR statistics.
- (B4) Repeat the last (B1-B3) steps a large number of times using Boo, and build the bootstrapped distribution

of LR statistics, from which one can calculate the critical values $\alpha\%$ ($\mathrm{CV}_\alpha$) as $\alpha\%\cdot$Boo The null of linearity is not rejected if the test statistic (ST) is below ($\mathrm{CV}_\alpha$).

Similarly, the bootstrapped confidence bounds around the threshold estimate can be obtained using the following steps:

- Estimate Equation (6) regarding the regressors and the threshold as fixed. Save the historical residuals $(\varepsilon_{i,1},\ldots,\varepsilon_{i,n})$ and create a multivariate empirical distribution function $EF_i(t)$.
- (B1) Draw the bootstrapped residuals $\left(\varepsilon^*_{i,1},\ldots,\varepsilon^*_{i,n}\right)$ in $EF_i(t)$. Note that we draw vertical blocks to preserve the cross-sectional dependence of the panel.
- (B2) Build a bootstrapped pseudovariable $\left(y^*_{i,1},\ldots,y^*_{i,n}\right)$ using Equation (3).
- (B3) Estimate a threshold $(\hat{\gamma}^*)$ using the bootstrapped variable $\left(y^*_{i,1},\ldots,y^*_{i,n}\right)$.
- (B4) Repeat the last (B1–B3) steps a large number of times, such as Boo, and build the bootstrapped distribution of thresholds, from which one can calculate the confidence bound around $(\hat{\gamma})$.

## APPENDIX B: FUNDS SUB-GROUP RESULTS' TABLES

**TABLE B1** Growth funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp |
|---|---|---|---|---|---|---|---|
| $\hat{\alpha}$ | −0.018 | −0.061 | 0.52 | 0.11 | −0.05 | −0.032 | −0.005 |
| $\hat{\beta}_{r^m}$ | 0.986*** | 0.990*** | 0.955*** | 0.984*** | 0.974*** | 1.015*** | 0.978*** |
| $\hat{\beta}_{\mathrm{SMB}}$ | 0.065*** | 0.087*** | 0.009 | 0.048** | 0.100*** | 0.088*** | 0.065*** |
| $\hat{\beta}_{\mathrm{HML}}$ | −0.042** | −0.073*** | 0.004 | 0.029 | −0.082*** | −0.123*** | −0.016 |
| $\hat{\alpha}_s$ | | 0.214*** | −0.569*** | −0.170** | 0.079 | 0.019 | −0.133** |
| $\hat{\beta}_{s,r^m}$ | | 0.014 | 0.036 | 0.01 | 0.047*** | −0.034** | 0.043*** |
| $\hat{\beta}_{s,\mathrm{SMB}}$ | | −0.057** | 0.096** | 0.059** | −0.058** | −0.019 | 0.023 |
| $\hat{\beta}_{s,\mathrm{HML}}$ | | 0.134*** | −0.102* | −0.123*** | 0.090*** | 0.109 *** | −0.144*** |
| Thresholds | | 0.43 | 1.23 | 0.482 | 2.97 | −0.594 | 133.41 |
| CI Up | | 0.43 | 1.3 | 0.82 | 3 | 2.165 | 140.67 |
| CI Low | | 0.421 | 1.225 | 0.404 | 2.22 | −1.369 | 124.17 |
| $\mathrm{LR}_t$ | | 784.639 | 1344.538 | 888.658 | 523.456 | 390.65 | 618.224 |
| $\mathrm{LR}_{\mathrm{CV}}$ | | 168.035 | 161.9 | 179.227 | 178.721 | 174.835 | 172.973 |
| $R^2$ | 0.775 | 0.777 | 0.779 | 0.778 | 0.777 | 0.776 | 0.777 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the subgroup of Growth mutual funds. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.

**TABLE B2** Growth-income funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp |
|---|---|---|---|---|---|---|---|
| $\hat{\alpha}$ | −0.094 | −0.091 | 0.068 | −0.105 | −0.135* | −0.065 | −0.11 |
| $\hat{\beta}_{r^m}$ | 0.913*** | 0.938*** | 0.898*** | 0.923*** | 0.917*** | 0.919*** | 0.911*** |
| $\hat{\beta}_{\mathrm{SMB}}$ | −0.073*** | −0.037*** | −0.086*** | −0.071*** | 0.002 | −0.015 | −0.069*** |
| $\hat{\beta}_{\mathrm{HML}}$ | 0.178 *** | 0.078*** | 0.303*** | 0.302*** | 0.096*** | 0.067*** | 0.225*** |
| $\hat{\alpha}_s$ | | −0.035 | −0.19 | 0.002 | 0.071* | −0.052 | −0.015 |
| $\hat{\beta}_{s,r^m}$ | | −0.019 | 0.027 | 0.004 | 0.008 | 0.003 | 0.038** |
| $\hat{\beta}_{s,\mathrm{SMB}}$ | | −0.023 | 0.060** | 0.045** | −0.106*** | −0.058** | 0.03 |
| $\hat{\beta}_{s,\mathrm{HML}}$ | | 0.205*** | −0.211*** | −0.214*** | 0.122*** | 0.156*** | −0.183*** |
| Thresholds | | 0.32 | 1.37 | 0.721 | 2.62 | −0.594 | 125.16 |
| CI Up | | 0.356 | 1.425 | 0.903 | 2.66 | 0.14 | 137.205 |
| CI Low | | 0.29 | 1.35 | 0.614 | 2.24 | −1.41 | 124.17 |
| $\mathrm{LR}_t$ | | 1877.816 | 2717.058 | 2166.928 | 1239.708 | 913.823 | 1226.009 |
| $\mathrm{LR}_{\mathrm{CV}}$ | | 169.342 | 146.544 | 166.746 | 199.485 | 185.421 | 216.914 |
| $R^2$ | 0.843 | 0.849 | 0.851 | 0.849 | 0.847 | 0.846 | 0.847 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the subgroup of Growth-Income mutual funds. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.

**TABLE B3** Income funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp |
|---|---|---|---|---|---|---|---|
| $\hat{\alpha}$ | 0.181* | 0.191* | 0.098 | 0.185* | 0.164 | 0.277** | 0.154 |
| $\hat{\beta}_{r^m}$ | 0.857*** | 0.912 *** | 0.825*** | 0.875*** | 0.864*** | 0.864*** | 0.859*** |
| $\hat{\beta}_{\mathrm{SMB}}$ | −0.076*** | −0.051*** | −0.057* | −0.081*** | 0.018 | −0.031 | −0.065*** |
| $\hat{\beta}_{\mathrm{HML}}$ | 0.308*** | 0.152*** | 0.506*** | 0.493 *** | 0.195*** | 0.158*** | 0.378*** |
| $\hat{\alpha}_s$ | | −0.051 | 0.058 | −0.018 | 0.009 | −0.135 | −0.012 |
| $\hat{\beta}_{s,r^m}$ | | −0.063*** | 0.059 | −0.004 | 0.008 | 0.007 | 0.048** |
| $\hat{\beta}_{s,\mathrm{SMB}}$ | | 0.003 | 0.027 | 0.072** | −0.126*** | −0.039 | 0.01 |
| $\hat{\beta}_{s,\mathrm{HML}}$ | | 0.294*** | −0.332*** | −0.298*** | 0.175*** | 0.215*** | −0.259*** |
| Thresholds | | 0.301 | 1.44 | 0.49 | 2.62 | −0.594 | 125.16 |
| CI Up | | 0.32 | 1.46 | 0.589 | 2.69 | 1.689 | 133.41 |
| CI Low | | 0.256 | 1.38 | 0.441 | 2.24 | −1.355 | 124.17 |
| $\mathrm{LR}_t$ | | 1545.182 | 2150.534 | 1626.572 | 805.258 | 607.122 | 859.713 |
| $\mathrm{LR}_{\mathrm{CV}}$ | | 121.108 | 109.514 | 131.461 | 156.491 | 166.257 | 146.646 |
| $R^2$ | 0.833 | 0.847 | 0.852 | 0.848 | 0.841 | 0.839 | 0.841 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the subgroup of Income mutual funds. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.

TABLE B4 Large cap funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp |
|---|---|---|---|---|---|---|---|
| $\widehat{\alpha}$ | −0.015 | −0.084 | 0.208 | 0.136 | 0.036 | −0.078 | 0.027 |
| $\widehat{\beta}_{r^m}$ | 1.007*** | 0.993*** | 1.056*** | 1.063*** | 1.025*** | 0.986*** | 1.196*** |
| $\widehat{\beta}_{\mathrm{SMB}}$ | −0.161*** | −0.164*** | −0.129*** | −0.121** | −0.091** | −0.144*** | 0.014 |
| $\widehat{\beta}_{\mathrm{HML}}$ | 0.036*** | 0.022*** | 0.105 | 0.130* | −0.012 | 0.017* | 0.163 |
| $\widehat{\alpha}_s$ | | 0.395 | −0.294 | −0.206 | −0.099 | 0.189 | −0.087 |
| $\widehat{\beta}_{s,r^m}$ | | 0.133 | −0.054 | −0.064 | −0.033 | 0.075 | −0.204 |
| $\widehat{\beta}_{s,\mathrm{SMB}}$ | | 0.094 | −0.043 | −0.041 | −0.093 | 0.002 | −0.192 |
| $\widehat{\beta}_{s,\mathrm{HML}}$ | | 0.189 | −0.09 | −0.119 | 0.053*** | 0.087 | −0.132 |
| Thresholds | | 0.43 | 1.64 | 0.697 | 2.22 | 4 | 75.33 |
| CI Up | | 0.43 | 2 | 2 | 3 | 4 | 140.67 |
| CI Low | | 0 | 1.17 | 0.35 | 1 | −1.437 | 75 |
| $\mathrm{LR}_t$ | | 16.86 | 7.93 | 7.64 | 7.70 | 7.74 | 21.64 |
| $\mathrm{LR}_{\mathrm{CV}}$ | | 218.91 | 154.73 | 191.30 | 170.44 | 166.44 | 231.85 |
| $R^2$ | 0.322 | 0.323 | 0.323 | 0.323 | 0.323 | 0.323 | 0.324 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the subgroup of Large Capitalization mutual funds. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.

TABLE B5 Medium cap funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp |
|---|---|---|---|---|---|---|---|
| $\widehat{\alpha}$ | −0.095 | −0.186 | 0.911** | 0.085 | −0.13 | −0.147 | −0.083 |
| $\widehat{\beta}_{r^m}$ | 1.029*** | 1.024*** | 1.169*** | 1.113*** | 1.006*** | 1.082*** | 1.023*** |
| $\widehat{\beta}_{\mathrm{SMB}}$ | 0.315*** | 0.353*** | 0.299*** | 0.333*** | 0.370*** | 0.315*** | 0.312 *** |
| $\widehat{\beta}_{\mathrm{HML}}$ | −0.071** | −0.120*** | 0.162 | 0.163** | −0.128*** | −0.187*** | −0.019 |
| $\widehat{\alpha}_s$ | | 0.442*** | −1.076*** | −0.254 | 0.095 | 0.076 | −0.072 |
| $\widehat{\beta}_{s,r^m}$ | | 0.100** | −0.139 | −0.087* | 0.086** | −0.065** | 0.014 |
| $\widehat{\beta}_{s,\mathrm{SMB}}$ | | −0.091* | 0.072 | 0.038 | −0.096* | 0.012 | 0.068* |
| $\widehat{\beta}_{s,\mathrm{HML}}$ | | 0.254*** | −0.324** | −0.322*** | 0.131** | 0.156*** | −0.135*** |
| Thresholds | | 0.43 | 1.23 | 0.424 | 2.99 | −0.594 | 115.92 |
| CI Up | | 0.43 | 1.32 | 0.672 | 3 | 3.443 | 138.69 |
| CI Low | | 0.421 | 1.225 | 0.375 | 2.08 | −1.41 | 79.785 |
| $\mathrm{LR}_t$ | | 542.16 | 903.71 | 656.58 | 274.65 | 184.92 | 178.75 |
| $\mathrm{LR}_{\mathrm{CV}}$ | | 138.38 | 125.58 | 128.01 | 132.74 | 149.19 | 146.59 |
| $R^2$ | 0.81 | 0.815 | 0.819 | 0.817 | 0.812 | 0.811 | 0.811 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the subgroup of Medium Capitalization mutual funds. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.

**TABLE B6** Small cap funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp |
|---|---|---|---|---|---|---|---|
| $\widehat{\alpha}$ | −0.048 | −0.097 | 0.582 | 0.009 | −0.057 | −0.082 | −0.042 |
| $\widehat{\beta}_{r^m}$ | 0.963*** | 0.964*** | 1.031*** | 1.021*** | 0.938*** | 1.004*** | 0.948*** |
| $\widehat{\beta}_{\mathrm{SMB}}$ | 0.556*** | 0.581*** | 0.500*** | 0.570*** | 0.615*** | 0.556*** | 0.563*** |
| $\widehat{\beta}_{\mathrm{HML}}$ | 0.139*** | 0.103*** | 0.273** | 0.364*** | 0.088*** | 0.033 | 0.168*** |
| $\widehat{\alpha}_s$ | | 0.215* | −0.668** | −0.092 | 0.02 | 0.049 | −0.104 |
| $\widehat{\beta}_{s,r^m}$ | | 0.042 | −0.069 | −0.061* | 0.087*** | −0.048* | 0.076*** |
| $\widehat{\beta}_{s,\mathrm{SMB}}$ | | −0.061 | 0.115* | 0.039 | −0.107*** | 0.012 | −0.042 |
| $\widehat{\beta}_{s,\mathrm{HML}}$ | | 0.173** | −0.207* | −0.293*** | 0.115** | 0.146 *** | −0.166*** |
| Thresholds | | 0.43 | 1.23 | 0.366 | 3 | −0.594 | 133.41 |
| CI Up | | 0.43 | 1.41 | 0.432 | 3 | 2.777 | 140.67 |
| CI Low | | 0.381 | 1.22 | 0.35 | 2.5 | −1.41 | 114.93 |
| $\mathrm{LR}_t$ | | 507.51 | 1184.28 | 1076.76 | 575.87 | 323.91 | 406.85 |
| $\mathrm{LR}_{\mathrm{CV}}$ | | 212.30 | 222.38 | 177.71 | 202.14 | 228.12 | 228.12 |
| $R^2$ | 0.769 | 0.771 | 0.774 | 0.774 | 0.772 | 0.77 | 0.771 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the subgroup of Small Capitalization mutual funds. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.

**TABLE B7** Mixed equity and fixed income funds.

| | Benchmark | T-Bill | Dividend yield | Term spread | CPI | IPI | EPU 3Comp |
|---|---|---|---|---|---|---|---|
| $\widehat{\alpha}$ | −0.058 | −0.065 | −0.068 | −0.093** | −0.033 | −0.035 | −0.083** |
| $\widehat{\beta}_{r^m}$ | 0.651*** | 0.679*** | 0.615*** | 0.641*** | 0.633*** | 0.691*** | 0.640*** |
| $\widehat{\beta}_{\mathrm{SMB}}$ | 0.011 | 0.019 | 0.034** | 0.026** | 0.051*** | 0.025 | 0.018** |
| $\widehat{\beta}_{\mathrm{HML}}$ | 0.082*** | −0.013 | 0.175*** | 0.147*** | 0.021 | −0.02 | 0.124*** |
| $\widehat{\alpha}_s$ | | −0.032 | −0.01 | 0.055 | −0.06 | −0.023 | 0.025 |
| $\widehat{\beta}_{s,r^m}$ | | −0.022 | 0.055** | 0.038** | 0.057*** | −0.048* | 0.072*** |
| $\widehat{\beta}_{s,\mathrm{SMB}}$ | | 0.013 | −0.015 | −0.001 | −0.043** | −0.008 | −0.026 |
| $\widehat{\beta}_{s,\mathrm{HML}}$ | | 0.172*** | −0.160*** | −0.141*** | 0.123*** | 0.138*** | −0.208*** |
| Thresholds | | 0.221 | 1.455 | 1.175 | 2.59 | −0.594 | 133.74 |
| CI Up | | 0.331 | 1.575 | 1.72 | 2.82 | 0.752 | 139.515 |
| CI Low | | 0.161 | 1.37 | 0.944 | 2.005 | −1.369 | 125.49 |
| $\mathrm{LR}_t$ | | 899.39 | 1108.62 | 788.96 | 630.79 | 620.64 | 1181.16 |
| $\mathrm{LR}_{\mathrm{CV}}$ | | 200.84 | 208.67 | 182.09 | 187.17 | 182.89 | 162.25 |
| $R^2$ | 0.655 | 0.660 | 0.662 | 0.66 | 0.659 | 0.659 | 0.662 |

*Note*: This table reports the estimates of the T-ICAPM model coefficients for the subgroup of Mixed Equity & Fixed Income Funds mutual funds. *, ** and *** indicate significance at 90%, 95% and 99%. Threshold estimates and their 99% confidence bounds (CI UP and CI Low) are reported alongside the respective statistic ($\mathrm{LR}_t$) and 99% critical value $\mathrm{LR}_{\mathrm{CV}}$ of the linearity test.