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Christos Argyropoulos, Lancaster University, University of Essex
Bertrand Candelon, Université Catholique de Louvain
Jean-Baptiste Hasse, Aix-Marseille University
Ekaterini Panopoulou, University of Essex

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Christos Argyropoulos[a,b], Bertrand Candelon[c], Jean-Baptiste Hasse[d], Ekaterini Panopoulou[b]

[a] *Lancaster University Management School, United Kingdom*
[b] *University of Essex, Essex Business School, United Kingdom*
[c] *Université Catholique de Louvain, Louvain Finance, Belgium*
[d] *Aix-Marseille University, AMSE, France*

Abstract

This paper highlights the procyclical and unstable behaviour of mutual fund returns. It proposes a novel factor model that allows for regime changes associated with macroeconomic 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 and the industrial production coincide with regimes switches in the Fama-French factors. Furthermore, the estimated regimes perfectly match 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.

Keywords:

Financial Stability; Mutual Fund Industry; Regulation; Macroprudential Framework.

JEL Classification: G18; G23; G28

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Email addresses: c.argyropoulos@lancaster.ac.uk (Christos Argyropoulos), candelonb@gmail.com (Bertrand Candelon), jb-hasse@hotmail.fr (Jean-Baptiste Hasse), a.panopoulou@essex.ac.uk (Ekaterini Panopoulou)

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 US, and 14.1 trillion (EURO) in the EU.[1] The sheer size of the asset under management and the fact that retail and institutional investors fuel the demand for mutual funds, qualify 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, on 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 US. These regulatory initiatives focused on the microeconomic dimension and relied on individual funds' reporting. Furthermore, they were imposing restrictions on investment policies in order to reduce liquidity risk, requiring also more transparency and more information, especially about financial and climate risks exposure. However, compared to the banking and insurance sectors' regulations, these attempts are incomplete as they do not take into account the macroeconomic risk. Specifically, Mugerman et al. (2019) show that regulation frameworks do not have a market risk quantification component (see Table 1 page 52). To gain an insight into the effects of macroeconomic risk on mutual funds, we

[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 (2020) about systemic risk contribution of the mutual funds industry.

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

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 of macroeconomic variables and the mutual funds' return dynamics under a non-linear specification of the Fama and French (1993) model variables. Furthermore, through these relationships, we aim to investigate whether there are unstable and pro-cyclical patterns in mutual fund performance.

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 SMB and HML are good predictors of GDP growth, while MOM plays only a minor role in predicting GDP growth. Similarly, Vassalou (2003) finds that news related to GDP growth coupled with the market factor, can explain returns as good 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 one-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 considers 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) suggest that misspecification of the relationship between the parameter and the economic 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 CAPM (ICAPM) and conditional CAPM (cCAPM) approaches mentioned above. 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 the returns for a broad set of US equity mutual funds to be unstable with respect to the parameters of an unconditionally estimated Fama and French (1993) model. We also find evidence in support of the presence of performance regimes (high-low) that coincide with the term spread, the dividend yield and the industrial production, providing therefore further evidence of procyclical behaviour. We also observe that linearity is rejected for all mutual funds categories except for large-cap funds. The different behaviour of large-cap mutual funds is consistent with Eun et al. (2008)'s results about international diversification. Indeed, the authors show that large-cap stocks tend to comove 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 regulation 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 methodology to evaluate mutual funds' performances and in particular the threshold intertemporal CAPM ($T - ICAPM$). Section 3 is devoted to the empirical analysis, whereas Section 4 concludes the paper.

2. Mutual Funds' Performances: Methodology

In this analysis, we evaluate equity mutual funds' performance, following the traditional performance literature where asset pricing models are used to identify skill in terms of abnormal returns, after controlling for various source of systematic influences. However, in our case, we focus mainly on the sources of risk and not the persistence of alpha as we are not interested in the managers' skills rather than the managers' risk taking strategy. Therefore, using the parameters of the factors of an asset pricing model, we implicitly quantify the riskiness of the mutual funds and its 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 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:

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

where $\epsilon_{i,t}$ is a zero-mean residual series and $r_{f,t}$ is the risk-free rate at time t. The estimated values of β 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 to provide 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:

$$E(r_{i,t}) - r_{f,t} = \alpha_i + \beta_{im}(E(r_{m,t}) - r_{f,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_{i,t}, \quad (2)$$

Momentum (MOM) has been identified as another pricing anomaly in the early 1990s (De Bondt and Thaler (1985); Jegadeesh and 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) have introduced a five-factor model, adding RMW (*Robust minus Weak*) and CMA (*Conservative minus Aggressive*) to proxy for the profitability and investment premium respectively. 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 these factors underlying risks remains. Indeed, Fama and French (1996) and Lewellen (1999) convene that the economic link between systematic risk and these factors remains weak: Why investing in small firms' stocks or low book-to-market stocks lead to risk premiums that should be both rewarded? Why investing in firms stocks that have a bad momentum should lead to a reward? What is the link with the macroeconomic variables and regimes ?

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) use the framework proposed by Merton (1973), relying on the Consumption CAPM and the Intertemporal CAPM (ICAPM). They proposed as validation criteria for the choice of these economic factors the ability to forecast the stock market return (via a VAR methodology) 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 investigates 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 GDP growth while

[4]MOM is often denoted WML in the literature.

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

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 license" (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 one-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 βs as follows:

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

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 one-month $T-Bill$ rates on the time-varying β. Specifically, the conditional CAPM has the following form:

$$E(R_{it}|Z_{t-1}) = \gamma_0(Z_{t-1}) + b_{im,t-1}\gamma_m(Z_{t-1}) + \epsilon_{i,t}, \tag{4}$$

where R_{it} is the rate of return of asset i between times $t-1$ and t; $b_{im,t-1}$ is the market β, Z_{t-1} is the information available at time $t-1$, $\gamma_m(Z_{t-1})$ is the price of the market β, and γ_0

is the expected return of all portfolios with a market β equal to zero. Ferson (1989) shows that (4) can be estimated using either Least Square or GMM via the simple regression:

$$E(r_{it}) - r_{ft} = \alpha_{0t} + \beta_{mt} z_{t-1} (E(r_{m,t-1}) - r_{f,t-1}) + \epsilon_{i,t}. \tag{5}$$

Several extensions have been proposed as Shanken (1990) or Ferson and Schadt (1996) who propose to modify to separate the unconditional and conditional part of systematic risk. Still, Ghysels (1998) empirically shows that cCAPM performs as poorly as CAPM: cCAPM appears to be a sophisticated but fragile model. Lewellen and Nagel (2006) analytically demonstrate that the cCAPM differs from the CAPM via its covariance among βs but that covariance cannot explain CAPM's large pricing errors.

2.3. The T-ICAPM model

As described earlier, the objective of the present paper consists of testing for the instability and the procyclical behaviour of mutual funds' performances. To this aim, we propose a Threshold-ICAPM (T-ICAPM) approach under the following form:

$$E(r_{i,t}) - r_{f,t} = \alpha_i(s_t) + \beta_{im,t}(s_t).(E(r_{m,t}) - r_{f,t}) + \beta_{SMB}(s_t).SMB_t + \beta_{i,t}(s_t)_{HML}.HML_t + \epsilon_{i,t}, \tag{6}$$

where s_t is a regime variable which is driven by the economic factor ef. If $ef_t > \gamma$ (resp. $ef_t < \gamma$) then $s_t = 1$ (resp. 0), γ being estimated. 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 α and β as well as in the factors and determine which macroeconomic 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 such factor to our proposed specification.

Model (6) can be estimated for a peculiar mutual fund (i), a cluster of homogeneous mutual funds or more generally in a panel set-up for $i = 1, ..., N$ and $t = 1, ..., T$, N, T being large and $\Sigma = \epsilon'_{i,t}\epsilon_{i,t}$ (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. Following Hansen (1996), (6) can be estimated via GLM, considering independently or simultaneously several economic variables as transition variables. The threshold estimate ($\hat{\gamma}$) is the value that maximizes the log-likelihood. As indicated by Hansen (1996), or by Andrews (1993, 1998), a trimming value is imposed to be 15% of the sample size. Confidence bounds are obtained via bootstrap in which cross-sectional structure is conserved. A Wald linearity test described in Appendix 1 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 four variables that describe the investment opportunity environment alongside four variables that describe the macroeconomic environment. Specifically, to describe the investment opportunity environment, we use the one-month $T - Bill$, the dividend yield, the term spread calculated as the ten-year government bond yield minus the 1-year treasury yield and the default spread calculated as the ten-year Baa corporate bond yield minus the yield of the ten-year government bond. For the macroeconomic environment, we use the growth of the consumer price index (CPI) and industrial production index (IPI), the level of the composite currency index (CCI) and, finally, the level of the three-component economic uncertainty index ($EPU3Comp$). Table 1 reports the descriptive statistics for the threshold variables.

For mutual fund returns, we use the monthly returns available on the CRSP survivorship bias-free mutual fund database. In total, we find $40,500$ funds reporting as least one return observation within the period of interest. To proceed with our analysis and ensure that there are sufficient returns covering the 01/1990-12/2018 period, we select the funds that reported at least 300 observations. This exclusion of new and short-lived funds leads to a sample of $3,052$ funds overall. Each mutual fund is then classified into one of 7 categories depending on its objective (growth, growth-income and income) and its size (large, medium and small capitalization). When a mutual fund cannot be precisely classified, it is excluded from the sample. We thus end up with 825 mutual funds. To create a balanced panel and to 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), we use the risk-adjusted returns and perform a 4-factor CAPM (Carhart, 1997) using a single-index model. However, our approach differs from those of previous studies, as we complete missing returns not only at the end of the sample period but also for the missing returns of mutual funds at the beginning of the sample. Indeed, we take into account newly born funds as soon as they exist for at least two years. 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. In addition, completely excluding these "newborn" funds would reinforce the issue of selection bias. 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 one-month $T - Bill$, for both the backfilled and non-backfilled cases. The descriptive statistics are similar in both samples, confirming that the backfilling process has no impact on the distribution of mutual fund returns.

Table 1: Descriptive Statistics: Threshold Variables

	T-Bill	Dividend Yield	Term Spread	Default Spread	CPI	IPI	CCI	EPU 3 Comp
Mean	0.225	2.078	1.519	2.357	2.473	1.942	105.024	107.246
St.Dev	0.191	0.590	1.033	0.751	1.279	3.937	15.321	32.899
Skew	0.294	0.829	-0.004	1.654	-0.022	-1.894	-0.541	1.009
Kurt	1.837	3.209	1.843	7.718	4.257	8.209	2.566	3.741
$Q_{1\%}$	0.000	1.140	-0.360	1.380	-1.232	-14.787	70.500	59.316
$Q_{99\%}$	0.680	3.721	3.330	5.600	6.170	8.460	128.549	194.677

Note: This table reports the descriptive statistics of the macroeconomic variables, i.e., mean, standard deviation, skewness, kurtosis, and 1% and 5% quantiles.

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
	St.Dev	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
	St.Dev	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 5% quantiles.

3.2. Preliminary Stability Tests

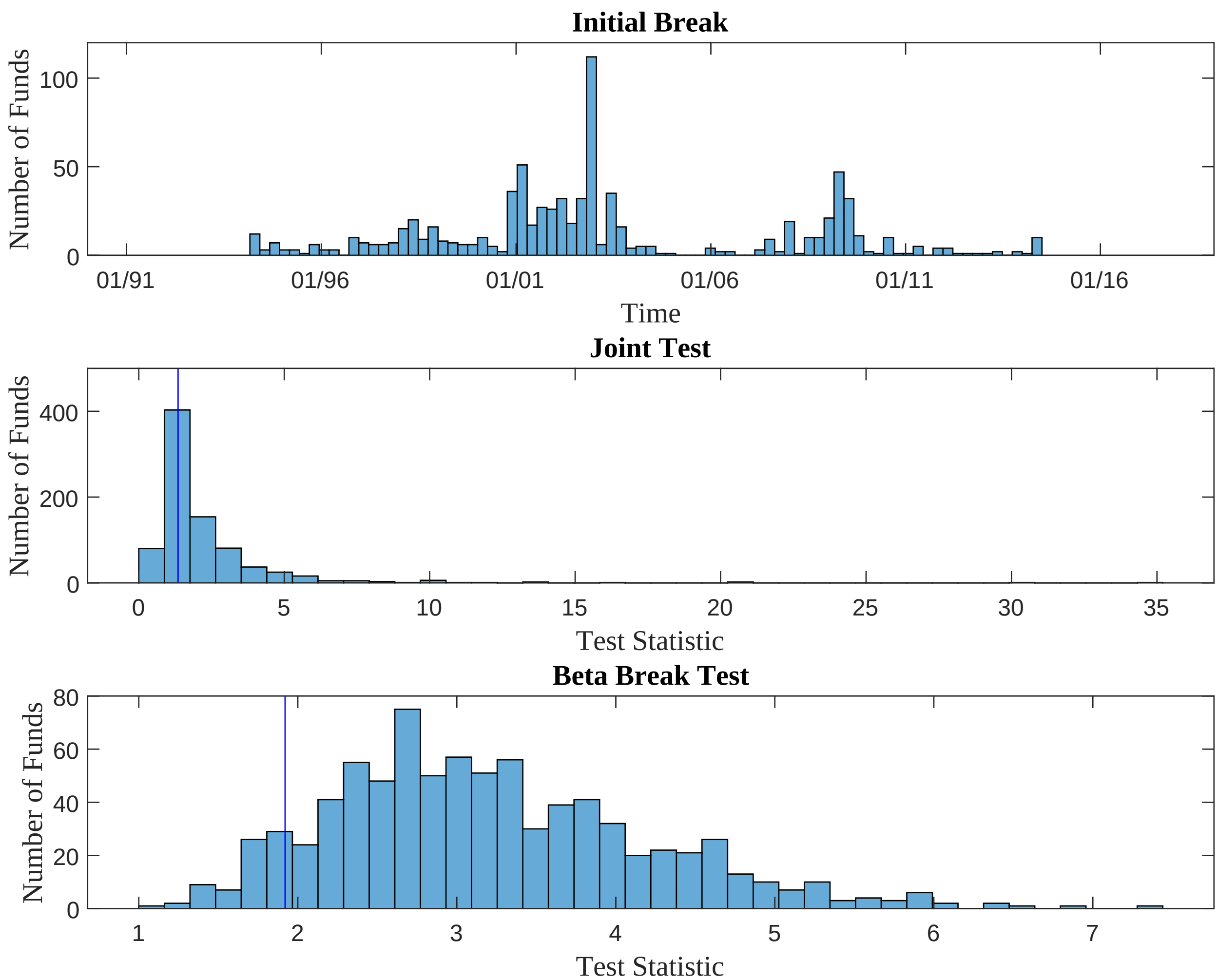
Existing ICAPM and cCAPM studies have implemented simple stability tests à la Andrews (1993) for known or unknown break dates. For example, Ghysels (1998) (in a cCAPM framework) or Vassalou (2003) and Li et al. (2006) (in an ICAPM framework) use the $SupLM$ test of Andrews (1993) to test for the stability of the SMB and HML factors in the Fama-French CAPM model for mutual funds extracted from the CRSP database for a relatively long pre-crisis period.[6] Nevertheless, these LM tests have been shown to have several limitations: they may rely on an incorrect specification of the likelihood function, as they limit the change in the parameters α and β 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 at the border of the sample. To tackle these issues, Pouliot (2016) proposed a specific stability test for ICAPM factors in individual funds. In complement to Pouliot's stability test, the bootstrap-based log likelihood ratio test, similar to that in Hansen (1996), is performed. It is important to stress again that these tests can be implemented simultaneously for all the parameters of (6) or for a restricted subset.

[6]See also Guidolin and Timmermann (2008) and Chincoli and Guidolin (2017) about SMB and HML returns instability.

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 time t, we estimate a possible point of instability for the parameters. Then, we proceeded to test the joint null hypothesis of no breaks in either alpha or betas (joint test) and the null hypothesis of no breaks in βs (beta break test). Figure (1) reports the distribution of the time of the break estimates and the test statistic values for the joint parameters of the CAPM (α and β) and for the test statistics for the sole β parameter. 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 $2009-2010$. The main reason for the rejection of the joint hypothesis seems to be a break in at least one β coefficient since, for the majority of the individual funds, the null of no breaks in the β coefficients is rejected. Similar tests have been performed when considering two thresholds and have concluded against rejecting the null hypothesis of a single threshold.

This preliminary analysis hence supports the idea that the parameters of a CAPM model are not stable over time and are subject to regime changes. This result is in line with Ghysels (1998).

Figure 1: Equity Aggregate Fund Tests for Breaks in the Parameters



Note: 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 critical values of the Pouliot (2016) joint test for all funds. The third subplot reports the histogram of the critical values 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.

3.3. Testing and Estimating the $T - ICAPM$

Our findings for both the standard ICAPM model (2) and T-ICAPM (6) for the full sample (aggregate mutual funds) are reported in Table 3. Figure 2 illustrates the threshold and shows the historical regime break. In this analysis, regimes are driven by a single macroeconomic variable (one-month $T - Bill$, dividend yield, term spread, CPI or IPI).

Note that estimation of the standard ICAPM (Panel A) confirms the Fama-French findings, i.e., the 3 factors (market, HML and SMB) are highly significant. Specifically, the sensitivity to the market risk factor (β_{rm}) is lower than 1, suggesting that, on average, mutual funds provide a hedge against market downturns. The magnitudes of the SMB and HML factor loadings are approximately one-tenth of the market loading, albeit positive and highly significant. It also turns out that the excess premium (α) is not significantly different from 0, meaning that fund managers do not have a permanent positive effect on the performance of mutual funds. Finally, the R^2 measuring the fit of the model is approximately 70%, which is relatively high for such a high-dimensional panel.

The first threshold macroeconomic variable considered is the 1-month Treasury bill ($T - Bill$), which reflects short-term investment opportunities and the monetary stance. Since the 2008 crisis and the implementation of quantitative easing (QE) policy by almost all central banks around the world,[7] the values of $T - Bill$ have been quite low. The QE regime is evident in Figure 2, Panel 1, as is the low interest rate regime in the first half of 2000. This indicates that mutual fund performance coincides with monetary policy (which is a basic result of many models such as the Dornbusch-Fisher model).[8] T-ICAPM estimates with $T - Bill$ as the transition variable are reported in Table 2. Let us recall that the upper part of the table reports the CAPM estimates over the full sample, whereas the lower part of the table shows the estimates when the transition variable exceeds the estimated threshold. First, the LR test rejects the linearity hypothesis and signals that $T - Bill$ is an adequate transition variable. Looking at the lower part of the table (CAPM estimate when $T - Bill$ is above

[7]The US Federal Reserve Bank began in November of that year to purchase 600 billion in mortgage-backed securities and stopped purchasing at the end 2014.

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

the threshold), it turns out that the QE regime does not seem to impact the relationship between mutual fund performance and the market. SMB does not appear to be affected by QE. Such a finding is also quite intuitive, as the Fed mainly bought shares in listed firms, which are by definition medium or large. Small businesses were not impacted by this policy. In contrast, mutual funds' returns are much sensitive to the HML factor when QE is not implemented (i.e., the $T - Bill$ rate is above the estimated threshold). Indeed, the massive purchase of stocks in the QE regime smooths the link to the HML factor. As a result, the excess premium turns positive (0.135) outside the QE regime, suggesting that extra return cannot be attributed to active management but instead to a higher sensitivity to the HML factor.

Looking now at the dividend yield (DY) (Figure 2, Panel B), we observe a low DY regime covering the period $2001 - 2018$ determined by an estimated threshold of 1.23%. When DY is above this estimated threshold, it appears that the sensitivity of mutual fund returns to the market is unchanged. In contrast, in the regime characterized by high DY, we observe positive factor sensitivities for the SMB but negative sensitivities for the HML factor. Such a finding regarding factor sensitivity is also 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 value stocks and thus more affected than large firms, their returns tend to be positively linked to a high dividend yield. We also observe that the excess premium (α) is negative and significantly different from 0. This signals that asset managers underperform in a regime of high dividend yield.

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 (2020) and thus should impact mutual fund performance. In Figure 2, Panel C, it is possible to clearly detect both the dot-com bubble, the 2008 crisis and the recent period. When analyzing the results of the estimation, we observe that in the high term spread regime, the sensitivity to HML is reduced, whereas the sensitivity to the SMB factor is reinforced. 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 the future performance of the economy and growth stocks leads to a more negative 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 NBER cycle dating is 0.46 ($pv < 0.01\%$). 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. This can be explained by the difference between value and growth stocks. The only difference lies in their sensitivity to market factor. Whereas sensitivity is reinforced in high-inflation regimes, it is reduced in high-growth regimes.

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.

EPU, when considering the dividend yield, is the only variable that generates statistically significant results for all factors. Both also exhibit similar behavior with respect to the signs of the coefficients. Specifically, mutual fund performance is less sensitive to HML but more sensitive to the market factor.

3.4. Testing and Estimating the $T-ICAPM$ – A composite transition variable

In a second step, we build the transition variable as a weighted average of all the macroeconomic variables. The sum of weights is constrained to be 1, but each weight is estimated following the $T-ICAPM$ parameters via a recursive procedure intended to maximize the log-likelihood. The last 2 columns of Table 2 report the $T-ICAPM$ estimates and the composite index estimated weights. Figure 3 depicts the estimated threshold and the corresponding regimes. It turns out that four out of five variables are significant: 1-month $T-Bill$, dividend yield, IPI and the term spread. These variables appear to adequately summarize the macroeconomic regime. In contrast, the weight for CPI is close to and not significantly different from 0. This finding is driven by the high degree of endogeneity of this variable. 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. The regimes defined by the composite indicator closely match the business/financial cycle, mimicking the *dotcom*, 2009 and recent sovereign debt crises. Not surprisingly, we observe in Table 2 (last two columns) that mutual fund performance is more sensitive to the SMB (in a positive way) and HML (in a negative way) factors. Such a result is also intuitive, as it mimics the results obtained for each macroeconomic variable. Again, we want to emphasize that interpretation cannot be interpreted in terms of causality.

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 objectives or the size of the mutual fund, the dependence on the macroeconomic factors may differ. In other words, it would be interesting to analyze whether the behavior of the funds is heterogeneous with respect to the transition variable. To this end, $T-ICAPM$ is estimated for each of the 7 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 macroeconomic variable and for the estimated composite index. The results are reported in Tables 3 to 8.[9] Several results can be inferred.

It turns out that the linearity hypothesis is rejected for all types of mutual funds, except for the large-cap funds. This finding indicates that macroeconomic stance is not associated with mutual fund performance. It also confirms the conclusion of Eun et al. (2008), who show that as large-cap stocks receive the dominant share of fund allocation, they become more diversified [10] and thus isolated from macroeconomic regimes. Such a result also suggests that this type of mutual funds does not trigger financial instability. Macroprudential regulation would be useless for mutual funds oriented toward large-cap funds. Such a result could also suggest that regulators require other types of mutual funds to hold a part of their holdings in large-cap assets.

[9]To save space, we do not report the 49 figures associating each type of fund to each macroeconomic transition variable, but they are available from the authors upon request.

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

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 3-factor Fama-French model 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 11. It appears that the macroeconomic stance that matters depends on the type of mutual funds considered. More in detail, the returns of medium, small-cap and growth-income mutual funds evolve according to a composite index integrating the five macroeconomic variables. The largest weight is taken by the term spread. In contrast, the income mutual funds' returns do 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. Growth-income funds have a mixed position, as their composite index simultaneously includes the dividend yield and the industrial production (but not inflation). Finally, the returns of the mixed funds tend to vary with Treasury Bills. Therefore, all these funds present returns dependent on macroeconomic conditions. A macroprudential regulatory framework would thus be able to improve financial stability. Nevertheless, it cannot be uniform but should instead take into account the specificities of types of mutual funds.

Table 3: Equity Aggregate Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	-0.088	0.073	-0.100	0.080	0.440***	0.161	-0.006	0.098	0.074	0.073
$\hat{\beta_{r^m}}$	0.893***	0.010	0.909***	0.012	0.882***	0.045	0.902***	0.022	0.896***	0.027
$\hat{\beta}_{SMB}$	0.114***	0.015	0.148***	0.013	0.065*	0.038	0.107***	0.021	0.112***	0.021
$\hat{\beta}_{HML}$	0.078***	0.018	0.002	0.017	0.157 ***	0.063	0.185***	0.029	0.196***	0.033
$\hat{\alpha_s}$			0.023	0.059	-0.562***	0.154	-0.113	0.076	-0.136*	0.077
$\hat{\beta}_{s,r^m}$			-0.008	0.019	0.014	0.046	-0.001	0.024	0.006	0.028
$\hat{\beta}_{s,SMB}$			-0.023	0.023	0.094***	0.039	0.050***	0.024	0.044**	0.024
$\hat{\beta}_{s,HML}$			0.164***	0.030	-0.141***	0.064	-0.173***	0.032	-0.197***	0.036
Thresholds			0.342		1.230		0.490		-0.450	
CI Up			0.372		1.280		0.614		-0.429	
CI Low			0.296		1.230		0.441		-0.467	
LR_t			2618.480		4789.366		3555.314		4524.951	
LR_{CV}			414.217		368.670		398.192		362.576	
R^2	0.697		0.700		0.702		0.701		0.700	

Panel B	CPI		IPI		EPU 3 Comp		Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e.*
$\hat{\alpha}$	-0.117	0.082	-0.086	0.090	-0.093	0.077	1M T-Bill	0.240
$\hat{\beta}_{r^m}$	0.881***	0.009	0.921***	0.020	0.884***	0.010	Dividend Yield	0.360
$\hat{\beta}_{SMB}$	0.170***	0.013	0.137***	0.026	0.117***	0.015	Term Spread	0.320
$\hat{\beta}_{HML}$	0.014	0.016	-0.022	0.025	0.112***	0.017	CPI	0.000
$\hat{\alpha_s}$	0.057	0.053	-0.003	0.071	-0.065	0.064	IPI	0.080
$\hat{\beta}_{s,r^m}$	0.044***	0.017	-0.030	0.022	0.053***	0.019		
$\hat{\beta}_{s,SMB}$	-0.073***	0.022	-0.018	0.030	0.004	0.030		
$\hat{\beta}_{s,HML}$	0.112***	0.030	0.138***	0.030	-0.171***	0.029		
Thresholds	2.620		-0.594		133.410			
CI Up	2.830		1.023		140.010			
CI Low	2.165		-1.369		125.820			
LR_t	1964.965		1615.882		2310.075			
LR_{CV}	469.895		410.800		406.3124			
R^2	0.699		0.699		0.699			

Note: This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 4: Growth Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	-0.018	0.107	-0.06 1	0.108	0.520	0.177	0.110	0.136	0.043	0.078
$\hat{\beta}_{r^m}$	0.986***	0.010	0.990***	0.010	0.955***	0.050	0.984***	0.023	0.993***	0.021
$\hat{\beta}_{SMB}$	0.065***	0.016	0.087***	0.015	0.009	0.045	0.048**	0.029	-0.016	0.017
$\hat{\beta}_{HML}$	-0.042**	0.018	-0.073***	0.019	0.004	0.061	0.029	0.028	0.046**	0.026
$\hat{\alpha_s}$			0.214***	0.082	-0.569***	0.151	-0.170**	0.084	-0.127	0.083
$\hat{\beta}_{s,r^m}$			0.014	0.018	0.036	0.050	0.010	0.025	-0.002	0.023
$\hat{\beta}_{s,SMB}$			-0.057**	0.028	0.096**	0.046	0.059**	0.031	0.113***	0.021
$\hat{\beta}_{s,HML}$			0.134***	0.035	-0.102*	0.063	-0.123***	0.033	-0.139***	0.031
Thresholds			0.430		1.230		0.482		-0.480	
CI Up			0.430		1.300		0.820		-0.465	
CI Low			0.421		1.225		0.404		-0.480	
LR_t			784.639		1344.538		888.658		1348.637	
LR_{CV}			168.035		161.900		179.227		153.608	
R^2	0.775		0.777		0.779		0.778		0.778	

Panel B	CPI		IPI		EPU 3 Comp				Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*				
$\hat{\alpha}$	-0.050	0.111	-0.032	0.124	-0.005	0.110			1M T-Bill	0.120
$\hat{\beta}_{r^m}$	0.974***	0.010	1.015***	0.017	0.978***	0.011			Dividend Yield	0.200
$\hat{\beta}_{SMB}$	0.100***	0.012	0.088***	0.025	0.065***	0.016			Term Spread	0.400
$\hat{\beta}_{HML}$	-0.082***	0.017	-0.123***	0.029	-0.016	0.017			CPI	0.080
$\hat{\alpha_s}$	0.079	0.068	0.019	0.081	-0.133**	0.074			IPI	0.200
$\hat{\beta}_{s,r^m}$	0.047***	0.019	-0.034**	0.020	0.043***	0.018				
$\hat{\beta}_{s,SMB}$	-0.058**	0.029	-0.019	0.030	0.023	0.030				
$\hat{\beta}_{s,HML}$	0.090***	0.032	0.109 ***	0.034	-0.144***	0.033				
Thresholds	2.970		-0.594		133.410					
CI Up	3.000		2.165		140.670					
CI Low	2.220		-1.369		124.170					
LR_t	523.456		390.650		618.224					
LR_{CV}	178.721		174.835		172.973					
R^2	0.777		0.776		0.777					

Note: This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 5: Growth-Income Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	-0.094	0.081	-0.091	0.090	0.068	0.163	-0.105	0.098	0.003	0.090
$\hat{\beta}_{r^m}$	0.913***	0.010	0.938***	0.008	0.898***	0.038	0.923***	0.022	0.914***	0.027
$\hat{\beta}_{SMB}$	-0.073***	0.019	-0.037***	0.011	-0.086***	0.031	-0.071***	0.021	-0.092***	0.022
$\hat{\beta}_{HML}$	0.178 ***	0.018	0.078***	0.013	0.303***	0.045	0.302***	0.024	0.316***	0.034
$\hat{\alpha}_s$			-0.035	0.062	-0.190	0.156	0.002	0.070	-0.111	0.093
$\hat{\beta}_{s,r^m}$			-0.019	0.019	0.027	0.039	0.004	0.023	0.008	0.028
$\hat{\beta}_{s,SMB}$			-0.023	0.023	0.060**	0.032	0.045**	0.023	0.073***	0.024
$\hat{\beta}_{s,HML}$			0.205***	0.025	-0.211***	0.047	-0.214***	0.026	-0.221***	0.036
Thresholds			0.320		1.370		0.721		-0.505	
CI Up			0.356		1.425		0.903		-0.500	
CI Low			0.290		1.350		0.614		-0.505	
LR_t			1877.816		2717.058		2166.928		2809.690	
LR_{CV}			169.342		146.544		166.746		136.399	
R^2	0.843		0.849		0.851		0.849		0.851	

Panel B	CPI		IPI		EPU 3 Comp		Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*		
$\hat{\alpha}$	-0.135*	0.090	-0.065	0.094	-0.110	0.083	1M T-Bill	0.240
$\hat{\beta}_{r^m}$	0.917***	0.009	0.919***	0.016	0.911***	0.012	Dividend Yield	0.280
$\hat{\beta}_{SMB}$	0.002	0.013	-0.015	0.020	-0.069***	0.017	Term Spread	0.400
$\hat{\beta}_{HML}$	0.096***	0.016	0.067***	0.021	0.225***	0.018	CPI	0.000
$\hat{\alpha}_s$	0.071*	0.052	-0.052	0.065	-0.015	0.052	IPI	0.080
$\hat{\beta}_{s,r^m}$	0.008	0.015	0.003	0.019	0.038**	0.017		
$\hat{\beta}_{s,SMB}$	-0.106***	0.023	-0.058**	0.026	0.030	0.028		
$\hat{\beta}_{s,HML}$	0.122***	0.027	0.156***	0.027	-0.183***	0.024		
Thresholds	2.620		-0.594		125.160			
CI Up	2.660		0.140		137.205			
CI Low	2.240		-1.410		124.170			
LR_t	1239.708		913.823		1226.009			
LR_{CV}	199.485		185.421		216.914			
R^2	0.847		0.846		0.847			

Note: This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 6: Income Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	0.181*	0.120	0.191*	0.111	0.098	0.206	0.185*	0.143	-0.060	0.157
$\hat{\beta}_{r^m}$	0.857***	0.013	0.912 ***	0.012	0.825***	0.054	0.875***	0.026	0.832***	0.050
$\hat{\beta}_{SMB}$	-0.076***	0.025	-0.051***	0.018	-0.057*	0.040	-0.081***	0.029	-0.064**	0.038
$\hat{\beta}_{HML}$	0.308***	0.024	0.152***	0.017	0.506***	0.059	0.493 ***	0.036	0.503***	0.056
$\hat{\alpha_s}$			-0.051	0.080	0.058	0.179	-0.018	0.109	-0.017	0.160
$\hat{\beta}_{s,r^m}$			-0.063***	0.023	0.059	0.055	-0.004	0.029	0.053	0.051
$\hat{\beta}_{s,SMB}$			0.003	0.035	0.027	0.042	0.072**	0.033	0.033	0.040
$\hat{\beta}_{s,HML}$			0.294***	0.034	-0.332***	0.061	-0.298***	0.040	-0.330***	0.058
Thresholds			0.301		1.440		0.490		-0.514	
CI Up			0.320		1.460		0.589		-0.486	
CI Low			0.256		1.380		0.441		-0.514	
LR_t			1545.182		2150.534		1626.572		2158.020	
LR_{CV}			121.108		109.514		131.461		109.880	
R^2	0.833		0.847		0.852		0.848		0.851	

Panel B	CPI		IPI		EPU 3 Comp		Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e.*
$\hat{\alpha}$	0.164	0.111	0.277**	0.137	0.154	0.122	1M T-Bill	0.280
$\hat{\beta}_{r^m}$	0.864***	0.014	0.864***	0.025	0.859***	0.015	Dividend Yield	0.560
$\hat{\beta}_{SMB}$	0.018	0.020	-0.031	0.030	-0.065***	0.024	Term Spread	0.160
$\hat{\beta}_{HML}$	0.195***	0.021	0.158***	0.029	0.378***	0.025	CPI	0.000
$\hat{\alpha_s}$	0.009	0.075	-0.135	0.100	-0.012	0.074	IPI	0.000
$\hat{\beta}_{s,r^m}$	0.008	0.023	0.007	0.029	0.048**	0.026		
$\hat{\beta}_{s,SMB}$	-0.126***	0.034	-0.039	0.039	0.010	0.042		
$\hat{\beta}_{s,HML}$	0.175***	0.036	0.215***	0.038	-0.259***	0.033		
Thresholds	2.620		-0.594		125.160			
CI Up	2.690		1.689		133.410			
CI Low	2.240		-1.355		124.170			
LR_t	805.258		607.122		859.713			
LR_{CV}	156.491		166.257		146.646			
R^2	0.841		0.839		0.841			

Note:This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 7: Large-Cap Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	-0.015	0.022	-0.084	0.070	0.208	0.175	0.136	0.162	-0.016	0.019
$\hat{\beta}_{r^m}$	1.007***	0.017	0.993***	0.004	1.056***	0.095	1.063***	0.091	0.989***	0.006
$\hat{\beta}_{SMB}$	-0.161***	0.017	-0.164***	0.010	-0.129***	0.055	-0.121**	0.068	-0.171***	0.011
$\hat{\beta}_{HML}$	0.036***	0.012	0.022***	0.007	0.105	0.087	0.130*	0.098	0.032***	0.010
$\hat{\alpha}_s$			0.395	0.334	-0.294	0.239	-0.206	0.227	0.625	0.602
$\hat{\beta}_{s,r^m}$			0.133	0.149	-0.054	0.095	-0.064	0.091	0.195	0.175
$\hat{\beta}_{s,SMB}$			0.094	0.149	-0.043	0.056	-0.041	0.069	0.272	0.294
$\hat{\beta}_{s,HML}$			0.189	0.200	-0.090	0.087	-0.119	0.098	0.332	0.340
Thresholds			0.430		1.640		0.697		0.675	
CI Up			0.430		2.000		2.000		0.675	
CI Low			0.000		1.170		0.350		-0.627	
LR_t			16.862		7.933		7.639		30.950	
LR_{CV}			218.913		154.725		191.299		251.111	
R^2	0.322		0.323		0.323		0.323		0.322	

Panel B	CPI		IPI		EPU 3 Comp		Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*		
$\hat{\alpha}$	0.036	0.064	-0.078	0.071	0.027	0.153	1M T-Bill	0.360
$\hat{\beta}_{r^m}$	1.025***	0.031	0.986***	0.006	1.196***	0.208	Dividend Yield	0.280
$\hat{\beta}_{SMB}$	-0.091**	0.051	-0.144***	0.009	0.014	0.168	Term Spread	0.000
$\hat{\beta}_{HML}$	-0.012	0.017	0.017*	0.012	0.163	0.160	CPI	0.000
$\hat{\alpha}_s$	-0.099	0.131	0.189	0.196	-0.087	0.197	IPI	0.360
$\hat{\beta}_{s,r^m}$	-0.033	0.032	0.075	0.070	-0.204	0.208		
$\hat{\beta}_{s,SMB}$	-0.093	0.052	0.002	0.056	-0.192	0.168		
$\hat{\beta}_{s,HML}$	0.053***	0.021	0.087	0.072	-0.132	0.160		
Thresholds	2.220		4.000		75.330			
CI Up	3.000		4.000		140.670			
CI Low	1.000		-1.437		75.000			
LR_t	7.704		7.741		21.637			
LR_{CV}	170.441		166.436		231.848			
R^2	0.323		0.323		0.324			

Note: This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 8: Medium-Cap Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	-0.095	0.120	-0.186	0.116	0.911**	0.445	0.085	0.231	0.058	0.182
$\hat{\beta}_{r^m}$	1.029***	0.019	1.024***	0.019	1.169***	0.124	1.113***	0.050	1.128***	0.052
$\hat{\beta}_{SMB}$	0.315***	0.032	0.353***	0.028	0.299***	0.108	0.333***	0.083	0.147***	0.041
$\hat{\beta}_{HML}$	-0.071**	0.031	-0.120***	0.032	0.162	0.150	0.163**	0.076	0.125**	0.064
$\hat{\alpha_s}$			0.442***	0.174	-1.076***	0.420	-0.254	0.208	-0.112	0.189
$\hat{\beta}_{s,r^m}$			0.100**	0.050	-0.139	0.125	-0.087*	0.053	-0.102**	0.055
$\hat{\beta}_{s,SMB}$			-0.091*	0.069	0.072	0.109	0.038	0.085	0.231***	0.044
$\hat{\beta}_{s,HML}$			0.254***	0.103	-0.324**	0.152	-0.322***	0.080	-0.286***	0.068
Thresholds			0.430		1.230		0.424		-0.480	
CI Up			0.430		1.320		0.672		-0.465	
CI Low			0.421		1.225		0.375		-0.480	
LR_t			542.161		903.708		656.577		1043.384	
LR_{CV}			138.379		125.577		128.014		113.479	
R^2	0.810		0.815		0.819		0.817		0.820	

Panel B	CPI		IPI		EPU 3 Comp		Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e.*
$\hat{\alpha}$	-0.130	0.117	-0.147	0.151	-0.083	0.131	1M T-Bill	0.120
$\hat{\beta}_{r^m}$	1.006***	0.018	1.082***	0.032	1.023***	0.027	Dividend Yield	0.200
$\hat{\beta}_{SMB}$	0.370***	0.020	0.315***	0.046	0.312 ***	0.038	Term Spread	0.400
$\hat{\beta}_{HML}$	-0.128***	0.025	-0.187***	0.041	-0.019	0.044	CPI	0.080
$\hat{\alpha_s}$	0.095	0.132	0.076	0.137	-0.072	0.110	IPI	0.200
$\hat{\beta}_{s,r^m}$	0.086**	0.038	-0.065**	0.038	0.014	0.036		
$\hat{\beta}_{s,SMB}$	-0.096*	0.072	0.012	0.059	0.068*	0.050		
$\hat{\beta}_{s,HML}$	0.131**	0.066	0.156***	0.055	-0.135***	0.055		
Thresholds	2.990		-0.594		115.920			
CI Up	3.000		3.443		138.690			
CI Low	2.080		-1.410		79.785			
LR_t	274.649		184.918		178.749			
LR_{CV}	132.737		149.194		146.591			
R^2	0.812		0.811		0.811			

Note:This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 9: Small-Cap Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	-0.048	0.083	-0.097	0.086	0.582	0.406	0.009	0.172	-0.021	0.162
$\hat{\beta}_{r^m}$	0.963***	0.015	0.964***	0.015	1.031***	0.113	1.021***	0.036	1.023***	0.043
$\hat{\beta}_{SMB}$	0.556***	0.022	0.581***	0.024	0.500***	0.084	0.570***	0.053	0.476***	0.039
$\hat{\beta}_{HML}$	0.139***	0.025	0.103***	0.025	0.273**	0.150	0.364***	0.087	0.314***	0.058
$\hat{\alpha}_s$			0.215*	0.153	-0.668**	0.405	-0.092	0.161	-0.063	0.167
$\hat{\beta}_{s,r^m}$			0.042	0.043	-0.069	0.114	-0.061*	0.039	-0.058	0.045
$\hat{\beta}_{s,SMB}$			-0.061	0.064	0.115*	0.086	0.039	0.056	0.115***	0.044
$\hat{\beta}_{s,HML}$			0.173**	0.100	-0.207*	0.151	-0.293***	0.090	-0.252***	0.061
Thresholds			0.430		1.230		0.366		-0.480	
CI Up			0.430		1.410		0.432		-0.465	
CI Low			0.381		1.220		0.350		-0.480	
LR_t			507.508		1184.278		1076.756		1246.361	
LR_{CV}			212.296		222.381		177.712		166.780	
R^2	0.769		0.771		0.774		0.774		0.774	

Panel B	CPI		IPI		EPU 3 Comp				Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*				
$\hat{\alpha}$	-0.057	0.089	-0.082	0.116	-0.042	0.089			1M T-Bill	0.120
$\hat{\beta}_{r^m}$	0.938***	0.013	1.004***	0.029	0.948***	0.016			Dividend Yield	0.200
$\hat{\beta}_{SMB}$	0.615***	0.017	0.556***	0.040	0.563***	0.023			Term Spread	0.400
$\hat{\beta}_{HML}$	0.088***	0.019	0.033	0.028	0.168***	0.030			CPI	0.080
$\hat{\alpha}_s$	0.020	0.106	0.049	0.109	-0.104	0.099			IPI	0.200
$\hat{\beta}_{s,r^m}$	0.087***	0.029	-0.048*	0.032	0.076***	0.030				
$\hat{\beta}_{s,SMB}$	-0.107***	0.042	0.012	0.047	-0.042	0.049				
$\hat{\beta}_{s,HML}$	0.115**	0.056	0.146 ***	0.041	-0.166***	0.040				
Thresholds	3.000		-0.594		133.410					
CI Up	3.000		2.777		140.670					
CI Low	2.500		-1.410		114.930					
LR_t	575.867		323.914		406.850					
LR_{CV}	202.139		228.120		228.120					
R^2	0.772		0.770		0.771					

Note: This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 10: Mixed Equity & Fixed Income Funds

Panel A	Benchmark		1M T-Bill		Dividend Yield		Term Spread: 10Y-1Y		Composite Index	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*
$\hat{\alpha}$	-0.058	0.053	-0.065	0.066	-0.068	0.079	-0.093**	0.053	-0.079	0.063
$\hat{\beta}_{r^m}$	0.651***	0.013	0.679***	0.020	0.615***	0.024	0.641***	0.012	0.734***	0.023
$\hat{\beta}_{SMB}$	0.011	0.012	0.019	0.022	0.034**	0.018	0.026**	0.013	-0.005	0.026
$\hat{\beta}_{HML}$	0.082***	0.020	-0.013	0.027	0.175***	0.030	0.147***	0.021	-0.078***	0.027
$\hat{\alpha}_s$			-0.032	0.061	-0.010	0.080	0.055	0.059	0.081	0.070
$\hat{\beta}_{s,r^m}$			-0.022	0.022	0.055**	0.027	0.038**	0.022	-0.091***	0.025
$\hat{\beta}_{s,SMB}$			0.013	0.025	-0.015	0.023	-0.001	0.024	0.035	0.028
$\hat{\beta}_{s,HML}$			0.172***	0.032	-0.160***	0.036	-0.141***	0.033	0.219***	0.031
Thresholds			0.221		1.455		1.175		-0.414	
CI Up			0.331		1.575		1.720		-0.327	
CI Low			0.161		1.370		0.944		-0.475	
LR_t			899.390		1108.622		788.964		1500.143	
LR_{CV}			200.841		208.665		182.089		168.886	
R^2	0.655		0.660		0.662		0.660		0.661	

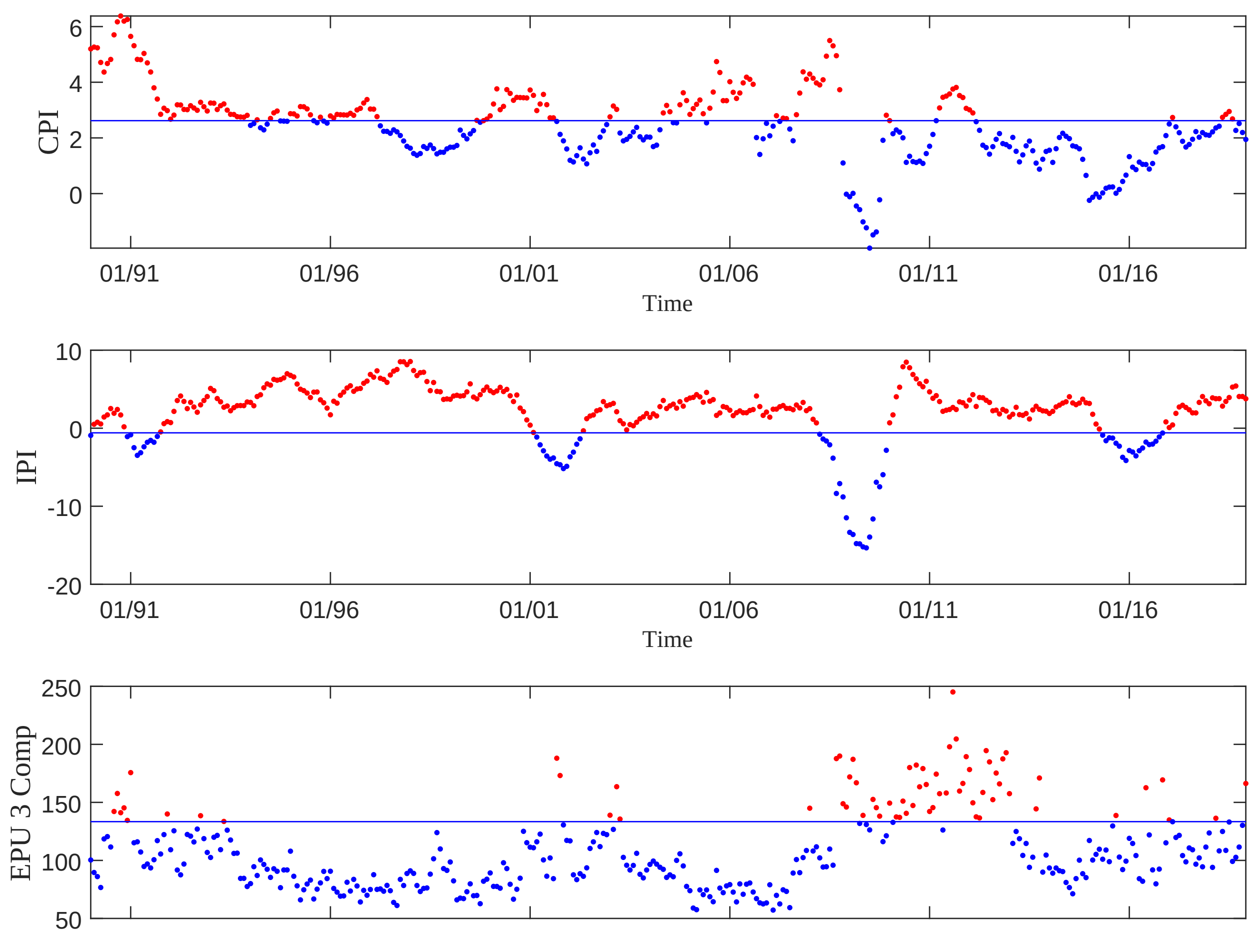
Panel B	CPI		IPI		EPU 3 Comp		Index Composition	
	Estimates	*s.e.*	Estimates	*s.e*	Estimates	*s.e.*		
$\hat{\alpha}$	-0.033	0.055	-0.035	0.107	-0.083**	0.047	1M T-Bill	0.560
$\hat{\beta}_{r^m}$	0.633***	0.011	0.691***	0.030	0.640***	0.009	Dividend Yield	0.080
$\hat{\beta}_{SMB}$	0.051***	0.019	0.025	0.036	0.018**	0.010	Term Spread	0.120
$\hat{\beta}_{HML}$	0.021	0.021	-0.020	0.037	0.124***	0.015	CPI	0.000
$\hat{\alpha}_s$	-0.060	0.059	-0.023	0.097	0.025	0.093	IPI	0.240
$\hat{\beta}_{s,r^m}$	0.057***	0.021	-0.048*	0.031	0.072***	0.027		
$\hat{\beta}_{s,SMB}$	-0.043**	0.023	-0.008	0.037	-0.026	0.040		
$\hat{\beta}_{s,HML}$	0.123***	0.033	0.138***	0.040	-0.208***	0.038		
Thresholds	2.590		-0.594		133.740			
CI Up	2.820		0.752		139.515			
CI Low	2.005		-1.369		125.490			
LR_t	630.790		620.637		1181.157			
LR_{CV}	187.165		182.891		162.247			
R^2	0.659		0.659		0.662			

Note: This table reports the GLS estimates of the T-ICAPM model considering the different macroeconomic transition variables and a composite index. Estimates and standard errors (*s.e.*) are reported. *, ** 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.

Table 11: Composition of the Composite Index

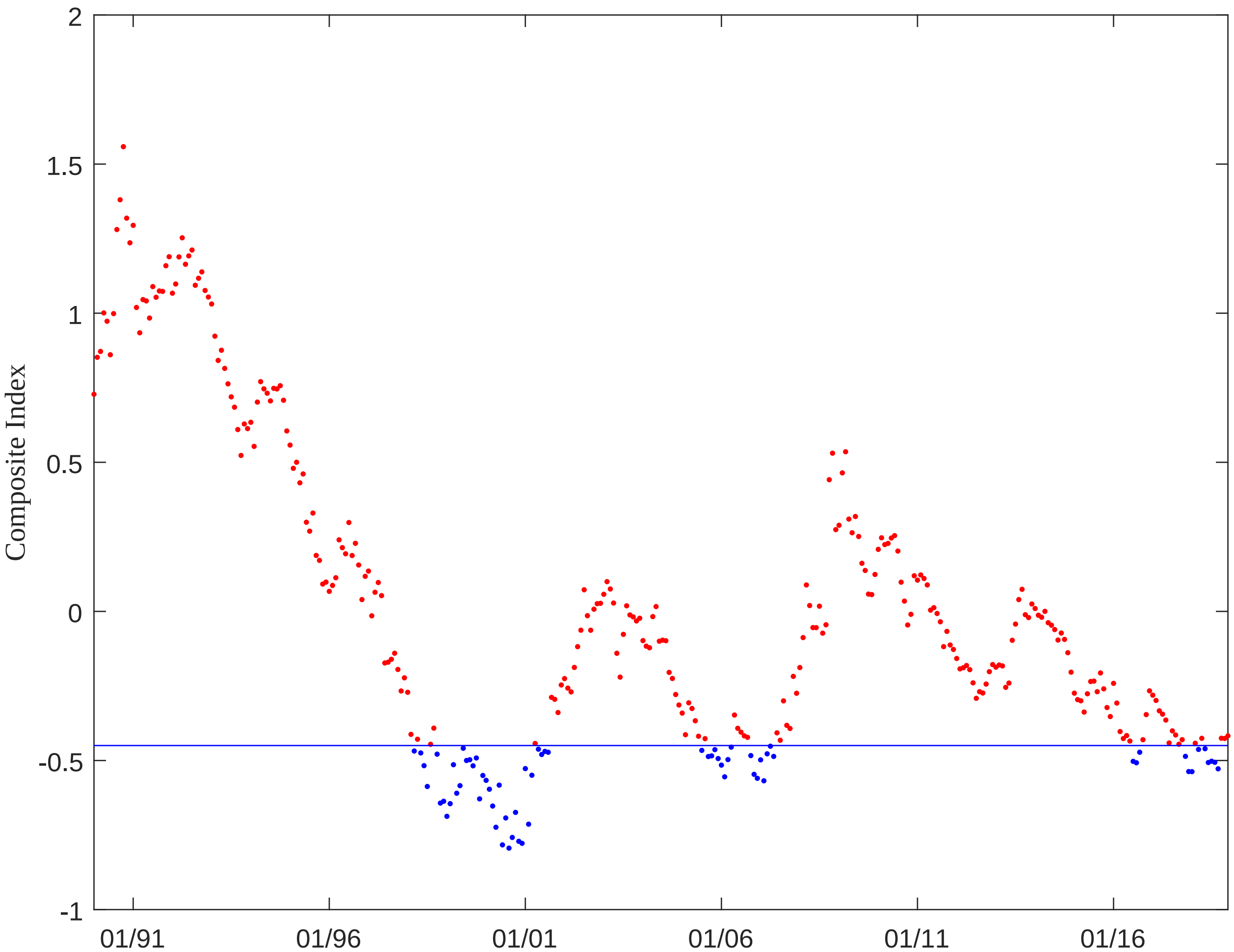
	GFunds	GIFunds	IF	MCap	SCap	Mixed E
$T - Bill$	0.120	0.200	0.280	0.120	0.120	0.560
DY	0.200	0.280	0.500	0.200	0.200	0.080
$T - spread$	0.400	0.400	0.160	0.400	0.400	0.120
CPI	0.080	0.000	0.000	0.080	0.080	0.000
IPI	0.200	0.080	0.000	0.200	0.200	0.240

Figure 2: Equity Aggregate Fund Threshold and Regime Estimates



Note: The figure reports the evolution around the estimated threshold of the CPI growth rate, IPI growth rate and term spread variables respectively.

Figure 3: Equity Aggregate Fund Test Threshold and Regime Estimates.



Note: The figure reports the evolution around the estimated threshold of the composite index.

4. Conclusion

This paper demonstrates that mutual fund performance is unstable and 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 variables. Using a dataset including the returns of 825 US equity mutual funds over a period of 30 years, we find that linearity in the traditional Fama-French model is rejected for most 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 and industrial production. Moreover, regime shift dates almost perfectly match financial crises and economic downturns. The only exception is observed for large-cap mutual funds, which are more diversified and thus less sensitive to reversals in macroeconomic conditions.

Coupled with the systemic role of asset managers, such unstable and procyclical features constitute a threat to financial stability. 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). Procyclical and unstable characteristics hence constitute a major risk for the whole financial industry.

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. Specifically, regulators should condition the prudential rules (e.g., leverage ratio, risk exposure and diversification risk) on macroeconomic stances. Another possible approach would be to oblige asset managers to hold a part of their portfolios in large-cap funds, as these investments are not sensitive to economic regime changes because of their diversification abilities.

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 US, 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 these rules in the regular stress tests developed by the European Securities Market Authorities (ESMA) or in Financial Sector Assessment Program (FSAP) of the International Monetary Fund and the World Bank. Such a practice would help to monitor the mutual funds' sensitivity to the macroeconomic stances.

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Appendix 1: 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), i.e., without a threshold (under the null hypothesis of linearity [H_0]) and the log-likelihood under the alternative (LL_1), i.e., 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:

- (1) Estimate (6) regarding the regressors and the threshold as fixed. Save the historical residuals $(\epsilon_{i,1}, ..., \epsilon_{i,n})$ and create a multivariate empirical distribution function, $EF_i(t)$.

- (B1) Draw bootstrapped residuals $(\epsilon^*_{i,1}, ..., \epsilon^*_{i,n})$ 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 $y_{i,1} = E(r_{it}) - r_{ft}$, $(y^*_{i,1}, ..., y^*_{i,n})$ 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 $\alpha\%$ (CV_α) as $\alpha\%.Boo$ The null of linearity is not rejected if the test statistic (ST) is below (CV_α).

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

- (1) Estimate equation (6) regarding the regressors and the threshold as fixed. Save the historical residuals $(\epsilon_{i,1}, ..., \epsilon_{i,n})$ and create a multivariate empirical distribution function $EF_i(t)$.

- (B1) Draw the bootstrapped residuals $(\epsilon^*_{i,1}, ..., \epsilon^*_{i,n})$ in $EF_i(t)$. Note that we draw vertical blocks to preserve the cross-sectional dependence of the panel.
- (B2) Build a bootstrapped pseudovariable $(y^*_{i,1}, ..., y^*_{i,n})$ using equation (**??**).
- (B3) Estimate a threshold $(\hat{\gamma}*)$ using the bootstrapped variable $(y^*_{i,1}, ..., y^*_{i,n})$.
- (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 $(\hat{\gamma})$.